# RISING ABOVE THE DELUGE

UNIVERSITY OF MICHIGAN

Prepared by Taubman College of Architecture and Urban Planning Capstone, Winter 2022

# ABOUT THIS PROJECT

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

# ACKNOWLEDGEMENTS

Our team would like to acknowledge all the support and resources provided by our client, the National Disaster Preparedness Training Center at the University of Hawai'i. In addition we would like to ackowledge Taubman College of Architecture and Urban Planning for providing the support necessary to make this project happen. Lastly, we would like to extend our sincerest gratitudes to all our parnters in Louisiana who provided their input and knowledge about disaster recovery in their communities.

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## SPECIAL THANKS TO:

Cajun Navy
Dr. Robert Collins, Dillard University
Jefferson Parish Council on Aging
lowernine.org
New Orleans Preservation Coalition
NOLA Ready
Tab Troxler, St. Charles Parish
The Descendants Project
United Houma Nation

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# BOOK ONE

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# PLANNING AND RESILIENCE:

*Opportunities in Early Disaster Recovery*

# EXECUTIVE SUMMARY

Early recovery is a critical juncture point in the disaster cycle to uplift people from hardship and instability while preparing, communicating, and understanding the geospatial terrain of damage. To better understand early recovery, our team set out on a field visit to Southeastern Louisiana to gather fundamental knowledge about gaps in early recovery that exist within communities. In speaking with a range of stakeholders, including residents, organizations, and government officials, fractures began to emerge that illuminated the gaps that were stalling early recovery functions. Our takeaways revealed the distrust of institutional support, voids in services, strained communication networks, and uncoordinated damage assessment methods. These emerging themes contextualized the complex process of early disaster recovery that includes a multitude of actors and specialties.

Urban planners are in a unique position to align the functions and actors within early disaster recovery, yet their role has been limited. In bringing planning to the forefront of early disaster recovery, we can shorten the time for restoration of critical services and meet long-term resilience goals. Drawing from our field visit experiences, in conjunction with our research, we developed three takeaways for innovation within the field, specifically at the intersection of planning and early disaster recovery. These include planners as intermediaries, the merging of technology and local support, and the use of damage assessments.

## 1.1 Introduction

As global temperatures continue to rise, coastal communities are bearing the brunt of the impacts of climate change. More intense storms, rising sea levels, and extreme heat are just a few of the impacts that have placed communities at greater risk. This is true of Louisiana, where the lower parishes have been subject to repeated climate disasters, most recently Hurricane Ida in August 2021. The Gulf of Mexico is predicted to experience up to two feet of sea level rise by 2050, and storms will continue to become more frequent and more powerful, threatening the displacement of entire coastal communities.[1] The frequency of severe weather events can leave certain communities in a constant state of recovery with each disaster compounded by the last. Further, many communities find themselves without the resources or tools to properly recover and build resiliency.

Recovery is a complex process involving many interconnected functions that fall within social, environmental, and built systems. Each function plays an important role in bringing communities out of distress and back to a functional state. Urban planners are at the intersection of many of these cross-cutting fields, yet their role in early recovery has been limited. Additionally, planners are often situated at the local or regional level, allowing them to work closely with communities and conduct field work. The absence or limited role of planning in early recovery and the unpredictable nature of disasters produces unplanned activities that can further harm vulnerable communities. In bringing planning to the forefront of early disaster recovery, timelines for the restoration of critical services can be shortened and long-term resilience goals can be met.[2] Through exposing these critical gaps in the early recovery phase, this paper aims to outline juncture points in which urban planners can intervene for increased decision making support.

## 1.2 Early Disaster Recovery

Early recovery occurs just after emergency relief and life-saving support following a natural disaster but before long-term recovery efforts. In the emergency phase of recovery, first responders execute immediate disaster response decision making to address emergency needs, such as medical attention or evacuation assistance. On the contrary, long-term recovery is a period of infrastructure and housing reconstruction, workforce development, and, in general, large-scale programs. Long-term recovery entails significant rehabilitation to the urban environment as funded through large grant programs and massive aid packages. Early recovery, therefore, represents a middle ground between emergency needs and long-term projects. In this stage of recovery, local disaster professionals offer cash assistance, rental stipends, food distribution, and temporary housing assistance.[3] The motivations of this stage are to protect people from continual hardship and instability while preparing, communicating, and understanding the geospatial terrain of damage. Early disaster recovery toes a fine line between balancing speed in resolving immediate damage, and addressing long-term disaster goals that promote resilience. While early recovery is currently understudied and seemingly inefficient, this period of rebuilding programs and redevelopment has the potential to increase overall recovery effectiveness and instill greater resilience in communities.[4]

Organizations such as the National Disaster Preparedness Training Center (NDPTC) at the University of Hawai'i at Manoa offer tools, workshops, and training materials to educate and prepare local communities and responders for natural disasters. With interests in federally managed programs and local community capacity building, these organizations can provide fundamental training for each stage of recovery. To aid in early disaster recovery, the NDPTC is currently developing tools and training designed to be leveraged in this disaster period. One of these tools is the Rapid Integrated Damage assessment (RIDA), a method intended to intervene in disaster management for improved discovery and prioritization of needs in communities. The mission of this project is to generate innovative, equitable, transferable, and actionable solutions that enhance on-street image capture and satellite imagery machine learning processes while integrating social methods that can offer insights into vulnerabilities and social assets.

To understand the organization's role, and other disaster recovery roles at large, we looked toward the lower parishes in Louisiana that have dealt with and recovered from a series of natural disasters. Using fieldwork and on-the-ground experiences of community restoration, we uncovered what early recovery looks like, how disaster professionals alleviate obstacles, and what tools are needed to increase recovery speeds through decision making support.

## 1.3 Hurricane Ida and Louisiana as a Case

To better understand early recovery, our team of University of Michigan graduate students visited Southeastern Louisiana in February 2022 to observe damage and recovery efforts through talking with residents, organizations, and officials who experienced the impacts of Hurricane Ida in August 2021. Hurricane Ida caused parishes such as Jefferson, St. Charles, and Lafourche major destruction and damage. Homes were uprooted entirely from wind, neighborhoods experienced flooding, and lives were lost. These communities have experienced natural disaster events for years. With residents staying in their neighborhoods regardless of disaster damage, informal and formal networks of resilience and recovery have emerged using their extensive recovery knowledge from prior experiences. Figure 1.1 below highlights the purposeful selection of the lower parishes of Louisiana as a case study. Being in the midst of early recovery and the beginning stages of long-term recovery, it provided a

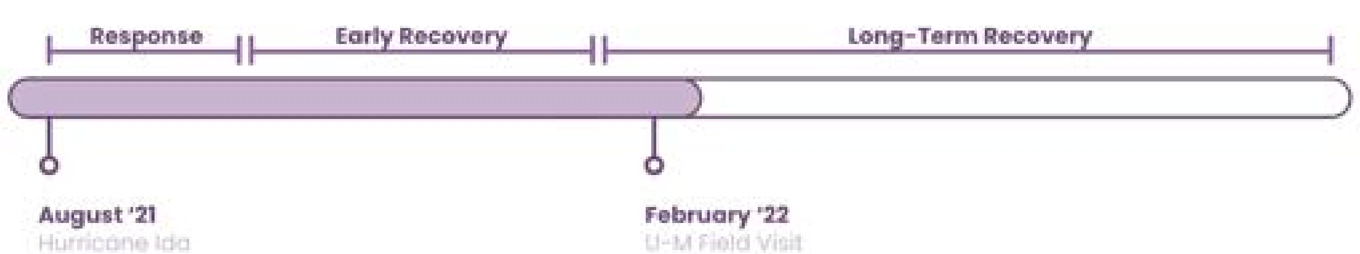


*Figure 1.1: A disaster timeline including the landfall of Hurricane Ida and our field visit to the Louisiana lower parishes.*

unique opportunity to learn from these on-the-ground experiences and to identify particular challenges such as resource distribution and data access.

Our team designed a field visit grounded at the local level to draw from the wealth of knowledge that exists in these communities to gather fundamental knowledge about the gaps in early recovery. We strategically sought to speak with organizations that were independent community actors and organizations, such as small scale non-profits, faith-based organizations, and micro-level disaster responders. Additionally, these stakeholders represented geographical differences in the urban and rural contexts that brought light to the differing recovery timelines.

Once on the ground, our team observed the complex environment of disaster recovery. In Southeastern Louisiana, various parishes had commonalities in structural damage, as seen through indicators like blue tarps and trailers. We heard from disaster professionals and affected residents alike about the challenges in communicating information with one another, the frustrations in receiving aid, and the communal distrust of institutions and government. On the ground research illuminated gaps in early recovery that permeate through communities. Following our field visit, we used an affinity diagram to distill fundamental themes taken from our observations and conversations.

Through this method, four primary areas of interest become evident: governmental mistrust, strained organizational capacities, uncoordinated communication, and damage assessment methods.

### Observations

In Southeastern Louisiana, locals expressed that there are fractures in the early recovery process. The key takeaways comment on the distrust of outside organizational support, gaps in services, and strained communication networks. Altogether, while notable gaps stall recovery, local actors and organizations step up to provide the most tailored, effective, and efficient solutions for repair and resilience.

### Trust in Government is Low

The Descendants Project, an organization whose mission is to support descendant communities in the river parishes, did not plan to provide disaster relief when they began operating in 2020. Jo Banner, a founder of the non-profit group now says it is a central piece to their organization following Hurricane Ida. Before and after Hurricane Ida, environmental advocacy groups contacted Banner, offering to provide resources and financial support to the community. The groups offering assistance trusted The Descendants Project, as Banner says, because they were non-governmental. That same sentiment was also ingrained in the community, as they turned to organizations like the Descendants Project to ask for resources such as food assistance, ice and water, and tarps. Some of the requests were beyond their capabilities. "We can't help them in that extent to what they need. We can try, but we are limited. But so was the trust they had with us versus going to the administration for help," Banner says.

The lack of faith in government is multifaceted, and

*Image 1.1: Members of our team with Jo Banner (center-right) of the Descendants project at Banner's cafe, Fee-Fo-Lay Cafe*

*Image 1.2: Members of our team with Laura Mann (left) of lowernine.org*

oftentimes lies in the collective memory of previous disaster events and recovery actions. Following Hurricane Katrina, neighborhoods within New Orleans were faced with disparate recovery options predicated on their access to resources, levels of income/wealth, and overall vulnerability. Laura Mann, Executive Director of lowernine.org, an organization focused on long-term recovery in the Lower Ninth Ward, discussed the discriminatory nature of federal aid and how that impacted recovery in the Lower Ninth Ward. Of note was the disbursement of aid based on indicators such as pre-storm property values, but not on the overall resilience or financial ability of households to successfully recover. In effect, the Federal Government failed to provide adequate support to some of the most vulnerable communities who had been impacted by the storm, thus compromising the trust of community members in a larger institutional response.

In addition to inadequate federal and state responses, local governance, according to Banner, also falls short in preparation for disaster response. "We are Louisiana, hurricanes are not new, but we have a government that acts like it is. So every storm that comes, here we are acting like it is the very first time we are going through a storm." Further, Banner attributes the inaction to the political fractures that exist between the Parish President and the Parish Council that prevent them from coordinating efforts following a storm. After Hurricane Ida, Banner says the neglect of the parish caused her to not even pay attention to what they were doing. The inaction of the parish has led Banner to stop relying on the government as being able to help. "I hate to say it, but I don't even consider them as part of the equation anymore," says Banner.

While The Descendants Project will move forward with the resources, connections, and contributors they have for now, Banner does acknowledge the benefits that could come out of coordinating with the parish. However, that process will not happen by accident; it will need to happen with intention. "There is some healing that needs to take place and some bonds that need to be restored." Banner further says, "Maybe what we need is a mediator to get us where we are all working together so we are not so disjointed where bitterness is coming out, because we could utilize some tools that the parish have and make that work for us." For Banner, it also means coming to the community outside of disasters to build connections with the community and to learn about its culture. It also means placing trust in the community itself. One example of this is how some of The Descendant Project contributors, such as Bloomberg and The Rockefeller Foundation, take bureaucratic red tape out of the process. In doing this, it gives organizations the trust to spend money how they want, and the flexibility to get the supplies they need following a disaster.

## Voids are Closed by NGO's

Local knowledge that percolates in communities flows first to non-governmental organizations, which fill the civil society space created in the void where the government and firms do not effectively operate. In the event of a disaster, relief and recovery activities are conducted by a wide range of organizations, but as discovered in research in Louisiana, the organizations with an ear closest to the ground are the non-profits, faith-based entities, and community organizations. Local governments will not have enough resources to handle such an event. Dr. Robert Collins at Dillard University confirmed this by testifying to the fact that, "Resources needed [to face] a disaster event exceed the capacity of city government." He also notes that "FEMA comes in to support but much of the response is non-profit driven." However, in many instances, local organizations are being stretched thin and are not adequately supported for the roles they have evidently taken on.





However, while governmental entities cannot take on the burden alone, their rigid protocols hinder recovery efforts led by local organizations to bridge the gap. Lanor Curole from the United Houma Nation says FEMA's system is a fundamental flaw in the governmental disaster process. "FEMA is structured on this military model that is supposed to address people in their most vulnerable time. And the last thing that non-military people need is a rigid structure in that time." Further, Curole believes if FEMA were willing to structure their system differently, that it would result in a more efficient process in the distribution of resources. Though, the existing procedures FEMA rely on end up being an additional stressor, says Curole, instead of being a helper. The United Houma Nation ends up allocating resources and energy to help individuals navigate that process. These rigid systems are not malleable to the situation that further strains organizations.

Allocating resources to help those navigate bureaucratic systems only strips organizations' limited capacity away from the many other needs that they are relied upon to assist with. It is this compounding nature that tribes like the United Houma Nation, along with other community-based organizations, have to navigate to ensure needs like mental health are being addressed in their communities. The impact of Hurricane Ida was also heightened from organizations having to respond to two distinct disasters: a biological disaster in the COVID-19 pandemic and the natural disaster of the hurricane itself.

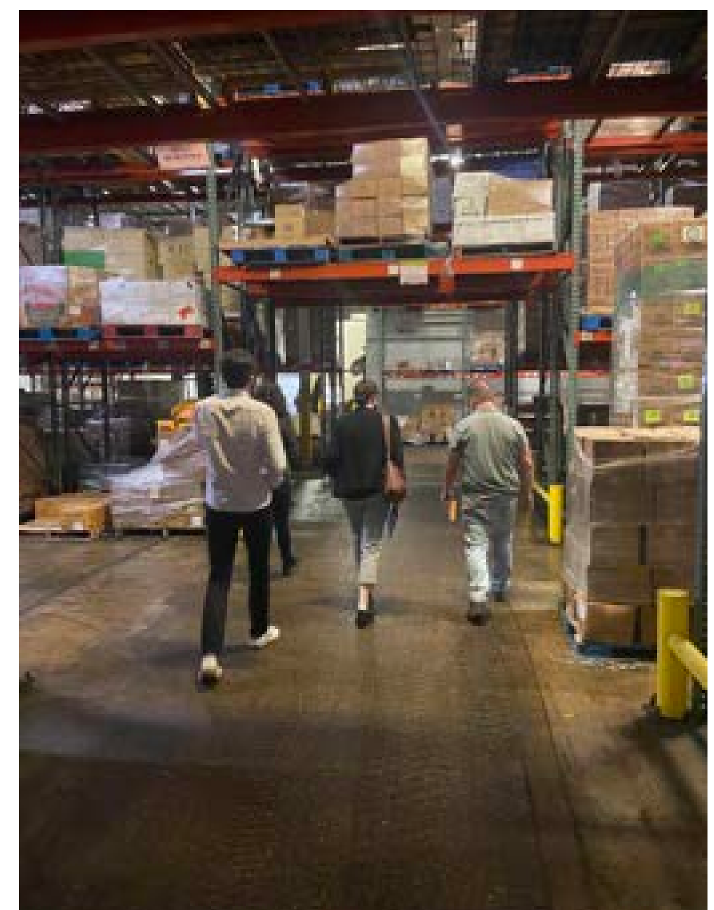

*Image 1.3: Members of our team take a tour at Second Harvest Food Bank with Jay Vise (right)*

To layer onto these strained organizational capacities, storms only continue to increase in frequency and severity. However, even after rebuilding over and over, the same issues persist. Some of this can be attributed to FEMA and other aid that is strictly focused on building back what existed prior to the storm. "They're very much about mitigation," says Curole in talking about FEMA, "There's no room for adaptation. And so, it's all about, let's get you back to where you were before, but there's nothing about planning or addressing the issues to prevent further damage or adapting to the environment to address future issues to those extents." A different process, focused on creating resilient futures, could prevent organizations from having to repeatedly address the same gaps that are exposed when disasters strike.

## Communication Networks are Strained

As soon as meteorological reports begin tracking storms to the area, organizations start reaching out to one another. For the United Houma Nation, Curole says environmental justice organizations reach out prior to a storm letting them know they are on standby to assist with relief and recovery resources. The Second Harvest Food Bank of Greater New Orleans and Acadiana also send out similar messages to their networks by sending out emails and calls as soon as they receive a report showing a potential disaster. Connecting with their networks not only builds capacity for food distribution, but also opens communication channels for the transfer of information about what is happening in communities, if there is damage, and what resources those communities need. No matter how much legwork is put in before the storm, they must stay nimble. As Curole points out, "We kind of have a go-to of what we know are like the basics that everybody will really need, but no two storms are ever the same." It is for this reason that coordination and communication are so important. In talking about responding to community needs, Paige Vance, Impact Operations Manager at Second Harvest Food Bank, says "it's like walking on a beach, it is shifting all the time."

To navigate the changing landscape, Vance leans heavily on her coordinators who are on the ground and have established relationships. Second Harvest also relies on informal reports from phone calls or emails sent to them by partner organizations. The employees at Second Harvest maintain strong personal social networks, which allow them to see for themselves what is going on. Jay Vise, Director of Marketing and Communications, says they have run out of room on their T-shirts for all the disasters they have responded to, but that is also a testament to the strength of the relationships they have built over the years. Vance further accentuates the strong relationships by saying how the coordinator's ties to the community are so strong that they are familiar with the social cues of who might exaggerate a little or, conversely, who never complains, which helps in assessing the validity of certain reports. As much as these relationships are a strength, the rapid influx of information following a disaster makes it difficult to keep up. While Vise places deep value in their relationships, he also acknowledges its limitations. "It has always been a challenge to successfully share information about who is responding where, where the need is, and where the duplication is. There has got to be a better way to track who is doing what." Other organizations, like the Descendants Project, shared similar sentiments, questioning how they can build greater network connectivity of partner organizations and disaster professionals.

For other organizations, it is not so easy to extract information on specific individuals who might have been significantly affected by a disaster. The Jefferson Council on Aging is a specific example, since the senior population can become isolated from their communities. One of their primary missions is to deliver meals to seniors, using meal deliveries as an opportunity to check in with the senior population and communicate information to them. "The best eyes and ears we have to the seniors is through the

> "How do we layer all those things together, so that we can make the best educated decision?"

people who deliver the meals. Before they hand over the meal, they're supposed to check in on them and make sure that person is okay, that they're not experiencing food shortages, and that their house is fairly clean." The United Houma Nation conveyed similar sentiments of having difficulty getting in touch with certain individuals who are more isolated than others. To combat this, they developed a database that includes individuals' plans for where they will be during the storm and following the storm. Knowing the plans of all its members allows them to narrow in on individuals who may be isolated from social networks and resources. It is also just a way to remind their community to prepare for the storm.

In addition to communicating operations with partner organizations following a disaster, places like Second Harvest also need to communicate their daily operations and schedule to the wider community. But for Vise, it is more than just sharing information. "Managing the output of information is almost as important as finding out where the need is because you want to be proactive and tell people, here is where we are responding right now, but [you don't want] two days later someone sees that post and goes there and no one is there." But even with rapidly updating schedules and communicating operations with community leaders and organizations, managing the flow can only do so much when most information is spread through word of mouth. The United Houma Nation and the Descendants Project both indicated that word of mouth is the main source of spreading information, especially following a disaster when electricity and Internet services are likely down.

New agencies and organizations such as NOLA Ready echo these remarks on formal and informal communication channels. The agency works primarily in response compared to long-term recovery, yet as one staff member highlights, "where I wish we had more help is on the planning and preparedness side." It is not easy managing multiple response and recovery efforts post-disaster, exacerbating information sharing channels. Before and after storms, NOLA Ready says how connections to "small scale partnerships really ramps up so we're filtering information from just all over the place." While the local office staff still work closely with the state and other parish governments, one of the main objectives is to filter information received through channels such as social media and word of mouth from community contacts. The filtering of information that groups like NOLA Ready perform is imperative to life saving efforts. Some of the biggest obstacles that lie ahead is sorting through information in a timely manner, and making this information relevant to people ahead of time.

## Gaps in Damage Assessments

Governmental institutions and organizations all have different processes and methods to assess damage following a storm. Damage assessments create a contingency for aid, which is why it is paramount for organizations to have their communities prepared. In our interview with the Jefferson Council on Aging, Al Robichaux, the Executive Director, mentions that they give thumb drives to their seniors for them to have their insurance, their birth certificates, their marriage license, and all other documents that are relevant following disasters in one place. Robichaux says the importance of thumb drives lie in there ability to store any documents seniors will need immediately after a disaster to begin the insurance process and to get timely FEMA assistance. Other groups use similar tactics to have their communities prepared for insurance claim processes. In addition to using their disaster survey to assess needs, The United Houma Nation also encourages tribal members to upload photos of damage in their communities to advocate for their needs and document the disaster's impacts. It also aids in collecting information from their communities to see where damage is located. Both instances underline the importance of putting systems in place during the prepardness stage to increase recovery timelines.

Some organizations attempt to make navigating these processes easier through spatial assessment from aerial imagery. We discovered from the United Houma Nation how aid organizations like the Red Cross started using comprehensive imagery to assess housing damage for determining access to benefits. Curole says the Red Cross would input an address and make aid determination based on what they saw in the drone imagery. However, as Curole points out, "unless you're very quick about getting it [image capture] done immediately after the storm, it tends to penalize people that are quick about responding."

In this process, Curole says the Red Cross did not factor in common elements following disasters, such as tarps covering the roof. This prevented families and individuals who were quick to place tarps over their damaged roof before the image capturing from being able to receive aid from the Red Cross since they did not recognize tarps as a viable proof of damage. In other damage assessment processes, blue tarps are a strong indicator of the prevalence of damage. In talking with Tab Troxler, St. Charles assessor, we gained insight into how his office used aerial and street level imagery to discount property taxes as a form of aid. Troxler's office took the extra step to classify damage on a 0-4 scale, ranging from undamaged to destroyed, to better reflect the damage evident to the structures and closer aligned with the FEMA classification.

But tools used in the field are duplicative and vast. The NOLA Ready team recognizes the helpfulness of tools for, say, debris management but with a cautionary note. "There are a lot of tools that don't end up getting used… the struggle I feel that we've had [is] user acceptance like user accessibility and functional aspects of the tool. You know, it gets complicated when you have a tool that can do too much stuff." Organizations are overwhelmed with complex tools, even deciphering information and streamlining communication channels. NOLA Ready highlights that the operators of the tool are important considerations for development. If a damage assessment or debris management mapping tool does get created, NOLA Ready questions who should use the tool and "how do we layer all those things together, so that we can make the best educated decision?"

## 1.4 Spaces for Intervention

The themes taken from our field visit offered a nuanced understanding of on-the-ground responses and recovery. The fractures we observed in planning and prioritization of efforts for recovery illuminate the need for emerging technology and social methods that have the ability to merge the gaps that impede early recovery in communities. Drawing from our field visit experiences, in conjunction with our research, we developed three opportunities for innovation within the field, specifically at the intersection of planning and early disaster recovery. These include planners as intermediaries, the merging of tech and local support, and the use of damage assessments.

### Planners as Intermediaries

Following a disaster, community trust can be damaged when recovery decisions are not grounded in an understanding of the cultural norms, local leadership, and nuances of a specific locality. As we heard from the United Houma Nation and the Descendants Project, localized context is fundamental in early recovery not only to properly leverage assets and leadership, but to also ensure the whole community is included. Planners are in a unique position to be an intermediary between the communities and broader relief and recovery organizations. With knowledge of local context and community assets, planners bring an important perspective of how early recovery can be best undertaken in these communities.

Further, planners have a range of tools that can be used to set the foundation for understanding the dynamics of communities such as social network analysis, asset mapping, and vulnerability assessments. These are tools that are utilized prior to a disaster in the preparedness stage and are vital for an effective early recovery. As such, the role of planners as intermediaries is not exclusive to the early recovery stage and requires consistent communication and coordination with communities.  Planners serve as a critical linkage between local officials, responders, planners, and community leaders; these relationships can be leveraged to build cohesion and strengthen partnerships prior to a disaster event.

### Merging of Technical and Local Support

The use of technology and its applications in disasters has rapidly progressed, but as we heard on the ground, these techniques often do not include localized knowledge, assets, or networks. The lack of integration between technology, such as machine learning and aerial imagery, and local techniques creates fractures within the disaster recovery field that result in inequitable recoveries. While technical support may be efficient in locating damage following a disaster; it does not offer critical information about local leadership and social networks that can then be relied upon for maximization of resource deployment.

> "It has always been a challenge to successfully share information about who is responding where, where the need is, and where the duplication is."
>
> *-Jay Vise*

Planners have a role in layering these two distinct support types to give greater contextualization of damage within communities. The achievement of integrating the two rely on building vertical and horizontal connectivity with the many organizations and stakeholders that are involved in disaster recovery. This includes the sharing of information and data that can offer greater representation of local realities. In aligning aspects such as data sharing, planners can aid in producing a more coordinated recovery where each action is folded into other measures to prevent it from happening in isolation.

Additionally, technical operations need to be mindful of usability for communities. Community organizations that we spoke with understand the importance of leveraging online systems; however, they also recognize their own technical limitations and shared concern about algorithms behind certain systems. Therefore, planners should work with technologists to develop tools that can be leveraged by communities and can offer guidance on more technical products used by emergency professionals and technologists following disasters.

### Damage Assessment

No two storms are alike, which is why rapidly understanding damage in the aftermath of a disaster is essential in providing resources to communities which align with their needs. Further, damage assessments influence the amount of aid and the communities it flows into. However, assessments of damage occur in a multitude of ways, both formally and informally. As we heard from partners on the ground, organizations compile and use their own damage assessments in a variety of ways to determine resources distribution or to just make it easier for their communities to navigate the FEMA claims process. The different techniques and strategies to damage assessment is not necessarily unwelcome, as it offers greater understanding of damage, but the way it is communicated and transferred creates barriers in fully realizing its potential. As we saw with the St. Charles Assessors office, when damage assessments are used properly, they can have significant impacts. By using aerial imagery to classify structure damage on a 0-4 scale, the Assessors Office is able to extract a greater contextualization of damage while aligning their process with FEMA's damage scale for efficient aid distribution.

Planners can play a central role in working with communities and institutions to create a system where damage assessments are better shared and understood. In doing so, it will produce a more detailed picture of where the damage is located for more accurate resource deployment and will streamline financial aid to communities to rebuild.

## 1.5 Conclusion

Early disaster recovery is not a process that can happen in isolation, especially in areas where the frequency of storms is as pronounced as Southeastern Louisiana. Planners have an integral role to play in coordinating efforts throughout the entire disaster process. Carrying out pre-disaster assessments such as identifying vulnerable communities, synthesizing social networks, and performing asset mapping are just a few of the tools planners could use to foster enhanced coordination within and between communities and governments.

In addition to building out local knowledge connectivity within communities, planners also have a role in creating continuity between interested communities, organizations, and governmental entities of varying scales. Our field visit illuminated a wide-ranging scope of efforts, from the micro grassroots level operating on residential knowledge to technically-oriented efforts that assess damage nodes. While there are certainly ways to improve on the tools used in the field, the more pressing concerns lie in aligning the efforts to create a unified and holistic response.

While both local support tools and technical support tools are powerful in their own right, on their own, they leave out crucial considerations that can bring greater contextualization to disaster recovery. By incorporating the speed and informational insights technologies provide and layering it with social vulnerability and social network considerations, resources and support can reach those who need it most in a more timely manner.

In our partnership with the NDPTC, our team has worked with the development of a decision support tool that assists with early recovery efforts. The method is complex, built on many stages and intricate processes, still in its earliest inceptions. The method has the potential to intervene in the current state of early recovery efforts to recognize local capacities, linkages, and knowledge. Our field visit played a critical role in influencing the development of the method so that community voices were built into the process and its methods. In addition, our on the ground experience guided our technical work bringing insights from local professionals and the gathering of context-sensitive data. To uncover and learn more about early recovery and our research, our team has developed a series of white papers and working papers on machine learning, aerial imagery, and social methods.



## ENDNOTES

1. Parker, H. (2022, March 3). Climate change could prove more deadly in Louisiana without immediate action, report says. WWNO. https://www.wwno.org/coastal-desk/2022-03-03/climate-change-could-prove-more-deadly-in-louisiana-without-immediate-action-report-says.

2. March, A. & Kornakova, M. (2017). Urban Planning for Disaster Recovery. Butterworth-Heinemann.

3. March, A. & Kornakova, M. (2017). Urban Planning for Disaster Recovery. Butterworth-Heinemann.

4. March, A. & Kornakova, M. (2017). Urban Planning for Disaster Recovery. Butterworth-Heinemann.

RISING ABOVE THE DELUGE

Planning and Resilience: Opportunities in Early Disaster Recovery

Prepared by U-M Deluge Capstone Team

### about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

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white paper series: machine learning

# SOCIAL BIAS

*In Machine Learning and Early Recovery*

# EXECUTIVE SUMMARY

Machine learning is a branch of artificial intelligence that uses various data sources to train an algorithm for a specific purpose. Machine learning simplifies and automates diagnostic or identification processes in various industries like healthcare, finance, and urban planning. Recently, data scientists have started using trained machine learning algorithms to speed up the early recovery process after natural disasters. As a result of climate change, scientists and disaster professionals must plan for considerable sea level rise and increasing severity and frequency of natural disaster events. The more frequently natural disasters occur, the greater the need for faster recovery and stronger resilience. Government entities like the Federal Emergency Management Agency (FEMA) have yet to start utilizing machine learning to standardize property damage assessments in the natural disaster recovery process.

Machine algorithms can assess property damage based on collecting and labeling perishable data such as photos of damaged buildings. The data used to train an algorithm is typically perishable, meaning that the data becomes less relevant over time as those affected by natural disasters work to fix their homes. Perishability creates temporal restraints for data collection. Although this technology can accelerate the relief and recovery process, the use of highly technological tools without assessing their impacts on people can further existing inequalities in the recovery process. Human-induced biases in machine learning appear in data input, collection, algorithmic frameworks, and the application of models. If machine learning is to be relied on by organizations as a method to understand damage and prioritize resources, there must be deliberate action to control bias.

## 2.1 Introduction

The field of disaster response and recovery has grown steadily over the last few decades as climate change has caused more frequent and severe natural disasters. As this field has grown, emergency management professionals have begun to explore the use of data science techniques that can predict the severity of a disaster before it happens and helps assess damages in communities post-disaster. In the context of federal disaster recovery, damage assessment is a foundational step in an aid-distribution process that guides resource distribution.

Damage assessment as a tool is deployed by both the private and public sectors based on community capacity or grant requirements. Assessments are currently conducted by on-the-ground responders. Their efforts help provide decision makers key insights and summarizations of post-disaster conditions. The limitations to understanding damage through property assessment are not necessarily visible, as social infrastructure such as community networks become fractured in line with physical damage post-disaster. Integrating data science technology into fields like emergency management could aid in making communities more resilient, as technology helps shorten the recovery timeline through faster processing speeds. Rather than human input assessment, technology such as machine learning can streamline and reduce bias.

Perishable data becomes less relevant over time as those affected by natural disasters work to fix their homes and thus eliminate pertinent data. It becomes imperative for emergency and first responders to collect data within hours to days after a natural disaster, a constraint acknowledged by residents and responders. Machine learning algorithms that assess property damages rely on collecting and annotating perishable data such as photos of damaged buildings.

This paper discusses how machine learning tools can store and analyze perishable data from natural disasters by integrating data collection, damage assessments, and aid recovery operations.

## 2.2 Early Recovery Demands

There are additional issues with the integration of data driven tools into early recovery. Under the constraints of weather, time, road access, local demand, and disaster damage, emergency managers are pressured by private and public organizations, such as FEMA or insurance companies, to increase recovery speeds and resource allocation distribution. Local emergency managers, or prominent community leaders, may be tasked with undertaking data collection to inform planning support for faster recovery aid and management. There are many dimensions that contribute to the demand for faster early recovery. For example, conversations with local residents and leaders from Southeastern Louisiana highlighted local concerns for how recovery from previous disasters would directly affect a vulnerable community's ability to recover from the next.

Another pressure to increase the speed of decision making stems from delayed and uncoordinated long term recovery. In the wake of Hurricane Ida, we see early recovery action influencing long term recovery effectiveness. As mentioned previously, local residents whose homes were most impacted struggled with the ability to receive relocation cash assistance or rental assistance until a damage assessment could be conducted. Faster early recovery speeds may eliminate the induced trauma of displacement and evacuation through faster access and distribution of life essential aid and resources.[1] While the process will likely continue to rely on human input for verification of damage, technology can better inform actors on the likelihood of damage for rapid deployment of people and resources.

## 2.3 Perishable Data

A limitation related to damage assessments and early recovery is the lack of data that would enable a comprehensive analysis of damage. In general, rebuilding occurs almost immediately after the period of sheltering or relocation is over. The measures used to address damage may also inhibit the ability to understand the extent of damage. To study disaster recovery at the community level, researchers have an inherent need for the rapid collection of damage

## DEFINITIONS

**MACHINE LEARNING**
A branch of Artificial Intelligence and Computer Science in which computer systems are able to learn and adapt without following human instructions. Data patterns are inferred by model algorithms and statistical models.

**IMAGE CLASSIFICATION**
Labeling and classification of digital photos. For example, an image of a damaged home is classified based on the extent of aethestic and structural damage.

**OBJECT DETECTION**
Object detection can locate specific features within an image. For example, an image including yard debris and a home will only detect damage to the building. Bounding boxes are utilized to identify the specific object feature as distinct from others.

**COGNITIVE BIAS**
The tendency for people to perceive information in different and distorted ways based on their own experiences and preferences. How information is framed, as well as the context in which it is given (or lack thereof) affects ones perception of reality.

**ACCURACY**
An overall metric that determines how often the machine learning algorithm correctly identifies images or object in the model.

**PRECISION**
A categorical metric that determines the number of correct observations the model predicts over the total number of correct and incorrect observations of a class.

**RECALL**
A metric that determines how often the machine learning algorithm correctly identifies images or object in the overall model.





data. The data, known as perishable data, are measures that are vital to capture, analyze, and understand immediately following a disaster event when contextual information is clear in the memory of residents. However, the prioritization of needs by local actors with limited capacities in the aftermath of disasters means collecting perishable data for research purposes is not of the utmost importance.

A temporal gap exists around the timeline for perishable data capture while a capacity-gap furthers organizational issues. Therein lies the outlet and potential for utilizing data science methods to increase prioritization and local support through rapid and efficient collection methods. While data science tools can capture that perishable data, they can also be leveraged to store, understand, and communicate damage data in a timely manner.

## 2.4 Machine Learning

Based on early recovery demands and perishable data constraints, deep learning is one emerging technology that has the potential to be adapted for equitable, efficient operations. Deep learning is a type of machine learning that learns through neural networks. The name neural network refers to its algorithms as modeled from human cognitive function. Convolutional neural networks are a special focus of deep learning aimed to identify and classify images. All deep learning models have one thing in common—the data used to train the algorithm is understood through weights of certain characteristics. These weighted characteristics, also referred to as weights, instruct the model to make decisions. As a process for identification or classification, machine learning works best when provided clear and measurable data.[2] Altogether, the complexity and novelty of deep learning triggers barriers to entry outside of typical data science fields. Civicly minded analytics, apart from data technologists, may help bridge the informational knowledge gap.[3] Civic analytics can include pre-existing roles in government who learn to incorporate data science into decision making processes.

As the uses of machine learning continue to expand, the urban planning field turns to deep learning to improve the planning practice. Urban planners will need education training in data science and awareness of the biases in machine learning to navigate complex environments. Multilayered urban problems already garner immense interagency coordination and require profound organizational knowledge. As a field classically trained with skills in research, mapping, and community engagement, urban planning both pursues yet lacks comprehensive data science knowledge related to machine learning. If urban planners continue to turn towards data science as an approach to tackling complex, interconnected issues, they must recognize the inherent limitations and biases of data-driven decisions using neural networks.[4]

## 2.5 Damage Assessment with Machine Learning

Integrating various sources of information from communities and infrastructure affected by natural disasters into rapid damage assessment increases the accuracy of learning-based models. Training models that combine data from multiple hurricane events can accurately predict the estimated damages of a test-case hurricane event.[5] Collecting images from a combination of sources increases machine learning algorithms' accuracy, precision, and recall. Incorporating pictures posted to social media platforms of damages due to earthquakes from multiple events[6] with similar images from Google optimizes the performance of deep learning models.[7]

Two vital needs have emerged during this project's research into artificial intelligence algorithms for

*Image 2.1: A manufactured home in Dulac, Louisiana damaged from Hurrican Ida*

damage assessment. First, there is a need for an abundance of training data and imagery specifically curated to assess infrastructural damage in post-natural disaster communities.[8] Open-sourced datasets, such as Crisis NLP and the Qatar Computing Research Institute, contain images collected from social media after natural disasters; however, the pre-annotated images do not align with FEMA Preliminary Damage Assessment guidelines.[9] Second, the post-natural disaster images accessible through media sources, open-sourced datasets, and stock photography outlets results in severely imbalanced training datasets for machine learning models[10]. In general, open-sourced datasets contain an overrepresentation of images classified as severely damaged. To correct for the underrepresentation of other damage types, CrisisNLP datasets perform Google image searches to assist with training machine learning models. While correcting for underrepresentation is considered good practice for increasing overall model accuracy, sourcing images from Google does not equitably represent the communities impacted by natural disasters.

Similarly, datasets sourced from social media also contain a large portion of imagery unrelated to assessing damage to a home. The poor signal-to-noise ratio of relevant images sourced from social media can be addressed by direct human-input selection or creating a separate machine learning program to filter for useful images .[11] Regardless of the methods one uses to select relevant images for input into a damage assessment model, biases can be introduced into the created dataset.

## 2.6 Biases of Machine Learning

All machine learning models require training data that is generated and collected from human experiences.[12] Human experiences and memories of past events affect thinking, behaviors, and the decision-making of current events. To err is human; errors in mental processing and interpretation of information define cognitive bias. Everyone exhibits cognitive bias. It occurs when we self-select news sources that reflect our political viewpoints or assume another person's beliefs and opinions.[13] When biases refer to an individual's or group of people's social identities, such as race, gender, or religion, we identify these as social biases. Since all data is generated or affected by human decision-making, all data is inherently biased.

*Image 2.2: The last reminents of a stilted home in Chauvin, Lousiana after Hurricane Ida swept through the Houma Nation*

There is a need to design machine learning methods with intention that can control for biases. Many types of biases exist within machine learning processes; each type has its own potential method for control. Social bias refers to an individual being in favor or against others based on their race, gender, or other social identities. Machine learning can control for social bias during the data collection process. During the data collection process, the inclusion of historically disadvantaged communities, such as the Houma Nation in Louisiana, into training datasets ensures equitable representation within the model. In damage assessment, an assessor or local official with prior knowledge of a neighborhood might classify damage differently based on location; this type of bias is known as confirmation bias. Confirmation bias occurs when individuals go into a decision-making process with subjective thoughts about their tasks. Confirmation bias is controlled for during the annotation process by standardizing labeling protocols with clear guidelines.

To further support the adoption of machine learning processes, there are a host of limitations that can produce bias and inequity and must be addressed. Machine learning assemblage, or the process of creating a machine learning cycle from collection to training, holds different biases than its application in the field. Researchers and planners must protect local communities from undue harm or negligence through assembling and applying machine learning with transparent, robust methodology.

*Image 2.3: Image classified as "none" for damage assessment by open-sourced database*

## 2.7 Reducing Bias of Machine Learning Algorithms for Damage Assessment

The use of machine learning algorithms in disaster recovery is all but inevitable. Machine learning models can better predict future events and accelerate recovery.[14] However, no two natural disasters impact communities in the same manner. Each subsequent natural disaster generates more data than past disasters as new prediction techniques become operational. Before, during, and after disasters, digital information is collected from sensors, satellite and surveillance imagery, drones, smartphones, and many other Internet-connected devices. Survivors of natural disasters also use social media platforms to communicate with relief and recovery professionals, often posting images with location data[15], which allows the targeting of recovery efforts. All relevant data points must be collected and analyzed quickly to ensure their usefulness in recovery operations. Perishable data must also be collected and made available to data science researchers as inputs in machine learning models, such as those used for preliminary damage assessments.

There is a need for data scientists to have comprehensive imagery datasets of damaged structures following natural disasters to train, validate, and test machine learning algorithms.[16] To have an inclusive nationwide recovery process, community partners need to communicate with the technical knowledge and capacity of data science teams to build equitable machine learning models for future disaster events. In fact, recovery can have different meanings depending on who uses the term.[17] Developing an algorithm to accelerate the recovery process and rapidly assess property damage without incorporating the social context of local communities has the potential to exacerbate the economic inequities currently exhibited in the United States. Neither an emergency manager nor an algorithm can determine a household's ability to rebuild and recover simply from analyzing images of damaged homes without first understanding the local context and social networks available to a specific community. Therefore, machine learning algorithms that detect damage should not be the sole determinant of prioritization given highly connected, wealthier, or well designed households may recover more quickly and effectively compared to less connected, lower income, or less structurally sound households.

**Annotation Protocols**

Standardizing annotation protocols for categorizing damage assessment images controls human-induced biases in datasets. Annotation standardization based on FEMA's Preliminary Damage Assessment Guide can help to reduce prejudices and increase model precision through clear definitions of categorical damage. Minor damage can be defined or classified with clear differences than other levels of damage such as severe. Rather than use personal bias of damage, standardization eliminates human error. Collection of data, annotation of images, and training of machine learning models for damage assessment is best completed in preparation for a natural disaster, rather than post-disaster. Exposure to traumatic events can lead to cognitive biases through changes to an individual's locus of control or how one perceives the control one has over external events.[18] Therefore, once disaster strikes, cognitive biases can be amplified, particularly for local emergency personnel.

Properly categorizing the distribution of damage assessment through combining data points from multiple disaster events also controls for biases in datasets when training a machine learning algorithm. The severity of a single natural disaster can lead to an overrepresentation of houses assessed as having major or destroyed levels of damage. Overrepresentation of damage categories can have real-world consequences when distributing aid such as household assistance funding. A household with income levels below or near the federal poverty level may not have the ability to recover from minor levels of damage from a natural disaster.

Elements of social recovery — providing shelter and long-term housing, food and financial assistance, resilience, and psychological support — should be prioritized at the same level as economic and infrastructure systems recovery. One's perception of recovery is determined by how well they return to normal or begin a "new normal" after recovering from the mental, financial, and physical impacts of natural disasters. Compressing the timeline for damage assessments does not exclusively accelerate recovery for communities. Our team sees the need for data science, artificial intelligence, and urban planning professionals to work together to improve the future of equitable natural disaster recovery.

## 2.8 Implementation Considerations

In joining the fields of data science and urban planning, those applying and training machine learning algorithms must consider the implications for planning decision support. For damage assessment processes, machine learning may eliminate potential social bias held by assessors or local emergency responders. On the other hand, it does have the potential to direct resources based on inaccurate or misleading machine learning results. While algorithmic bias may occur, there are direct steps to take to prevent imprecise damage assessments.

*Image 2.4: This home in the Garden District celebrates Mardi Gras in Louisana after the neighborhood suffered damage from flooding*

Admittedly, machine learning is not the complete solution for damage assessment. For example, tools such as the Rapid Integrated Damage Assessment model, developed by the National Disaster Preparedness Training Center (NDPTC), must rely on other output steps to accurately identify damage results for improved accuracy. The tool does not rely on just machine learning outputs to assess damage, rather it is the last step to capture damage likelihoods. Therefore, machine learning should supplement damage determinations in the initial parts of early recovery with the understanding that machine learning outputs are not the final determination for damage. One researcher presses that "because AI can cause considerable harm to individuals and groups, it is not sufficient to leave their development and regulation to those without expertise in this area."[19] Outputs of severe or moderate damage should be validated in two ways. The first is auditing the outputs through monitoring results. When testing an image dataset on a model, there are no checks and balances on the system unless built in through human review.[20] Additionally, damage can be validated through a two way feedback. Residents in some areas, such as the St. Charles Parish in Southeastern Louisiana, allows residents to review their households' damage score post-disaster. In one case, a family home that was destroyed was initially determined to be minorly damaged. The family was provided the opportunity to challenge the score, and was justly awarded aid and recovery support. Empowering local voices through a feedback system enhances results through verification or contestation of damage. It also allows emergency managers and planners more outlets to capture data that is overlooked through street-level machine learning, notably damage inside of homes.

Algorithmic bias makes machine learning applications in the real world questionable. Many cases of improper machine learning detection and misclassification have been uncovered through practice.

While feedback systems may be effective for damage validation, there are limitations with this method. First, it assumes people know about the neural network

*Image 2.5: Despite the appearance of damage, this local flower shop is back in operation just five months after Hurricane Ida destroyed neighborhood buildings*

process, can access its information, and have the time, internet access, and other resources to contest damage scores. Therefore, there should be control measures outside of local feedback. Monitoring matters because in some instances, researchers have observed egregious racial and gender biased outcomes from machine learning.[21] Researchers and local responders must be able to not only conduct machine learning damage assessments, but also to properly manage its outcomes. There are many tools that help understand machine learning bias such as Audit-AI or AI Fairness 360.[22] Altogether, an auditing process is an essential step towards implementation of neural network tools.

It is notable that all on-the-ground assessments lacks the ability to understand damage located inside of a structure or home. Natural disasters such as fires or hurricanes present varying damage inside of houses and buildings that may be overlooked by aerial, street-level, or in-person drive-by assessment. Fires can cause soot buildup and unsafe air qualities in and around a home not completely visible in imagery. In hurricane events, flooding infiltrates lower level floors which tend to hold infrastructure systems like HVAC systems, fire protection, electrical networks, and even plumbing systems. Water damage can even impact walls and facade elements of a building through mold or staining. Some damage is life threatening, such as

Image 2.6: A boarded up community recreation center with no apparent damage stands out with colorful murals of the rising seas levels in New Orleans

electrical shut offs or improper heating and cooling. In alleviating the burden to capture, process, and diagnose visible damage, local officials should also develop tools for faster in-unit or in-house damage detection.

There are positive impacts of machine learning if organized and applied correctly. By controlling human bias and relying on data-driven tools, the speed in which data is processed and managed can reduce the local burden placed on emergency management. As the process to diagnose and determine damage rapidly increases, it allows emergency managers the ability to focus their attention on other pertinent needs. Rather than use ground methods to holistically assess damage, technology can reduce personnel needed to capture and process the data. The reduced local burden could benefit a community by heightening the ability to reach more community members, especially the most vulnerable. Rather than wait for residents to access convoluted communication channels to express damage, local officials can begin to assess damage to prioritize areas regardless of perceived demand to recover. Data-driven tools in this application can reduce mismanagement of aid being directed to the most vocal or most connected networks, steering large organizations and government entities toward the residents that need more assistance and support.

## 2.9 Conclusion

The current damage assessment process is human-reliant and burdensome. Incorporating machine learning into rapid damage assessment can eliminate the potential for human error and prejudice, controlling bias more than ever before. Taking a note from the planning and the data science fields respectively, machine learning can enhance damage assessment processes and applications in early recovery.

In doing so, the combination of the two fields' expertise and knowledge can increase capacity building of local disaster recovery networks. On the ground organizations and local emergency response professionals collect and process data in scattered ways to organize aid, distribute resources, and promote speedy recovery. Due to the nature of highly perishable data, technology based tools offer a unique solution to these complex problems in both encouraging the sharing and storage of perishable data and reducing problematic assessment practices, all while reducing burdens on local recovery networks.

## ENDNOTES


1. Hu, Z, Sheu, J, Y, Wei, C. (n.d.). Post-disaster relief operations considering psychological costs of waiting for evacuation and relief resources. Transportmetrica (Abingdon, Oxfordshire, UK). Taylor & Francis.
2. Kleinberg, J., Ludwig, J., & Mullainathan, S. (2016, December 8). A Guide to Solving Social Problems with Machine Learning. Harvard Business Review. https://hbr.org/2016/12/a-guide-to-solving-social-problems-with-machine-learning
3. Kontokosta, C. E. (2021). Urban informatics in the science and practice of planning. Journal of Planning Education and Research, 41(4), 382-395.
4. Ibid.
5. Chen, Y., & Ji, W. (2021). Rapid Damage Assessment Following Natural Disasters through Information Integration. Natural Hazards Review, 22(4), 04021043. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000504
6. (Nepal, 2015 and Ecuador, 2016)
7. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017). Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109
8. Ibid
9. Ibid
10. Amini, A., Soleimany, A. P., Schwarting, W., Bhatia, S. N., & Rus, D. (2019). Uncovering and Mitigating Algorithmic Bias through Learned Latent Structure. Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society, 289–295. https://doi.org/10.1145/3306618.3314243
11. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017). Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109
12. Alelyani, S. (2021). Detection and Evaluation of Machine Learning Bias. Applied Sciences, 11(14), 6271. https://doi.org/10.3390/app11146271
13. Cherry, K. (2020, July 19). What Is Cognitive Bias? [Psychology]. Very Well Mind. https://www.verywellmind.com/what-is-a-cognitive-bias-2794963
14. Elichai, Am. (2018, December 13). How Big Data Can Help in Disaster Response. Scientific American. https://blogs.scientificamerican.com/observations/how-big-data-can-help-in-disaster-response/
15. Ibid
16. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017). Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109
17. Quarantelli, E. L. (1999). The Disaster Recovery Process: What we Know and Do not Know From Research. 19.
18. Croft, J., Martin, D., Madley-Dowd, P., Strelchuk, D., Davies, J., Heron, J., Teufel, C., & Zammit, S. (2021). Childhood trauma and cognitive biases associated with psychosis: A systematic review and meta-analysis. PLOS ONE, 16(2), e0246948. https://doi.org/10.1371/journal.pone.0246948
19. White, James M ; Lidskog, Rolf. (2021). Ignorance and the regulation of artificial intelligence. Journal of Risk Research. Abingdon: Routledge.
20. Ibid
21. Cerrato, P., Halamka, J., & Pencina, M. (2022). A proposal for developing a platform that evaluates algorithmic equity and accuracy. BMJ health & care informatics, 29(1).
22. Ibid


RISING ABOVE THE DELUGE

# Social Bias: Machine Learning and Early Recovery


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## about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

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3

white paper series: machine learning

# CUTTING THE CODE

*Accessible machine learning*

# EXECUTIVE SUMMARY

This paper investigates the use of low-code machine learning tools for determining the severity of structural damage following natural disasters. The proposed model determines the relevance for damage assessment of images posted to Twitter and then provides damage severity levels to images taken in the aftermath of 2021's Hurricane Ida in Louisiana. A low-code framework for damage assessment through geo-located social media imagery provides viable training data points for machine learning algorithms. It lowers the barriers to entry into the field of artificial intelligence for disaster preparedness professionals and has the potential to accelerate recovery in regions with limited resources.

## 3.1 Introduction

Two anthropogenic forces, the expanding volume of data generated through social media and the increasing severity and frequency of natural disasters drive the convergence of the fields of artificial intelligence and natural disaster recovery.[1] On average, Twitter users post half a billion Tweets every day.[2] A growing global population and increasing anthropogenic atmospheric warming accelerate the number, severity, and frequency of extreme weather events and "natural" disasters.[3] However, after natural disasters occur, the generation of social media posts can spike. On August 30th, 2017, after Hurricane Harvey made landfall in South Texas, 2 million tweets were generated containing the keywords "Hurricane Harvey," "Harvey," or "HurricaneHarvey."[4] Increases in global populations and adoption of smartphone technologies will result in a higher volume of disaster-related crowd-sourced data. This data has the potential to be an important resource to further the understanding of natural disaster recovery.

Consequently, data generated from social media is perishable; the contextual details that accompany an image posted to Twitter become less relevant as time progresses. Therefore, it is necessary to rapidly analyze this data to ensure its useability in disaster recovery.

Field-tested research suggests integrating hazard characteristics, community exposure and vulnerability, and social media information into rapid damage assessment processes.[5] For emergency managers, community organization leaders, and damage assessors, identifying areas requiring higher support levels and properly assessing damaged structures helps speed up informed decision-making and recovery.[6]

Regardless of location, anyone can post images to social media after a natural disaster. A significant challenge when using images sourced from social media for decision-making purposes is validating if the datapoint is accurate and authentic.[7] Geolocated Tweets within an affected region in post-disaster communities offer a higher level of validity and reliability, allowing researchers to use imagery data for accelerating recovery efforts. However, an estimated

1% of Twitter users have precise location tracking turned on, which is necessary to identify locations of damaged structures and accellerate recovery efforts.[8] Further, of the 6.7 million tweets collected by Alam et al. from Hurricane Harvey, 115,525 (1.7%) contained an image, with only 1,155(0.17%) of them having precise geographic location necessary to identify areas in need.[9]

Analyzing large image datasets requires powerful algorithms to automate the analytical process. Artificial intelligence and machine learning techniques can be applied to images taken in post-disaster communities to help prioritize areas in need of higher levels of assistance.[10] Preliminary damage assessment through image classification of damaged buildings can help prioritize distribution of resources following disasters.

Typically, innovative uses of AI are spearheaded by computer science experts with programming knowledge capable of creating models. However, for planners, emergency managers, and first responders, taking advantage of state-of-the-art AI and machine learning techniques often has a steep learning curve. More recently, machine learning tools are becoming accessible to broader audiences due to tech start-ups specializing in low-code modeling interfaces. Lowering the barriers to machine learning increases opportunities for the use of models.

One example of a low-code machine learning platform is Lobe.ai. Through Lobe.ai, users can annotate whole images by filling out a text box and training machine learning models with the click of a button. This study uses Lobe.ai and open-source imagery datasets to train machine learning models for damage assessment. Additionally, a field experiment in Louisiana, where participants generate imagery data of structural damages in the aftermath of Hurricane Ida, provides a testing dataset for the model. This study aims to provide disaster recovery professionals with an accessible model of how the use of artificial intelligence for damage assessment through social media imagery can accelerate the recovery of affected communities.

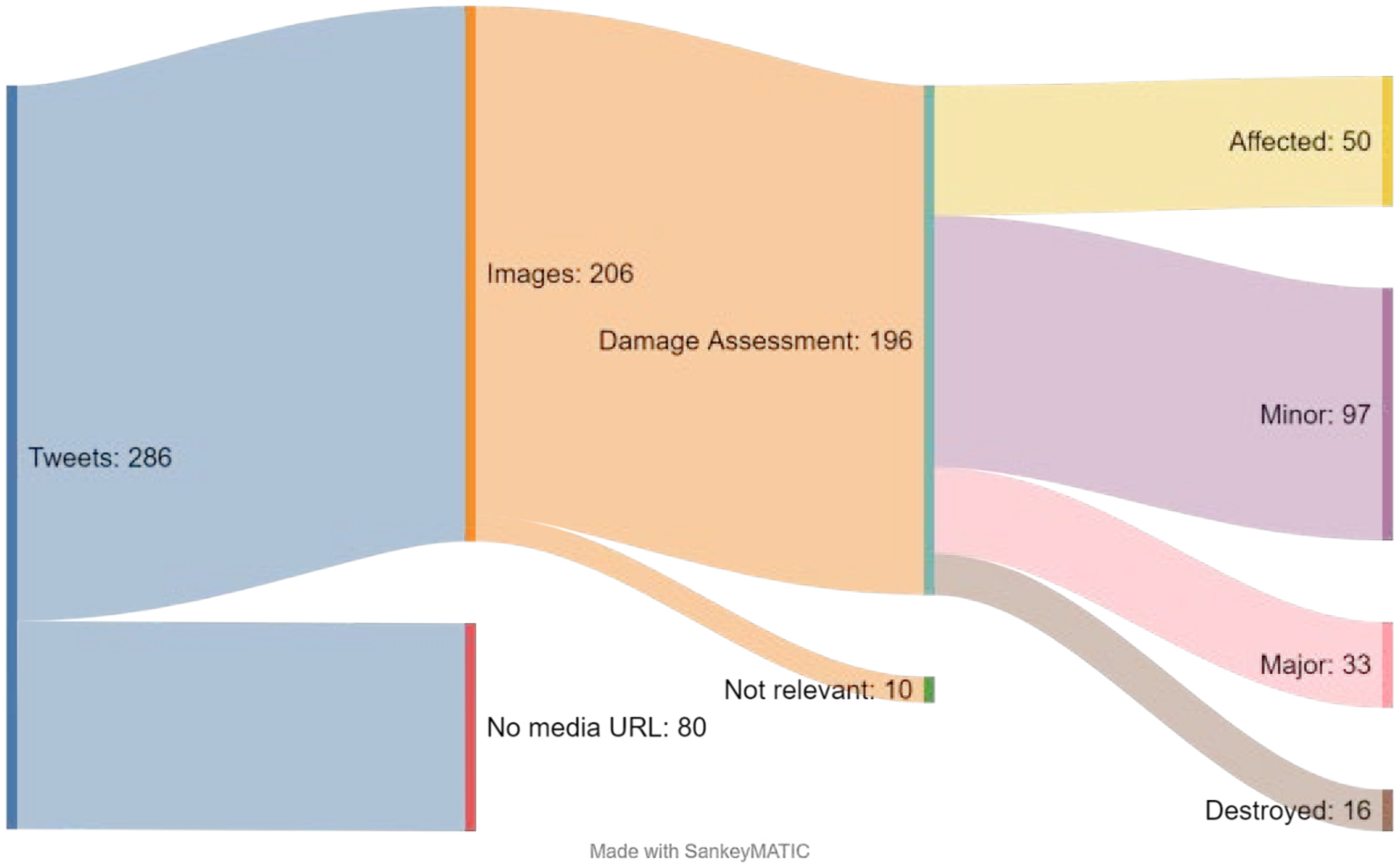


*Figure 3.1 - Image classification of sequential machine learning models*

## 3.2 Datasets

This model uses three datasets from recent natural disasters.

**1. Hurricane Matthew (2016):** 407 images from Hurricane Matthew that struck Haiti in October of 2016. Researchers from the Qatar Computing Research Institute collected images from Twitter and host disaster related datasets for public use on their Crisis Natural Language Processing (CrisisNLP) data-portal.

**2. Typhoon Ruby (2014), Nepal Earthquake (2015), Ecuador Earthquake (2016), and Hurricane Matthew (2016):** 662 images selected as being relevant to machine learning for damage assessment from CrisisNLP datasets.

**3. Hurricane Ida (2021):** 216 images collected via Twitter by the University of Michigan "Rising Above the Deluge" Urban Planning Masters Capstone team.

## 3.3 Classification

This method for categorizing damage assessment of imagery from social media posts requires two sequential machine learning models.

### Filtering Images for Damage Assessment

The first model categorizes images based on their relevancy to damage assessment (Assessment, Non-relevant). If a building or partial building is included in the image, it is deemed relevant for damage assessment. *See Image 3.1 for examples.*

### Assessing Damages

The second model classifies damage severity according to FEMA's Preliminary Damage Assessment Guide (Affected, Minor, Major, Destroyed).[11]

**Affected:** no damage, aesthetic damage
**Minor:** non-structural damage, loose siding/roofing
**Major:** structural damage to roof or walls
**Destroyed:** no structure remains, imminent threat of collapse

Selecting FEMA's damage classification scale in this machine learning model provies annotations with rigid guidelines for annotation protocol. Additionally, results from this machine learning model can be given to damage assessment professionals without the need for translating scales of damage.

## 3.4 Methods

In this section, we describe the collection of relevant data and categorical assessment of damages from natural disasters through minimal-code machine learning models.

### Generate and Retrieve Twitter Data

Our team, consisting of graduate students from the University of Michigan, collected data related to structural damage and conducted community outreach interviews in New Orleans, Louisiana, and surrounding parishes from February 16th to February

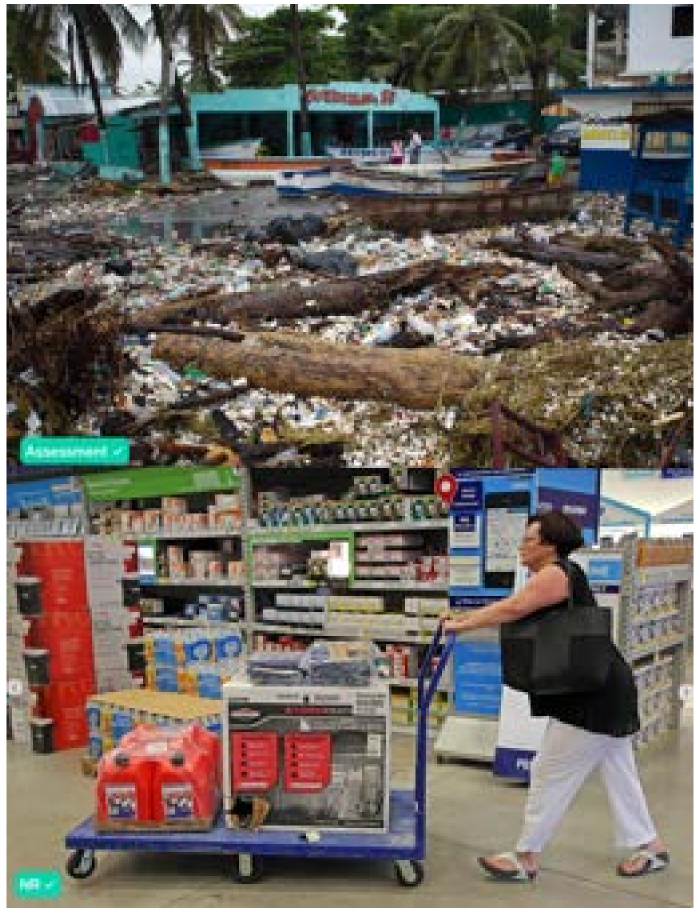

*Image 3.1: Images classified by Lobe.ai as Assessment and NR (not relevant) for machine learning.*

19th, 2022. Although it was a limited purposeful sample, it allowed us to understand the salience of using this technology under the most ideal of circumstances.

Ten student participants split into two study groups with instructions to capture images on smartphones and post images to Twitter of damages to infrastructure caused by Hurricane Ida. Instructions for one group include turning on precise location tracking on their smartphones and through the mobile Twitter app. Other participants were instructed to turn off locational data on Twitter. Participants were provided with disaster-related keywords from CrisisLex to assist with crafting tweet texts. Still, they were given free rein to post Tweets as if they were pursuing damage assessment following a natural disaster event.[12] Unknown to the reseachers for this project, participants deliberately posted tweets with misleading information and unrelated imagery to better mimic social media during natural disasters.

Additionally, participants were asked to post 50% of their tweets with the hashtag #MURP_Deluge. The inclusion of specific hashtags in disaster recovery social media posts significantly improves researchers' ability to identify and collect relevant imagery.

Using Twitter's API platform and filtering by participants' unique usernames, we identified 286 tweets posted to Twitter during the experiment, and 216 contained images (Figure 3.1). To better simulate an actual disaster event, researchers must assume no knowledge of an individual's username. By filtering for the hashtag #MURP_Deluge, researchers were able to identify all 169 tweets containing images. However, only 4 of the remaining 117 tweets (3.4%) were able to be identified using selected disaster verbiage ("Assessing Damage," "Buildings damaged," "Nothing Left," "In bad shape").

## Use of Low-Code Machine Learning

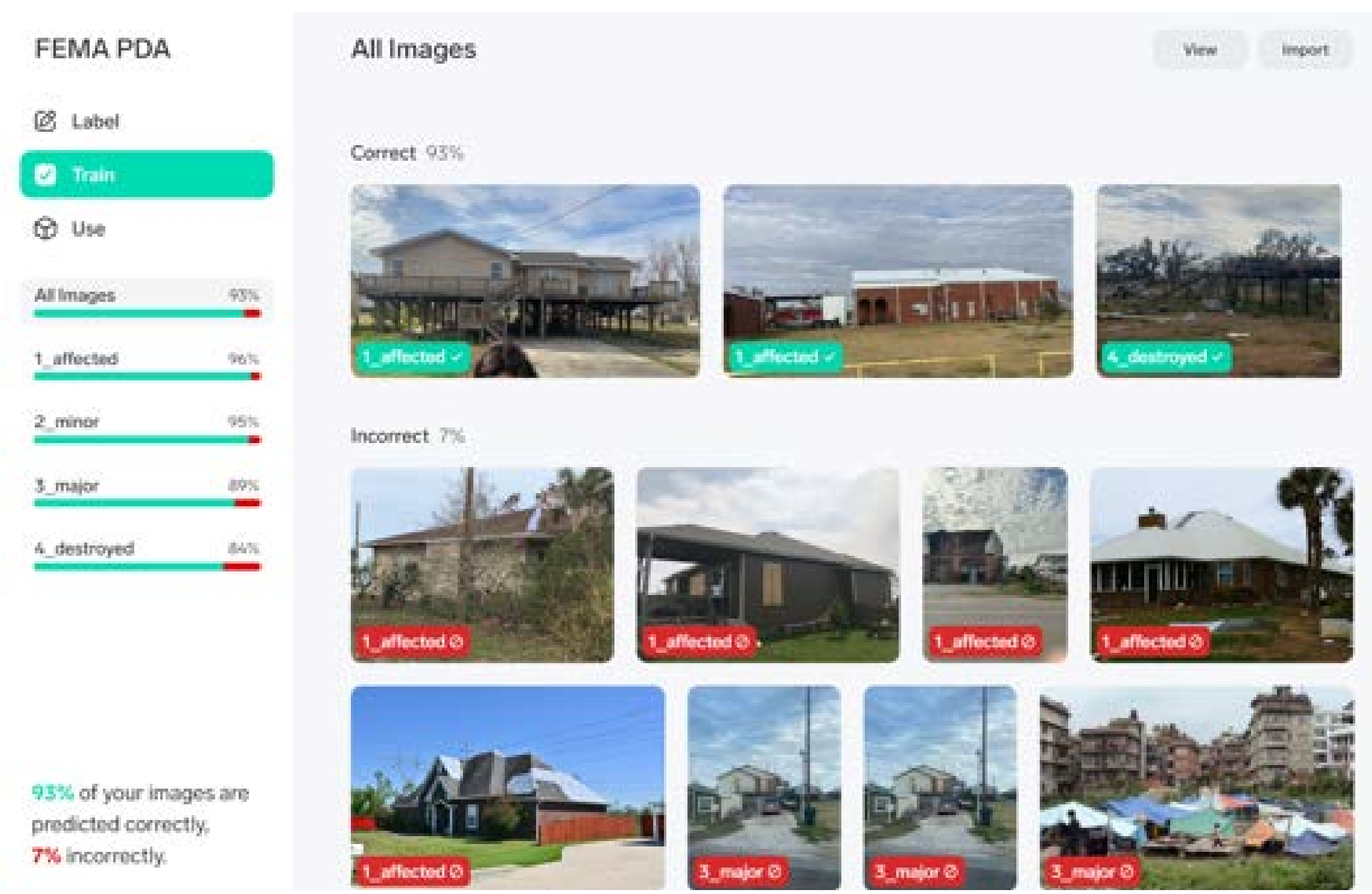


*Image 3.2: Lobe.ai's training interface for the damage assessment model.*

Lobe.ai simultaneously trains with two machine learning algorithms to improve the model's speed and accuracy (MobileNetV2 and Resnet-50V2, respectively). Developing a model begins with uploading a training dataset and labeling images via image classification (Image 3.2). Image augmentation includes adjustments to brightness, contrast, saturation, hue, rotation, zoom, and noise of images. Image augmentation alters existing data, providing additonal inputs for training the model and increasing the likelihood that a new image will be classified correctly.

| Crisis NLP Dataset: Social Media Images for Damage Assessment | | | |
|---|---|---|---|
| Event | Total Images | Assessment Images | % |
| Ecuador | 1438 | 204 | 14% |
| Matthew | 596 | 278 | 47% |
| Nepal | 18456 | 108 | 1% |
| Ruby | 833 | 90 | 11% |

*Table 3.1: Percentage of social media images relevant to damage assessment under FEMA's PDA. Dataset: 1 - Hurricane Harvey*

Lobe.ai, currently in its beta phase of development, only allows testing of one image at a time. After the model guesses the classification of the uploaded image, the user confirms if the model made a correct assumption. After confirmation, the image is placed in the training dataset. Lobe.ai continuously runs and updates the model throughout the annotation process as more images are added.

## Manual Tracking of Testing Images

| Lobe.ai Damage Assessment: Model Output | | |
|---|---|---|
| Damage Type | Images | Correct |
| Affected | 337 | 96% |
| Minor | 303 | 95% |
| Major | 142 | 89% |
| Total | 858 | 93% |

*Table 3.2: Accuracy from Lobe.ai Damage Assessment Machine Learning Model. Datasets: 2 and 3 - CrisisNLP and University of Michigan*

| Lobe.ai Damage Assessment: Hurrican Ida (Testing Data) | | | |
|---|---|---|---|
| Damage Type | Count | Correct | % |
| Affected | 50 | 33 | 66% |
| Minor | 97 | 72 | 74% |
| Major | 33 | 11 | 33% |
| Destroyed | 16 | 9 | 56% |
| Total | 196 | 125 | 64% |

*Table 3.3: Accuracy from manual calculations as testing images are uploaded. Dataset: 3 - University of Michigan, Hurricane Ida*

This study tracks image classification accuracy manually in a spreadsheet to understand how accurately new imagery is classified when introduced into a model. Manual tracking is necessary because Lobe.ai provides the accuracy of the entire dataset and individual classes after the model trains through several iterations. This step analyzes how low-code machine learning models perform under real-world testing conditions.

## 3.5 Results

Of the 216 images collected from the Twitter experiment, 196 contained relevant images for damage assessment (91%). The percentage of relevant images is exceptionally high compared to real-world datasets (Table 3.1). A higher rate of relevant images is likely due to the idealistic nature of the field visit.

If location is turned on when posting tweets, the geo coordinates associated with the tweet can be retrieved by Twitter API. During the Louisiana field experiment locational data is available through Twitter's API on 37 of the 216 total images (17%). This result shows a 100-fold increase in social media posts with images and precise location coordinates included in the tweet data compared to the estimate for Hurricane Harvey (0.17%). While this experiment is likely an idealized scenario for locational data collection, it provides strong evidence for increasing two-way communication on social media platforms.

Increasing two-way communication through social media platforms can increase public understanding of the importance of data in disaster recovery. If in the days leading up to Hurricane Harvey, people were given instructions on how to turn on precise location data and use event-specific hashtags for requesting aid or assessment, a significant quantity of images would be available to researchers of damage assessment. Generation of data at scale provides the necessary data inputs to train machine learning algorithms accurately for extremely low upfront costs. Machine learning algorithms become more accurate as more training data is made available.

The damage assessment model on Lobe.ai states that 93% of the images in the entire dataset (858) are predicted correctly (Table 3.2). However, manual tracking of model performance during individual image uploads from testing data shows a lower overall model accuracy at 64% (Table 3.3). The ~30% difference in accuracy results is likely due to Lobe.ai and its ability to retrain the model in real-time. However, real-world use mimics the results shown by the manual output accuracy in Table 3.3. Field use of image classification and machine learning in damage assessment would not be able to retrain a model until well after the preliminary damage assessment is conducted.

The accuracy of the current Lobe.ai damage assessment model is currently too low for utilization in a pilot study on preliminary damage assessment. The risk for miss-classification of damaged structures assessed as "Major" (33%) and "Destroyed" (56%) is high, to the point where recovery operations would be further inhibited using this tool. Higher quantities of image data are required to increase the accuracy of multi-class machine learning models.

## 3.6 Discussion

Findings from this study indicate that the current state of no-code machine learning platforms is achieving their goals of increasing accessibility. However, scalable use-phase implementation of no-code models remains uncertain. Further iterations of this study should export Lobe.ai models to no-code apps, such as Microsoft's Power Platform, to collect and test larger quantities of images. One-thousand images from each class should be included in the training dataset to better address the accuracy concerns with damage assessment models.

Collecting images from site visits is a massive time commitment by community organizations and disaster recovery agencies. The use of social media platforms as a means for data collection might provide the quantity of data required to more accurately train machine learning algorithms and speed up disaster recovery.

## 3.7 Conclusion

The current frameworks in place for disaster recovery and damage assessment cannot adapt to increasingly volatile global weather events. As a higher share of the global population gains access to smartphone technology and interconnectivity through social media platforms, government agencies must change how they collect valid data points. Machine learning and disaster recovery are on a collision course for implementation in real-world scenarios. How we construct new tools for expediting preliminary damage assessment processes and which communities are included in their creation will affect survivors of natural disasters over the coming decades.

Using social media as a platform for two-way communication for disaster preparedness can drastically increase the amount of valid and relevant data points for image collection. Images from a single natural disaster event can assist in decision-making for the prioritization of aid and can be made available to researchers for improving machine learning models.

Low code tools have a significant role in the future of disaster recovery operations. However, two impediments to adoption remain; first, higher levels of public understanding of machine learning will be required to gain acceptance. Secondly, increasing the accuracy of low code models to an acceptable level requires additional data points. Low code tools provide the means to solve complex problems intuitively by lowering the technical barriers to entry into machine learning. Without the use of artificial intelligence in disaster recovery, the billions of data points generated through social media remain inaccessible.

## 3.8 Resources for Next Steps

Research teams looking to replicate this paper's image collection method can use Twitter's API and the Tweepy Python library to parse image URLs from tweets.

Twitter API documentation
Tweepy documentation

A researcher with introductory-level programming knowledge will be able to search tweets by hashtags, sort by location, and determine if images are present. Upon creating a dataframe of individual tweets, image URLs can be parsed from the media entity of each tweet. If the quantity of images is low, saving unique images from a web browser is also a viable option.

Tutorial for gathering images from Twitter

Machine learning models created on Lobe.ai can be exported to no-code apps, such as Microsoft's Power Platform, or as Python-based notebooks as Tensorflow.

Intregrating Lobe.ai and Microsoft Build

## ENDNOTES


1 Kontokosta, C. E. (2021). Urban Informatics in the Science and Practice of Planning. Journal of Planning Education and Research, 41(4), 382–395. https://doi.org/10.1177/0739456X18793716

2 Omnicore. (2022, February 22). Twitter by the Numbers (2022): Stats, Demographics & Fun Facts. https://www.omnicoreagency.com/twitter-statistics/

3 Bhaskara, G. I., Filimonau, V., Wijaya, N. M. S., & Suryasih, I. A. (2021). The future of tourism in light of increasing natural disasters. Journal of Tourism Futures, 7(2), 174–178. https://doi.org/10.1108/JTF-10-2019-0107

4 Alam, F., Ofli, F., Imran, M., & Aupetit, M. (2018). A Twitter Tale of Three Hurricanes: Harvey, Irma, and Maria. ArXiv:1805.05144 [Cs]. http://arxiv.org/abs/1805.05144

5 Chen, Y., & Ji, W. (2021). Rapid Damage Assessment Following Natural Disasters through Information Integration. Natural Hazards Review, 22(4), 04021043. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000504

6 Chen, Y., & Ji, W. (2021). Rapid Damage Assessment Following Natural Disasters through Information Integration. Natural Hazards Review, 22(4), 04021043. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000504

7 Tapia, A. H., Bajpai, K., Jansen, B. J., & Yen, J. (2011). Seeking the Trustworthy Tweet: Can Microblogged Data Fit the Information Needs of Disaster Response and Humanitarian Relief Organizations. 10.

8 Rowe, W. (2019, February 15). How To Track Tweets by Geographic Location. BMC Blogs. https://www.bmc.com/blogs/track-tweets-location/

9 Alam, F., Ofli, F., Imran, M., & Aupetit, M. (2018). A Twitter Tale of Three Hurricanes: Harvey, Irma, and Maria. ArXiv:1805.05144 [Cs]. http://arxiv.org/abs/1805.05144

10 Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017). Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109

11FEMA. (2020). Preliminary Damage Assessment Guide (p. 127)

12 Temnikova, I., & Castillo, C. (2015). EMTerms 1.0: A Terminological Resource for Crisis Tweets. 13.


RISING ABOVE THE DELUGE

# CUTTING THE CODE: ACCESSIBLE MACHINE LEARNING


Authors: Jeffrey Pritchard, Danielle Stewart, Kiley Fitzgerald


### about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

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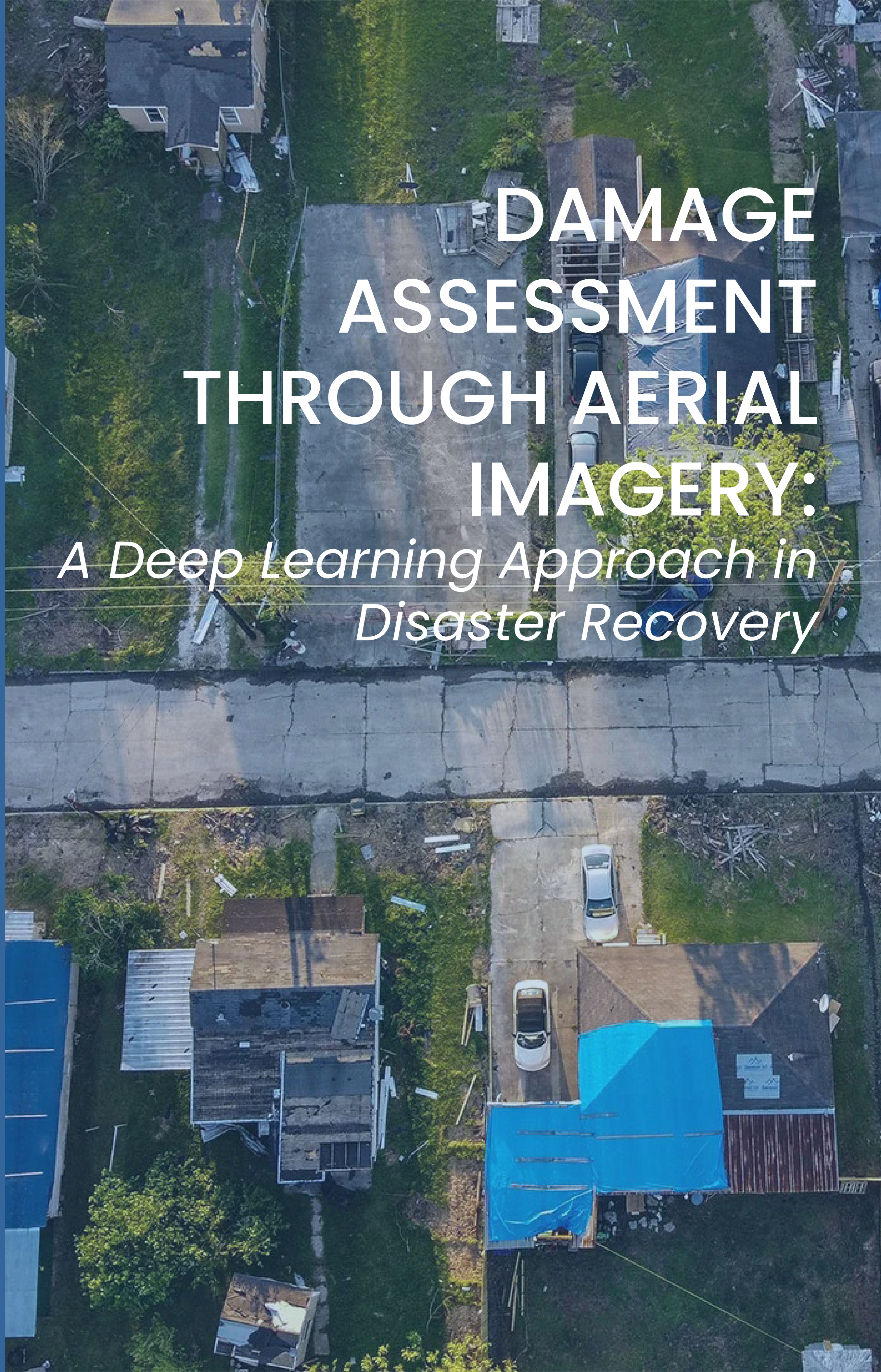
white paper series: aerial assessment



# DAMAGE ASSESSMENT THROUGH AERIAL IMAGERY:

*A Deep Learning Approach in Disaster Recovery*

# EXECUTIVE SUMMARY

This white paper focuses on the application of deep learning approaches for image classification, object detection, and change detection. Implementation of aerial image analysis and particularly the advanced deep learning analysis is imperative in returning a more accurate, efficient, and consistent damage assessment process. This paper argues that it is a net positive to increase the automation of aerial imagery analysis in order to improve rapid damage assessments. To explain this innovative approach the paper will 1) review relevant literature on the topic; 2) align this process with the Federal Emergency Management Agency (FEMA) framework; 3) address the role of object classification in aerial imagery to rapid damage assessments; 4) review technical processes which can benefit damage assessment; 5) assess the strengths, challenges, and barriers to utilizing such technology; and 6) observe findings and recommendations from experiments using these techniques.

## 4.1 Introduction

This white paper will focus on how deep learning approaches for image classification, object detection, and change detection can be applied to aerial imagery to improve rapid damage assessments. In order to explain this innovative approach the paper will 1) review relevant literature on the topic; 2) align this process with the Federal Emergency Management Agency (FEMA) framework; 3) address the role of object classification in aerial imagery to rapid damage assessments; 4) review technical processes which can benefit damage assessment; 5) assess the strengths, challenges, and barriers to utilizing such technology; and 6) observe findings and recommendations from experiments utilizing these techniques. Implementation of aerial image analysis and particularly the advanced deep learning analysis is imperative in returning a more accurate, efficient, and consistent damage assessment process. This paper argues that it is a net positive to increase the automation of imagery analysis. Hurricane Ida, which made landfall in late August , 2021 in Southeastern Louisiana, serves as a case study for evaluating this type of analysis. This paper also looks specifically at wind and flooding disaster events such as tornadoes and hurricanes, while also incorporating literature drawn from earthquake and wildfire events. The aim for this research, which includes the technical capacities demonstrated within it, is to aid emergency managers, assessors, and any entity conducting damage assessments in improving damage assessment processes through use of aerial imagery and technical solutions.

Damage assessment following disasters has traditionally been a very manual process which requires significant resources, staff and volunteer time to conduct. As noted by FEMA in the Preliminary Damage Assessment Guide, "A one size-fits-all approach to damage assessments is unrealistic."[1] The use of technology plays a role in fieldwork and in machine learning beyond improving efficiencies in manual data collection and bureaucratic documentation. As the FEMA Preliminary Damage Assessment Guide states, "understanding the technologies available (e.g., aerial imagery and ground-level photography) and ensuring the relevant stakeholders are familiar with the technologies being acquired and used for damage assessments is important for pre-incident readiness."[2] Thus, while challenges remain, FEMA encourages the use of new technologies, aerial imagery, ground-level photography, and other new innovations to improve damage assessment practices.

There is a need for rapid methods to be employed in the aftermath of a disaster event. With perishable data and the impacts of the disaster evident following the event, it is necessary to collect data as quickly as possible within the first 72 hours following a disaster before a more extended recovery begins. In this time period, the presence of roof damage including holes or exposed plywood on rooftops, changes to building footprints, and vegetative debris will be most evident.[3]

Aerial imagery is a critical tool in capturing the perishable data and real world impacts of a disaster from a high vantage point. In the initial three days to first two weeks following an event, presence of blue tarps and debris removed from the interior of structures for collection at the curb will become more apparent in aerial and satellite imagery.[4] Thus, aerial imagery collection has a temporal nature which must be considered alongside the hardware technologies deployed to capture the pictures and the software employed to analyze the images. Another key characteristic of aerial imagery is that it is also spatial in nature. Aerial imagery analysis and remote sensing capabilities have the capacity to interpret real world events in time and space through the lens of a camera. Throughout this paper, the nuances of time, spatial complexity, and technical capacity will be considered in each approach.

## 4.2 Literature Review

Computer vision has achieved significant improvements with deep learning methods, which have been successfully applied to a number of several types of aerial imagery analysis, such as object detection, object segmentation, hyperspectral image classification, and change detection. The use of machine learning and deep learning in damage assessment remains a novel process in the research of disaster recovery. The nature of the existing research

## DEFINITIONS

**DEEP LEARNING**
Deep learning is a class of machine learning algorithms that use artificial neural networks inspired by the human brain's neural networks. These algorithms use raw data to abstract and identify concepts relevant to human understanding. For the purposes of this paper, we employed a supervised deep learning method.

**IMAGE CLASSIFICATION**
Image classification labels and classifies digital photos. GIS deep learning processes can be utilized to categorize features.

**OBJECT DETECTION**
Object detection can locate specific features within an image. In GIS this can be used to identify individual objects from satellite, aerial, or drone imagery in a spatial format.

**CHANGE DETECTION**
Change detection utilizing deep learning identifies changes to structures between pre-event and post-event dates and mapping this change with a spatial component.

**IMAGE TRANSLATION**
Image translation can improve image quality and resolution. A deep learning process such as image-to-image translation can be employed to improve image quality and prepare an image for an image classification, object detection, or change detection.

**REMOTE SENSING**
Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft).

remains highly technical and focuses on accuracy and efficiency in algorithm type and training classifiers. This often leaves a gap in understanding how these technical resources effectively shape real-world disaster recovery.[5]

Recent research has worked with building footprint features as a pre-classifier for the damage assessment process. Given that much of damage assessment is focused on damage to structures, this method has contributed to a more efficient and accurate process. The research has emphasized three main methods for incorporating building footprints as a preliminary sorting of the aerial data: with pre-built shape files, ArcGIS Pro, eCognition, and analysis of blue tarps covering damaged structures via Convolutional Neural Networks (CNN). All three of these approaches showed promising results.

### OPEN SOURCE BUILDING FOOTPRINTS

Microsoft has produced high quality building footprint datasets with 129.6 million buildings in the United States. These building footprints were computer generated by Microsoft and use AI and computer vision to extract building footprints from Bing Maps imagery. This open data set is available to download for locations with clear imagery available. The vintage of the building footprints can vary widely from 2014 to 2021. The individual footprints are tagged when possible with the known date.[6] These datasets tend to be highly accurate, but have limitations given that the data is more than a few years old. More up-to-date information is needed in disaster prone areas. As in the case of hurricane impacted locations, one storm may follow another and altered building footprints, structure features, and properties can be difficult to measure using a static file from the year prior.

### GOOGLE EARTH ENGINE

Google Earth Engine is a free to use open source tool that offers access to extensive remote sensing data. This tool helps practitioners develop CNN frameworks. Multiple CNN frameworks have been created to detect building footprints. The latest Mask R-CNN algorithm developed in 2019 has proven highly effective in detecting detailed building footprints from complex

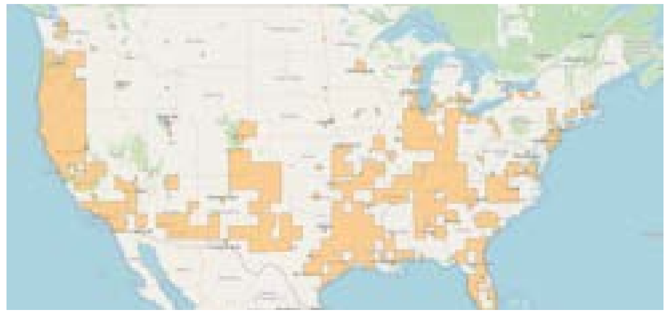


*Image 4.1: Areas of the United States with significant building footprint data sets available through Microsoft. Credit Bing Blogs*

photographs. While requiring additional effort, this method offers an additional free open source program to supplement existing building footprint datasets (Google, 2022).

### ESRI ArcGIS

ESRI has piloted multiple programs to create a visual interface that allows practitioners involved with disaster recovery an easy entry point into the execution of deep learning techniques. Similar to Google Earth Engine, ArcGIS can be utilized to extract building footprints from imagery. ArcGIS Pro has an established prebuilt deep learning process that provides one of the simplest ways to perform building footprint extraction to assist in damage assessments. ArcGIS Pro has created a deep learning package for US based building footprint extraction, making it easy for almost anyone to run the extraction and produce a layer with building footprints detected. ESRI has piloted multiple tutorials on use cases and explanations for practitioners, making a process that can be deployed in minutes and can be fed into the rest of the ArcGIS damage assessment workflow. ArcGIS Pro can also use an existing shapefile where recent building footprint data is available from other sources.[7]

### eCOGNITION

A study of the 2018 Woolsey Fire in Southern California performed damage assessment on approximately 1,000 structures in the affected Los Angeles County area. The study used 2017 processed building areas that were then clipped to generate image chips to isolate the target image outlines.[8] The study then used eCognition, an advanced object-based image analysis software for geospatial applications to classify buildings as damaged or undamaged. Notably,

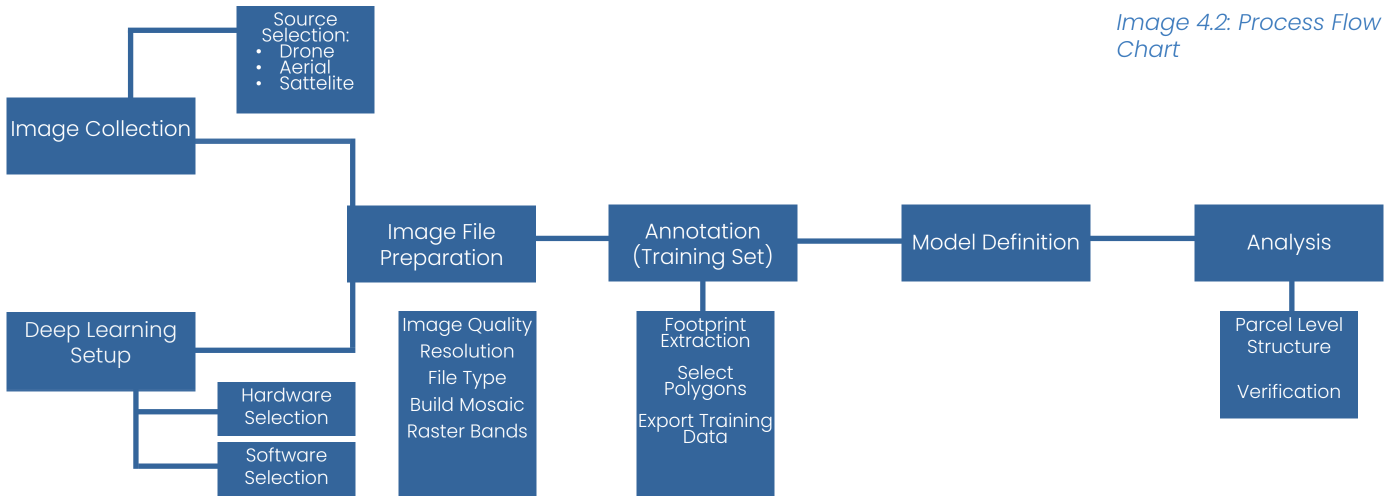



*Image 4.2: Process Flow Chart*

the footprint objects were classified as 'buildings' and the remaining background was classified as 'background' allowing for the ruleset to consider the changes in texture, mean color, and mean brightness on the 'buildings' only. Using eCognition allows for greater customization in the rulesets and custom feature calculations than the prebuilt ArcGIS Pro mechanism for model training. It is important to note that due to the nature of the fire, structures were either completely destroyed or preserved, which allowed for the binary classification. The results produced an 85% overall accuracy, and a 93% accuracy for damaged buildings.[9]

## 4.3 Alignment with the FEMA Framework

Almost all disaster recovery in the United States is influenced in some way by the Federal Emergency Management Agency (FEMA). FEMA structures aid and assistance through multiple frameworks and regulations affecting how state, local, and non-profit agencies operate and assist communities and individuals. Therefore, it is important that any damage assessment tool or technical process be aligned with these FEMA frameworks, allowing for their use to be easily adopted into the existing processes.

The National Response Framework outlines the "foundational emergency management doctrine for how the Nation responds to all types of incidents."[10] The key goal for active, effective response is integration and coordination of efforts across sectors and levels of government. Large-scale aerial imagery assessment can readily provide information that creates an understanding of damage at both a macro and micro scale allowing for greater coordination. Local government agencies are specifically tasked with assisting in the rebuilding of housing units. Aerial damage assessment can help local emergency responders understand and prioritize damage in recovery efforts, while also freeing up time and resources enabling them to perform other critical response tasks.

Most pertinent to this process is the FEMA Damage Assessment Operations Manual which promotes three goals: accuracy, efficiency, and consistency.[11] The use of deep learning in aerial damage assessment promotes all three of these goals. Deep learning can improve accuracy in damage evaluation and verify field assessments to ensure consistency. Although there are potential biases in deep learning assessments, there is also the potential for greater consistency in assessment as long as the human annotation is rigorous. Deep learning analysis can apply an "even hand" ensuring that attention is not unevenly distributed within and across communities. Overall, automating what is typically a manual process will increase efficiency. However, that efficiency should not be accepted without accuracy or consistency. That said, there are ways to address concerns of accuracy, consistency, and biases to make the benefits of deploying this process outweigh its limitations.

The onus in damage assessment is largely placed on the individual impacted by the disaster event. FEMA damage assessment guidelines suggest, "potential applicants are encouraged to photograph damage in order to expedite damage assessment verification".[12] Per the FEMA framework, much responsibility is placed on the individual. Individuals whose lives were upended in an instant are expected to fill out pages and pages of forms to comply with government requests. The government operates in a 'pull' mentality. FEMA is pulling information from residents, but only if the information is provided by citizens. Implementing a technical assessment to collect damage imagery can help alleviate the personal burden of documentation on the individual. This burden has the ability to prevent impacted individuals from being able to access much needed funds and resources in order to successfully recover long term.

What if instead of operating under a 'pull' mentality, the government utilizes wide-scale aerial analysis to 'push' aid to impacted individuals and communities? This would mean aid is not contingent on submission of paperwork by impacted individuals, but rather the onus is placed on government, assessing damage and delivering aid. By assessing structures and properties using aerial imagery in an automated fashion, government agencies can quickly assess damage and deliver aid to impacted individuals more rapidly. Under-assessments can be handled in a simplified challenge process. It should be noted that when dealing with structures, this type of aid primarily impacts property owners and more aid benefits should address impacts to renters including displacement and property damage. As a start, multi-family dwellings should receive a larger disbursement of aid relative to the assigned damage score and number of units to be delivered to tenants. This broad aerial damage assessment provides a mechanism to do the most good for impacted areas, delivering significant aid efficiently. It is a paradigm shift in pushing aid out for damage to individual structures rather than pulling information and property assessments from the public.

## 4.4 Role of Deep Learning in Rapid Damage Assessment

In Louisiana, following Hurricane Ida in 2021, a local assessor reassessed the property value for 20,000 properties in a parish through a process which incorporated aerial imagery into a workflow to assess each property, provide a damage assessment score to each structure, and deliver a discount on the taxes

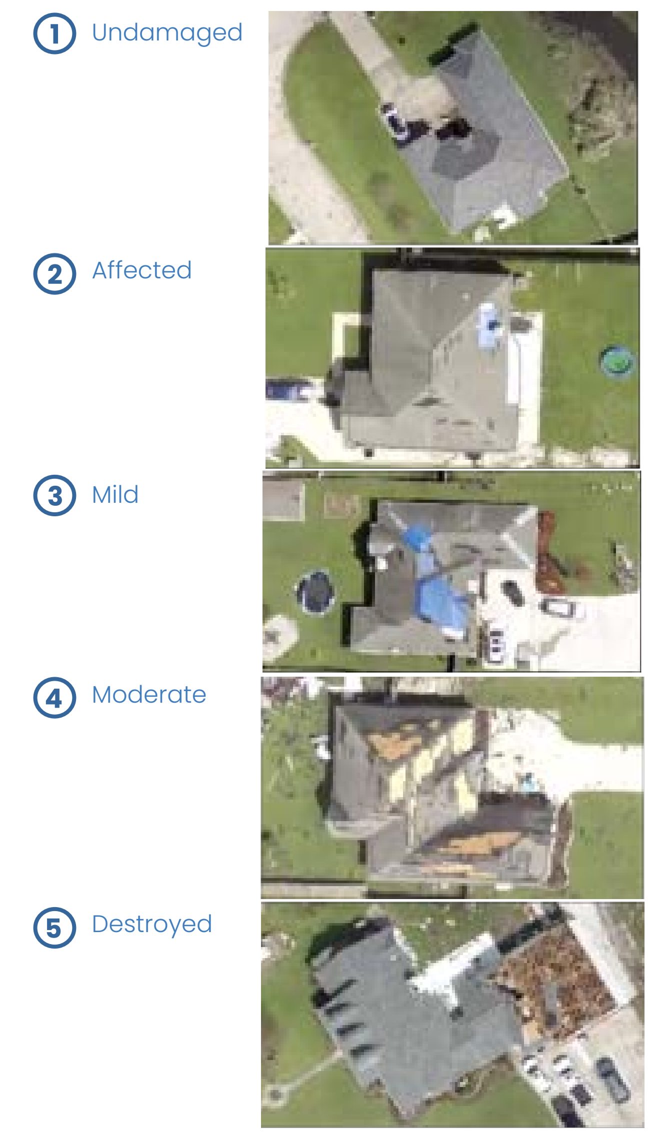



*Image 4.2: Aerial photos signifying Level 3 damage included in guidance materials for damage assessment in St. Charles Parish. Level 3 damage indicates visible structural damage with large areas of roof underlayment missing. It also signifies that the property likely has significant water damage. While the damage is not a total loss, it will require significant funds and work to repair.*

to that property owner as a form of aid.[13] This process represents an intensive effort to assess damage for an entire community. Relative to the commonly accepted standards, this assessor's office went out of its way to provide aid to a community in need. In a push mentality, this government entity took action on behalf of the community to get the work done through an innovative, time-saving methodology of aerial image review. Any disputes were taken on a case by case basis to address concerns on the assigned damage scores. The records show that very few disputes occurred out of the 20,000 assessments, showing the value of providing for the entire community when in other circumstances many community members may never receive this aid.

Such a manual process deployed in the field provides valuable lessons and insight on available tools for future damage assessments of this kind. A key lesson is that some components of the process deployed in this case study do not need to be abandoned for more automated methods. Images of disaster damage are a representation of real world impacts. The ultimate focus is on delivering aid and resources to residents who require the most assistance. While this should be based on the level of damage sustained to the individual's residence (in alignment with the FEMA framework), the human element consequences cannot be lost in the analysis. A remotely sensed damage assessment or on one conducted in the field can determine the level of damage inflicted by the disaster. But do they conduct this assessment with the same level of accuracy, efficiency, and consistency? In some sense, a remote sensing approach conducted behind a computer screen removed from the disaster site provides a level of protection from bias or serendipitous events on the ground which could alter an assessment. However, this distance from the site removes potential for understanding intangible considerations, connection to the space, and local knowledge. If damage assessments are moving increasingly towards incorporating imagery analysis rather than just field visits, it is appropriate for machines to be engaged more in this work.

Incorporating analysis of aerial imagery along with ground level imagery is a positive direction for emergency managers, assessors, and other disaster response professionals to move in. Utilizing imagery with geospatial qualities to review damage over wide areas can make a traditionally ground level process more efficient by providing a panoramic view of wide scale damage. This can inform need and priority for ground level decisions. With more time and resources, evaluation of damage to individual homes can be conducted. Automation can inform a more advanced model. Yet, if this process moves completely away from a field assessment to a more sterile environment and takes the form of a remote process for a staff member to conduct behind computer screens, then it seems appropriate for the machine to start doing more of the work. Deep learning techniques enable software and computation to evaluate properties, identify structures with signs of damage, and assess changes between a pre-event and post-event images. In the next section, the various available deep learning methods and training approaches will be discussed.

## 4.5 Technical Process Overview

Deep learning and image classification can assist with rapid assessment by augmenting the integrated data types available in damage assessment methods. Those integrated data types include: aerial imagery from multiple sources, available static files for structures, a recombinant collection of objects to identify, and additional parcel level information to provide a granular understanding of damage and change to structures post-disaster. Using a machine to produce a spatial dataset which identifies roof damage and change in building footprints can enable disaster recovery teams, emergency managers, assessors, and the broader community to optimize and prioritize areas, structures, and families that need assistance thereby enabling more targeted response and recovery. To investigate this further, the various deep learning techniques available to analysts are outlined below:

### IMAGE CLASSIFICATION

Image classification labels and classifies digital photos. For example, the image here shows classification by damage score to the individual photo of a structure. GIS deep learning processes can be utilized to categorize features. Image classification can be utilized to label structures in a binary manner such as damaged or undamaged, or on a scale, categorizing based on level of damage. Both methods are most effective when used in tangent with existing building footprints.

Building footprints are then annotated based on the classification model, and the deep learning analysis is limited to the structures. ArcGIS was selected due to its availability in most municipal offices, and also because it offers a visual interface making it easier to maneuver than other GIS tools, however, this process could be performed in an alternative program. The building footprints can be loaded into ArcGIS Pro or other geospatial analysis tools as shapefiles or extracted using the deep learning package for USA building footprints. Once that layer is established, a class field and class name is added to the attribute table and a sample is labeled for damage. The data is then exported using the Export Training Data for Deep Learning tool within the geoprocessing suite of ArcGIS Pro.

That data is then used as an input into the Train Model for Deep Learning module of ArcPro. This

Image 4.3: Image Classification using ArcGIS Pro

Image 4.4: Object Detection using ArcGIS Pro

process makes the intricately technical process more accessible for those unfamiliar with deep learning. The model is then used to classify the objects within the aerial image. Accuracy can vary dramatically depending on the accuracy of the annotation and number of training samples.

### OBJECT DETECTION

Object detection can locate specific features within an image. For example, the Image 1.3 shows a blue tarp being detected on a rooftop. A bounding box is used to identify the specific object feature as distinct from the other objects in the image. In ArcGIS Pro this can be used to identify individual objects from satellite, aerial, or drone imagery in a spatial format. This technique can be applied to other types of damage such as debris piles, fallen trees, and exposed plywood roofs. Identification of these features can functionally serve as a heatmap for damage assessment.

This process can be performed using the deep learning object detection tools in ArcGIS Pro. Practitioners can identify the desired features using polygons within their imagery to create a new training set that will be saved within the project folder. Similar to the classification tool, this training set is exported to create a model. The model is then used when running the Detect Object

Deep Learning geoprocessing. Ideally, the analysis then produces a new layer with all objects detected.

### CHANGE DETECTION

Change detection utilizes deep learning to identify changes to structures between pre-event and post-event dates while mapping this change with a spatial component. Change detection can be performed as a stand alone process or coupled with one of the above methods. ArcGIS Pro has a prebuilt change classification wizard that can determine the type, magnitude, and location of change. At least two raster image datasets or a time series set of imagery must be provided. The change detection wizard tool then allows these to be saved as a new raster image that shows the differences. If two raster images are being used, the output change detection can be saved as a raster function template that can be used for further geoprocess. This allows for polygon feature classes to be added as an additional step in tandem with object detection or classification. In fact, in order to tailor change detection to structural damage assessment most efficiently it should be used with object detection or object classification.

## 4.6 Strengths and Challenges of Technology

Advancing the use of these technologies is imperative in returning a more accurate, efficient, and consistent damage assessment process. Yet, there are challenges and drawbacks to the approaches of analyzing aerial imagery and utilizing machines to assess damage which should be considered. However, concerns for 1) human error; 2) resolution and image quality; 3) geospatial nature of aerial imagery; 4) proprietary and temporal aspects of aerial imagery; 5) hardware constraints; 6) software limitations; and 7) secondary data access should be evaluated when incorporating this approach into rapid damage assessments.

### HUMAN ERROR

Manual aerial imagery analysis leaves room for human error in the inspection of each home. In this process, staff members will review aerial images of each structure to determine the integrity of the roof and note any signs of damage. This primarily impacts the consistency and accuracy of the assessment. There can be mistakes made in the analysis of each individual parcel, particularly as fatigue sets in.

Running an automated analysis can reduce human error with regard to consistency and accuracy, and should also improve efficiency. However, in an automated analysis utilizing deep learning techniques and other feature detection capabilities, decisions in choice of analysis, geoprocessing tools, as well as image and evaluation criteria can result in poor results. Mistakes made in training the algorithm or model in selection of objects or placement of bounding boxes can have significant impacts. Choices made at the outset can produce domino effects at later steps resulting in cascading impacts. Here, the use of robust testing, statistical observations, and spot checking can reduce wide-scale error. The entire intent of remote sensing or aerial imagery analysis utilizing deep learning techniques is to relate image data to features on the ground. Validation by means of comparing output from the analysis with damage assessments collected via field work, comparable secondary data, or manual review of the imagery can help reduce this error.

### IMAGERY OVERVIEW

***Passive***
- Uses the Sun as a source of illumination that measures energy that is reflected back
- Aerial photography, infrared, thermal

***Active***
- Sends out pulse that has the capability to penetrate objects/surfaces that gets reflected back
- Radar, Sonar, LiDAR, SAR

***Multi-Spectral***
- Between 3-10 spectral bands

***Hyper-Spectral***
- As many as 200 or more spectral bands
- The narrower the wavelength, the finer the spectral resolution





### RESOLUTION AND IMAGE QUALITY

Imagery data collection must include close quality assurance which inspects the image for resolution issues. This is particularly true of satellite images which may not have a high enough image quality and resolution for deep learning analysis of individual structures. To truly conduct a granular damage assessment of buildings located on individual parcels, high resolution imagery at 1.5 meters will be necessary. Commercially available satellite photos may only provide 3 meters resolution which is not a well-defined image for this analysis. Firms like Planet Labs, Maxar, or even publicly available information from NASA will provide images which can be utilized for change detection if the resolution is closer to 1.5 meters, particularly for distinct colors such as blue tarps, at the census tract level but not for individual properties.

Aerial photography collected by airplane flyovers will likely deliver a higher resolution for this type of inspection, however such photography is often proprietary to firms such as EagleView or Nearmap and can be costly. Drone photography may also offer high quality enough imagery, though for a smaller geographic area. The National Oceanic and Atmospheric Administration will take photos in the aftermath of disaster events to monitor impacts to coastal areas and infrastructure. For instance, following Hurricane Ida, images were taken over interstates, highways, and coastlines in Louisiana. Firms like EagleView offer a proprietary solution which tracks new developments using an aerial image technology which can also measure dimensions of structures. While the primary use case for this offering is assessment of structures for valuations and property taxes, the aerial orthophotos are high resolution enough to be used for a deep learning analysis.

### GEOSPATIAL NATURE OF AERIAL IMAGERY AND ORTHOPHOTOS

When evaluating imagery from a satellite, plane, or drone for disaster recovery and damage assessments it is critical to account consider the geolocation of certain features. The image of a rooftop must be tied to a certain set of coordinates, address, or parcel in order for that resident to receive appropriate relief. Certain file types such as a GeoTIFF provide a spatial element to the photograph. Orthophotos are aerial photographs which have been geometrically corrected, or orthorectified, in order to follow a specific map projection and measure true distance[14] Aerial images, when compiled in a mosaic can cover vast swaths of a geographic region. It is critical that the spatial aspect of this type of photography be evaluated in the collection of imagery and the following analysis.

### PROPRIETARY AND TEMPORAL ASPECTS OF AERIAL IMAGERY

All imagery analysis must consider the temporal nature of any photography which is procured. Images are collected at a specific point in time. The conditions of light, shadow, contrast, alterations to photos, and weather should be recognized in not just the taking of the photos but in the selection of such. Satellite images of a certain geography are collected at a point in time when the orbiting device and its cameras are thousands of miles above those coordinates. The orbit controls the schedule for collection of photography and can result in the presence of clouds obfuscating structures. Aerial photography taken by a plane has much more flexibility in terms of timing as flights can be arranged to follow disaster events or if demand for coverage over a certain region is critical to observe. Alongside more flexibility in timing, there is less land coverage when compared with satellite photos. Access to such photography may also be more difficult to procure as public entities may not arrange flights over all territory while private providers do so at the behest of clients. Drone systems may provide an alternative to damage assessment teams to conduct such evaluations. However, these systems require an operator either in house or contracted with a longer timeframe required for collecting such photos than a satellite or plane.

All forms of aerial photography have some proprietary constraints. This makes much of the highest quality imagery taken of specific sites at specific times very inaccessible. Unless the entity doing the damage assessment has total control over the source of such photos, there will likely be a delay in the retrieval of photos. Satellite photo providers and aerial

Image 4.5: Aerial Imagery captured following a disaster.
Source: Planet Labs

photography have control over such imagery and unless a public entity such as NASA, NOAA, or otherwise is releasing the files, the entity conducting the damage assessment will need to access photos from a private firm which requires a financial commitment. Drone operation will require the purchase of a drone system and attainment of a trained operator, in-house or outsourced.

### SOFTWARE LIMITATIONS

A critical inaccessibility of these softwares is the perceived black box nature of deep learning or other techniques which fall under the manifold of artificial intelligence. These tools consist of a complex algorithmic design but can be layered over with buzzwords and oversimplifications. The complexity involved should not be a restraint to engaging with such tools, nor should they be given only cursory attention. Deploying this technology should warrant a deeper investigation into ins and outs of the algorithm in order to understand these technical components. Deep learning is a powerful force for interpreting real world patterns. This process should be made accessible to geographic information system (GIS) analysts everywhere. Analysis of this nature should not be under lock and key only for advanced computer scientists.  There are avenues both in traditional enterprise software systems such as ESRI ArcGIS Pro as well as other open source options which can make this analysis more readily available. This paper focuses on how ArcGIS can be deployed to conduct this analysis. In addressing next steps and how to move forward in advancing this type of analysis, open source options are raised as alternatives and future methods.

ESRI's ArcGIS Pro product has made deep learning techniques more accessible to GIS analysts, however technical challenges remain. Most governmental authorities which operate with a clear political boundary maintain some kind of GIS staff whether on payroll directly or via a consulting relationship. Disaster management agencies, counties, local municipalities, and regional authorities typically have access to a GIS capability. The dominant software used by these analysts is the ESRI ArcGIS suite, thus the deep learning tools for imagery analysis included in ESRI tools should be more readily available to any GIS analyst. However, barriers to entry remain as the deep learning techniques require training outside of standard GIS curriculum. Additionally, this software is proprietary in nature and requires a contract with ESRI in order to have access to its toolset. ArcGIS Pro has constraints in file inputs and particularities which must be reckoned with in an advanced analysis such as this. Beyond this, hardware constraints remain which limit deep learning process speeds.





### HARDWARE CONSTRAINTS

Hardware constraints can limit the level of analysis a GIS professional conducting a damage assessment may achieve. Several operations to prepare image files and other geospatial information can be run on a CPU which are provided on standard personal computer systems which typically run ArcGIS. However, the deep learning processes available through ArcGIS deep learning libraries and packages require a more robust computing system with a graphics processing unit (GPU) in order to efficiently and rapidly analyze photos using object detection, image classification, and change detection processes. NVIDIA CUDA is one such GPU and complementary software platform recommended for and capable of running this analysis, there are others.

These hardware constraints can also be overcome by the use of virtual computing services, which offer GPU powered processing through a web browser. Cloud computing will allow for the deep learning processes to be performed quickly and efficiently, potentially creating better process outcomes. However, these services, such as Amazon Web Services, Google Cloud Compute, and Microsoft Azure, can be costly and need to be closely monitored to ensure excess costs are minimized.

### SECONDARY DATA ACCESS

Challenges also exist in access to secondary sources of data and geospatial files which can validate deep learning methods and results. Shapefiles, JSONs, and other geospatial information may not be available or up to date for a specific structure or unit of analysis. This kind of information can aid in the analysis by providing a reference point to verify analysis of the imagery. Typically, this will be publicly available data from a local county assessor's office or other governmental entity. For instance, in building footprint extraction, a polygon file of building footprints can verify the presence of a structure against the extracted footprint from the photo. A static polygon file of this type can be useful in change detection as well. However, while a file of this kind is useful in terms of providing a large dataset, there may be discrepancies in the file such as lack of building footprints for mobile homes, out of date information, or discrepancies on specific parcels.

## 4.7 Findings

Utilizing deep learning in aerial damage assessment requires some technical knowledge, but can be deployed by almost anyone with enough resources, capacity, and time. The unit of analysis is at the parcel level as the focus is on indicating damage impacting structures on individual properties.

ArcGIS Pro provides a guided workflow and many tutorials for practitioners to use deep learning for aerial damage assessment. These visual based workflows make this technology much more accessible to those who may not be technical experts. Alternative methods require knowledge of coding languages and a steeper learning curve to get started. However, ArcGIS Pro does not allow for as much flexibility to refine the model for accuracy and efficiency. This can lead to a cap on accuracy expectations with ArcGIS Pro that could be potentially overcome through other methods.

#### Pixel Classification

In an attempt to cut down on annotation and pre-work, our team performed classification trials outside of the predetermined building footprint polygons. The hypothesis was that practitioners could classify damaged and undamaged structures with polygons using the training classification tool to eliminate the building footprint detection or import. Through this training the aim was for the tool to capture other damaged or undamaged structures. However, the results proved almost unmanageable. We believe the tool has difficulty distinguishing pixel groups when having to calculate for other materials which produces large swaths of rectangles with very little of meaning identified.

#### Classification of Objects

Using the pre-built deep learning model to extract building footprints has proven highly accurate using Arc Pro. This method, however, potentially biases away from impermanent structures such as mobile homes. These types of structures may be excluded from historic data in open source or institutional files as their footprints do not require permanent footings such as a basement. Additionally, when using the building footprint extraction, especially on post-event imagery, there is a higher likelihood of the non-permanent structures being missed because they may already be destroyed. This is more likely to occur when mobile homes are on large lots or outside of planned developments. Deep learning must be accompanied with human supervision to ensure that these types of structures are not missed. Special attention should be paid to areas that are known to have these types of structures, exemplifying why local knowledge is important in the assessment process.

**Classification Scale**

Classification of damaged structures through an attribute table of the existing buildings resulted in the most usable classification. An image annotation guideline was created based on the input of the local assessment workflow and the FEMA damage assessment framework. This scale ranges from a 0 indicating no damage to a 4 indicating complete destruction. These guidelines should be used in the future to create cohesive training sets that ensure the FEMA framework is being emulated and allowing for easier incorporation of multiple training sets. Standardization of the classification system also minimizes potential bias as it gives structure to the humans annotating images.

These classifications offer something novel to practitioners and researchers alike. Studies thus far have focused on binary classification of damaged or undamaged structures. Classification based on a scale created from the FEMA framework offers greater nuance and potential for the expedition of a disaster declaration. The scale is translated into color coded polygons making it visually easy to understand types of damage and clusters or trends. Coupling this method with change detection offers a particularly strong methodology that can hopefully extend to more accurate assessments and insurance processing.

Damage classification on a scale can create the potential for greater biases in the deep learning analysis. Training sets of annotated structures must be much larger to provide an adequate sample of each category to the model. This can create a heavy burden on practitioners attempting to create datasets individually. In addition, it can be difficult to discern between levels of damage, leading to greater levels of human error. However, given the fact that assessors and the FEMA framework use a scale for structural damage assessment, this method can create greater value for practitioners. Understanding the level of damage on individual structures can help create a faster assessment process for residents, allowing individuals to access aid more quickly and begin rebuilding sooner. It also allows for a more equitable assessment process in states (such as Louisiana) that require property reassessment post-disaster. Rather than a one size fits all property assessment deduction the classification of levels of damage can create a right size approach.

In an attempt to cut down on annotation and pre-work this team performed classification trials outside of the predetermined building footprint polygons. The hypothesis was that practitioners could classify damaged and undamaged structures with polygons with the training classification tool to eliminate the building footprint detection or import. Through this training the hope was the tool would be able to pick up other damaged or undamaged structures. However, the results proved almost unmanageable. It appears the tool has difficulty distinguishing pixel groups when having to calculate for other materials and produces large swaths of rectangles with very little of meaning identified.

Alternatively, annotation and training for a binary classification model can be less labor intensive and potentially reduce biases. When labeling a training set of images it is simpler to detect whether damage exists creating more accurate models for deep learning to use. However, it is important to remember the context, certain disaster types are more likely to accurately follow binary outcomes. For instance, wildfire response tends to leave homes destroyed or intact, whereas wind events may only partially destroy a structure making it more difficult to annotate and assess damage. Detecting damaged or undamaged structures can give emergency responders a quick visual cue to allow for prioritization of areas of need.

*Image 4.6: Deployment of blue tarps following Hurricane Ida*
*Source: New York Times*

**Object Detection**

Object detection can be utilized to detect debris areas as well. This can serve as another useful aspect of general aerial damage detection as it can capture types of damage that may not be evident based off of roof analysis. Just as roof detection is most useful after wind events, damage detection could also be useful in capturing flooding and internal structural damage. Debris damage is potentially more temporally sensitive and must be captured quickly as individuals are likely to clear out damaged personal property from their homes. If performed in real-time there is potential that this information could benefit trash haulers as well, but further research is needed to determine its usefulness.

Detecting exposed plywood on roofs can aid in the immediate recovery response and aid in disbursement of blue tarps. Plywood and blue tarp detection can offer an alternative overview of damage assessment. Given that roof integrity is one of the most essential aspects of structural integrity, detection of damage and exposed roofing can highlight structures that can be efficiently preserved from continued damage especially during rain events. Further evolution of blue tarp and plywood detection could create a percentile index where calculations and prioritization during aerial assessment are based on the percentage of exposed roof. However, since tarping sometimes occurs preemptively to a storm it is important to look at pre and post event imagery. In addition this method may not accurately capture the area of damage when tarps cover significantly larger portions of the roof than the area of damage.

Blue tarp detection should be conducted with a focus on identifying the presence of a tarp on a rooftop to indicate a binary presence (0 or 1) at the parcel level. This can assist in identifying areas which need assistance and closer assessment of disaster damage. Additionally, a parcel level score can include the presence of blue tarps as a weighted factor in a score. Analyzing images for blue tarps is useful in that the sharp blue coloration of these tarps has a distinct contrast to other land cover and structural imagery. This makes for a straightforward analysis to quickly capture damaged areas in the aftermath of a storm. Of course, concerns with this process include the failure to capture tarps of other color, exposed plywood, or distinct instances of roof damage.

**Change Detection**

Change detection is a simple, straightforward deep learning technique as it does not require annotation of a training set or training of a model. This single click can take a macro level assessment of the damaged areas, going beyond structure specific assessment. If emergency responders are looking to understand trends and clusters of damage within the area this can be a useful approach. The usefulness may be limited by the timing of the pre-event imagery, the further back dated the image is from the event the more non-event related change could be detected adding non-pertinent visual clutter. Using change detection can help verify the damage in post-event imagery. Incorporating pre-event imagery allows emergency responders to understand if the damage was caused by the event or if it was a pre-existing condition, ensuring that resources are not misallocated. This could significantly strengthen the confidence in deep learning damage assessment.

## 4.8 Recommendations

Deep learning models require less human input than machine learning algorithms that may only utilize a linear regression or decision tree because of the nature of the artificial neural network that is complex and intertwined like the human brain. Deep learning requires much more data to feed these algorithms, where machine learning potentially works with a thousand data points, deep learning often uses millions.[14] This ensures that the complex multi-layer structure has enough data to eliminate fluctuations and make high quality interpretation. Therefore, there is a need to increase the size and amount of training samples available in the disaster response context. Training sets can also be created pre-disaster using previous disaster imagery. While there are some existing image sets for training, most are not open source or readily available to be utilized within ArcGIS. Expanding on the established image sets that the National Disaster Preparedness Training Center has previously created and making them available to emergency managers could significantly reduce the time it takes to perform deep learning aerial damage analysis, by reducing the need for emergency managers to create their own training sets and models.

Exploration of other machine learning techniques would also benefit this area of study. Analysis of aerial imagery containing individual structures could be conducted utilizing an approach deployed for street level imagery. However, a critical piece of the work conducted utilizing aerial imagery is the geospatial nature of the analysis. Thus, a unique geospatial identifier such as coordinates or parcel number will need to be assigned to each individual aerial structure. Practitioners could potentially use ArcGIS Pro to manipulate the imagery and clip the building images and use the individual images in Google Colab or a similar software to analyze the individual structures. Additionally, use of other spatial softwares should be explored including Google Earth Engine and QGIS. Alternatively, exploration of options like change ChangeOS and other open source methodologies available to the general public is worth the time in each new analysis as the deep learning landscape is changing rapidly and new tests, experiments, and tutorials become available frequently.

Another area of rapid transformation relevant to this research and methodology are trends in availability of open source satellite imagery and aerial photography. Following the advent of digital cartography and GIS in the 1960s “the abilities of geospatial data collection and problem-solving have exploded. Innovations in digital tools for gathering, visualizing and analyzing geospatial information created new possibilities for public and private sector organizations alike.”[15] Now, a proliferation of satellites has grown the number of devices orbiting Earth for photography collection purposes into the thousands.[16] Private firms like Maxar, Planet Labs, SPOT, Airbus, and others have launched numerous satellites and innovated in this sector alongside government programs like the NASA and USGS landsat program. As space launch and satellite component costs fall, there is potential that higher quality imagery of large geographic areas will become more readily available with greater frequency. Given that, “companies that once had to pay hundreds of thousands of dollars to put a satellite into orbit can now do the same for a fraction of that price,” imagery may quickly become more available at lower prices with these economies of scale.[17] With this potential, privacy concerns may also escalate which should be monitored and evaluated in advancing rapid damage assessment solutions.[18] However, while this concern should be taken seriously, the need for delivering aid quickly is real and these trends in imagery availability should be seen positively with potential for community benefit.

Further research should explore creating linkages between aerial analysis and street level view of structures. The street level imagery would need to have location data attached either by parcel or by coordinates. Combining aerial data with street level imagery would not only create a more complete understanding of  structural damage, but also further expedite insurance claims. Allowing residents to click on individual parcels and print a report with street view imagery and the official damage assessment would create a uniform damage report that would take the guesswork out of requesting aid. This could significantly increase the level of aid to individuals in socioeconomic groups that typically lose out. Often lower income individuals do not have access to the resources or understanding to request aid, allowing their homes to remain damaged until the next disaster occurs compounding even more damage.

Nonprofits and community based organizations regularly try to bridge these gaps, but they are often overtaxed and under-resourced as well. Producing a public facing tool powered by both aerial and street level assessment would create greater cross-sector integration and improve equity in disaster recovery.

## 4.9 Conclusions

Although these technical solutions are complex and require advanced computing workloads and skills, there remains a net positive increase to the accuracy, efficiency, and consistency of rapid damage assessment. These advances further the goals of the Federal Emergency Management Agency and assist emergency managers, assessors, and community leaders to make informed decisions for better recovery. However, these solutions should be made more accessible with attention given to both hardware and software constraints. The current ArcGIS Pro deep learning framework provides a visual based tool that allows practitioners with an intermediate level of digital literacy an entryway into deep learning assessment work. While this is a good step, these tools need to continue to evolve to be more inclusive and create an impactful tool for the community at large. Disaster Managers, emergency managers, assessors who might not have mapping, machine learning, or an intermediate level of digital literacy. Implementation of aerial image analysis and particularly the advanced deep learning analysis should be advanced as a method in returning more accurate, efficient, and consistent damage assessment results.

## ENDNOTES


1. *Preliminary damage assessment guide - fema.gov. (2021, August). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/documents/fema_2021-pda-guide.pdf*

2. *FEMA (2021).*

3. Tab Troxler Intervew, St. Charles Parish Assessor, lives in Louisiana, USA personal communication, March 2022

4. Troxler (2022).

5. *Dell'Acqua, F., & Gamba, P. (2012). Remote Sensing and earthquake damage assessment: Experiences, limits, and perspectives. Proceedings of the IEEE, 100(10), 2876–2890. https://doi.org/10.1109/jproc.2012.2196404*

6. Microsoft. (2022, January 14). *New and Updated Building Footprints*. Bing. Retrieved April 11, 2022, from https://blogs.bing.com/maps/2022-01/New-and-updated-Building-Footprints

7. Microsoft. (2022).

8. Kulbacki, J. (2019, October 14). *Building Damage Assessment: 2018 Woolsey Fire, Southern California.* ArcGIS StoryMaps. Retrieved April 11, 2022, from https://storymaps.arcgis.com/

9. Kulbacki, J. (2019)

10. *National Response Framework*. (2019). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/2020-04/NRF_FINALApproved_2011028.pdf Preliminary damage assessment guide - fema.gov. (2021, August). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/documents/fema_2021-pda-guide.pdf

11. *Damage Assessment Operations Manual: A Guide to Assessing Damage and Impact*. FEMA. (2016, April 5). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/2020-07/Damage_Assessment_Manual_April62016.pdf

12. *FEMA (2016).*

13. Troxler (2022).

14. *Deep learning in arcgis pro. Deep learning in ArcGIS Pro-ArcGIS Pro | Documentation. (n.d.). Retrieved April 11, 2022, from https://pro.arcgis.com/en/pro-app/2.7/help/analysis/image-analyst/deep-learning-in-arcgis-pro.htm#:~:text=Deep%20learning%20is%20a%20type,object%20classification%2C%20and%20image%20classification.*

15. *Wolfewicz, A. (2022, April 21). Deep Learning vs. machine learning – what's the difference? Levity. Retrieved April 24, 2022, from https://levity.ai/blog/difference-machine-learning-deep-learning#:~:text=Machine%20learning%20works%20with%20a,and%20make%20high%2Dquality%20interpretations.*

16. *Maxar Technologies. (2020). Advances in Satellite Imagery and Technology Cause a Basemap Evolution. Maxar Blog. Retrieved April 25, 2022, from https://blog.maxar.com/earth-intelligence/2020/advances-in-satellite-imagery-and-technology-cause-a-basemap-evolution*

17. *UNOOSA. (2022). United Nations Office for Outer Space Affairs. Search OSOidx. Retrieved April 25, 2022, from http://www.unoosa.org/oosa/osoindex/search-ng.jspx?lf_id=*

18. *Chow, D. (2022, April 8). To cheaply go: How falling launch costs fueled a thriving economy in orbit. NBCNews.com. Retrieved April 25, 2022, from https://www.nbcnews.com/science/space/space-launch-costs-growing-business-industry-rcna23488*

19. *Brown, S. (2019, October 29). If you're worried about surveillance from space, read this. CNET. Retrieved April 25, 2022, from https://www.cnet.com/science/turns-out-satellite-surveillance-only-sounds-like-a-major-privacy-concern/*


RISING ABOVE THE DELUGE

# DAMAGE ASSESSMENT THROUGH AERIAL IMAGERY


Authors: Jane Dixon, Jon Haadsma, Rob Svoboda


### about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN

5

white paper series: local support

# COMMUNITY NETWORK ANALYSIS FOR DISASTER RECOVERY

# EXECUTIVE SUMMARY

Community networks are the relationships among community members that result in the provision and sharing of support, information, and resources. When identified and analyzed, these networks can be integrated into local disaster recovery and preparedness frameworks to better assess community needs and recovery capacities, especially when the presence of federal aid is no longer available or difficult to access. In addition, geographically and socially vulnerable communities still do not receive the adequate support or aid needed for equitable and resilient recovery.

This white paper aims to provide an understanding of how networks between community organizations and households influence disaster recovery. In addition, this paper identifies gaps in current disaster management frameworks, and encourages the implementation of participatory asset mapping and social vulnerability assessment processes. Finally, this paper provides a roadmap for how these strategies can be incorporated into disaster preparedness, immediate recovery, and long-term recovery frameworks.

## 5.1 Introduction

As global climate change worsens, the frequency and intensity of natural disasters, such as hurricanes and wildfires will continue to increase. This increase in the number of disasters will have widespread financial, health, and societal impacts on residents and communities across the United States. In the first nine months of 2020 alone, 16 separate one-billion-dollar natural disasters impacted residents across the US, resulting in significant displacement of households. [1] To address these challenges, disaster management frameworks must acknowledge and respond to the social dimensions of disaster recovery. This is essential to creating equitable, efficient, and resilient disaster recovery models that can help uplift communities following major disasters. Currently, inequities in disaster recovery can be attributed to recovery assistance largely being based on the amount of damage sustained to structures rather than a household's or community's ability to recover. This is often reflected in recovery frameworks that tend to favor "white disaster victims more than people of color, even when the amount of damage is the same."[2] Moreover, there is often an inattention to the lived experiences of individuals impacted by structural inequality within historically marginalized and rural communites that directly and indirectly impact pre-disaster conditions and vulnerability.[3] This, coupled with a general inattention to community networks and social capital as a significant variable in disaster vulnerability, justifies the need for a new approach to disaster recovery decision making.

This white paper aims to provide an understanding of how networks between community organizations and households influence disaster recovery. In addition, we offer ways beyond current disaster response frameworks to leverage existing social connections within communities to more effectively target communities for disaster preparedness training and distribution of recovery resources. Together, this white paper will introduce a method for incorporating social networks, community assets, and social capital into disaster recovery efforts.

## DEFINITIONS

### SOCIAL NETWORKS
Structures of connected individuals and organizations that interact and share information and resources that can support a holistic approach to disaster response. These networks often have overlapping commonalities, for example location, mission, industry, or cultural and social ties.

### SOCIAL CAPITAL
A form of social support that bridges resources and knowledge shared between local residents and across networks outside of their immediate community.

### CAPACITY
A measure of organizational strength, reach, and ability to mobilize resources to prepare for and respond to disaster events.

### RESILIENCY
The ability of communities to adapt to, respond to, and recover from disaster events.
Together, these concepts form the basis of a Community Network Analysis Framework for equitable disaster management.

### CURRENT AND EMERGING APPROACHES TO DISASTER RESPONSE

The Federal Emergency Management Agency (FEMA) published its second edition of the National Disaster Recovery Framework (NDRF) in 2016 with the goal of establishing "a common platform and forum for how the whole community builds, sustains, and coordinates delivery of recovery capabilities."[4] The framework documents values of resiliency and sustainability and challenges past recovery models that have focused primarily on rebuilding a community's physical infrastructure to its pre-disaster state. It also placed the ability of communities to coordinate local partners and resources as a guiding metric of future recovery success. In 2019, the FEMA National Response Framework introduced the concept of Community Lifelines as a focal point of immediate response. According to the framework, community lifelines are "those services that enable the continuous operation of critical government and business functions and are essential to human health and safety or economic security."[5] By prioritizing lifeline services, such as water and electric power, and approaching disaster preparedness by building capacities to "stabilize and restore community lifeline services", communities can more effectively recover from the infrastructural, economic, and social service loss.

Both frameworks place great emphasis on the FEMA Whole Community Approach to Disaster Management, which offers a strategy to engage the full capacity of private and nonprofit partnerships within the disaster preparedness context. FEMA defines the Whole Community as a "means by which residents, emergency management practitioners, organizational and community leaders, and government officials can collectively understand and assess the needs of their respective communities and determine the best ways to organize and strengthen their assets, capacities, and interests.[6] Together the collaboration of institutional and local community leaders can shape equitable and resilient disaster recovery by combining technical capacity, local knowledge, and trust to inform disaster planning.

Although these new frameworks for disaster response have been presented by FEMA, there is still a lack of action towards equitable and robust implementation and ensuring that all communities have the resources and support needed to pursue disaster planning through a Whole Community Approach. In addition, there is insufficient literature on how successful locally-scaled coordination of leaders and disaster management policy structures can occur.

### A COMMUNITY NETWORKS APPROACH: LESSONS FROM NEW ORLEANS

A field visit to New Orleans showed our research team that disaster response, specifically within the context of Hurricane Ida recovery period, is driven by a network of local leaders who are taking the initiative to protect and restore their communities when external support is not always guaranteed. This was evident in many of our conversations with local parish organizations, university scholars, and community members who spoke about the unmet needs of their communities, disconnections across the region, and the roles they were finding themselves filling during immediate and later recovery periods. We learned that through these roles, leaders from faith-based organizations, cultural organizations, and nonprofits have become hubs for communication, long term resource collection, and emotional support for residents following a disaster. However, during our field visit we also learned from organizations such as Second Harvest Food Bank, United Houma Nation, and Lower Nine that while communication between organizations and residents is strong, communication with other local and federal organizations is lacking. This leads to the duplication of work by multiple organizations and low levels of trust especially in federal organizations and agencies. In addition, other local organizations such as The Descendants Project expressed that existing communication structures resulted in the over distribution of resources such as ice rather than resources that were identified as high-priority aid.

Therefore, identifying where community assets and robust organization-resident communication channels already exist can help to identify where linkages in a network can be made. Furthermore, identifying and leveraging key leaders and organizations can help to understand a community's capacity to coordinate its networks to more equitably and efficiently prepare and respond for future disasters. With this in mind, our team guided our research questions to address these social network complexities.

## 5.2 Network Analysis as Disaster Preparedness Framework

A community's ability to prepare for any type of disaster can be strengthened by acknowledging and supporting the resources, knowledge, and relationships that already exist from within. Together, these factors form the foundation of community-based networks that evolve and expand as individuals establish roots within a community, maintain cultural traditions, form relationships, and learn to adapt to unique, context-specific challenges.[7] Once identified, community networks and community challenges can present a roadmap for disaster preparedness reflecting the unique experiences, vulnerabilities, and local capacities of a community. This community network-based approach to disaster management can shift the reliance on distant, higher levels of government to networks of established community partners. Ultimately, this can place communities in a position to establish resilient systems that can efficiently mobilize resources and communicate the needs of their most vulnerable populations.[8]

Network identification and network building are strategies that can be incorporated into municipal disaster preparedness plans and training. These strategies can range from traditional needs assessments that are completed for external state and federal recovery funding to less traditional participatory network mapping and vulnerability assessments that aim to build community-based recovery from within.[9] Establishing a disaster management plan that incorporates both strategies can lead to a holistic understanding of the needs, vulnerabilities, and local capacities present within a community. Yet, the latter strategy is often left out or not intentionally pursued within the disaster preparedness process, leading to equity gaps, miscommunication of needs, and preparedness and recovery plans that do not consider unique cultural and historic contexts of a whole community. Therefore, techniques to approach vulnerability assessments and participatory community network mapping are explored within the following sections.

### COMMUNITY NETWORK ANALYSIS

Identifying formal and informal networks within a community is by no means an easy task. Community ties and relationships are often very complex and are built over time, therefore requiring just as much, if not more time to fully understand every role and relationship.[10] Within the context of disaster preparedness, identifying community organizations and local businesses and the services they provide can present a holistic picture of the skills and resources available within a community. Moreover, these local institutions are often sources of trust and local knowledge, offering direct linkages to individual households and resident voices and needs. Identifying these linkages can be leveraged for faster and equitable communication and collaborative resource mobilization strategies even beyond the scope of the disaster context.

Asset mapping can be a first approach to visualizing these community networks. In addition, it can become the basis for community engagement and participation strategies that may establish relationships among community organizations, municipalities, and local businesses. Assets can be mapped through two approaches, first as an assessment of physical infrastructure assets, or specific equipment or facilities that can be utilized during disasters, and second as an assessment of social infrastructure, or specific organizations and individuals that provide communities with essential service.[11] These services range from food, utilities, shelter, and healthcare services to emotional support services that are often provided by local church groups and cultural organizations. The data collection process itself can take place either through survey distribution, interviews, or through mapping workshops that invite local leaders to participate in the creation of a community database of essential services and community contacts. Data collected during these workshops can be mapped using GIS or other mapping technologies to show geographic proximity and density of resources. This participatory approach to network mapping can ensure that individual communities guide the identification of community assets that are the most meaningful to them. These assets are often overlooked when asset mapping is approached using traditional asset definitions and categories.

A community network analysis goes a step further by defining how these sources of community assets communicate and to what extent organizations interact or collaborate with other local and regional organizations. The process establishes local organizations and leadership as nodes, or central hubs of communication that are essential to providing services and communication across local and regional scales. Local leaders are often city managers, first responders, administrators of public and private social organizations, coordinators of volunteers, and skilled workers.[11] By identifying these individuals and by analyzing the geographic reach for which their organizations serve, disaster management can tailor disaster preparedness plans to include formal and informal community leadership that can efficiently communicate and distribute resources that meet the needs of community residents. In addition, recovery from disasters rarely occurs immediately, as the physical and emotional impacts on communities can extend years after a disaster occurs. Therefore, identifying and strengthening these networks can create systems of support that can offer community members encouragement and tangible resources that may protect residents from future displacement during the rebuilding phase of recovery. Image 1 below illustrates just one example of how these asset maps can be visualized to be impactful tools for planners and emergency managers.

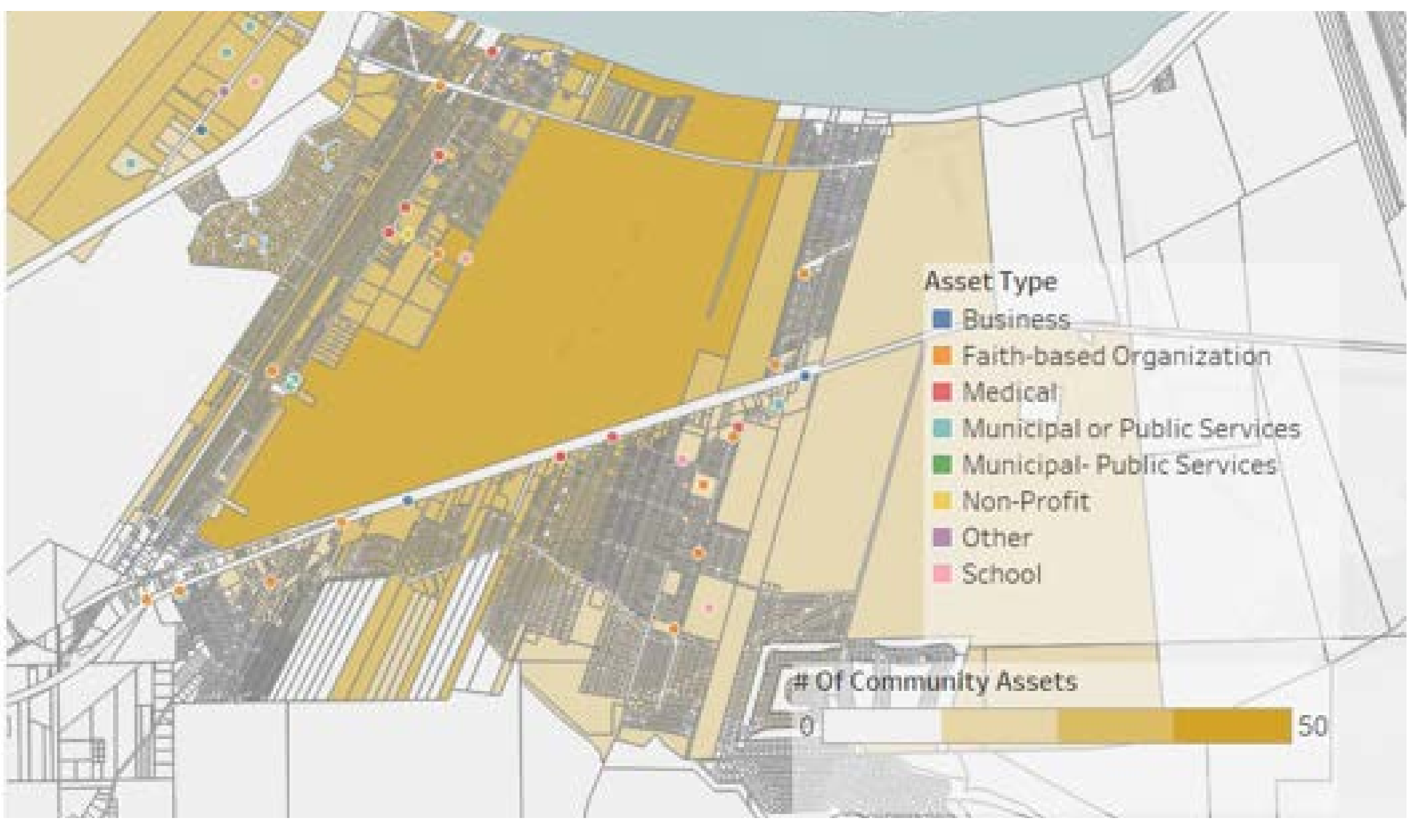



*Image 5.1: Map illustrating density of community assets in St. Charles Parish. Households with greater access to assets and resources are shown in dark yellow.*

## VULNERABILITY ASSESSMENTS

Assessing community vulnerabilities is yet another layer of preparedness that can be combined with network mapping to understand which areas of a community may be experiencing a gap in essential services. Specifically, it is important to identify at-risk populations first. The CDC defines at-risk populations as "individuals or groups whose needs are not fully addressed by traditional service providers or who feel they cannot comfortably or safely use the standard resources offered during preparedness, response, and recovery efforts."[12] These groups are often identified as those with limited English language skills, individuals with unique medical needs, geographically or culturally isolated individuals, homeless individuals, historically and economically disadvantaged individuals, elderly, and children. Identifying these sub-populations, knowing where they are located, and considering who their strongest community ties are can be invaluable to the identification of unique community needs and already-established leadership and resource communications structures.

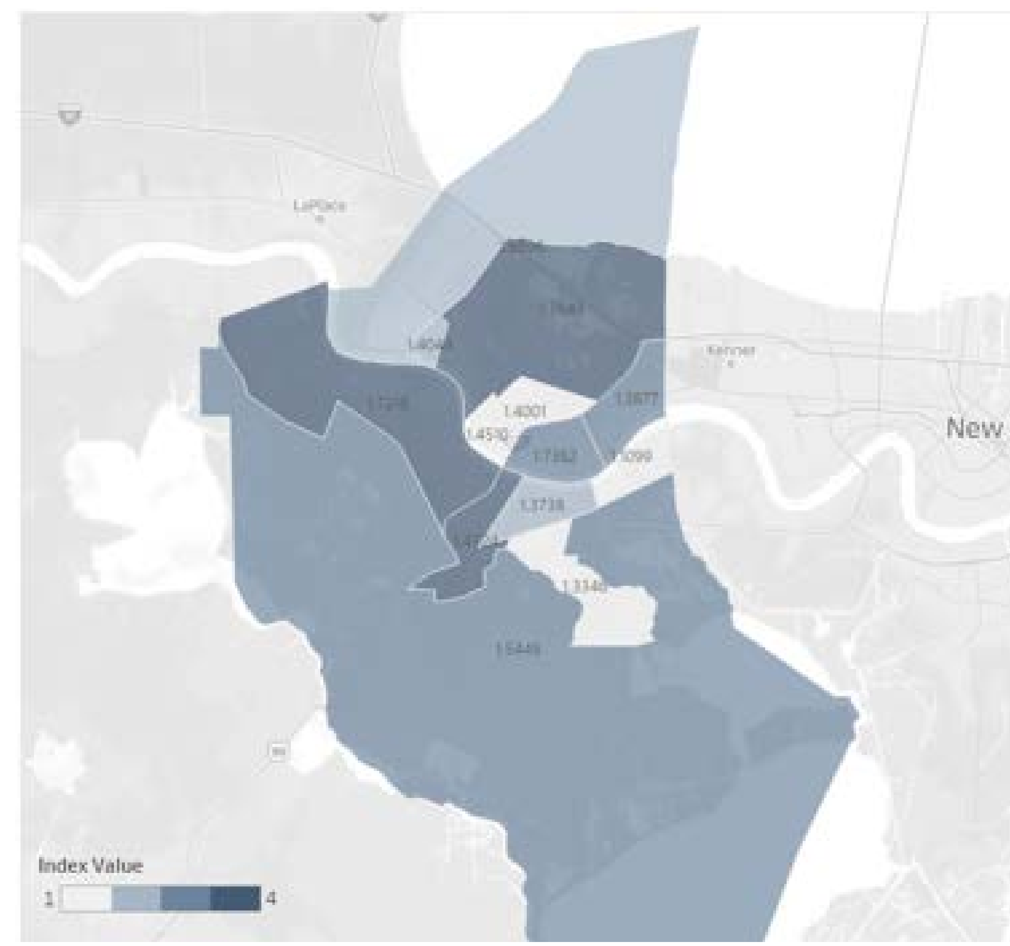



*Image 5.2: Map illustrating vulnerability in St. Charles Parish. More vulnerable census tracts are indicated by dark blue.*

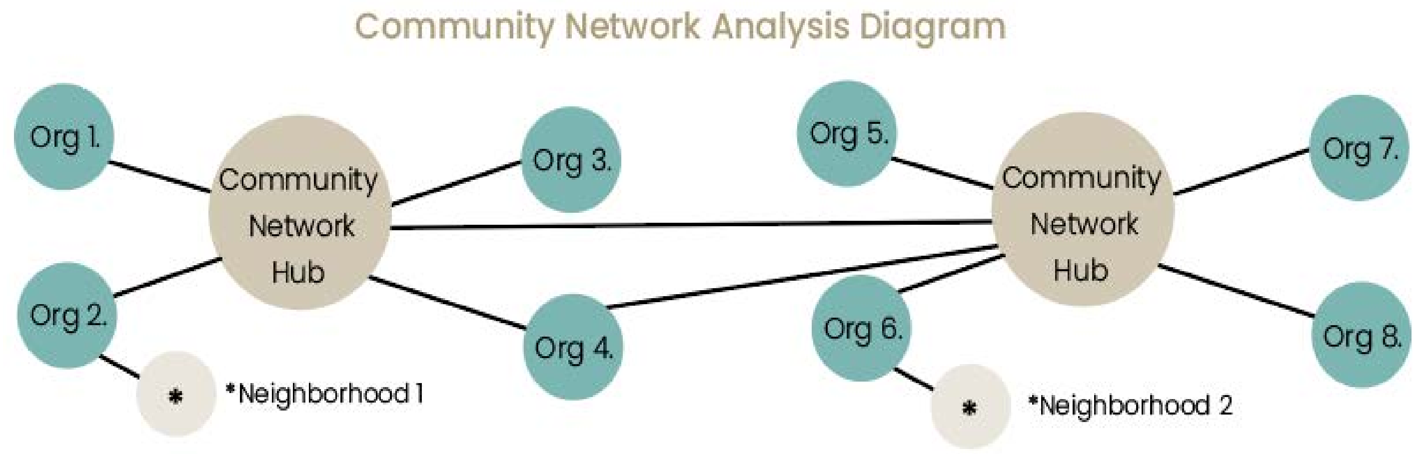



*Figure 5.3: Diagram illustrating a network of community organizations. Representations such as these can aid in community network analyses.*

There are many tools available to city planners, managers, and first responders that can be used to assess and visualize community vulnerabilities. One of the most well known is the use of a Social Vulnerability Index (SVI). SVI's can be used to understand geographically where certain vulnerabilities are densely located within census-defined boundaries. However, traditional social vulnerability measures focus primarily on demographic characteristics of households such as race, income, and age. In addition, these measures of social vulnerability are often executed by professionals in state and local emergency management roles, with very little input from local organizational leaders.[13] While these measures help to provide a baseline understanding of vulnerability, they are unable to assess the more nuanced characteristics of a community, such as social networks and personal ties, which are just as impactful for disaster recovery. Therefore, social vulnerability indices should be paired with other social analyses such as network analyses and asset mapping. Pairing them together allows disaster managers and planners to identify where socially vulnerable populations live and what kind of social resources they have at their disposal to help them to prepare, respond, and recover from disasters. For more information on how to create SVIs useful for disaster contexts, see our working paper on the rSVI.

## 5.3 Role of Strong Social Networks During Recovery

### IMMEDIATE POST-DISASTER RECOVERY

Social networks act as a powerful, localized tool for communities to more effectively mobilize and respond to a disaster event in the immediate post-disaster phase. Pre-planning within social networks can enable rapid mobilization, allowing for deployment of resources not limited to response times of larger regional or national agencies. Organizations within strong social networks are geographically well positioned to respond to the immediate aftermath of a disaster event due to their proximity to the communities impacted. This proximity can inform real-time decision making processes as organizations/agencies within the network recognize immediate needs of the community within the context of the disaster event. Short-term needs post-disaster include food, water, shelter, emergency services, and transportation needs that necessitate the ability to deploy resources rapidly. Strong social networks, particularly those who have engaged in thorough pre-planning activities, serve as a mechanism of delivery of resources to their communities in the absence of larger agencies who generally arrive later in the disaster cycle.

The embedded nature of social networks is useful in linking organizations to community members more effectively. First, local organizations and agencies enjoy higher levels of community trust and buy-in due which is crucial in the immediate aftermath of a disaster event. These trust relationships can be leveraged as both a form of information sharing, and for resource allocation/distribution; expanding the reach of organizations while simultaneously linking people to services. Disaster preparedness and response professionals should recognize the advantages of strong social networks, and more importantly how resources are attained in their absence. Communities with less social capital and network strength experience worse outcomes in the immediate aftermath of a disaster event, which thus impacts both overall community resilience as well as long-term recovery prospects.

### LONG-TERM DISASTER RECOVERY

Beyond the immediate post-disaster phase, social networks are impactful for long term recovery. The presence of strong community assets such as schools, businesses, and non-profit organizations has been linked to the ability for communities to recover after a disaster.[13] This is in part due to social systems "influeinc[ing] human interactions such as how information is shared,... decisions are made, resources are mobilized, and local activities are organized."[14] This highlights the importance of understanding social networks in disaster contexts, especially within socioeconomically disadvantaged areas which tend to rely on personal networks for disaster assistance.[15] Communities that are supported by strong networks of organizations experience better, more streamlined communication which allows them to recover faster than if they were disconnected from community members and organizations.

A study following major tornado events in rural Indiana, researched the impact of social capital and personal networks in post-disaster recovery and resiliency. The researchers found that household characteristics such as time spent in their current home, density of personal networks, and trust in government institutions all impacted the speed of recovery. In some cases, households with strong personal networks were able to recover more than twice as fast as households without strong networks. Overtime, this impact of social networks on recovery is particularly important for preventing displacement of residents.[16] Once communities become fractured after displacement, collective resources and communication between organizations and residents is impeded and recovery time slows down. Therefore, identifying existing social networks and facilitating communication between them can provide an effective strategy for helping communities to recover faster and prevent displacement.

## 5.4 Applications for Community Resiliency

Resilience is the ability of a household or community to adapt to, respond, and recover from a disaster event. Community resilience more specifically has been defined as "a process linking a set of networked adaptive capacities to a positive trajectory of functioning and adaptation," and is a crucial characteristic for emergency managers and planners to evaluate when addressing disaster response and recovery.[17] In contrast to measuring social vulnerability, resilience focuses on a community's potential to become more adaptable through risk reduction and planning practices. Resilience also informs a community's recovery process - a more resilient community will see better outcomes in both physical and mental health, mobilization of resources, and decision making processes supported by local knowledge and community buy-in.

Study of community resilience has highlighted the opportunities and challenges presented when measuring resilience, particularly in identifying indicators that can be broadly applied in different geographic contexts. Current literature highlights the lack of cohesive metrics of analysis across agencies in defining resilience, and has led to a call for more subjective indicators to be included in evaluation of community resilience. While common factors such as income, employment, population, education, and other basic demographic characteristics are important in assessing resilience, practitioners have begun to advocate for inclusion of qualitative data in resilience measurement. Qualitative metrics, while more difficult to measure, can provide important insights into distinct localities, and respond to the specific needs of communities. The resilience approach acknowledges that a "one size fits all" application of disaster response and recovery is not as effective without incorporation of local knowledge and capacities. Recent scholarship has called for the incorporation of contextually specific indicators including household perceptions of recovery, neighborhood and community values, and the interaction of social and organizational systems within the community.

The assets present within a community, and particularly how they engage as a network of connected resources and local leadership, can strengthen resilience in all stages of the disaster cycle. Strong social networks can serve as a critical linkage between community members, small scale organizations, and larger agencies before, during, and after a disaster event. Community assets and social networks can engender resident trust in institutions, resulting in more timely and efficient recovery processes. Additionally, networks can enhance resiliency through building out of processes and responses through each stage of the disaster cycle to provide culturally specific aid to communities.

## 5.5 Applications for Disaster Response Training

Building network analysis, asset identification, and vulnerability assessments within existing disaster management training modules is an important step towards equitable and efficient disaster preparedness and response. By introducing first responders and city managers to these processes, municipalities can practice identifying trusted sources of services, knowledge, and communication flows that ensure disaster management strategies are leveraging the strengths and leadership structures present within their community. Identification of these assets can be a first step towards making lasting relationships with local organizations, businesses, and, to a certain extent, individual households. This is especially important to ensure that organizations and businesses that serve isolated communities have the resources and capacities needed to support the residents they serve. As stated earlier in this document, these relationships often have the deepest reach within a local community. That is, local community organizations often provide services catered to specific populations that naturally establish trust and community-specific support. Therefore, training first responders to effectively coordinate with local leadership can establish two-way communication strategies that can lead to equitable and efficient disaster management.

In addition, as damage assessment and communications technologies for disaster management continue to evolve, it will become even more important that these emerging technologies and techniques acknowledge the network complexities and community vulnerabilities that occur within the local context. First responders, city managers, or disaster response teams must be trained to perform network analyses and to use this information to tailor communication strategies to local community contexts. Network analysis can also help guide emergency leaders to leverage the strength of existing local networks, both in acknowledgement of existing capacity structures and in the identification of external or regional partners who could be called upon for resources or advice.

In terms of emerging damage assessment technologies, offering training in network analysis in addition to technical training may ensure that technologies that are moving away from on the ground, human-driven analysis and towards more computerized approaches can still accurately assess damage in a way that prioritizes vulnerable communities for resource distribution efforts. For example, machine learning, or the process of training computerized programs to identify damage from collected real-time image capture, is becoming an increasingly attractive and promising approach to faster damage assessment. Yet, if not supplemented by an assessment of both geographic and social vulnerability, this data may fail to prioritize communities that need immediate assistance or who may not have the resources to recover as quickly as others. This can create inequitable distributions of resources and slow the overall recovery process for a region. Therefore, training that coordinates both network analysis and damage assessment technology may support a holistic and equitable strategy for disaster management.

## 5.6 Recommendations

For planners, disaster managers, and other disaster related professionals interested in implementing social equity components to their disaster management frameworks, there are four key steps for moving towards more holistic and equitable recovery outcomes. Adopting the following recommendations can provide the first steps to approaching disasters from a social network perspective that allows for greater local participation and incorporation of local knowledge.

1. **Adopt vulnerability assessment methodologies that are specific to disaster contexts.**
   *More specific measures, such as a household's time spent in their current home and access to an internet connection, can help to provide a better baseline understanding of the capacity of a community to recover. In addition, a catered social vulnerability index can integrate with social network analyses to help identify gaps between the presence of vulnerable communities and robust networks of communities with the capacity to aid in disaster recovery.*

2. **Adopt a social infrastructure approach to asset mapping.**
   *Social infrastructure approaches to asset mapping emphasize the role of services and organizations in a community. This identification of significant resource providers can later be further developed into a more comprehensive and robust network analysis that identifies key relationships and linkages between organizations. In addition, the process of asset mapping can help identify local leadership in an area, relationships with whom may be leveraged to access local knowledge.*

3. **Use local knowledge to broaden scope of resilience indicators.**
   *Communication with local leadership can help to yield identification of community specific assets and vulnerabilities. This information can be used to develop more contextual indicators of local resilience as opposed to relying exclusively on standard resilience indicators that are unable to account for the nuance of a local community.*

4. **Train disaster responders to identify local social networks.**
   *Training disaster responders to be more aware of existing local assets and networks can help to build trust between disaster planning and management professionals and the communities they work in. Further, training disaster responders to recognize existing communication networks can help to expedite the recovery process by utilizing trusted and verified local leadership to distribute information and resources.*

## 5.7 Conclusion

When implemented together, these four recommendations may result in better recovery outcomes for communities. Instead of the traditional, bureaucratic approach to disaster recovery which focuses primarily on providing financial compensation for damaged structures, this whole-community approach informed by research on community capacities, vulnerabilities, and resilience narrows in on the relationships and support systems which keep communities together. Framing disaster management and recovery efforts in this way allows for local inputs and perspectives which can help to lift marginalized communities and improve disaster recovery equity.

## ENDNOTES


1. National Oceanic and Atmospheric Association (2020). U.S. hit by 16 billion-dollar disasters this year, so far. (link)

2. Flavelle, Cristopher. (2021). Why Does Disaster Aid Often Favor White People?. New York Times.

3. Joseph, Jacquleen, Irshad, S. Mohammed, & Alex, Athen Matthew (2021). Disaster recovery and structural inequalities: A case study of community assertion for justice. International Journal of Disaster Risk Reduction, 66 102555. https://doi.org/10.1016/j.ijdrr.2021.102555

4. FEMA (2016), Natural Disaster Recovery Framework, Second Edition. 1-59 (Link)

5. FEMA (2016).

6. FEMA (2011), A Whole Community Approach to Emergency Management: Principles, Themes, and Pathways For Action. 1-24 (Link)

7. Tierney, K., & Oliver-Smith, A. (2012). Social Dimensions of Disaster Recovery. International Journal of Mass Emergencies & Disasters, 30(2).

8. FEMA (2011).

9. Schiffer, Eva & Hauck, Jennifer (2010). Net-Map: Collecting Social Network Data and Facilitating Network Learning through Participatory Influence Network Mapping. Field Methods 22:231 DOI: 10.1177/1525822X10374798

10. Schiffer et. al (2010).

11. O'Sullivan, Tracey L., et al., Citizen Participation in the Specification and Mapping of Potential Disaster Assets. Proceedings of the 10th International ISCRAM Conference–Baden-Baden, Germany, May 2013 pg. 890-895

12. CDC (Office of Public Health Preparedness and Response (OPHPR)), PUBLIC HEALTH WORKBOOK: To Define, Locate, and Reach Special, Vulnerable, and At-risk Populations in an Emergency, 1-63.

13. O'Sullivan (2013)

14. Emergency Demonstration Project, 2009.

14. Sadri, Arif M., et al (2018). The role of social capital, personal networks, and emergency responders in post-disaster recovery and resilience: a study of rural communities in Indiana. Natural Hazards, 90, 1377-1406.

15. Sadri (2018)

16. Hawkins, R. L. & Maurer, K (2010). Bonding, bridging, and linking: how social capital operated in New Orleans following Hurricane Katrina. British Journal of Social Work 40(6): 1777-1793.

17. Aldrich, D. P. (2010). Building resilience: Social capital in post-disaster recovery. University of Chicago Press.

18. Gil Rivas, V., & Kilmer, R. P. (2016). Building Community Capacity and Fostering Disaster Resilience. Journal of clinical psychology, 72(12), 1318-1332.


**Other Resources**


Townshend, I., Awosoga, O., Kulig, J., & Fan, H. (2015). Social Cohesion and Resilience Across Communities That Have Experienced a Disaster. Natural Hazards, 76(2), 913-938.

CDC (Office of Public Health Preparedness and Response (OPHPR)), PUBLIC HEALTH WORKBOOK: To Define, Locate, and Reach Special, Vulnerable, and At-risk Populations in an Emergency, 1-63 (Link)

Buckle, P., Marsh, G., & Smale, S. (2003). The Development of Community Capacity as Applying to Disaster Management Capability. Research Project Report, 14, 2002.

Hossain, L., & Kuti, M. (2010). Disaster Response Preparedness Coordination Through Social Networks. Disasters, 34(3), 755-786.

Mayer, B. (2019). A Review of the Literature on Community Resilience and Disaster Recovery. Current Environmental Health Reports, 6(3), 167-173.


RISING ABOVE THE DELUGE

# COMMUNITY NETWORK ANALYSIS FOR DISASTER RECOVERY


Authors: Laura Malendez, Elise Grongstad, Hannah Boettcher


## about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN

# BOOK TWO

*working paper series on process updates and improvements*

1

working paper series: RIDA+

# ADVANCING RIDA:

*Rising Above the Deluge*

# EXECUTIVE SUMMARY


The National Disaster Preparedness Training Center (NDPTC) is developing a decision support tool known as the Rapid Integrated Damage Assessment (RIDA) model. The RIDA model aims to assist early disaster recovery efforts, such as distribution of financial assistance or needed supplies through enhanced understanding of damage and vulnerability. The objective of the RIDA model is to provide decision support and prioritize hazard mitigation efforts so that resources are distributed to those most in need post-disaster. It is conceptually designed to encourage and enable integration of machine learning imagery analysis into damage assessment processes. Additional ways to understand disaster recovery in local communities include vulnerability assessments, asset mapping, and social network analysis.

This project explored such solutions in a case study observing Southeastern Louisiana following Hurricane Ida to interview local community organizations and visit impacted areas amid the early recovery period. From this case study, we find RIDA, in its current form, to be a powerful tool necessitating the incorporation of equity and local knowledge into its evaluation of disaster environments alongside improved technological processes.

This collection of papers focuses on how the local and technical support interventions provided in this project seek to augment NDPTC's RIDA model. To convey this, the paper will discuss the current RIDA model; the utility of the current RIDA model; the need for an evolved model (RIDA+); field work findings; technical support recommendations; local support recommendations; the gaps in the overall model; specific interventions and deliverables produced in this research, and a prioritization of RIDA+ interventions.




## 1.1 Introduction

A deluge of impacts and information face communities and disaster recovery professionals amid disaster events. The National Disaster Preparedness Training Center (NDPTC)'s decision support and prioritization tool, the Rapid Integrated Damage Assessment (RIDA) model, aims to assist early disaster recovery efforts. Enhanced understanding of damage and vulnerability can allocate resources such as financial assistance or protective materials more equitably. The objective of the RIDA model is to improve the decision support process so that resources are distributed equitably to the most impacted communities post-disaster. It is conceptually designed to encourage integration of aerial and street level imagery analysis through machine learning processes that assess damage. There are additional ways to understand damage, including vulnerability assessments. Vulnerability evaluates a household's ability to recover and complements the aim of understanding damage. Therefore, we recommend that the model adapt its processes to include other tools such as community network analysis, asset mapping, and a refined social vulnerability index to work toward a more equitable recovery following disasters. Specifically, this paper focuses on how the local and technical support interventions provided in this project fit into the NDPTC's RIDA model. To convey this, the paper will discuss the current RIDA model and its capabilities. Then, we will address our fieldwork findings and the need for tools like RIDA in the early recovery environment. Additionally, we will highlight necessary model improvements that advance the RIDA model by integrating equity, localization, and technical progress into its processes. We will then comment on the gaps in the overall model, highlight the interventions proposed, and line out the related working papers that further detail how to advance RIDA to a next iteration. Finally, we prioritize the interventions for the next iteration of this work.

## 1.2 The RIDA Model

Figure 1.1 illustrates the elements of the RIDA decision support model. In the first stage of the model, pre-storm data is collected from public agency reports and weather trajectory maps to understand highly susceptible areas for weather destruction. To further narrow the potential geography of damage impacts, the model then assesses vulnerability using the spatial areas identified in the initial storm trajectory step. The CDC/ATSDR Social Vulnerability Index is applied to census tract data to indicate neighborhood-level vulnerability to damage. Once these steps are complete, the resulting areas in the storm trajectory with a likelihood of damage impacts are mapped for further assessment post-storm. After the storm hits, aerial imagery is captured in those predetermined areas to triangulate roof damage and changes to building footprints. Using ArcGIS deep learning, modeling algorithms use imagery pre- and post-disaster to detect the presence of damage at a parcel level. Thus far, the process is non-invasive since it can be conducted remotely and without human input or on-the-ground collection of data.

However, the proposed RIDA+ model takes things one step further to categorize severity of damage while also tracking geolocation data. The framework then applies machine learning damage detection models to street level imagery which is captured based on the reports from the aerial imagery step. Once aerial detection and vulnerability narrows the scope of perceived and probable damage, a vehicle geared with 360 street level capture capabilities drives around the post-disaster destruction and takes images of parcel level damage. This step helps categorize the severity of damage while documenting and validating actual damage. The current RIDA model leaves room for iteration and produces damage assessment information, however a concrete, final output must still be defined. How can the RIDA model produce an assessment of damage for every structure in a defined area of need? How can this deluge of data, images, and unique local response be distilled in a solution that is actionable, equitable, and impactful for people in need?

## 1.3 Utility of RIDA Model

In the recovery process, it can take months to evaluate the extent of damage to a community after a natural disaster. To accelerate this process, emergency managers and disaster recovery professionals are developing data driven tools like RIDA that can expedite damage assessment and supplement planning decisions. Expedited damage assessment processes allow communities to receive more timely aid where it is most needed. However, the RIDA model's current operational period spans several months. In the initial steps, the gathering of pre-event data in the weeks and days before the event takes considerable time and local capacity to conduct. Analysis of pre-event modeling and actual event tracking to identify sites to target for the next phase must be expedited. While analysis of aerial damage detection influences street level imagery capture, it is unclear how each of these data points contribute to overall decision making or planning support related to damage. Since there are no indicators or thresholds to determine where to send field crews for on-the-ground street level machine learning, it is conducted via processes and assessments which need more rigor and robustness.

To summarize, there are two main areas of improvement needed in the current RIDA model. First, analysis of social vulnerabilities is only conducted during the pre-event stage of RIDA's deployment. As the impacts of natural disasters are unpredictable, integration of social vulnerability and equity of assessments should be intentionally designed in each step of RIDA's deployment. Secondly, each type of data collection and analysis within the current RIDA process is only linked by manual processes. Integration of systems as well as use of end-to-end software solutions is necessary to improve the capacity of RIDA, from a technical standpoint. A truly integrated RIDA model will enable the equitable distribution of aid to vulnerable communities in an automated and efficient fashion. Collecting and processing massive amounts of data, the RIDA model can quickly analyze the situation on the ground for emergency responders and more rapidly deliver aid to communities.

## 1.4 Field Visit Observations

The next iteration of the RIDA model offers an opportunity to build more robust processes that honor local community knowledge and streamline recovery decision support. Further integration of field work experience, research, and technical experimentation influenced our view of the RIDA tool and its methods. To better understand disaster recovery and where

## RIDA Interventions

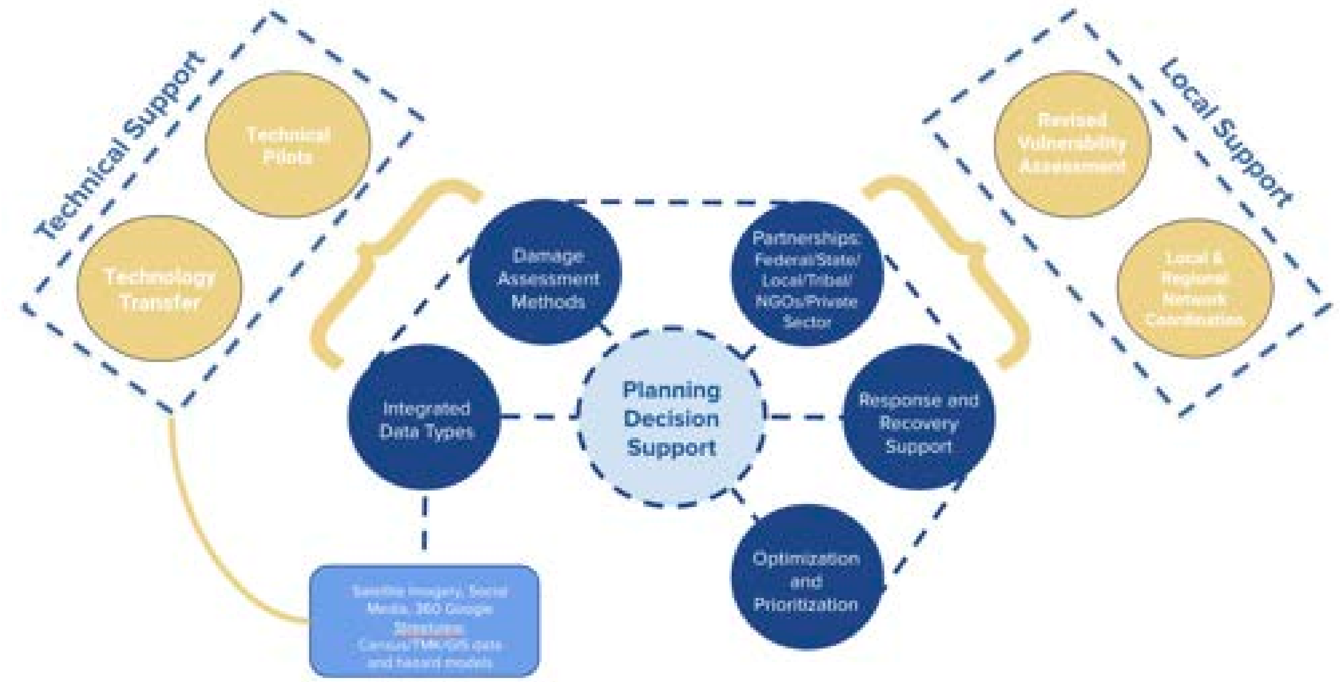



*Figure 1.1: Diagram of RIDA+. Existing RIDA framework is featured in blue while the RIDA+ additions are shown by the yellow extenstions of the diagram. Iterating on the existing RIDA framework creates opportunity for greater efficiencies and equity.*

## RIDA+ Model

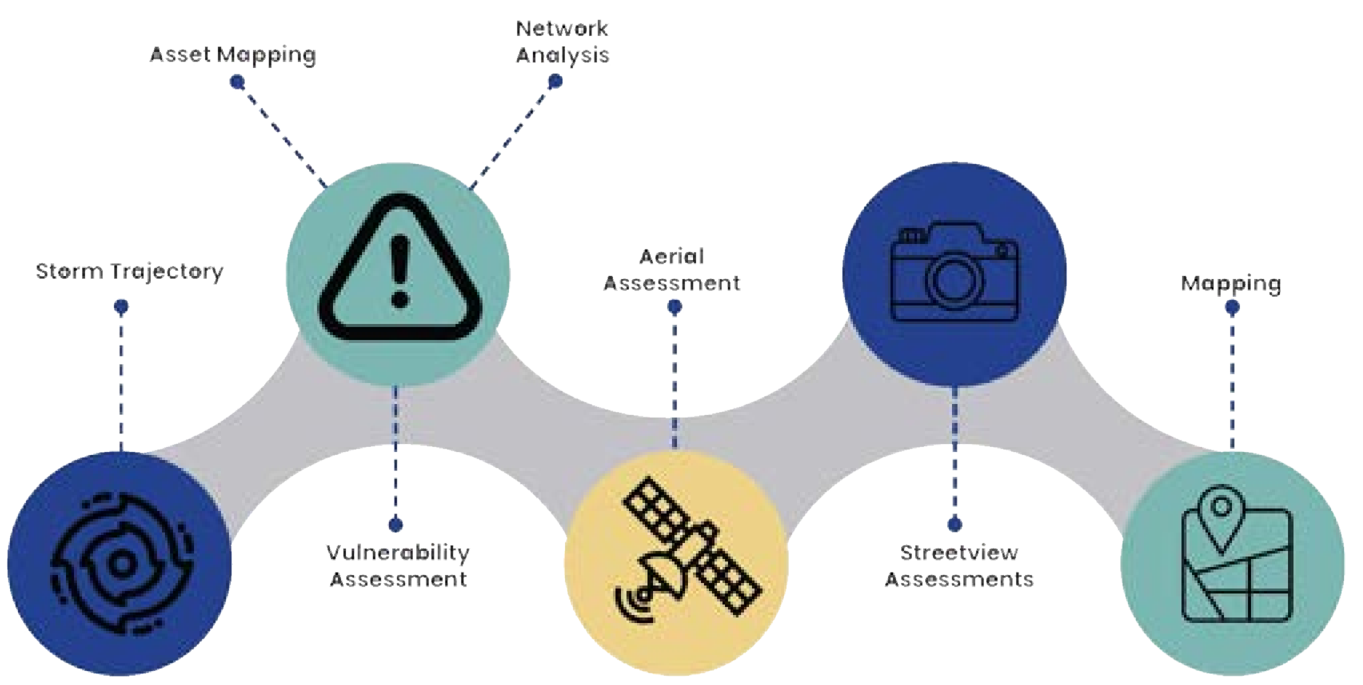



*Figure 1.2: Diagram of RIDA+ model indicating the chronological order of steps and interventions*

RIDA fits in, our research team visited Southeast Louisiana in February 2022 to meet with and learn from communities and organizations who responded (and continue to respond to) devastation from Hurricane Ida. Intentionally, we visited at time when Louisiana was still in recovery, yet the community and timing offered the benefit of hindisght with regard to response and relief as early recovery was underway. We entered the field with our own assumptions about disaster recovery; some notions were solidified while other hypotheses were interrogated. We were able to get a sense for the challenges professionals on the ground face. Through discussions with community advocacy groups, relief organizations, governmental partners, individuals in academia, and through informal conversations with residents, we garnered a more complete understanding of relief and recovery efforts in addition to the challenges communities in the region have faced since Ida. This field visit aided our understanding of disaster recovery, early recovery, where damage assessment fits in, and why RIDA is a needed tool.

### IMAGE COLLECTION

The field visit was a prime platform to test hypotheses and collect relevant data aligned within the context of our work on street level machine learning. We were particularly interested in gathering a wide range of built environment imagery that included varying levels of damage encompassing structures such as stilted homes, multi-dwelling structures, and commercial buildings. In addition to collecting images, some were posted to Twitter to test social media data collection. Using Twitter 's API, our team attempted to extract both geotagged and non-geotagged images to use for machine learning algorithm training. In total, we posted 286 tweets using different hashtags and keywords attached to each image and had success identifying 60 percent of the images that were posted. While the results of social media data collection were mixed, the overall takeaway was that data collection using only event images can be skewed for machine learning purposes.

Imagery collection beyond in-person collection is limited in the field. Local emergency managers and FEMA offices do not typically share nor post Hurricane Ida datasets containing street level images with damage. Often datasets are found through third parties. This comments on the perishability of disaster related damage. Perishability and collection tactics are important considerations as expressed from local residents who have been previously neglected as a result of imagery based damage assessments.

### ORGANIZATIONAL CONNECTIVITY

Communication channels between organizations and actors was a central focus of many of our conversations. Multiple organizations conveyed how strong their relationships were with partner agencies, and how fundamental they were in disaster situations to extract insights following an event. From the first meteorological forecasts to the days and weeks following a storm, organizations we talked to, such as the Second Harvest Food Bank and the United Houma Nation, use email and phone as their primary way to talk with partner organizations and residents. The Second Harvest Food Bank relies on the information that is gathered through these channels to coordinate where the need is for resource distribution. Though, the deluge of information (about power outages, urgent rescue needs, where shelter locations are, and more) following a disaster is so rapid that it is difficult to reliably coordinate resource distribution efforts. Further, organizational networks often find themselves siloed from one another leaving certain underserved communities left without vital access to information.

When further questioned about communication techniques, organizations began to acknowledge the limitations of the current methods they relied on and how there were missing links. While strong relationships are important, there was consensus that better communication methods existed to see who was doing what, where resources were going, and where there was still a need. Improving coordination following a disaster can have significant impact in generating effective and equitable resource deployment to guarantee those who are most vulnerable are getting the resources needed to recover. In hearing these sentiments, our team saw RIDA as having the potential to intervene and build better connectivity among local organizations. In integrating the layers of data and networks together under a single platform, organizations can rapidly identify areas most affected by a disaster, see what resources are needed, and what other organizations are responding in the area.

### DISJOINTED RESPONSE

Our findings from the field visit also conceptualized the disconnects that impede an integrated disaster recovery. The misalignment and inaction of governmental responses often creates gaps that fall on non-governmental organizations. Professor Robert Collins at Dillard University in New Orleans noted that the resources required for disaster response and recovery greatly exceed the resources of local governments. This demands resources from FEMA, and it also requires support from non-profit organizations to fill any void in local response. Already beyond their means, organizations attempt to meet a range of community needs with limited resources. Information sharing has its own difficulties, and while damage assessments have proven to be successful in creating reliable insights post disaster, if damage information is not properly shared, it can leave organizations excluded from broader relief efforts. These are just some of the ways in which the fractured nature of disaster response and recovery in Ida manifested, but they represent primary points of friction currently in the disaster recovery field.

While we heard about the many challenges in disaster recovery, we also learned of the many efforts underway aimed at a successful recovery. Second Harvest Food Bank runs a massive operation to face disaster events with an extensive network of assets and people. Community organizations maintain local knowledge of the area and individual households. We heard how the United Houma Nation had an image database of residential properties, how the Cajun Navy provided critical post disaster imagery, and how the St. Charles' Assessor uses aerial imagery to assess damage and provide discounts on properties as a form of aid. However, we found that these actions were disjointed and isolated from one another. We learned that this is often caused by local communities being left out of decision making. When outsiders came into communities, they weren't considering the social networks or culture of neighborhoods. In this vein, we saw the need to bring local knowledge and support into the RIDA process. By taking steps within community structures, disaster recovery can have more alignment in the coordination of efforts and resource distribution.

## 1.5 What is RIDA+

Based on the field visit, we infused observations from this experience and research into various steps of the RIDA model. Further research and testing helped guide our iterations and recommendations as discussed in supplementary working papers. Our team ran pilot programs and experiments on the ground to test and validate certain approaches. Our pilots include a SVI method at the parcel level, a community asset mapping process, a range of scalable methods for aerial and street level imagery machine learning analysis, an evaluation of various technical solutions, and a repository of annotated images. Working papers included in this document outline the finer details of the three core steps in the RIDA process: community network analysis, aerial assessment, and street-level assessment (see Figure 1.2). The working papers dig into each approach. Chapter 2 will cover the "Basics of Machine Learning" and "Street-level Imagery: Machine Learning for Damage Detection." Chapter 3 evaluates the technical tools and processes involved with "Aerial Imagery Deep Learning for Damage Detection." Local support and community network analysis methods are then discussed in Chapter 4, "Community Assets and Networks for Resiliency," and Chapter 5, "Recovery Social Vulnerability Index for Improved Equity."

In general, our final iteration of methods engages with data processing and advancement of local support analysis. The following depictions provide a high-level view of these iterations.

### TECHNICAL SUPPORT

**Enhancements to Machine Learning Algorithms**
Damage assessment machine learning algorithms cannot predict a household's ability to recover from a natural disaster by looking at a single image. Tools like RIDA can be improved to increase damage assessment performance through process standardization and increased representation of communities. To improve the existing RIDA model, disaster professionals should curate a tailored dataset for damage assessment that will lead to higher recall and avoid using trained algorithms that fail to address the needs of vulnerable communities. While all model performance metrics are important

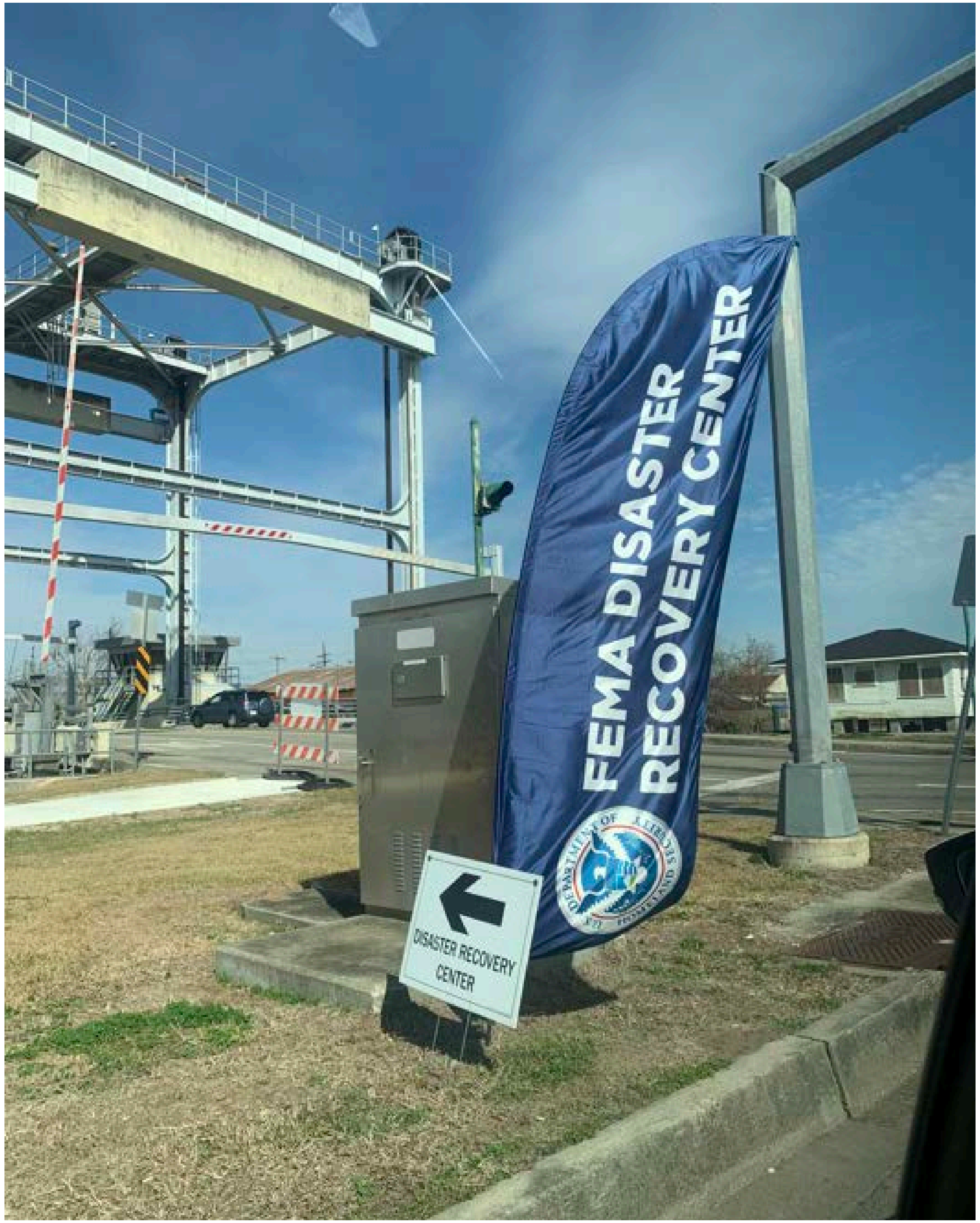



*Image 1.1: Sign for a FEMA Disaster Recovery Center in Houma, Louisiana*

for analysis, recall improvement should be prioritized at this stage of model development. Recall in damage assessment refers to the number of correct damaged structures detected divided by the total number of structures considered as damaged by the algorithm. A higher recall value can better avoid false negatives in damage detection. This assesses how correctly a machine learning algorithm can determine damage classifications based on its training. Curating a context-specific dataset supports the model in accurately identifying various levels of damage. Incorporating context-specific datasets into machine learning models produces more accurate identification of damage severity to homes within a community. This identification can provide emergency responders with the information needed to quickly identify and prioritize aid in areas that are hardest-hit by a disaster. Damages from disasters can vary by event, by region, and by home type, so it is imperative that neighborhoods are adequately represented when training and implementing the RIDA model.

Additionally, the RIDA model should pivot away from its current damage annotation process provided by CrisisNLP. When dataset annotations are boiled down to none, mild, or severe classifications, this opens the potential for introducing bias into the algorithm. To mitigate potential biases in the model, RIDA should be trained using FEMA's Preliminary Damage Assessment Guide classifications of affected, mild, major and destroyed. Homes are considered affected if the damage is mostly cosmetic. Homes in the minor damage classification have repairable non-structural damage. Homes in the major classification have structural damage or other significant damage that requires repairs, and homes in the destroyed classification have an imminent threat of collapse. These classifications are specifically defined and supplemented with examples in the Preliminary Damage Assessment Guide to prevent subjective classifications that could negatively influence the model.

Finally, the RIDA model should be audited regularly to determine who is not included in the model and to continue training it on a variety of home types. Auditing the performance of a machine learning model for damage assessment is necessary for two reasons. First, comparing the model-predicted damage severity with actual damage categorization of structures determines to what extent the machine learning algorithm is performing its intended function. Analyzing damage classification after each event keeps the model up to date with the changing conditions of natural disasters. Additionally, a qualitative analysis of which impacted communities are not represented in the training datasets provides a foundation for addressing equity concerns using machine learning models. Equity remains of the utmost importance as disaster recovery efforts "often help white disaster victims more than people of color, even when the amount of damage is the same."[2] Disaster recovery, in its current conception, can often exclude marginalized and vulnerable populations, making it even more crucial to audit damage assessment models regularly. Through curating a tailored dataset, standardizing annotations, and auditing damage assessment machine learning algorithms like RIDA, the damage assessment process can highlight communities most affected by disaster and accelerate the recovery process.

For more information, please review Chapter 2 which includes "Basics of Machine Learning" and "Street-level Imagery: Machine Learning for Damage Detection."

**Enhancement to Aerial Damage Assessment**

The utility of aerial damage assessment can be significantly increased by adopting a classification

*Image 1.2: Street-level imagery of disaster damaged stilted homes*

scale for damage based on the FEMA framework's 1-4 scale. Additionally, the model can incorporate multiple layers of assessment to increase accuracy and provide a more holistic view of damage. Implementing a classification for damage assessment results in faster disaster declarations and more equitable distribution of aid. Further, by aligning damage assessments with FEMA, it helps individuals ensure they receive the maximum amount of aid since the system is contingent on the verification of damage. In addition, since FEMA uses geospatial inspections to verify losses, it is already a proven way to determine expedited eligibility and delivery of initial assistance, especially for large numbers of individuals.[1]

Aerial imagery also supports other objectives in disaster recovery outside of streamlining aid. Through the creation of a multi-faceted model, aerial imagery provides additional support for debris removal and roof repair. For instance, using deep learning techniques like object detection in combination with the damage classification supports individuals in accessing the blue roof program through FEMA. Openly providing this information to residents can support their insurance claims and significantly reduce the burden of providing documentation to access support through these programs. More broadly, the proliferation of aerial imagery via drone and satellite operations can allow for a more open source approach to disaster recovery. Analysis of photos can also be opened up not just to any GIS analyst but community members and volunteer actors operating online to evaluate on-the-ground circumstances. That open source imagery analysis can support local recovery organizations in efforts to understand damage and community needs. This can reduce friction in resource distribution and speed up recovery.

A key argument going forward is that aerial imagery has tremendous possibilities beyond just assessing damage hotspots. The analysis of imagery can still highlight areas of need but the output of this analysis can also factor into the broader RIDA model. Building and roof damage can be assessed at the structure or parcel level and factor into a broader model which ties in street level imagery and social factors. The tools and capabilities exist to merge all of these variables together.

More information is reviewed on the details of this process and specific techniques in Chapter 3 "Aerial Imagery Deep Learning for Damage Detection."

### LOCAL SUPPORT

To increase the robustness of the existing RIDA model, modifications to the vulnerability assessment process and additional local support practices are recommended. Doing so will help RIDA+ to better adapt to local contexts, prioritize tool deployment, and ultimately provide equitable and holistic disaster recovery. Iterating on the traditional social vulnerability index (SVI) to include disaster recovery specific variables can help disaster managers and local officials to better identify communities that may experience slower recovery times. Additionally, the creation of a parcel level SVI provides a greater level of nuance in vulnerability assessments, especially in rural communities where census tract level data may not accurately reflect the spatial distribution of resources. Importantly, these innovations help to better prioritize the deployment of street level damage assessments to help provide aid to communities who need it most following a disaster.

In addition to the social vulnerability index, participatory asset mapping processes and community network analyses provide a more comprehensive look at disaster recovery. A community's ability to prepare for any type of disaster is strengthened by acknowledging and supporting existing resources, knowledge, and relationships. When identified, community assets and networks present a roadmap for disaster preparedness that reflects the unique experiences, vulnerabilities, and


*Image 1.3: Initial Hurricane Ida impacts (New York Times)*





capacities of an area. This community network-based approach to disaster management shifts the reliance on distant, higher levels of government to networks of established community partners. By training disaster responders to work with communities to create asset maps and network analyses, NDPTC can help to build trust between disaster planning and management professionals and the communities they work in. Further, this information can be used to create locally contextualized vulnerability assessments that are able to incorporate characteristics of a community not captured in standardized datasets.

Local support is more fully investigated in the working papers contained within this book: Chapter 4, "Community Assets and Networks for Resiliency," and Chapter 5, "Recovery Social Vulnerability Index for Improved Equity."

## 1.6 Closing the Gaps

There remain gaps both in the current RIDA model and in the scope of what this research was able to achieve in recommending an advanced RIDA+ model. Key domains which can close the major gaps in the RIDA tool going forward include building a map which integrates both aerial and street level imagery, advancing the incorporation of a social vulnerability index, and more fully connecting local support and technical support in one final product.

### INTEGRATIVE MAPPING OF AERIAL AND STREET LEVEL IMAGERY DATA

Intersecting information gathered from both aerial and street level imagery is critical to gathering granular information on structures for damage assessments. If an aim of rapid damage assessment methods is to not only understand where areas of need exist following a disaster, but to also provide a textured and specific analysis of damage to structures, then the pairing of data is paramount. Key to the pairing of such aerial and street-level imagery data is a unique geolocated identifier. To evaluate structure by parcels, it makes sense for parcel IDs to be the link. Coordinates or another geolocated spatial fabric are other potential options. The spatial nature of geoTIFFs and other aerial imagery allows for a comparison with assessing parcel polygons to associate an ID number with a damage assessment score. However, street-level imagery is not as simple to associate with a parcel ID or individual home address. The geolocation of each photo is often the location of the vehicle mounted camera on the road. Thus, a process should be implemented which would capture the address, a more clear and informed association with the parcel number, as well as tagging a photo with more exact geolocated info in order to pair the information. Solving this geolocation issue will allow an exact pairing between the output of imagery analysis from the bird's eye view with the ground level.

### FURTHERING SVI

To increase the efficacy of the social vulnerability index (SVI), it is necessary to integrate additional measures that add nuance to our understanding of vulnerability. One way of accomplishing this is by using multiple units of analysis to capture both macro and micro perspectives of vulnerability. On the macro level, it is important to cater social vulnerability indices specifically to disaster contexts to capture the variables that speak directly to a household or individual's capacity to seek out recovery resources. These types of indicators, such as renter occupancy, and access to internet connections are widely available on the census tract level. Aggregating and averaging these types of variables across the census tract provide a sweeping overview of a large population and allow users of RIDA+ to make first level prioritizations for tool and resource deployment. For rural and sparsely populated regions where census tract level measurements are inadequate, parcel level SVIs provide a closer glimpse of vulnerability and enable us to identify clusters of at-risk households. This can further support the prioritization of RIDA+ deployment. For a more detailed look at SVI development, refer to our working paper on the topic.

In addition to the inclusion of a parcel level measurement of vulnerability, incorporating asset mapping processes can help the NDPTC and other emergency managers identify resource gaps in a region. This type of analysis contributes to our understanding of vulnerability and indicates which households may lack access to valuable resources that aid in the recovery process. Including an assessment of local assets and community networks will contribute to the overall equity embedded in the

RIDA+ model. In addition, the process of asset mapping in tandem with local communities can increase the level of trust that residents and local leaders have in disaster recovery frameworks such as RIDA+. These relationships can be leveraged to improve crowdsourced data and image collection following a disaster.

### BRIDGING LOCAL AND TECHNICAL SUPPORT

Output from this project focused on two discrete angles in bolstering the rapid damage assessment framework and decision support model: local support and technical support. However, incorporation of these interventions is not the final output. The connection between local knowledge and technological innovation is a critical juncture. These two arms of research and recommendations are deeply intertwined and each ought not exist in the absence of the other or independently in a vacuum. The two must be integrated and speak to each other coherently.

It can be tempting to deploy technology to solve a problem at a distance using computing capacity. However, reliance on technical solutions alone can do real harm. This trust in the machine can leave out particular communities and populations given certain programming or decision-making biases. Machine learning damage assessment without reference to social vulnerabilities and the historic context of a community may lead to interventions that further expand resource and recovery gaps among communities within a region. And while local knowledge is absolutely essential to understanding recovery processes following disasters, when this information goes uncaptured or unshared it can limit recovery timelines and resources delivered. Analog methods which utilize human processes to gather data, do so with less efficiency than machines, yet capture qualitative and unstructured data. Joining the output of SVI information, network analysis, and asset mapping with damage assessment date (output from machine learning analysis of imagery) at the parcel or structure level is key to bridging this gap in a future version of RIDA.

### TECHNOLOGY TRANSFER

To ensure that the technical support interventions outlined in this project are adopted, technology transfer needs to be carried out between all participating entities. In order to fully realize a more accurate, equitable, and powerful RIDA, entities engaging in research need to both produce findings and clearly communicate such output openly. This is crucial so that teams which run the gamut from technical to local, academic to disaster recovery can continue the work to build and improve the model.

This team is making available a Github repository and public website that hosts datasets, coding notebooks, and video tutorials on how to customize a machine learning algorithm. Additionally, process recommendation documentation, ample background in white papers, a presentation, and other means will transfer this information to NDPTC and those investing time and capacity in RIDA. However, while this technology transfer between organizations with planning and technical capacities should be sufficient for the project to be carried forward, a real question exists on how technology transfer to local communities can be executed. Local support relies not simply on analysis of the community using secondary data, but input directly from stakeholders, residents, and neighbors. These perspectives are critical to understanding community needs and capacities. But there is also value in opening the capabilities of the digital tools and technical processes necessary to rapidly assess damage to local communities. The technology transfer from technologists to community advocates is key to developing the process of decision support and analysis most fully and equitably. Opening the tools, processes, and data collection up to the community can allow for unlimited potential. Laboratories of experimentation will form and local knowledge will organically pair with technical analysis.

### PUTTING IT ALL TOGETHER

The research, experimentation, and evaluation of approaches undertaken in this project has produced local and technical support interventions which form an array of deliverables for the team at NDPTC to explore and pursue further.

While these products do not completely solve all of the challenges outlined here, these deliverables contemplate and craft approaches to close the gaps. There is not one final packaged solution or fully built out RIDA+ model. Instead, an evaluation of tools, methods, experiments, research, and recommendations are included. All of these products argue for advancing a RIDA+ model which incorporates equity, information sharing, open source tools, and local knowledge alongside emerging machine learning techical capacities. These deliverables outline a vulnerability index, community asset mapping, network analysis, a data repository, aerial imagery deep learning analysis, and street level imagery machine learning analysis. Now, the subsequent decision is where to focus attention in the next phase.

## 1.7 Advancing RIDA, Prioritizing Interventions

To advance RIDA, close the aforementioned gaps, and build upon the original conceptions and interventions proposed in this research proposal, more work must be done. More time, human capital, energy, resources, and funding must be marshalled. Building RIDA+ will require grant dollars, academic research, and technical capacities. Five key projects should be considered for funding going forward:

1) Vulnerability Assessment
2) Community Asset Assessment
3) Data Collection Repository
4) Advanced Aerial Damage Assessment
5) Advanced Street Level Damage Assessment

In this section, each project is evaluated and prioritized for future efforts that may include a grant funding proposal. Each effort will provide critical dimensions to the RIDA+ framework and model in the next iteration. The interventions are assessed based on cost, time, impact, innovation, and growth potential. Scored on a scale of low to high (1 to 3), the most points equate to the highest priority assigned. Cost is the anticipated dollar figure, and time required the expected amount of hours needed for research and production. These two criteria are scored with a higher point score for a lower number of dollars and hours required. Impact is the benefit to the public in a scenario where public grant funds are utilized in advancing research to benefit people in communities. Innovation expresses a novelty and uniqueness in approach which can be a technical solution or a

RIDA INTERVENTION PRIORITIZATION SCORING

| | Cost ($) | Time Required | Impact (Public Benefit) | Innovation | Potential | Total |
|---|---|---|---|---|---|---|
| Vulnerability Assessment | Low (3) | Low (3) | Medium (2) | Low (1) | Medium (2) | 11 |
| Community Asset Assessment | High (1) | High (1) | High (3) | Low (1) | High (3) | 9 |
| Data Collection Repository | Medium (2) | Medium (2) | Medium (2) | Low (1) | Medium (2) | 9 |
| Aerial Imagery Damage Assessment Analysis + | Medium (2) | High (1) | High (3) | Medium (2) | High (3) | 11 |
| Street Level Imagery Damage Assessment Analysis + | Medium (2) | Low (3) | High (3) | High (3) | High (3) | 14 |

*Figure 1.3: Table reflecting the scoring of recommended interventions/projects. The total signifies the prioritization based on scoring of 1-3 for each project.*

reconfiguration and reenvisioning of existing concepts. Finally, potential outlines the opportunity for expanded utilization and implementation of a method. Impact, innovation, and potential all weight more points towards high scoring projects.

Based on this assessment, the highest priority project in the next iteration is the Street Level Damage Assessment Analysis. This aspect of RIDA is high in impact, innovation, and potential. Next, the Aerial Imagery Damage Assessment Analysis and Vulnerability Assessment should be prioritized. Further improvements to the SVI and incorporation of vulnerability add value to RIDA by incorporating equity. Aerial analysis is also a significant public benefit and opportunity for growth potential. Aerial imagery analysis should be prioritized due to the critical capabilities this imagery has in identifying structural damage over wide regions and the ideal geolocated connection at the structure level which can be forged between aerial photos and street level photos. This project is a necessary companion to street level machine learning analysis. While the time required to advance this method is higher, there will be significant public benefit and there is growth potential as satellite and aerial imagery become more readily available.

*Image 1.4: Street-level imagery of disaster damaged homes*

Finally, Community Asset Mapping and Data Collection are important projects that are lower priority, however it should be noted that in both cases the mapping and data collection may be a necessary step in other higher priority projects.

## 1.8 Conclusions

Processing information in the aftermath of a disaster event is an enormous undertaking. This is true for impacted individuals, emergency responders, community-based organizations, disaster recovery professionals, communities, regions, and governments. The resources needed often exceed the those available in the community. Organizations must rapidly unleash efforts to distribute supplies in an equitable and efficient manner. A homeowner must interpret the rules and procedures for filing a FEMA claim for a roof destroyed by wind damage. A mother and her child must face the realities of a flooded apartment and lack of funds to recover or relocate, let alone pay the rent.

In early recovery, a confluence of residual storm impacts and long-term planning decisions must be navigated. All along the way, data and facts regarding real world devastation can be captured. Documentation of such damage and perishable data early on is valuable. Automated analysis of such data adds even more value. This is vital if emergency professionals, planners, and communities seek to effectively and efficiently manage the deluge of data as disaster events increase in frequency.

RIDA, in its current form, is an advanced model with unique capabilities and much potential. The next iteration can advance this powerful technology and include key components from the outset: equity, openness, and information sharing. The facts on the ground illustrated in street level imagery, aerial orthophotos, and other available data will point to built environment damage. But it is the impact on communities, households, and people that must be integral to the RIDA model and disaster recovery efforts. Taken further, the information must be made public, shared with little friction, and open sourced. More access will spur innovation and interest to innovate and advance RIDA. We offer a set of technical and local interventions, recommendations on how to advance RIDA, methods that can build a robust RIDA+, and a desire to rise above the deluge.

## ENDNOTES

1. Flavelle, Cristopher. (2021). Why Does Disaster Aid Often Favor White People?. New York Times.

2. Individual Assistance Program and Policy Guide, FEMA. p 74

RISING ABOVE THE DELUGE

# ADVANCING RIDA: RISING ABOVE THE DELUGE

Prepared by U-M Deluge Capstone Team

## about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, valuing local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN

2

working paper series: street level imagery

# Street Level Imagery
## *for Machine Learning*

## 2.1 Introduction

In early recovery, local responders operate under pressures from residential communities facing damage and destruction, as well as federal organizations and aid programs demanding damage reports. While one lever asks for help, the other demands information about damage through reporting. The two stand at odds with one another until damage is captured, documented, and processed. Typically, damage assessments are lengthy processes that require immense coordination and support. Assessors and emergency responders who conduct damage assessments travel to each household in a community to assess damage in person. The amount of time it takes to conduct door-to-door assessment is exhaustive, and the practice of locally administered damage assessments is unclear, nonuniform, and frequently biased.

Prolonged damage assessments not only prevent aid or support from timely distribution to residents in need, they also neglect to capture crucial data on damage. The inaccessibility of damage data is known as perishability. Perishable data is the loss of information, and its value, over time. For damage assessment practices, damage information is invaluable because it expresses the severity of harm and destruction.  When people work quickly to repair their homes, information about a broken window or concave roof is lost. Altogether, manual damage assessment practices create data collection and resource distribution problems. These problems stall aid and resource allocation but inevitably provide insight about structural damage. In this light, damage assessments can assist and hinder recovery efforts.

New techniques are being developed to streamline damage assessment processes through data-driven tools. Researchers at the National Disaster Preparedness Training Center (NDPTC) are developing a new non-invasive tool known as the Rapid Integrated Damage Assessment (RIDA). The goal of this tool is to alleviate the tension between time, damage data, and local recovery needs through innovative machine learning applications. To do so, the RIDA model integrates whole image classification through machine learning algorithms to efficiently analyze household or building level damage. In this application, the use of machine learning helps (1) promote the rapid capture of perishable street-level data, (2) analyze damage severity quickly, and (3) reduce local burdens for assessment.

## 2.2 The NDPTC Model

As it stands, the NDPTC RIDA model currently uses the latest version in a series of object detection models known as YOLOv5. YOLOv5 is a machine learning algorithm that reviews data such as street level imagery to detect objects within the data. The purpose of integrating any machine learning algorithm into damage assessments is to preserve and capture on-the-ground data of damage and to assess severity levels. Further, the specific purpose of YOLOv5 is to capture. and store street level imagery while detecting damaged structures.

YOLOv5 balances fast processing speeds and high accuracy. The YOLOv5 model analyzes the data to detect damage on a scale from no damage,moderate damage, and severe damage. Researchers at the NDPTC use these three categories to train the machine learning algorithm without defining or describing classification categories. Each image is labeled according to perceived damage level based on information from the entire photo. The YOLOv5 model learns how to detect damage based on inconsistent whole image classification. After the model assesses damage severity levels based on annotated, whole images, the results can be communicated with local communities, disaster response professionals, and federal organizations more quickly than manual assessment.

## 2.3 Alternative Models

Although YOLOv5 is the machine learning model currently being employed in RIDA, it is not the only algorithm that can be leveraged. Other popular machine learning algorithms include Grad-CAM, Mask R-CNN, and Lobe.ai. Each algorithm relies on different learning techniques than whole image classification.

**Grad Cam** *(Image 2.1)*
Grad-CAM, also known as Gradient-weighted Class Activation Mapping, uses pixelated color gradients of objects or regions to detect their location and/or classification. While Grad-CAM has been deployed in many instances for localization and classification, there are no accessible instances of its application for street-level type detection. Grad-CAM appears to be used most frequently with small objects such as medical x-rays and animals.


*Image 2.1: Example of Grad-CAM:: Application of pixel gradient maps on houses. Credits to Georgia Institute of Technology and Facebook AI Research.*

**Mask R-CNN** *(Image 2.2)*
The Mask R-CNN model is one of the most robust machine learning algorithms for instance segmentation, as well as classification and localization. Mask R-CNN has extended the usability of other popular networks for "predicting an object mask in parallel with the existing branch for bounding box recognition." The Mask R-CNN model can be trained to detect damage through retailoring introductory tutorials and sample algorithms. For example, one Mask R-CNN algorithm detects and masks street-level data

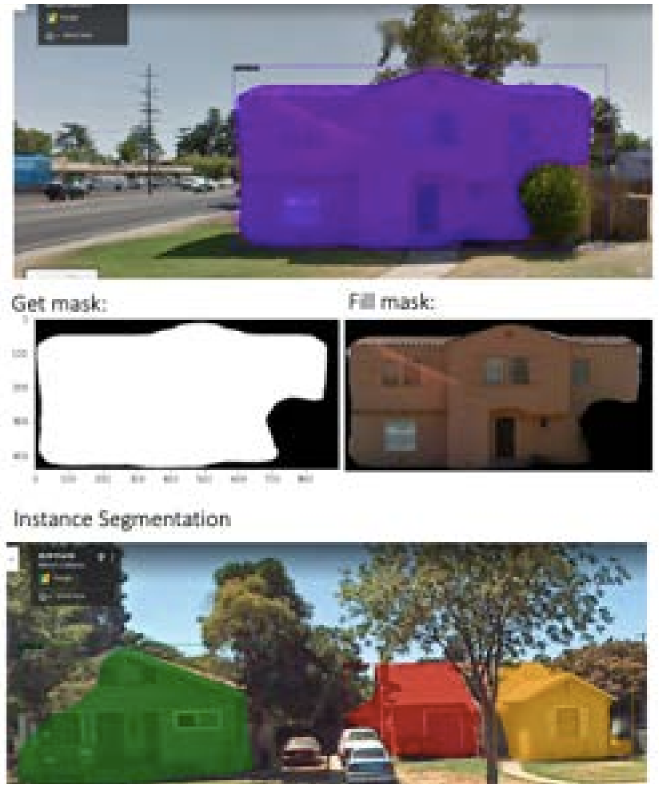



*Image 2.2: Example of Mask-R CNN:: Segmentation of Historic Buildings of the City of Merced. Credits to Alberto Valle, Anais Guillem, David Torres-Rouff, PhD.*

such as cars and houses through videos.

While many Mask R-CNN applications use binary classification and multi-classification to detect distinctly different objects from an image, there are no current models that replicate the nuances for disaster damage detection. To build a scalable model that incorporates the intricacies of damage detection is resource dependent and timely.

There are also developmental setbacks including annotation and training speeds that hinder the application of Mask R-CNN. Mask R-CNN online annotation platforms are moderately time consuming, taking roughly two hours to properly annotate, label, and download a dataset of only 100 images. The training speeds for Mask R-CNN tend to be much longer, averaging 5 frames per second (fps). For reference, YOLOv5 learns at a rate of 140 fps, which means it processes nearly 30 times more data per second than Mask R-CNN. Despite low fps rates, Mask R-CNN can be pre-trained for future application. Researchers at the NDPTC can prepare a model's algorithm beforehand to share in the future. Therefore, more exploration of testing speeds rather than training speeds on a pretrained Mask R-CNN model is necessary. Instance segmentation overall can increase data capture and generate faster insights on damage severity given a robust pre-trained model. However, for rapid training, deployment, or development, there are notable barriers compared to more basic, simplified models.

**Lobe.ai**

One last platform worth noting is Lobe.ai, an application that utilizes two machine learning algorithms simultaneously to improve the model's speed and accuracy (MobileNetV2 and Resnet-50V2, respectively). Developing a model on Lobe.ai begins with uploading a training dataset and labeling images via image classification. Lobe.ai continuously runs and updates the model throughout the annotation process. Image augmentation includes adjustments to brightness, contrast, saturation, hue, rotation, zoom, and noise of images. Since training data sets can contain hundreds or thousands of images, mistakes by humans during the classification of images may occur. Lobe.ai's user interface allows for easy review and analysis of those mistakes, and users can easily assess misclassified images even during model training. Machine learning models can be exported to no-code apps from Lobe.ai, such as Microsoft's Power Platform, or as Python-based notebooks. Lobe.ai is currently in beta development and only includes image classification but will release object detection models in the future.

## 2.4 Further Considerations

For other researchers interested in developing a machine learning damage assessment model, there are a few overarching considerations that contribute to the utilization of YOLOv5 over other described platforms. The key takeaways for a scalable model include the ability to adapt an algorithm, platform(s) accessibility and collaboration, and customization/replication. Video and written tutorials bridged the gap on machine learning coding, as well.

**Whole Image Classification**

The YOLOv5 model analyzes entire images and labels data using whole image classification. However, images contain much more data than what is being represented through a single label. If an algorithm is trained on whole images, then each pixel in the photo contributes to the algorithm's learning. This means that a YOLOv5 algorithm trained on whole images will detect damage severity levels based on all of the contents of an image. Street level images in particular capture data beyond the building, including other objects such as nearby forestry, shrubs, front yards, the sky, and vehicles. Therefore, machine learning decision making via whole image classification may inflate or deflate key data points outside the scope of structural damage. In the case of Hurricane Ida, the YOLOv5 model was unable to accurately detect damage levels of stilted houses due to potential influences of training data.

**Bounding Box** *(Image 2.3)*

The YOLOv5 algorithm is adaptable and can also learn to detect objects within a photo based on the bound box method. This method localizes the data inputs through user drawn and labeled boxes. The algorithm's training inputs are no longer an entire image when the bounding box method extracts only specified portions of the image for inputting. In this instance, the ability to detect structural damage to buildings and homes can be exclusively extracted and input into a model given a bounding box around the object. In Image 2.3, YOLOv5 detected a moderate level of damage to the structure. This determination was made because a machine learning algorithm only uses the data inside the bounding box for detection and classification.

**Platforms**

In addition, free, online platforms aided the process of developing and deploying YOLOv5 by enhancing the reliability of our methods and ability to test hypotheses. Since there are a few platforms available, the ones that were highly accessible aided the machine learning process through either collaborative annotation methods, succinct storage of data and images, and/or browser-based coding. Platforms like Roboflow allow cohesive annotation and dataset creation with potential extrapolation to different algorithms. Robodlow is a browser-based platform that encourages collaboration to rapidly assemble data sets for machine learning. Google Colaboratory is a platform that hosts many coding languages, and can be run on a web browser rather than a downloadable application. The user interface provides seamless access to strong computational power (GPU's) without any downloads. Altogether, accessible platforms with strong user interfaces increased the overall operating and testing speeds, all while increasing replicability of our methods. There are drawbacks to strictly relying on browser-based platforms such as the interconnected nature of coding. Each platform must grow and develop in tandem with one another, as each piece is essential to the overall machine learning pipeline. When one node changes, the process stops working. Therefore, we also caution that open, public platforms may adapt much faster than implementation of these tools.

*Image 2.3: Example of Bounding Box:: Implementation of the bounding box method comapred to whole image classification*

## 2.5 In Application and Practice

**FEMA's PDA as Annotation Framework** *(Image 2.4)*

The levels of damage assessment outlined by FEMA's Preliminary Damage Assessment Guide *(see Image 2.5)* provide the foundation for street-level machine learning annotations in two primary ways. Firstly, the severity level of damage (i.e., affected, minor, major, destroyed) includes clear instructions on categorizing assessment of both manufactured homes and conventionally built homes. Secondly, the terminology of damage assessment classification in the PDA is the primary source of communicating incident impacts contributing to Presidential disaster declarations decisions. One example of classifying a house as having "minor" damage in the event of a non-flood event is "nonstructural damage to roof components over essential living spaces (e.g., shingles, roof covering, fascia board, soffit, flashing, and skylight)." Incorporating strict guidelines for classifying and annotating images helps reduce the number of cognitive biases introduced to a dataset. In the event of a Presidential disaster declaration, more resources are made available through Federal funding to assist in recovery efforts.

**Collecting Imagery from Multiple Sources and Events**

Collecting natural disaster damage assessment imagery from multiple sources equalizes the


*Image 2.4: FEMA PDA Catergories:: There are four catergories that classify severity of damage. Credit to Federal Emergency Management Agency.*

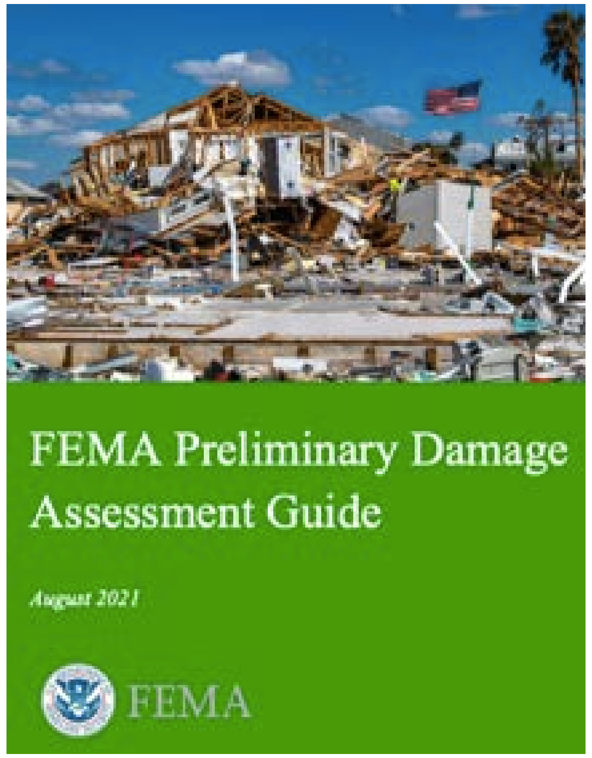



*Image 2.5: The federal emergency response agencies damage assessment guidleines. Credit to Federal Emergency Management Agency.*

frequency of damage assessment classifications in machine learning training datasets. Images obtained from a single source, such as conventional new media outlets, are designed to tell a compelling story of a natural disaster event. In this case, the likelihood of overrepresentation of more severe damage assessment categories is higher because the most compelling story is where the most damage occurs. In the article *Damage Assessment from Social Media Imagery Data During Disasters*, the authors provide evidence of increasing machine learning accuracy, precision, and recall by combining images from Google searches and multiple events of the same type (Nepal 2015, Ecuador 2016 Earthquakes). To increase machine learning model metrics and create a dataset with equal representation of damage assessment categories, the collection of images for this exploratory research model include:

- Social media platforms (Twitter)
- Open-source databases (Crisis NLP)
- Google images
- Stock photography websites
- NDPTC field visits *(see Image 2.6)*
- University of Michigan field visit
- Conventional local and national media sources for natural disaster reporting

Inspired by the research paper Damage Assessment from Social Media Imagery Data During Disasters and a research inquiry by the National Disaster Preparedness Training Center, this research dataset also includes imagery from different disaster events. This training dataset includes images from multiple hurricanes, earthquakes, and tornados both internationally and within the United States. Damage assessment photos from wildfires are excluded from the dataset due to the overrepresentation of images with live fires present and available through internet-based sources. Including more types and quantity of events in a dataset increases the chances the training images will have an equal representation of classifications. A machine learning model trained only on a Category 5 hurricane will have high precision for categorizing homes with severe damage but will not perform well at identifying lower levels of damage seen in weaker storms. Additionally, a model trained on images from a natural disaster in Louisiana will likely underperform if the model is tested on images from another country because the difference is building architecture is not represented in the training dataset.

*Image 2.6: Data from St Charles Parish, Louisana. Credits to NDPTC.*

**Model Testing on Hurricane Ida**

The adaptation of a pre-trained YOLOv5 model designed for damage detection in early recovery was tested on a recent natural disaster. If the goal of machine learning for damage detection is to be deployed post-disaster in early recovery, then incorporating and testing a model on recent natural disaster imagery is one way to observe its utility.

Hurricane Ida, a Category 4 hurricane, made landfall in Louisiana on August 26th, 2021. Data collection and capacity research was conducted to observe the effects of early recovery on communities and how to make improvements to the RIDA model's deployment. Just five months after the disaster, organizations and residents in the area were focused on recovery— rebuilding and repairing homes, finding more permanent solutions, and restarting local economies. In this recovery phase, the RIDA model could have enabled people through the FEMA aid process or insurance claims. Visiting the region at this point allowed researchers to take advantage of hindsight, asking the question, "how can we improve recovery?" At the same time, the event is still fresh in the minds of community members.

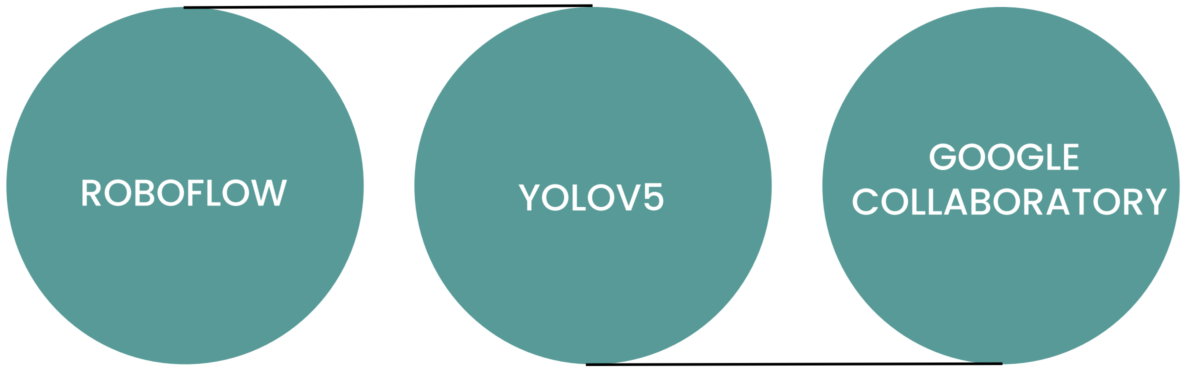
## 2.5 Programs, Processing, and Platforms

To make the tool accessible, the NDPTC should leverage pre-existing data platforms. These platforms should be highly accessible to any local planning or emergency management office. Platforms that are free of cost, user friendly, and browser/interest accessible are notable ways to ensure receptiveness. Listed below are some entry level platforms that could easily be used during training of machine learning processes.

### ROBOFLOW

**Collaboration and Configurations**

Researchers or planners must label images according to what is being detected or classified for machine learning algorithms to understand data. Roboflow is an online annotation platform that is free and browser based *(See 2.7)*. The platform allows multiple collaborators to upload individually collected photos regardless of format (.jpg, .png, etc). The Roboflow processes will take in a variety of data and produce a downloadable or accessible dataset in a variety of formats. The ability to produce different formats allows the dataset to be integrated into different algorithms, especially YOLOv5. Additionally, the pooled imagery can be divided among collaborators and researchers for annotation purposes, allowing cross collaboration on dataset creation. With the ability to upload multiple imagery sources, different natural disaster dataset configurations of considerable size can also be created and hosted on Roboflow. New imagery can be integrated into pre-existing datasets when a natural disaster occurs. Multiple events can be combined in different ways to test if certain elements of disaster damage from events mimic other natural disasters. More importantly, testing multiple natural disaster imagery configurations can help experiment to identify the most precise



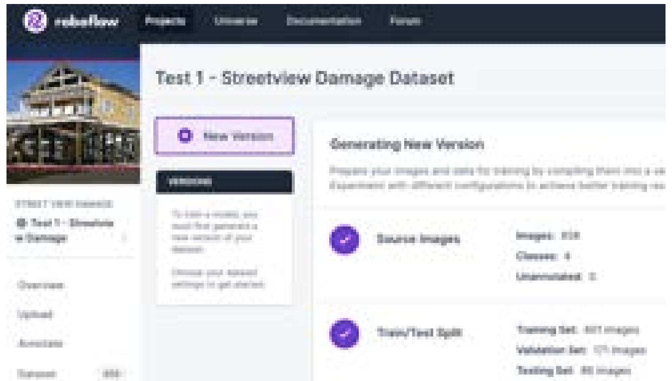



*Image 2.7: Overacrching view of the Roboflow API for dataset creation website. Credit from Roboflow.com.*

model for street level damage detection. The combination of multiple disaster event imagery enhances precision and recall for street level machine learning algorithms. For implementation purposes, we recommend entry entry level machine learners, such as local emergency responders, planners, and others leverage Roboflow to enable various configurations of model scaling for increased precision. Roboflow also allows a multitude of local recovery professionals the ability to create and contribute to datasets, access or utilize dataset configurations, and train and test on algorithms with ease.

### Integration with YOLOv5

In further support of Roboflow utilization for damage detection, the designers of the YOLOv5 model have strategically aligned their coding processes with Roboflow's Application Programming Interface (API), for seamless transition from dataset annotation to training. Other annotation programs such as VGG Image Annotator (VIA) or Labelme are applicable to object detection with bounding box methods. However, Roboflow directly integrates into YOLOv5 notebooks and prevents minor coding errors such as file misstructuring (.json, .csv, .text). Lastly, cloud-based notebooks allow for use without the need to download datasets to local drives and reduces the risk of error.

### Preprocessing and Augmentation

Roboflow enables image pre-processing and augmentation, in other words imagery alterations. Annotation platforms offer limited levels of alterations, whereas Roboflow offers a wide variety. Pre-processing and augmentation assist with what and how machine learning algorithms should understand data. Steps that Roboflow offers include resizing which either shrinks or expands an image's size. This step is both helpful for training speeds, but also for datasets with a variety of image sizes. Resizing can skew images and data, potentially to such extremes that it impacts the outcomes detrimentally.. While there are a myriad of image alterations, the field asserts these steps increase algorithmic precision, however there are unclear standards for best practices. This is due to how the model learns and what processing enhances detection, so pre-processing or augmentation changes based on the application of machine learning. For the purposes of damage assessment from street level machine learning models, there are a few imagery alterations that may align with damage detection goals.

## PREPROCESSING AND AUGMENTATIONS

**Horizontal flip:** This step flips or inverts the image. A machine learning algorithm can be trained on images of houses and structures with different orientations for better detection and classification.

**Auto-contrast:** This step enhances pixel contrast. A damage detection algorithm, or other imagery algorithms, use contrasting to increase the algorithm's ability to understand boundaries and lines.

**Image Resize:** This step alters image size. Damage detection images can vary in size, from phone cameras to social media to on the ground cameras, so the variability allows the machine learning algorithm to understand all of the data in a consistent manner while also making the training and testing faster.

**Shearing (+/- 15°):** This step distorts the image horizontally to mimic real world data capture. street level cameras used by organizations such as Mapillary or Google tend to have a warped or distorted view that mimics the shearing feature. This step enhances the model's algorithm by understanding different types of imagery.

## YOLOv5

These augmentations and preprocessing techniques can reduce model accuracy and precision. These steps should be constantly evaluated for best model performance. Since Roboflow allows multiple enhancements, researchers can generate multiple datasets and train or test based on alterations.

The decision to operate and experiment with the YOLOv5 framework is not an easy determination. As discussed previously, there are opportunities for other algorithms to not only detect damage, but detect, classify, and mask other pertinent indications of damage. With street level damage imagery being captured, other algorithms could produce insight into not only the severity of damage but variety. YOLOv5 is fast and accessible, while also producing strong results through accuracy and precision metrics such as Recall. Instance segmentation annotations are new features in Roboflow and if paired with a tutorial or custom notebook could allow NDPTC to develop targeted damage detection. This includes the ability to observe roof vs structural damage, or even the ability to detect debris, property, and landscaping damage. Segmentation could identify damage through the capture of other data points such as materiality of structure, height or level(s) of structure, and elevation from sea level. Perhaps machine learning can supplement that data collection and enhance damage detection simultaneously.
Altogether, YOLOv5 is a stand out machine learning algorithm that can adequately adapt to local capacities post-disaster to produce accurate, fast results. YOLOv5 is accessible and integrates annotation into its notebooks for customization and accessibility.

## GOOGLE COLABORATORY

A recommended platform for YOLOv5 implementation is Google Colaboratory notebooks. Google Colaboratory is a browser based, free platform that allows users to execute code with rich text in a single space. The integration of code and text allows for template notebooks to be organized pre-coding. Organizing a notebook allows multiple users access to code, while also understanding what each execution entails. For example, in the customizable notebook for YOLOv5, there were rich text, images, and gifs that explained the annotation processes all the way to training deployment.

Not only does Google Colaboratory notebooks allow collaboration for customization of notebooks, the platform ran code of Google's cloud servers. This means that the operation speed to run code is remotely managed, allowing users to utilize faster graphics processing units (GPU's).

With customization and processing speed, Google Colaboratory takes coding machine learning algorithms a step further. Machine learning developers create and share Google Colaboratory specific notebooks for replication of methods. This means that users can essentially copy and paste entire pre-built guidelines, minimally changing or altering just a few lines of code. This is the case for YOLOv5, which has a series of extremely digestible pre-built notebooks that run without error and consistently perform at fast rates.

The burden to organize machine learning algorithms and their corresponding code is significantly reduced due to formatted and organized Google Colaboratory notebooks, cloud-based processing, and pre-built guidelines. The integration of YOLOv5 and Roboflow into Google Colaboratory notebooks streamlines machine learning processes for faster, more robust experiments and applications.

## 2.6 Recommendations

If RIDA becomes a tool deployed at the local scale to be monitored by local emergency managers and disaster response professionals, the tool must be adaptable, accessible, and equitable. As it stands, RIDA has the potential to bridge the gap between the data science and planning fields. To bring that potential to light, the following steps should be taken to ensure proper use of the tool during the machine learning steps of the process.

**Pool and Share Data**
The ability to share and leverage pre-existing resources makes the production and training of machine learning processes faster, and more importantly, more accurate. From research articles or actual applications of machine learning, the integration of data that represents and documents various disaster related damage, housing typologies, level of damage, and in general a variety of imagery, enhances the models accuracy. To achieve data sharing, organizations can provide a host of open-sourced and public materials. These materials can include:

(1) a continuously growing dataset on general infrastructural damage
(2) annotation protocols designed for federal agencies (FEMA, HUD, etc)
(3) a pre-built machine learning algorithm
(4) annotated datasets for each natural disaster
(5) open source platforms for contributions of disaster damage and images

Those interested in damage assessment assistance through machine learning, such as the NDPTC, should recognize its position as a liaison between the local and federal actors. Large scale organizations or locally embedded recovery professionals can act as the host for materials, tools, processes, and data. Disaster recovery and preparedness organizations benefit from the data pooling and storage because it increases the damage assessment model accuracy and transferability. Altogether, sharing and pooling data helps eradicate the noted barriers of perishable data by directly sourcing disaster data throughout local networks and beyond.

Alternative Algorithms and Continuous Training
The YOLOv5's model accuracy and efficiency are two great assets for a street level machine learning model that detects severity of damage. The creators of the YOLOv5 algorithm are continually transparent with their improvements, modifications, and methods. The algorithm can be run using cloud based processing speeds which eradicates the requirement for individual users to operate or download multiple softwares and platforms. Google Colaboratory also has tutorials that are easily navigable for an entry-level practitioner. However, as mentioned previously, while the YOLOv5 algorithm is reliable for the NDPTC project, we strongly recommend continued exploration of more precise machine learning algorithms for street level damage assessment such as Mask R-CNN and Lobe.ai.

In the field, there are a few available solutions to continuous training. The first potential solution is utilizing a machine learning designed end-to-end platform. An end-to-end platform starts with processing multiple datasets using pre-existing or custom data parsers. Then within the same process, the code can run various algorithms including YOLOv5 or Mask R-CNN, to train images in one succinct process. The inspiration for an end-to-end machine learning platform was driven by the need to instill continuous learning and experimentation protocols, but also due to the need to organize each machine learning step into one coding narrative.

**Audit and Monitor**
To train and deploy models for testing, there are several qualitative metrics that determine model performance to review. It is important to include a coherent method for review to audit the model's performance both in training and in application. There are important metrics that should be evaluated for both steps to machine learning. The metrics related to training a model are mean average precision (mAP) and recall. Even training data can be monitored using Roboflows health check. Checking these metrics ensures data representation at each step is balanced. In Image 2.8, our dataset has notable variations of classification sizes which is less than preferable as described above in Section 2.5. With the curation of a widespread disaster damage dataset, these categories can be evened out over time.

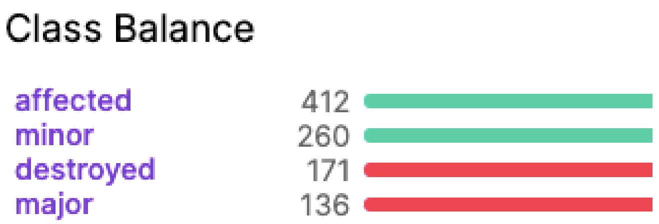



*Image 2.8: Roboflow Health Check: Totoal raining images per classification catergory. Credit from Roboflow.com.*

## 2.7 Conclusions

**The Case for Iterative Model Design**
The ability to iterate on model design allows machine learning researchers to better adapt to changing conditions of natural disasters and reflect upon model performance and community representation. As this is an academic project in understanding how artificial intelligence can aid disaster recovery, the initial exploratory analysis of data collection, annotation methods, and machine learning model selection mimicked the process of thoughtful and iterative model design. Through experimentation on machine learning model development, findings suggest collecting images with the intention of the model's primary objective. If the imagery intended for model training and validation does not aid in the damage assessment of buildings, it should be excluded from the dataset. FEMA's Preliminary Damage Assessment Guide helps researchers select relevant images and provide a framework for annotations.

Selecting preprocessing edits and augmentations to allow for more robust training datasets should be chosen based on the model's deployment phase. As discussed, preprocessing alters images by rotating, flipping, adding contrast, or cropping to provide more training data inputs in a model. A model with three preprocessing modifications can learn from three times the images, providing a catalyst to model performance while cutting down on time spent on data collection. The RIDA model ultimately collects images for preliminary damage assessment from a car-mounted 360-degree camera, including a modification for "shearing" images or rotating them +/- 15°, which is selected to mimic real-world conditions.

**Lowering the Barriers to Machine Learning**
The growth of programming-less machine learning programs, such as Lobe.ai, can also lower the barriers to entry into machine learning to the point that rapid adoption and progression of application techniques for artificial intelligence in disaster relief can become commonplace. In a brief experiment, annotation and training of a machine learning model capable of categorizing damage assessment following FEMA's PDA took a fraction of the time to develop compared to YOLOv5. Lobe.ai's damage assessment model's observed accuracy is 93%, while the highest accuracy of a YOLOv5 model observed through this research is 70%.

Based on research and experimentation, damage assessment as conducted through machine learning practices must continue to iterate on

*Image 2.9: Shearing Example: This picture is from the 360 imaging company NCTech's vehicle-mounted iSTAR Pulsar camera. The photo demonstrates potential distorted images for machine learning unless trained on these distortations know as shearing. Credit to GIS Lounge https://www.gislounge.com/next-generation-asset-management-with-istar-pulsar/*

its methods, while decreasing the barriers to the data-driven tool. For now, general findings identify the YOLOv5 model as the most accessible in terms of the availability of tutorials and supporting software, such as Roboflow. Though pre-coded notebooks are freely available for running YOLOv5, some programming experience is required to understand the complexities of operating machine learning algorithms.

For emergency managers, community organization directors, and other recovery personnel, the barriers to entry into machine learning models for damage assessment are much too high for practical adoption. At this stage in the development of artificial intelligence for disaster recovery, the benefits of integrating machine learning into preliminary damage assessments for rapid deployment are not yet visible. When a disaster strikes a community, it is often too late to learn and implement new tools into an overly complex recovery process. Machine learning tools for disaster recovery must be developed in anticipation of deployment.

**Going Forward**

Altogether, street level machine learning stands as a growing data-driven tool that reduces assessment delays through improved data collection and imagery analysis. This paper is far from comprehensive in regard to machine learning development, however it comments on the general industry trends from annotation platforms and protocols to useful machine learning algorithms. These considerations directly contribute to the design and development of damage assessment models in early recovery, including potential environments for bias. To learn more about machine learning bias, see "Social Bias in Machine Learning and Early Recovery." Nevertheless, for local disaster response professionals who are interested in the reduction of assessment bias or local capacity burdens, machine learning using accessible interfaces can streamline those processes and offer enhanced insight on damage.

To access more information on how to build your own model, there is a customized YOLOv5 template notebook in Google Colaboratory with Roboflow integrations. To assist with knowledge transfer, data sharing, and tools going forward, there are supplementary videos and the "Basics of Machine Learning Paper" that assist in the development. All of the work is hosted on the University of Michigan Capstone website and corresponding GitHub repository.

## ENDNOTES


1. Selvaraju, R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., and Batra, D. (2019) Grad-{CAM}: Visual Explanations from Deep Networks via Gradient-Based Localization. International Journal of Computer Vision, 128(2). 336-359. https://doi.org/10.1007%2Fs11263-019-01228-7

2. Xray Pasa, F ; Golkov, V ; Pfeiffer, F ; Cremers, D ; Pfeiffer, D. (n.d.). Efficient Deep Network Architectures for Fast Chest X-Ray Tuberculosis Screening and Visualization. Scientific Reports. 9(1), 6268–6268. doi:10.1038/s41598-019-42557-4.
Animals

3. He, K., Gkioxari, G., Dollár, P., and Girshick R. (2017) Mask R-CNN. IEEE International Conference on Computer Vision (ICCV), 2980-2988. hhttps://doi: 10.1109/ICCV.2017.322

4. Metallo, N., (2017) Using Mask R-CNN in the streets of Buenos Aires. Medium. Accessed on April 24, 2022. https://medium.com/@nicolas.metallo/using-mask-r-cnn-in-the-streets-of-buenos-aires-a6cb6509ca75

5. Labelme2. MIT, Computer Science and Artificial Intelligence Laboratory. labelme.csail.mit.edu/Release3.0/ https://www.robots.ox.ac.uk/~vgg/software/via/via_demo.html

6. Zhang, Q., Chang, X., and Bian, S. (2020). Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN. IEEE Access. Doi: 10.1109/ACCESS.2020.2964055.

7. Nelson, J. (2020) YOLOv5 is Here: State-of-the-Art Object Detection at 140 FPS. Roboflow. Accessed on May 1, 2022.

8. FEMA. (2020). Preliminary Damage Assessment Guide (p. 127).

9. FEMA. (2020). Preliminary Damage Assessment Guide (p. 127).

10. FEMA. (2020). Preliminary Damage Assessment Guide (p. 127).

11. Cherry, K. (2020, July 19). What Is Cognitive Bias? [Psychology]. Very Well Mind. https://www.verywellmind.com/what-is-a-cognitive-bias-2794963

12. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017) Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109

13. Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017) Damage Assessment from Social Media Imagery Data During Disasters. Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 569–576. https://doi.org/10.1145/3110025.3110109

14. Dutta, A., Gupta, A., and Zisserman, A. (2019) The VIA Annotation Software for Images, Audio and Video. In Proceedings of the 27th ACM International Conference on Multimedia. https://doi.org/10.1145/3343032.3350535

15. Labelme2. MIT, Computer Science and Artificial Intelligence Laboratory. labelme.csail.mit.edu/Release3.0/

RISING ABOVE THE DELUGE

# STREET LEVEL IMAGERY FOR MACHINE LEARNING

## about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, valuing local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN

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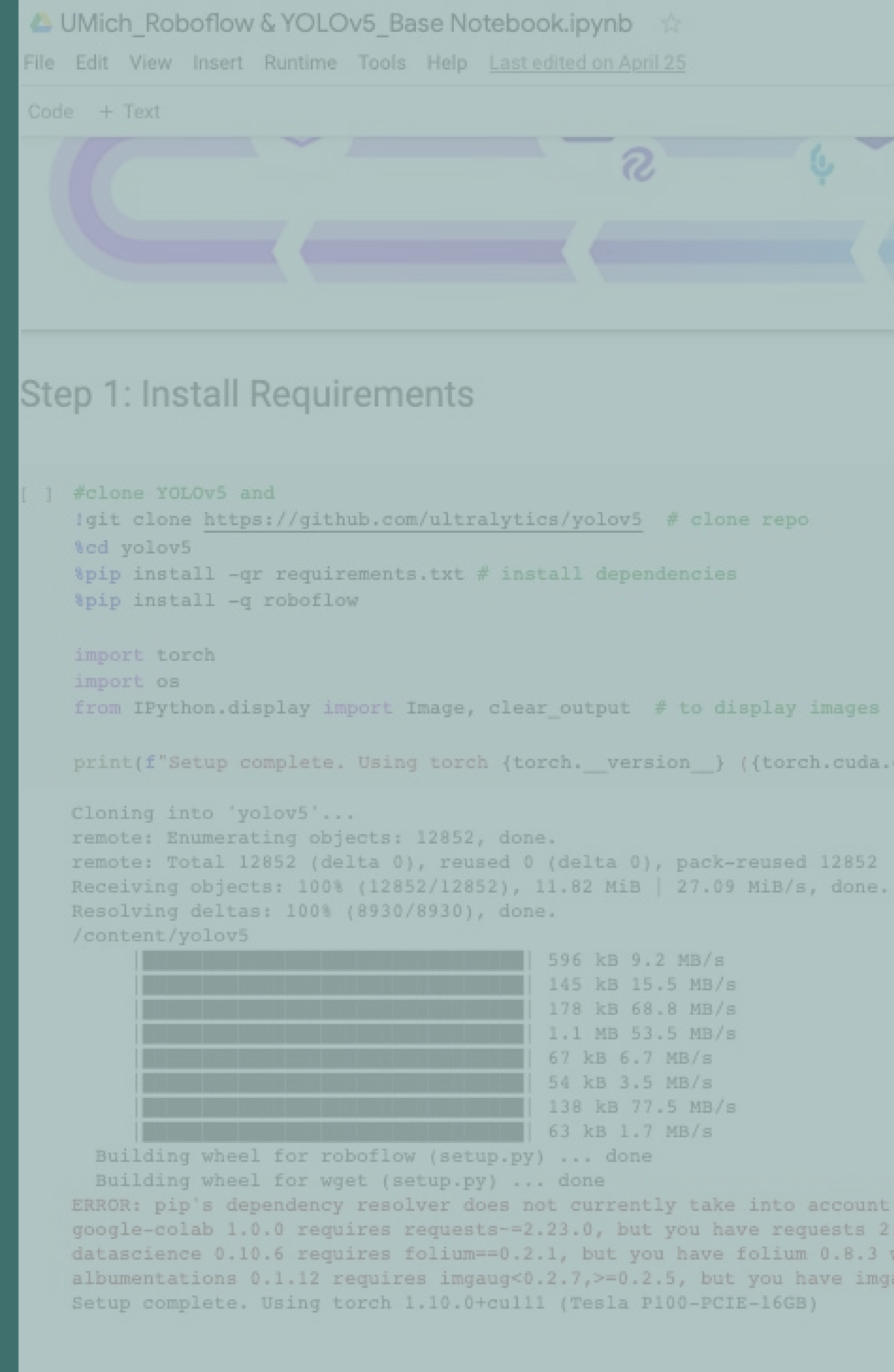
working paper series: Machine Learning 101



# MACHINE LEARNING 101

## 2a.1 Introduction

This paper is designed to communicate the foundations of machine learning for entry-level learners and to ease the barriers surrounding machine learning processes for any interested professional. We note, however, that anyone wishing to implement machine learning into their work should also consult external resources to understand the steps and ethical considerations required.

Oriented toward disaster recovery professionals, this paper supplements a tutorial for damage detection using machine learning. The tools to reproduce or recreate our work are linked within this paper and can be accessed through our website.

We present each section as a description of the considerations an entry-level professional should consider at each step of building a machine learning model: collection, annotation, training and application.

## 2a.2 Data Collection

In machine learning, the first critical step is collecting and labeling pertinent data. With the multitude of options in collecting and annotating, we must first take a step back and ground ourselves in our work's intentions, goals, and methodologies. What will using machine learning do? How will the biases implicit in machine learning impact the work? Can machine learning accomplish the goals of the project? Can other modeling techniques reach these outcomes? Is machine learning enough for this project? The answers to these questions may impact how we approach various choices in the process, or frame how we interpret our data. Once we define these intentions, collection and annotation can begin.

Your research intentionality and the implicit subjectivity in decision-making will directly impact the process of the collection and annotation. Since there is a variety of data used in machine learning, such as text, imagery, and film, the research objective, ideally, is the determinant of the data type you will use in your analysis. Once the type of data is established, the choice of how and from where the data will be collected must be identified. Researchers can seek pre-built datasets of images or text repositories to ensure data integrity. However, relying on a pre-existing data collection method is restricted to the dataset's availability, format, extensiveness, applicability, bias, precision, and reliability. In reality, projects sometimes require the creation of new datasets. Therefore, images must be collected based directly on how the model will be used.

*Image 2a.1: Debris Clearance in Southeastern Louisiana. This image demonstrates how perishable data is ripe only in short periods of time. In a few weeks, these debris piles that demonstrate community damage may be cleared, and destruction data eliminated. Machine learning can assit with the capture of data, but researchers should remember the evolution of data prevelance.*

### KEY TAKEAWAYS

1. Determine the type of data to collect (text, audio, image, or video)
2. Establish spatial and temporal boundaries for data gathering
3. Avoid selection/confirmation bias by collecting diverse data

One notable consideration for dataset creation is the perishability of data. Perishability, as it relates to data collection, is a phenomenon where data and information "becomes less valuable over time as the situation [or research] being predicted may be changing and the predicted event may already have happened." In the context of disaster recovery, the immediate indicators of damage, repair, and recovery evolve. The window for damage assessment narrows as increased recovery speeds and improved distribution of resources alleviates the need for damage-related data. Therefore, timing is strategic consideration in the collection process.

## 2a.3 Annotation

The next step toward machine learning utilization is to label and describe the data under a coherent, transparent process. Annotation transforms data of distinguishable inputs, such as images or text, and assigns them labels. These labels help machine learning algorithms consume and understand the connections between inputs. Annotations differ based on the machine learning algorithm. Object detection algorithms often require a bounding box to be drawn over detected objects for training purpose, whereas instance segmentation trains on images that have polygon shaping around the detected objects boundaries. (*See Image 2a.2*) Once the machine learning is selected the number of classes–what is to be extracted–can be determined. More specifically, classes are the labels assigned to the data, or parts of the data. With image annotation, one could annotate an image to highlight, extract, and evaluate specific sections of the image. These classes are directly related to the research objectives chosen. For example, segments and classes can identify bicycles on a street from street-level images or the colors of a specific flower within a garden. To summarize, the annotation step establishes a set of classes and corresponding definitions, that the machine learning algorithm will use to extract data. For best results, it is important to allocate an even number of images per class to eliminate sample bias in the model. Sample bias is when a certain class is misrepresented, which may skew a machine learning algorithm to better analyze and detect one class over another.

### KEY TAKEAWAYS

1. Choose one or more model: object detection, segmentation, and/or classification
2. Identify and describe the list of classes
3. Organize data with even amounts of images, audios, texts, or videos in each class
4. Select a platform to annotate data

Datasets may be limited to raw data without labels or annotations. There are many online platforms that specialize in annotation for machine learning. Despite the ease in accessing these platforms, there is no standard process for ascribing images or text with labels. As a starting point, you may consider what type of output your analysis requires. There are three major categories of annotation outputs: object detection, segmentation, and classification. These categories can also be used in tandem based on the machine learning algorithm employed. The

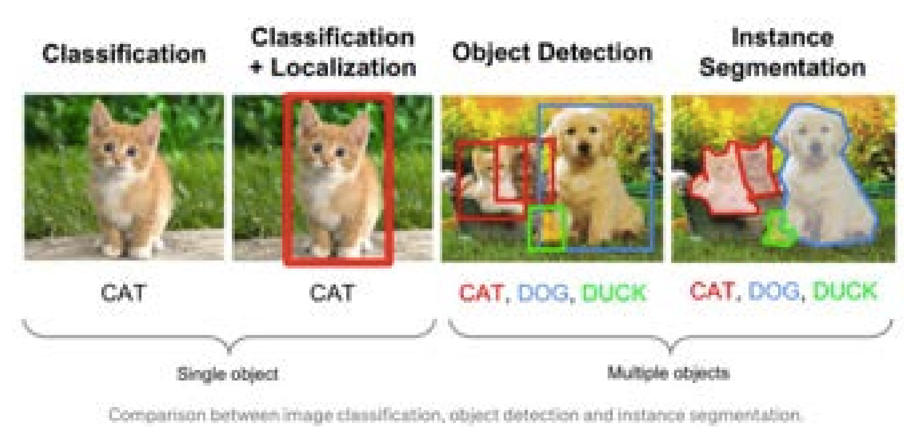



*Image 2a.2: Catergories for annotation. This image depicts the differences between different annotation types from object detection to instance segmentation.*

*Credits to Arthur Ouaknine.*

main differences between each category are the timeliness, accessibility/transferability, and accuracy of the outputs. While one object detection model may produce results quickly, it may not be as accurate.

As previously indicated, collection and annotation are far from a perfectly linear process. There are several considerations for each step that influence decision-making and outcomes. The subjectivity of the annotation process creates immense space for error and bias through the labeling process. Researchers must thoroughly ground their decisions with intention and documents in a way that makes their work publicly available for critique.

### CASE STUDY

To better understand classification, this example highlights the variety of catergories that contribute to a standard annotation protocol. This model is used in the context of disaster recovery for damage assessments. So, once a natural disaster hits, images of damage are collected to be annotated according to this guidance.

**Standardized Annotation Process for FEMA Disaster Assistance**

Based on the Federal Emergency Management Agency's (FEMA) Preliminary Damage Assessment guidance, there are four categorical levels of structural damage post-disaster: (1) affected, (2) minor, (3) major, and (4) destroyed (see Figure 2a.3). The FEMA Preliminary Damage Assessment guidelines indicate the differences between level of damage


*Image 2a.3: Examples of annotations. These images represent annoations on two opposite ends of the spectrum.*

| AFFECTED | |
|---|---|
| Description | - Partial missing shingles<br>- Paint discoloration<br>- Broken screens/Gutter damage<br>- Damage to landscaping |
| Key Phrases | COSMETIC, HABITABLE, NON STRUCTURAL LANDSCAPING |

| MINOR | |
|---|---|
| Description | - Nonstructural damage to roof<br>- Damage to chimney<br>- Multiple small vertical cracks in the foundation |
| Key Phrases | LIVABLE, SMALL, SURFACE LEVEL, EXTERIOR |

| MAJOR | |
|---|---|
| Description | - Significant structural damage<br>- Failure or partial failure to structural or walls or foundation<br>- Residences with a water line 18 in above the floor |
| Key Phrases | BROKEN, FRACTURED, CRUMBLING, DISPLACED, SHIFTED |

| DESTROYED | |
|---|---|
| Description | - Total loss<br>- Only foundation remains<br>- Imminent threat of collapse<br>- Completely unlivable |
| Key Phrases | MISSING, COLLAPSE, UNLIVABLE, DANGER |

*Image 2a.2: Catergories aligned with FEMA PDA guidelines. This chart depicts the differences between different annotation caterfories for damage detection.*

*Credits to FEMA Preliminary Damage Assessment.*






*Image 2a.3: Examples of annotations. These images represent annoations on two opposite ends of the spectrum.*

## 2a.4 Training

Once the collection and annotation of data is complete, the actual machine learning training begins. Based on the categories, object detection, classification, or segmentation of the data, there are many algorithms and models that can be deployed, each on multiple platforms and software programs. With many options, and the multitude of technical considerations involved, this process can be confusing for many entry-level practitioners.

There are several fundamental considerations to start. Machine learning algorithms may use one of many programming  languages to run and operate their models. Notable languages include Python, and sometimes R. Many pre-built libraries you will find are built using these common languages, but may not be available for all of them.

There are different applications or platforms to type, write, and run programming languages, and not all platforms can run all the languages. When running these analyses on your own, it is important to understand the technical requirements may limit the number of places you can perform the analysis. The number grows even smaller in terms of cloud-based or free platforms. Among the many cloud-based services are Google Colaboratory and Kaggle.  These websites understand a variety of languages, have no financial costs, and are fast, user-friendly tools.

The last critical step that is key to running and training an algorithm on your own is knowing how to code at notebook. Since there are many methods, each with coding and technical requirements, it can be confusing to understand where to start and how to implement. Online video tutorials and pre-built, tailored, notebooks can help the process. Following a step-by-step tutorial can make the process more knowable. (This is the reason for our tailored materials for disaster recovey.)

The training of machine learning models can be extremely complex, and is beyond the purposes of this paper. However, to aid understanding for beginners to machine learning, and potential users of these processes, we refer you to the aforementioned tutorials and notebooks.

### KEY TAKEAWAYS

1. Find a platform that uses the coding language of selected algorithm
2. Follow custom tutorials or pre-built notebooks for replication

RISING ABOVE THE DELUGE

MACHINE LEARNING BASICS

## about this project

This project is a joint effort by students and faculty within the Master of Urban and regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN

3

working paper series: aerial imagery

# Getting Started

## *Aerial Imagery - Deep Learning Approaches for Damage Detection*

## Introduction

Aerial imagery is utilized by FEMA, assessors, emergency managers, academia, and others in the evaluation and assessment of disaster damage. However, this work has typically been conducted in a manual process by going over each house across large orthophotos to evaluate damage to rooftops. New advances in machine learning offer novel options in the evaluation of such imagery. A deep learning assisted approach can process damage analysis at an unparalleled speed. Deep learning techniques can create an accurate, classified scale of damage by detecting objects such as blue tarps and debris. Capabilities to build a trained model to classify roof damage based on aerial imagery also offers avenues for detecting destruction. There is also potential in detecting change between pre- and post-event imagery.

Given the wide availability of ESRI ArcGIS to planners, assessors, and emergency managers, this paper will focus on deep learning solutions offered in this software. Anyone with access to ArcGIS Pro should be able to follow straightforward steps to analyze aerial imagery to identify damage and objects. Image Classification, Object Detection, and Change Detection are the primary deep learning techniques reviewed in this process recommendation and working paper. There are similarities here to the machine learning concepts laid out in Chapter 2. However, the focus of this paper is on aerial imagery which has a spatial and geographic nature as the photos cover a wider view of the built environment, not just a single structure. Machine learning techniques, tools, and methods (YOLOv5, Roboflow, Lobe.ai) could potentially be applied to aerial photos of single structures if a geographic reference can be coded to each photo. This is not explored in our research but merits further investigation. Additional tips on hardware, imagery collection, and other available and open source tools are also included.

## Computing Power Required

Deep learning analysis requires intensive computing power to execute the processes necessary for damage assessment. Most personal computers do not have the necessary hardware required to perform deep learning. Machines powered with a NVIDIA CUDA enabled graphics processing unit (GPU) will optimize the damage assessment within ArcGIS. Even if the local computer in use does not have a GPU there are many cloud computing options available. Google Cloud Compute, Amazon Web Services (AWS), and Microsoft Azure all offer computing options. Additionally, there are other alternatives to these three major suppliers that maintain advanced computing resources accessible through a web browser. Computing costs will vary depending on what source is used. Another condition that must be considered is the availability of the high-powered computing machines through these services.

## Setting Up Deep Learning for ArcGIS

**To get started you will want to download the ArcGIS Pro Deep Learning Package here.**

Also review the deep learning documentation here.

## Accessing High Resolution Imagery

**NOAA - National Oceanic and Atmospheric Administration**

Publicly available aerial photography is provided by NOAA online for certain disaster areas. Only limited geographies may be captured in these photos. Images must be retrieved through the NOAA data access portal, which should not be confused with the NOAA's Emergency Response Imagery. Imagery can be searched by address or a manually drawn boundary or the predetermined polygons. Blue polygons indicate available imagery from a post-event flyover. Once the imagery is selected the aerial will be added to the cart, once the "checkout" process is completed the file will be sent for download via email.

**Other Resources**

Private satellite imagery can be acquired from firms such as Planet Labs, Maxar, and others. This will require payment in most cases. Aerial imagery delivered as high resolution orthophotos is offered by firms like EagleView and Nearmap. Access to such photos requires a relationship with these providers and flights to capture these photos can be very expensive.

## Image Classification

Image classification labels and classifies digital photos. For example, Image 3.1 shows classification of damage score to the individual photo of a structure. GIS deep learning processes can be utilized to categorize features.

*Image 3.1: Image Classification for structeral damage undamaged vs. damaged classified in unique colors.Source: Esri*

## Object Detection

Object detection can locate specific features within an image. For example, Image 3.2 shows building footrpints being detected. A bounding box is utilized to identify the specific object feature as distinct from the other objects in the image. In ArcGIS Pro, this can be used to identify individual objects from satellite, aerial, or drone imagery in a spatial format.

*Image 3.2: Object detection to identify buiding footprints. Source: Esri*

## Change Detection

Change detection utilizing deep learning identifies changes to structures between pre-event and post-event dates and mapping this change with a spatial component. For example, Image 3.3 shows a structure from before Hurricane Ida in Louisiana. The image on the right shows the logical change map where damage to the structure occurred as well as installation of blue tarps which signify temporary repair to damaged roofs.

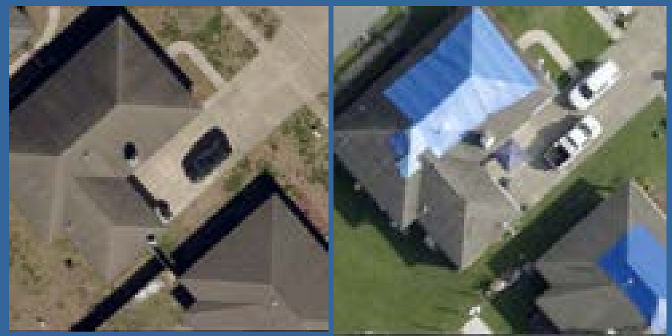


*Image 3.3: Change Detection to identify blue tarps.Source: Planet Labs*

## Image Translation

To prepare images for evaluation, image translation can improve image quality and resolution. For example, Image 3.4 contrasts an image from Planet Labs before image translation and after. A deep learning process such as image-to-image translation can be employed to improve image quality and prepare an image for an image classification, object detection, or change detection.

*Image 3.4: Image translation to improve image quality*
*Source: Esri*

## Further Resources

**Hardware**
NVIDIA CUDA
Paper space
Amazon Web Services (AWS)
Google Cloud

**Software**
*ArcGIS Pro*
*Geospatial Deep Learning with ArcGIS*
ArcGIS Hurricane Damage Assessments
ESRI Disaster Response Overview

**Image Sources**
NOAA
NOAA Ida Aerial Imagery
NASA Earthdata
NASA Ida Data
Maxar
Planet Labs
Planet Labs in ArcGIS
ArcGIS Image Discovery

**Aerial Damage Assessment Alternatives**
*ENVI*
*Dewberry*
*EagleView*
Nearmap

**Resolution Considerations**
Increase Image Resolution ArcGIS/Python
**ArcGIS Image Preparation**





# Image Classification

*Aerial Imagery Analysis*

## Introduction

Image classification labels and classifies digital photos. For example, Image 3.5 shows classification of a damage score to the individual photo of a structure. GIS deep learning processes can be utilized to categorize features.

Classification within an image can provide a more detailed understanding of the damage sustained throughout an area or region. Detecting whether an object has been damaged is limiting especially in cases where most structures have sustained some type of damage. With the classification method, emergency managers can understand the degree of damage.

## Overview

Image classification, uses convolutional neural networks (CNN) to identify and sort aspects within an image into a predetermined schema. The focal point of image classification within aerial damage assessment remains physical structures. This process classifies objects by programming the model to only classify the structures within a bounding box. Classifying objects within an aerial image provides a union of detail and extensive assessment of damage. This process also offers efficiency in analysis as it eliminates peripheral data for the model to analyze images which creates an easy visual hierarchy for manual analysis.

Post disaster manual classification of structural damage is already occurring in the field. Our team visited Southeastern Louisiana in February, 2022 to assess the disaster recovery process in the wake of Hurricane Ida. This informed our understanding of what kind of tools practitioners in the field currently deploy and those they could use. Interviews with St. Charles

*Image 3.5: Image Classification was used to classify the structural damage visible in aerial imagery.*

Parish Assessor Tab Troxler detailed a post disaster assessment process where Assessing Department staff members would manually classify the damage of over 20,000 structures. Staff would use aerial imagery to designate a damage score ranging from 0 to 4, with 4 being destroyed (Image 3.6). This process requires extensive labor resources, but even given these costs, the assessing office repeatedly highlighted the utility of this type of damage assessment. The conversation further underscored how paramount roof integrity is to structural soundness, which is one of the reasons this process is so important. In addition, providing an assessment relieves the individual homeowner of the burden of proof that would normally be required to receive aid. In deep learning, damage assessments are typically performed under a binary classification of undamaged versus damaged structures. Our team introduces training to the deep learning model that includes indicators of damage on a scale that reflects the FEMA framework and real world experience.

This process recommendation will walk through the specifics of image classification using a scale of damage for structures. Incorporating this model in the post disaster assessment of major storms can detect levels of roof damage.

## Image and Data Collection

In order to perform this process the resolution of the aerial imagery must be of at least a 5 meter per pixel resolution. This type of imagery is available in limited quantities and geographies from NOAA at a 3.5 meter per pixel resolution. Other sources of imagery may be used as outlined in Getting Started with Aerial Damage Analysis. Some local units may have access to professional aerial imagery from flights or drones, however these services remain costly and inaccessible.

Classification of structures requires the objects within the image to already be identified. Identification of structures within an image can take two forms: 1) pre-existing shapefiles of building footprints, 2) extracted building footprints using a deep learning package. Many local governments have already established building footprints within their ArcGIS platform. In addition, Microsoft has compiled an open source data base of multi millions of building footprints throughout the United States. For more information on identifying building footprints using object detection with deep learning please refer to Object Detection Process Documentation.

There is ample documentation available that provides step-by-step guides on how to perform damage assessment with ArcGIS deep learning. This project followed the steps provided by ESRI in a tutorial on automated fire damage assessment with deep learning. The purpose of the rest of this document is to provide critique, clarification, and explanation for process improvements. Practitioners wishing to implement this process on their own should follow the aforementioned tutorial supplemented by this documentation.

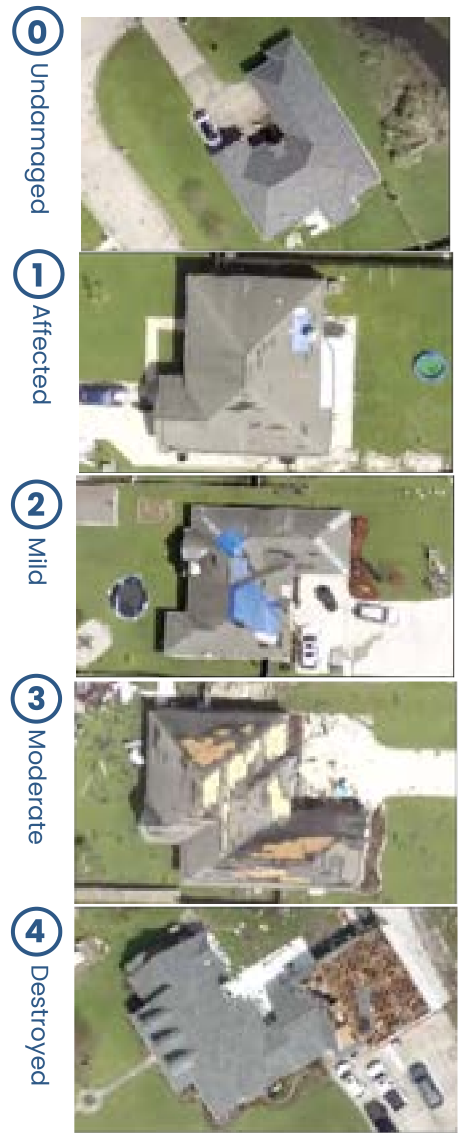



*Image 3.6: Damage Assessment Scale created based off FEMA and St. Charles Parish Assessment Framework*





## Annotation

Once the building footprints have been established, the objects must be annotated manually, which can be done using ArcGIS Pro. Annotation must be normalized using a standard scale with individuals trained to ensure high quality and accurate input for the model. The annotation scale created for this project incorporates feedback from on the ground practitioners as well as the FEMA framework for damage assessment. This classification ranged from undamaged to level 4 damage, which indicated almost complete destruction. Below is an image of examples of the annotation scale.

Annotation for this method takes place in the attribute table of the building footprint layer. Codes should be added for all five levels of damage that will be annotated: 0) undamaged 1) affected 2) mild 3) moderate 4) destroyed. The criteria for these categories is as follows. Undamaged displays no visible damage to the roof integrity, all shingles remain in place. Affected structures may have some shingle loss or less than 5% of the under roofing exposed. Structures with mild damage have less than 30% of the under roofing exposed. Moderately affected structures have less than 70% of the under roofing exposed. Destroyed structures are classified as more than 60% roof damage or complete exposure with all under roof material missing. Once the class value has been created it can be added to the layer in the contents panel by right clicking the layer and adding the appropriate field from the data drop down. This will make the features viewable on the map. The symbology then can be adjusted from the content panel to designate a useful visual hierarchy of damage. No less than 100 features per class should be annotated, additional samples will benefit the accuracy of the model. This training sample can then be exported as chips using the Export Training Data for Deep Learning module as outlined in the ESRI tutorial.

The predefined export process is an easy to navigate click-through process. Be sure to delete any null values in the class field prior to export otherwise you will not be able to create a training set. An alternative method of annotation was attempted, this workflow followed the training samples manager in ArcGIS. This process forgoes using the attribute table of the building footprint layer and labels both the polygons and the damage. While this method exported training samples consistently, it did not yield usable results once the model was run. Therefore, it is our recommendation that further research be conducted into alternative annotation and training sample creation.

## Training and Running the Model

Once the training set has been exported it can be used to train a deep learning model, as can be viewed in the tutorial ArcGIS Pro. This creates a model that is tailored to classified damage assessment. Practitioners who decide to use their own annotated training samples can benefit from the fact that the model was presumably trained on the specific kind of damage that has occurred by using a subset of the post-event imagery. This is because the pre-trained model could have been trained only on structures affected by tornado damage but is being used to assess earthquake damage. Different disaster events produce different damage typology and practitioners should be mindful of this when selecting a model. Alternatively, using a pre-trained model that has been trained on a wide variety of damage, of thousands of images, can offer validity that is not seen from models trained on smaller subsets. Special attention should be given on the distribution of training samples. Every class should have an even distribution of training samples

Additional options for training the model should be explored. These include ArcGIS Notebooks, Google Earth Engine, Pytorch Vision, and Keras. These methods require additional computer programming knowledge and a fluency in Python to be able to execute these trials. The additional knowledge and skill allows for the models to be designed with more customization. Further customization could create stronger models and higher rates of validity, and therefore trust in the assessment process.

# Object Detection

*Aerial Imagery Analysis*

## Introduction

Object detection can locate specific features within a sample set of images that can train a deep learning model to detect those features in a larger dataset. For example, Image 3.7 shows a blue tarp being detected on a rooftop. A bounding box is used to identify the specific object feature as distinct from the other objects in the image. In geographic information systems (GIS) methods, this training set will then be fed into a model to identify individual objects from satellite or aerial imagery in a spatial format. The identification of features such as blue tarps, exposed plywood, and household debris in the aftermath of a disaster can highlight hotspots or areas of significant damage. This type of object detection can output information at the parcel level or structure level to determine the presence of such features feeding into a damage assessment framework or score.

## Overview

In order to evaluate and assess damage at a more granular level, a process of detecting objects in satellite imagery can provide insight on the impact of a disaster. By analyzing both pre-event imagery and post-event imagery, the presence of certain elements which illustrate disaster damage can be analyzed in ArcGIS Pro to evaluate the damage level for a given structure. This process recommendation focuses on ArcGIS Pro as the software tool with the capability to run this object detection, however some alternative methods are also explored.

After a disaster with substantial wind damage, presence of blue tarps and exposed plywood are two primary indicators of roof damage to a property. As such, object detection for exposed plywood or extensive damage can be a powerful method. Additionally, presence of household debris can indicate a level of damage from flooding and/or potentially wind damage and rain. Other variables of interest could include RVs or trailers housing those rebuilding and recovering. These indicators can be identified from aerial imagery using deep learning techniques.

However, identifying the presence of a blue tarp is a straightforward feature for detection given the coloration and known presence in the aftermath of hurricanes (relevant to the Hurricane Ida case study). Blue tarps are not always immediately installed to roofs but are applied in the relief stage. These "band-aids" prevent more water damage and protect property. Tarping of roofs (often blue), can also be an indicator of a lagging recovery. It should further be noted that these tarps are not always the color blue and not all damaged structures will be patched, as they may have been totally destroyed or lack a response from a property owner or otherwise. However, these tarps can be a strong indicator of hotspots for wind damage which need relief and recovery support. This process recommendation will walk through the particulars of object detection in identifying blue tarps as a particular feature.

*Image 3.7: Object detection was used in this image to identify building footprints in a given location. Source: Esri*

## Image and Data Collection

Identifying blue tarps can be done at the parcel level or at a larger unit of analysis. However, this is largely dependent on the resolution and quality of the imagery available. NOAA provides high quality imagery at 3.5 meter per pixel resolution which is a high enough quality to see individual roofs and allows the possibility of identifying blue roofs at the parcel level. Other sources include NASA, Planet Labs, and those sources outlined under Further Resources. However the highest quality photos are likely to be aerial imagery which can include high resolution orthophotos taken from planes. These photos, however, can be costly and inaccessible. Firms like EagleView or NearMap are often contracted for the capture of such imagery.

*Image 3.8: Aerial Imagery can highlight where blue tarps have been deployed. Source: NOAA*

## Training and Analysis

Object detection can locate specific features within an image. For example, Image 3.9 shows detection of a blue tarp on a rooftop. A bounding box is used to identify the specific object feature as distinct from the other objects in the image. In ArcGIS Pro, this can be used to identify individual objects from satellite, aerial, or drone imagery in a spatial format. In the disaster context, this technique can be applied to other types of damage such as debris piles, fallen trees, and exposed plywood roofs. Identification of these features can functionally serve as a heatmap for damage assessment, determining where instances of blue tarps exist in the aftermath of a storm. One further step is to investigate the potential for object detection to inform damage assessments directly.

The object detection process can be performed using the deep learning object detection tools in ArcGIS Pro. Practitioners can identify the desired features using polygons within their imagery to create a new training set that will be saved within the project folder. Similar to the classification tool, this training set is exported to create a model. The model is then used when running the Detect Object Deep Learning geoprocessing. Ideally the analysis will then produce a new output with all objects detected. A simple analysis at the parcel or structure level could then be conducted to determine the presence of a detected object in that exact polygon. This could then inform the weighted damage score on a property.

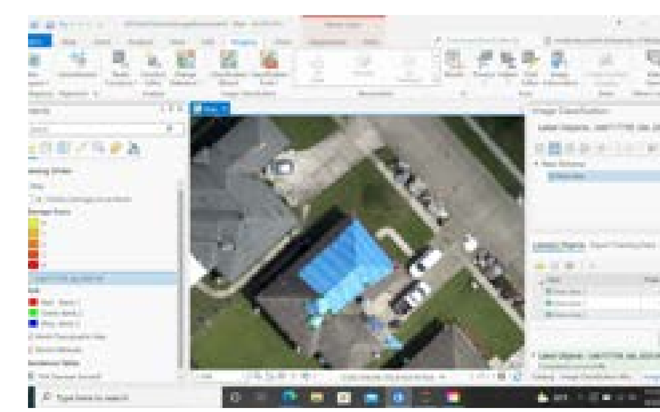


*Image 3.9: A blue tarp is labeled using the image classification deep learning tool.*

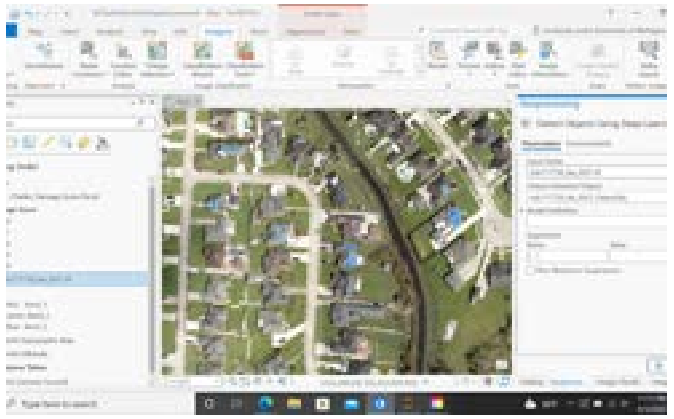


*Image 3.10: Once the data has been trained, the model is run using the detect objects using deep learning*

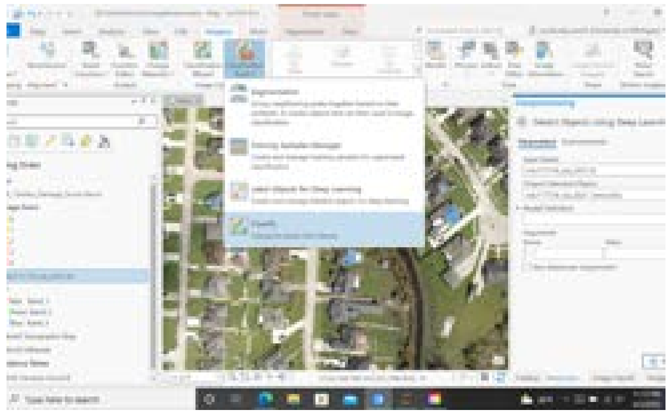


*Image 3.11: The classify option categorizes pixels into classes.*

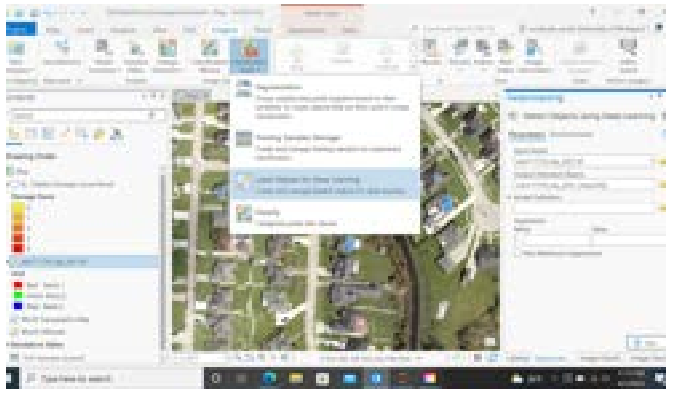


*Image 3.12: The label object for deep learning object allows users to label objects.*

## Other Methods

Beyond the ArcGIS approaches delineated here, certain methods are availalbe for object detection, image classification, and segementation. These include RetinaNet architecture, convolutional neural networks, and Mask R-CNN. Techniques that exist outside of proprietary platforms such as ArcGIS should be considered in future evolutions of this research to incorporate open sourced tactics for aerial imagery analysis.

**RetinaNet**

RetinaNet architecture, outlined in a 2017 paper, contains two categories of object detection: single-stage and two-stage. Two-stage categorizes objects into foreground or background categories (Faster-RCNN is an example of this two-stage architecture). Single-stage architecture does not classify foreground objects. This architecture trades accuracy for efficiency as it is a faster approach, but RetinaNet reached two-stage performance with single-stage speed. This model is a convolutional neural network (CNN) which processes images through multiple convolution kernels to output a feature map. This is a complex process which includes a Feature Pyramid Network, anchors identifying objects, a regression analysis, deduplification, and focal loss. RetinaNet can be implemented in Python with Keras utilizing Pandas DataFrames. An example of this implementation is for a NATO competition which used RetinaNet architecture to identify vehicles in urban areas. The Jaccard Index or Intersection-over-Union was computed to evaluate the detected cars and ground-truth cars.

**CNN for Blue Roof Object Detection**

Blue roof object detection is a method for identifying damage structures following a disaster using convolutional neural network (CNN) technology. This process was used to explore a damaged building inventory in a 2020 paper by Miura, Aridome, and Matsuoka that analyzed the 2016 Kumamoto and 1995 Kobe, Japan earthquakes. Roofs which are damaged but not entirely destroyed are covered with blue tarps after disasters. Aerial images and the building damage data obtained in the aftermath of these disasters show the blue tarps and the level of damage for structures, respectively. Collapsed, non-collapsed buildings, and buildings covered with blue tarps were identified using this method. CNN architecture deployed in this research correctly classifies building damage with 95% accuracy. The CNN model was later applied to aerial images in Chiba, Japan following a typhoon in September 2019. Results showed 90% of the building damage classified with the CNN model.

**Segmentation**

The next level of object detection is segmentation of aerial imagery. There can be interest in only some portions or features within an image representing different objects, rather than the entire photo. Segmentation is the best technique for identifying specific components of an image. In disaster recovery and damage assessments this would mean identification of multiple features including but not limited to blue tarps, exposed plywood, and household debris. Image segmentation can classify each pixel of an image into a meaningful classes related to a specific object. Those classified pixels represent independent features in the output. Identifying each feature or a combination thereof can then factor into a damage assessment score.

There are multiple options outside of ArcGIS deep learning that can implement image segmentation or object detection (Retinanet, CNN). However, these technologies are typically applied to street-level imagery with one house or structure in each frame. Aerial images present a challenge with complex foreground and background compositions. A potential avenue for evaluating aerial images with such methods is to take a geoTIFF and extract only the image geolocated within a certain parcel. Then running that image through these frameworks with a parcel ID (or other unique geolocated ID) in order to conduct object detection or segmentation. This also offers up the possibility of matching the aerial image damage assessment with the street-level damage assessment based on a join of unique identifiers. That is a critical next step in the effort to establish a more robust damage assessment score for individual structures.

# Change Detection

*Aerial Imagery Analysis*

## Introduction

Change detection utilizing deep learning techniques can identify changes to structures between pre-event and post-event photography. This process compares multiple raster datasets from the same geospatial location across a temporal spectrum to determine the magnitude of change. Change detection brings both the temporal and spatial elements of aerial photography together in one process. In disaster recovery, mapping this change with a spatial component in comparison with a pre-disaster photo can provide insight on areas of concern which need further ground-level damage assessment. Beyond this, change detection analysis can assist in building a parcel or structure level damage assessment by factoring in impact of wind or flooding damage.

## Overview

The image below shows a structure from before Hurricane Ida in Louisiana and the image on the right shows the logical change map where damage to the structure occurred illustrated by installation of blue tarps which signify temporary repair to damaged roofs.

Change detection can be a useful analysis in determining differences in the make up of structures as visible in aerial images. Automated change detection can be based on the building footprint or other features on roofs of structures. Analyzing this type of change requires a pre-event image and post-event image for the comparative analysis. The ChangeDetector model workflow in ArcGIS Pro can identify change in satellite imagery or aerial photography taken during two different time periods.

In damage assessment, this type of imagery can be utilized to identify areas which have experienced this persistent change. It is also a method in damage assessment that can be used for improving damage assessments and speeding up the identification of spatial units which need to be evaluated more closely. Analyzing areas of concern for active field assessments or further imagery analysis can save time and resources, providing aid to residents more expeditiously.

When working with ArcGIS Pro, there are three possible workflows: categorical change, pixel value change, and time series change. For disaster recovery purposes, pixel value change is likely the needed workflow as the pre-event and post-event imagery will most likely be orthophotos which are continuous raster data. The output of this workflow can be a raster dataset, polygon feature class, or raster function template which can be used to highlight areas of significant change. Ideally, this could be applied at a granular level down to the structure or parcel level, though given the currently available aerial photography, it is more likely that a spatial unit such as a census block or tract may need to be chosen as the unit of analysis for the output data.

ArcGIS Pro provides a relatively straightforward and accessible product in the geoprocessing suite which makes this workflow readily available to GIS analysts. The Change Detection Wizard via the Image Analyst extension enables users to compare continuous raster datasets with Band Difference. Typically, when selecting a difference type, Absolute is the default. This analyzes the mathematical difference between the pixel values in the pre-event raster image and post-disaster event image. The Band Index, Cell Size Type, and Extent Type will all need to be applied based on the output the analyst is aiming to achieve. The Change Detection Wizard output is a computation of the band index, computing the difference between raster images, and a histogram visualizing the difference values.

*Image 3.14: Change detection can be used in this image to identify change after a disaster.*

## RESOURCES


Preliminary damage assessment guide - fema.gov. (2021, August). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/documents/fema_2021-pda-guide.pdf

We spoke with Tab Troxler (St. Charles Parish Assessor, lives in Louisiana, USA personal communication, March 2022) about damage assessment practices following Hurricane Ida.

Deep learning in arcgis pro. Deep learning in ArcGIS Pro-ArcGIS Pro | Documentation. (n.d.). Retrieved April 11, 2022, from https://pro.arcgis.com/en/pro-app/2.7/help/analysis/image-analyst/deep-learning-in-arcgis-pro.htm#:~:text=Deep%20learning%20is%20a%20type,object%20classification%2C%20and%20image%20classification.

Dell'Acqua, F., & Gamba, P. (2012). Remote Sensing and earthquake damage assessment: Experiences, limits, and perspectives. Proceedings of the IEEE, 100(10), 2876–2890. https://doi.org/10.1109/jproc.2012.2196404

Microsoft. (2022, January 14). New and Updated Building Footprints. Bing. Retrieved April 11, 2022, from https://blogs.bing.com/maps/2022-01/New-and-updated-Building-Footprints

Wen, Q., Jiang, K., Wang, W., Liu, Q., Guo, Q., Li, L., & Wang, P. (2019). Automatic building extraction from Google Earth images under complex backgrounds based on Deep Instance Segmentation Network. Sensors, 19(2), 333. https://doi.org/10.3390/s19020333

Kulbacki, J. (2019, October 14). Building Damage Assessment: 2018 Woolsey Fire, Southern California. ArcGIS StoryMaps. Retrieved April 11, 2022, from https://storymaps.arcgis.com/

Miura, H., Aridome, T., & Matsuoka, M. (2020). Deep learning-based identification of collapsed, non-collapsed and blue tarp-covered buildings from post-disaster aerial images. Remote Sensing, 12(12), 1924. https://doi.org/10.3390/rs12121924

National Response Framework. (2019). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/2020-04/NRF_FINALApproved_2011028.pdf

Damage Assessment Operations Manual: A Guide to Assessing Damage and Impact. FEMA. (2016, April 5). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/2020-07/Damage_Assessment_Manual_April62016.pdf

Hurricane Ida Imagery. (n.d.). Retrieved April 11, 2022, from https://storms.ngs.noaa.gov/storms/ida/index.html#9/29.2029/-90.1932

EagleView US. (n.d.). Retrieved April 11, 2022, from https://www.eagleview.com/

Maxar Technologies. (2020). Advances in Satellite Imagery and Technology Cause a Basemap Evolution. Maxar Blog. Retrieved April 25, 2022, from https://blog.maxar.com/earth-intelligence/2020/advances-in-satellite-imagery-and-technology-cause-a-base-map-evolution

Chow, D. (2022, April 8). To cheaply go: How falling launch costs fueled a thriving economy in orbit. NBCNews.com. Retrieved April 25, 2022, from https://www.nbcnews.com/science/space/space-launch-costs-growing-business-industry-rcna23488

UNOOSA. (2022). United Nations Office for Outer Space Affairs. Search OSOidx. Retrieved April 25, 2022, from http://www.unoosa.org/oosa/osoindex/search-ng.jspx?lf_id=

Brown, S. (2019, October 29). If you're worried about surveillance from space, read this. CNET. Retrieved April 25, 2022, from https://www.cnet.com/science/turns-out-satellite-surveillance-only-sounds-like-a-major-privacy-concern/

Wolfewicz, A. (2022, April 21). Deep Learning vs. machine learning – what's the difference? Levity. Retrieved April 24, 2022, from https://levity.ai/blog/difference-machine-learning-deep-learning


RISING ABOVE THE DELUGE

# AERIAL IMAGERY: DEEP LEARNING FOR DAMAGE DETECTION

## about this project

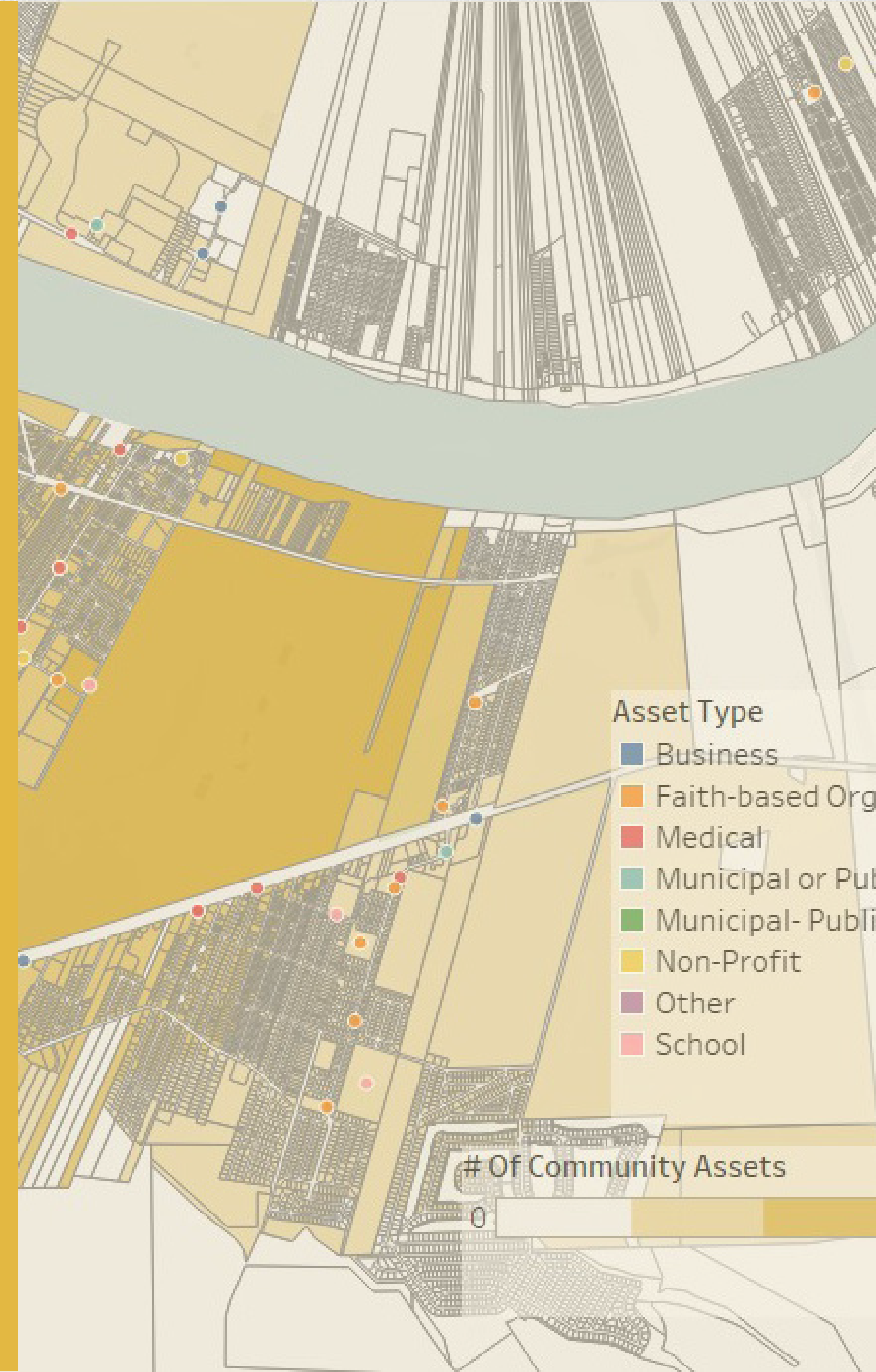
This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN

4

working paper series: community assets and networks



# Community Assets + Networks for Resiliency

## 4.1 Introduction

Community networks are the relationships among community members that can result in the provision of support, information, and resources. These networks are established over time, as households are able to remain in place for long periods of time and as community groups or individuals find ways to fill missing needs or resource gaps within a community.

From our research and field visits, we learned that these networks become essential sources of support within the local disaster recovery and preparedness context, especially when the presence of federal aid is no longer available or difficult to access. In addition, geographically and socially vulnerable communities still do not receive the adequate support or aid needed for equitable and resilient recovery. Therefore, as emerging disaster management policy and technology continues to evolve, it is imperative that the consideration of community networks and locally-identified assets are included in disaster planning.

This working paper documents our methods for identifying community assets and networks through outreach and participation strategies, data collection, and visualization techniques. This methodology should serve as a guide for future emergency manager training modules. It also creates a foundation for future research in integrating community asset mapping within emerging machine learning damage assessment models to better support a robust and accurate damage assessment tool for recovery.

To ground our work in the realities of disaster recovery, we used St. Charles Parish, Louisiana as a case study. However, our methods are broadly applicable and replicable for other parts of the United States.

## 4.2 Community Capacity Building Strategies

How might communities identify community networks before a disaster takes place?

### ASSET MAPPING

Asset mapping is the process of documenting key services and resources within a community, such as individuals' skills, organizational resources, physical spaces, sacred spaces, protected environmental systems, and local institutions. Through this process, communities can better understand the landscape of organizations, resources, and leadership present within the region. Together, these assets act as networks of support for households both within and outside of a disaster context.

In addition, identifying the variety and density of assets within a community can help to identify geographically or socially vulnerable communities. Asset maps can inform vulnerability analyses that highlight household barriers to efficiently prepare for and recover from a disaster. When the process itself is designed to allow for local community participation, asset mapping can strategically include community leaders who are often left out of the disaster planning process. This can encourage relationship building between community leaders and municipalities. Therefore, asset mapping should be targeted for emergency management and damage assessment training to ensure that resident engagement is equitable and that the prioritization of resource distribution is reflective of community needs.

To better understand how an asset mapping process can be transferable to disaster management training and processes, our team created an asset map for the St. Charles Parish, Louisiana region. Our methodology was informed by field visit observations of resource network structures within Southeastern Louisiana and asset mapping, survey, and vulnerability assessment strategies developed by emergency management organizations, public health institutions, and local municipalities.

The following provides a roadmap for effective asset mapping for disaster management as well as lessons learned. Municipalities and emergency responders can follow these steps to ensure that local leaders can be identified and contacted for participation in neighborhood-level asset mapping workshops.

#### Methods

The process of asset mapping a community can help identify community organizations and leaders that provide services to households. These relationships and resources can be called upon to better understand a community's needs and shared priorities. This understanding can contribute to the development of more accurate and local informed vulnerability assessments. In addition, the process of asset mapping identifies social infrastructure and places that are valued within a community. These are places that may offer support to individuals both outside of and within the disaster context. Community assets identified through asset mapping should be targeted for emergency management training and prioritized for resource distribution. Finally, this process can also encourage the identification of vulnerable communities that are often left out of the disaster planning process and with whom municipalities might not yet have strong established relationships.

To prepare for this process, municipalities and emergency responders can follow these steps to ensure that local leaders can be identified and contacted for participation in neighborhood-level asset mapping workshops:

#### 1 Complete a preliminary web-based search of local assets

To gain a general understanding of a community's asset landscape, we completed a preliminary search of organizations and essential services. This search was primarily done by searching terms such as "St. Charles nonprofits," "St. Charles community organizations," and "St. Charles churches." These search terms helped us to narrow down assets that were most likely to provide relief and assistance to residents following a disaster. This process informed the creation of six asset categories:

1. Nonprofit Organizations
2. Faith-based Organizations
3. Healthcare Service Providers
4. Schools
5. Businesses
6. Shelters

It was challenging to group assets into these six categories, as some organizations or service providers did not fall perfectly into one category. In addition, we observed that our own categorization may oversimplify the services provided by an organization and that we may have failed to identify key community assets not apparent in a general web search. Therefore, this process should be used to develop a baseline of present services that can guide the following community outreach and communication strategies.

#### 2 Prepare a baseline survey for local distribution

We first completed a search for disaster-specific and general surveying tools. The FEMA Engaging Faith-based and Community Organizations Survey was identified and used as a template to further adapt and respond to the challenges and needs voiced during our field visit to Southeastern Louisiana. The full version of the survey can be found in the appendix to this document.

The survey was informed by our research within the study of social networks and communication. With these considerations and the St. Charles Parish context in mind we created a survey that can:

- Identify services provided by local organizations or institutions
- Identify an organization's geographic reach
- Ask if an organization already is involved in disaster response or preparedness
- Ask whether they would be interested in getting involved in disaster response or preparedness
- Ask how organizations communicate to their members or community households
- Ask what other organizations, agencies, or institutions an organization currently communicates with

The data collected from this survey can be used to better understand the resources available within a community, and to further identify organizations who are essential community leaders within complex and hidden community networks and who may not be identifiable during a general web search.

We began preliminary outreach by contacting organizations identified during the initial asset search via email and phone call. The email introduced our project goals and directed respondents to both an online and printable version of the survey to accommodate for respondents' preference. We also called organizations to provide further context for our work before linking organizations to our survey.

After completing this preliminary outreach for survey distribution, our research team quickly learned that it would be very challenging to obtain survey responses from organizations who we had no previous connections to or relationships with. We received very few survey responses and had challenges reaching organizations by phone. This shows that this step can only be done by a team of locally-based leaders who have large reach within each community.

Local municipal officials or emergency managers who are aware of its historic context and have established trust and relationships within a local community are best equipped to utilize this strategy to recruit a diverse and robust group of local leaders and residents for asset mapping workshops.

### 3 Prepare for Asset Mapping

In order for asset maps to accurately document community assets that are essential to the community and are valued by diverse populations, it is important that recruitment for asset mapping workshops involves identified local leadership who are trusted within a community and who may have a range of connections with other organizations. For example, our field visit informed our understanding of who these leaders are within the Greater New Orleans context. These organizations ranged from local faith-based organizations, public libraries, food banks, and cultural heritage and preservation organizations, to regional nonprofit organizations such as the local affiliate Red Cross and Habitat for Humanity. Emergency managers, city planners, and other municipal departments must ensure that representatives from these organizations are present during asset mapping workshops.

One of the greatest benefits of producing a community asset map is the capacity building that occurs through the process of asset mapping. Specifically, asset mapping workshops can create the opportunity for community and relationship building between municipalities, emergency managers, and both large and small organizations who provide direct linkages to households.

Therefore, asset mapping workshops can take the form of community events that are not only designed to create these asset databases, but also as events to celebrate a community and its collective identity. Settings that welcome organizations to participate and contribute their local knowledge and expertise can create an environment that encourages equitable participation in this data collection process. Furthermore, this participatory process can also inform disaster preparedness and response strategies that respond to barriers or unique population vulnerabilities, such as language, age, ability, rural connectivity, socio-economic status, historic community disinvestment, and cultural differences.

### 4 Create Asset Map

Using the information collected in the first step, we created an asset map visualization using ArcGIS Pro and Tableau. (These tools were chosen due to their wide availability to planning professionals.) First, assets were mapped as points, then parcel boundaries were introduced. Using the parcel boundaries, a 1.5 mile buffer was calculated around each parcel. This distance was chosen based on accessible distances for households without access to a car. Once buffer distances were calculated, the number of assets that fell within each buffer was calculated, this analysis was performed with the spatial join tool in ArcGIS Pro. Based on the number of assets available to each household (parcel) we are able to identify low resource access and high resource access households. Image 1 shows this analysis visualized for St. Charles Parish.





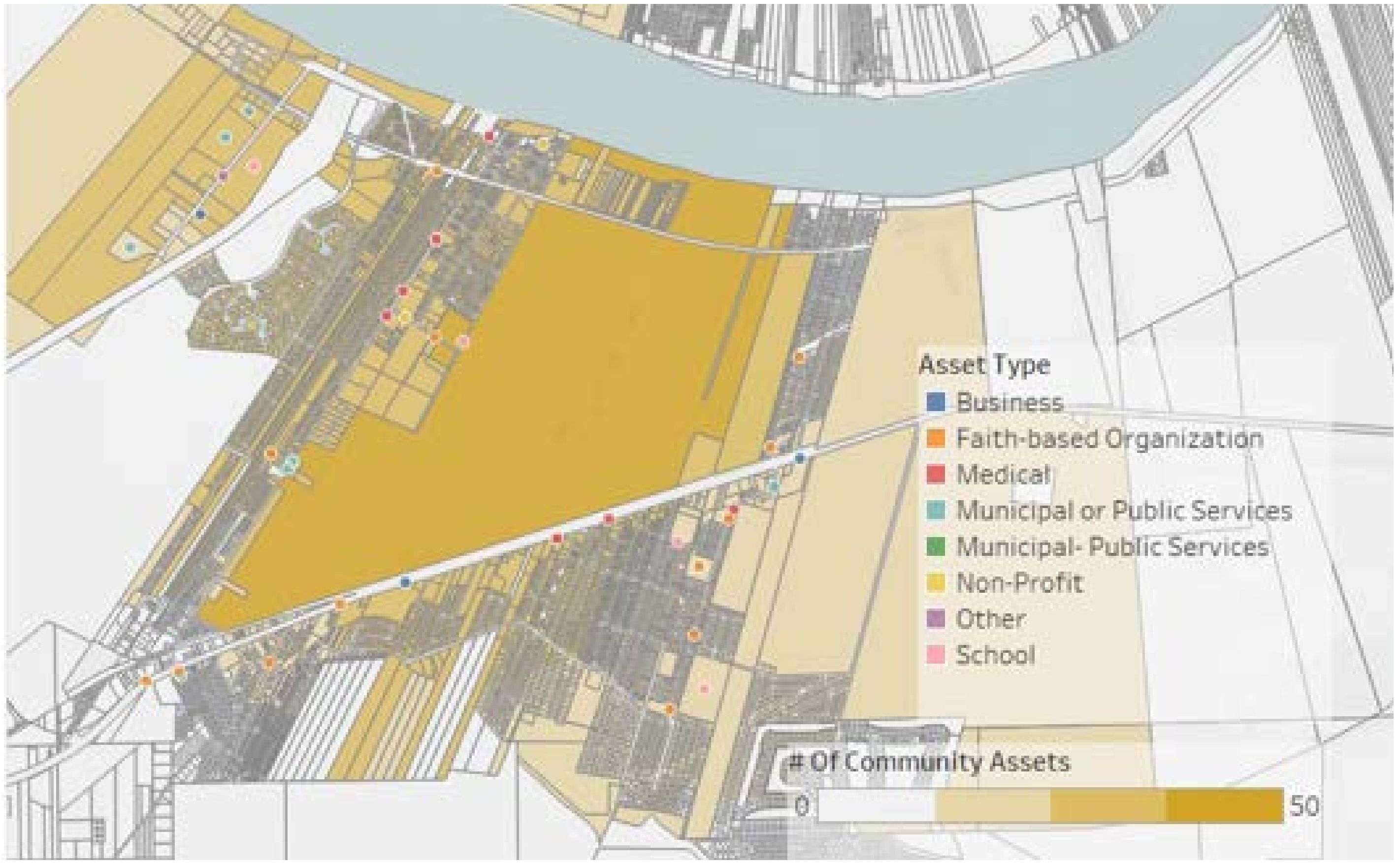



*Image 4.1: Map indicating asset accessibility by household. Greater resource density is indicated by dark yellow. Graphic made with ArcGIS Pro and Tableau.*

In future iterations of this process, local leaders and municipalities can work in small groups to collectively discuss and identify community assets that can be integrated into a mapping tool for further analysis. Assets can be documented through various techniques, such as providing groups with large-scaled printed maps which participants can use to mark the neighborhoods they serve, specific community spaces that are essential for providing their unique services, and spaces that can be utilized during and immediately after a disaster. These data points can also be collected on digital mapping platforms such as Google Maps if prefered to printed material.

Assets can also be documented through community walking tours that can highlight assets and community needs through first-hand experience. Walking routes can be divided across sections of a community and guided by small local groups. Selected participants can be tasked with documenting highlighted places and dialogue.

Once data has been collected, it can be incorporated into interactive asset maps that can show identified organizations and locations. Ultimately, these asset maps can help visualize the concentration of specific types of resources, where organizations overlap in the services provided, gaps in services offered, and unmet needs within a community. Our research team used Google Maps to perform the preliminary asset search. We also used Google Maps to collect asset addresses and coordinates into a spreadsheet to be later geolocated within ArcGis. This resulted in our own baseline asset map of St. Charles Parish.

## 4.3 Other Community Analysis Opportunities

Together with community asset mapping, the following processes can help to create a holistic community assessment that can be used by planners and emergency managers to better understand local context and prioritize resources more equitably.

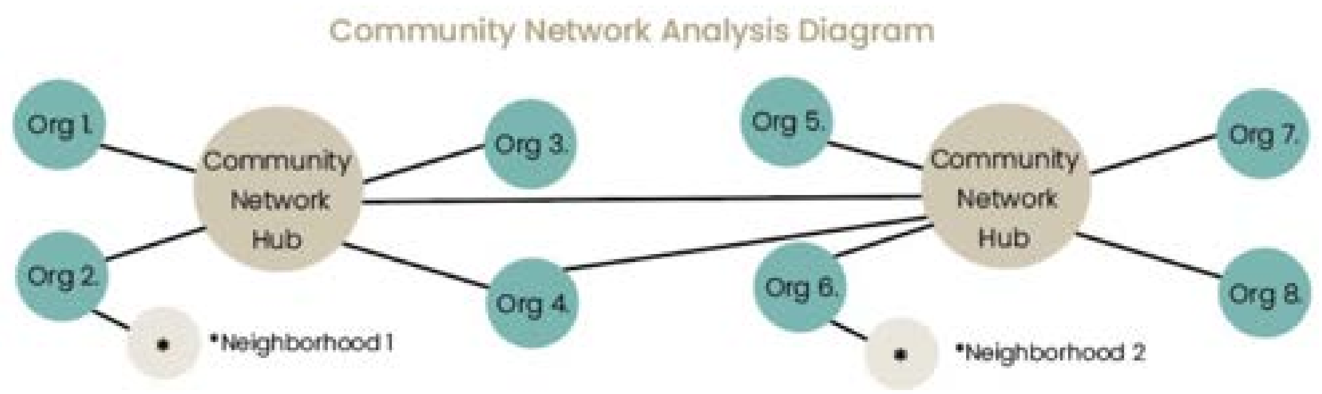



*Figure 4.1: Diagram illustrating a network of community assets.*

### COMMUNITY NETWORK ANALYSIS

Community network analysis is the process of identifying the relationships found within a community and exploring how these relationships can be leveraged to better streamline resource distribution and communication strategies before, during, and after a disaster takes place. Community network analyses can be further expanded to understand how these smaller networks connect to larger networks at the city level, and even larger networks at the regional level. By identifying larger organizations who have many relationships with smaller organizations, emergency managers can create a better picture of resource and communication streams that reach even the smallest of neighborhoods.

During our field visit, communication among organizations was one of the greatest challenges for community organizations who were not fully aware of the resources available or of other organizations participating in similar forms of outreach. Community networks can be generated by identifying community organizations who are able to reach many organizations as community hubs. Networks connecting these community hubs to smaller organizations and to other community hubs can further identify which organizations can be called upon for large-scale emergency communications strategies. Asset mapping and survey distribution similar to the methods described in previous sections can be an initial step towards understanding who communicates with whom both within and outside of the disaster context.

**Methods**

The following process recommendations should be understood as happening parallel to the asset mapping process. The two processes complement each other and accomplish similar goals.

1. **Utilize the baseline survey completed during the asset mapping process**

The surveys distributed during the initial asset mapping phase can not only serve the purpose of creating an inclusive and participatory approach to asset mapping, but can also collect data that can be used for the creation of community network analyses and visualizations. Outreach surveys should include questions that can help describe an organization's reach (number of households or organizations served) and connectedness within a community and surrounding region. Questions geared towards understanding methods of communication, frequency of contact among community organizations, and geographic reach can inform how multiple networks can be incorporated into disaster planning and response strategies. Refer to the appendix for the complete survey.

2. **Network Visulization**

Following the distribution of surveys and collection of survey results, local networks of community organizations can be visualized to better comprehend the complexity of relationships existing in a community. Our team recommends the use of Gephi, a free and open-source network analysis tool, to visualize survey results.

The combination of questions asked in our organizational capacity survey allow us to get an indication not only of an organization's resource capacity and breadth of services offered, but also its connections and relationships with other local, regional, and national organizations. The questions on cross-organization communication are particularly useful for determining network analysis measures such as node centrality and network density. These network measures provide an indication to emergency managers about the importance and impact of a particular organization within a community. This information can be used to prioritize resource distribution to these organizations which can be passed on to smaller organizations and households that they support. This dynamic of organizational relationships is represented in the diagram on the previous page.

### ENHANCING THE SOCIAL VULNERABILITY INDEX (SVI)

Asset mapping and community network data can be utilized within social vulnerability analysis through two modes. The first is using the asset mapping process to also identify communities or neighborhoods who are especially vulnerable during expected and unexpected disasters and who are not receiving prioritization during immediate and long term recovery periods. The second mode is using asset maps that have been visualized using GIS mapping tools, such as ArcGIS, to create datasets that can be used to analyze and visualize vulnerable communities.

To identify socially vulnerable communities found within St. Charles Parish, our team connected our asset map of services and organizations to an improved social vulnerability index (rSVI) to compare patterns of vulnerability identified by the rSVI with the community assets identified during the asset mapping process. For more information on vulnerability assessments, refer to rSVI the working paper.

Combining asset mapping, network analysis, and social vulnerability assessments opens opportunities to develop more holistic assessments of communities and their capacity to recover from disasters. In addition, the participatory nature of asset mapping can further contextualize community vulnerabilities through community-informed assessments of needs. This may lead to the development of disaster recovery plans that target specific community needs, rather than those informed by general definitions of vulnerability. This approach enables emergency managers to extend beyond traditional damage based assessments and consider additional social variables that are able to produce more equitable outcomes for communities impacted by disaster.

## 4.4 Applications for Emerging Technologies

In addition to complementing the processes needed for accurate and equitable community network and vulnerability analyses, opportunities presented by the asset mapping process can also contribute to emerging technologies within the disaster management sector.

For example, machine learning is currently being explored as a tool for more efficient and rapid damage assessment processes. Machine learning can utilize photo captured imagery to train computer software to identify and predict visual patterns. (For more information on emerging planning technologies, see Book 1, Chapter 3 and Book 2 Chapter 2.)

When combined with GIS data, a geographic layer can be added to these predictions. Within the disaster response context, a machine learning model can be trained to identify damage and connect this data to specific neighborhoods. This can inform at rapid speed which areas have been impacted by a disaster at various levels of severity and which areas should be prioritized for disaster aid.

This process, however, can result in emergency response that focuses solely on structural damage imagery which can miscategorize damage severity. This can also remove damage assessment from the surrounding local context that greatly informs household needs. It is this problem of context disconnect that participatory community asset maps and social vulnerability maps can address.

Future research can explore how machine learning models can combine data from image capture, locations, and geolocated social vulnerabilities to make rapid damage assessment and the prioritization of aid distribution as holistic and equitable as possible.

## 4.5 Conclusions

Our research team has outlined the importance of community analysis within the disaster management context as well as strategies and opportunities for integration within existing and emerging disaster vulnerability and damage assessment tools.

This working paper provides methodology for conducting asset mapping processes that are informed by existing community networks, local assets, and resource gaps. By taking the time to collect this data in a way that complements the importance of community building and capacity analysis, emergency managers and planners can better assess how best to plan for disasters and how best to respond when a disaster takes place.

Although these strategies focus primarily on pre-disaster preparedness, the information and knowledge sharing that occurs through these strategies ultimately informs how a community is able to mobilize disaster plans, communicate with local and regional service providers, and stay resilient during immediate and long term recovery periods. Therefore, funding opportunities at the local, state, and federal level should aim to provide support and training for local disaster response teams, especially those who are responsible for disaster management within geographically or infrastructurally disconnected communities to perform community asset and network analysis and vulnerability assessments.

Finally, as technology continues to evolve within the fields of urban and regional planning and disaster management, it will be important that social determinants of disaster vulnerability and historic context are acknowledged to inform technology-based data assessment methodologies.

### Additional Resources:

National Equity Atlas. (2022). Policy Link, USC Equity Research Institute https://nationalequityatlas.org/our-work/community/arts-culture/plan

Healthy City.(2012) A Community Research Lab Toolkit. A Community Research Lab Tool Kit. https://communityscience.com/wp-content/uploads/2021/04/AssetMappingToolkit.pdf

UCLA Center for Health Policy Research (http://healthpolicy.ucla.edu/programs/health-data/trainings/documents/tw_cba20.pdf)

https://www-tandfonline-com.proxy.lib.umich.edu/doi/

FEMA (2018) Engaging Faith-based and Community Organizations Planning Considerations for Emergency Managers (https://www.fema.gov/sites/default/files/2020-07/engaging-faith-based-and-community-organizations.pdf)

FEMA (2011), A Whole Community Approach to Emergency Management: Principles, Themes, and Pathways For Action. 1-24. (https://www.fema.gov/sites/default/files/2020-07/whole_community_dec2011__2.pdf)

Mitcham, D.; Taylor, M.; Harris, C. Utilizing Social Media for Information Dispersal during Local Disasters: The Communication Hub Framework for Local Emergency Management. Int. J. Environ. Res. Public Health 2021, 18, 10784. https:// doi.org/10.3390/ijerph182010784

# APPENDIX

## Organizational Capacity Survey

The goal of this survey is to indicate your organization's capacity for responding to disasters and to help determine how the National Disaster Preparedness Center (NDPTC) may best assist you in emergency management efforts. Additionally, this survey will help the NDPTC understand social networks in your community and how your organization works with its partners to best serve your community.

If you have any questions about this survey or how your answers will be used, please contact the University of Michigan researchers at *capstonew22@umich.edu.*

---

### Organization Information

**Name of Organization**: ____________________________________________

**Organization Address:**____________________________________________

**Organization Tel. #**: (____)____________ **Organization Email**:____________________

**Web URL:** ______________________________________________________

**Facebook:** Y / N **Twitter:** Y / N, **username:**@________________

**What kind of organization are you? (e.g., Faith-Based, Community, etc):**

______________________________________________________________

**How many people do you serve?:**__________ **Number of Permanent Staff:**__________

**Does your organization have a Disaster or Emergency Plan in place?:** Y / N







### Services Provided and Organization Capacities

**Which of the following services do you offer on a daily basis?**
*(check all that apply)*

| | | | |
|---|---|---|---|
| Child Care | ☐ | Shelter (long term) | ☐ |
| Elderly Services | ☐ | Shelter (temporary) | ☐ |
| Disability Services | ☐ | Case Management | ☐ |
| Counseling | ☐ | Goods/resource distribution | ☐ |
| Food Pantry/Kitchen | ☐ | Community Center | ☐ |
| Medical Services | ☐ | Legal services | ☐ |
| Transportation Assistance | ☐ | Information Sharing and/or Accessibility Services | ☐ |
| Other: ____________________ | | Other: ____________________ | |

**Is access to services provided restricted to certain members only?:** Y / N

**Are services provided during major disasters or emergencies?** Y / N
*If yes, explain:* ____________________________________________

**Does your organization use volunteers?**: Y / N
*If yes, how many volunteers can your organization support?* ___________

### Facility Capacities

The following questions are intended to assess your community's capacity to respond to a disaster event. Please answer the following questions assuming a major disaster scenario. Answer the questions from the perspective of your organization's response to this scenario.

**In the scenario described above, is your facility able to store goods and/or non-perishable items** (ex: canned food, water, batteries, household supplies, toiletries)**?** Y / N

**Is your facility equipped with a generator or able to generate energy?:** Y / N

**How many people could your facility shelter in the event of a disaster/emergency?**

____________________________

**Does your facility have access to reliable internet connection or able to make phone calls ?** Y / N

## Communication + Organization Relationships

**How does your organization typically communicate with the people or organizations your serve:** (check all that apply)

- ☐ Social Media (facebook, twitter, tiktok, etc)
- ☐ Email
- ☐ Phone (including text messaging)
- ☐ Mail
- ☐ Other: ________________________________________

**Does your organization have a communication system (ex: short range radio, automated messaging, sirens) in place for disaster response?** Y / N

*If yes, what type of system do you have?*

____________________________________________________________

**Who does your system reach?** *(check all that apply)*

- ☐ Individuals receiving services only
- ☐ Employees
- ☐ All residents
- ☐ Other organizations
- ☐ Other__________

**In the column on the left, list the organizations with whom you communicate the most. On the right, indicate how frequently you communicate with them.**

| | |
|---|---|
| _______________________________ | ○ Daily ○ Weekly ○ Monthly ○ Yearly |
| _______________________________ | ○ Daily ○ Weekly ○ Monthly ○ Yearly |



University of Michigan // NDPTC Organizational Capacity Survey

| | |
|---|---|
| _______________________________ | ○ Daily ○ Weekly ○ Monthly ○ Yearly |
| _______________________________ | ○ Daily ○ Weekly ○ Monthly ○ Yearly |
| _______________________________ | ○ Daily ○ Weekly ○ Monthly ○ Yearly |
| _______________________________ | ○ Daily ○ Weekly ○ Monthly ○ Yearly |

**On the left, list the organizations that have the greatest impact on your service mission. On the right indicate on a scale of 1 to 5, 1 being not at all impactful and 5 being extremely impactful, how impactful are these partnerships to providing your services?**

| | |
|---|---|
| ___________________________________ | ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 |
| ___________________________________ | ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 |
| ___________________________________ | ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 |
| ___________________________________ | ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 |
| ___________________________________ | ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 |
| ___________________________________ | ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 |

**During a disaster, how frequently do you communicate with the following groups/individuals about disaster preparedness, response, and recovery?**

| | |
|---|---|
| Local/municipal emergency managers | ○Daily ○Weekly ○Monthly ○Quarterly ○Never |
| FEMA | ○Daily ○Weekly ○Monthly ○Quarterly ○Never |
| Local Non-profits/community organizations | ○Daily ○Weekly ○Monthly ○Quarterly ○ Never |
| National Non-profits (i.e. Red Cross) | ○Daily ○Weekly ○Monthly ○Quarterly ○ Never |
| Local or county health departments | ○Daily ○Weekly ○Monthly ○Quarterly ○Never |
| Insurance Company representatives | ○Daily ○Weekly ○Monthly ○Quarterly ○Never |
| Other: ____________________________ | ○Daily ○Weekly ○Monthly ○Quarterly ○Never |

### Contact Information

Please provide contact information should we need to follow-up about your responses to this survey.

**Name:**_______________________________ **Email:** ____________________________

**Phone number:** _________________________________



RISING ABOVE THE DELUGE

COMMUNITY ASSETS AND NETWORKS FOR RESILIENCY

## about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

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5

working paper series: rSVI

# rSVI

*recovery social vulneriability index*

## 5.1 Introduction

Social vulnerability indices (SVIs) are tools used to indicate how vulnerable a community is based on selected social characteristics. SVIs adhere to the understanding that marginalized social groups in the US bear the burden of disasters inequitably and are disproportionately negatively impacted by disasters. Integrating SVIs into disaster management planning processes provides a first step towards identifying communities that demonstrate the greatest need proportional to the resources and capacities available to them.

Currently, the National Disaster and Preparedness Center (NDPTC) uses the CDC SVI in their vulnerability assessment. This assessment predicts the vulnerability to damage of an area based on the SVI, the FEMA Hazus dataset, and other NOAA storm predictors. While this methodology is adequate for ascertaining a general sense of vulnerability, it lacks granularity of data due to the nature of large national datasets which often aggregate data at the census tract level. Additionally, the current CDC vulnerability framework is not specifically catered with disaster recovery in mind. Therefore, some variables pertinent to recovery are not included in the CDC social vulnerability index.

Our team has developed a new SVI that updates the CDC SVI values, includes new variables, and incorporates parcel level data. This method of social vulnerability indexing allows for future integration with the YOLOv5 computer vision damage assessments. By including parcel level data, we are able to match damage assessments from geo-located images to vulnerability assessments. This creates a more complete picture of the extent of damage and the capacity for that area to recover from disaster. In addition, this method is able to account for the challenges of using census tract level data, particularly in rural areas where data aggregation eliminates geographic nuances of variables.

This new recovery SVI (rSVI) is just one piece of the recovery model presented in RIDA+. Considered in tandem with machine learning damage assessments and organizational capacity assessments, this disaster recovery decision making framework will provide a more holistic understanding of the social characteristics influencing individual capacity to recover and the support network of organizations that can enable faster recovery.

Our project focused on Hurricane Ida and St. Charles Parish, Louisiana as a case study for the piloting of this new rSVI methodology. The following pages of the document provides step-by-step details of our methodology as well as rationale for the changes made to the SVI currently used by the NDPTC. In addition, this paper will discuss the results of our findings and potential next steps for further improvements on the rSVI.

### TECHNICAL NEEDS

- ArcGIS Pro
- Tableau
- Microsoft Excel
- Database Manager

## 5.2 Methods

The following table shows the various datasets and variables that were compiled to calculate the rSVI. Data was collected at either the census tract or parcel level to simplify data aggregation and calculations. For the census tract SVI, a total of 18 separate social variables were included. For the parcel level social vulnerability index, an additional three parcel specific variables were added to the index. Data for the SVI was only collected for St. Charles Parish. However, we chose data sources that would aid in replicability of the index.

All of the variables used to compile the rSVI are publicly accessible either through government data portals or through obtaining data via a Freedom of Information Act (FOIA) request. Using low cost and publicly available data lowers the cost of performing this analysis and also reduces the risk of using personal homeowner information.

| DATA SOURCE | SCALE | DESCRIPTION | TABLE |
|---|---|---|---|
| US Census Bureau 2019 American Community Survey | Census Tract | Population below poverty | B17001 |
| | | Unemployed population | DP03 |
| | | Median income* | |
| | | Householders over 65 living alone | DP02 |
| | | Population with a disability | |
| | | Single parents | |
| | | Speaks English less than well | |
| | | Population under 5 years old | S0101 |
| | | Non-white population | B01001H |
| | | Less than high school education | S1501 |
| | | Mobile homes | DP04 |
| | | Renter occupied | |
| | | Crowded Households | |
| | | Multi-unit apartment homes | |
| | | Households without a car | |
| | | Less than 4 years in current home | |
| | | Group quarters | B26001 |
| | | No internet connection | S2801 |
| St. Charles Parish Assessors Office Planning Department | Parcel | Home Assessed Value | |
| | | Zoning District | |
| | | Home Assessed Value | |
| | | Post-Ida Damage Score** | |

* Inverse rank
** Used for validation only

## VARIABLE RATIONALE

### Poverty
Households living in poverty have less disposable income for investing in preparedness measures such as storm shutters and other structure fortifications. In addition, impoverished communities may struggle to finance evacuation and sheltering costs.

### Median Income
Median income provides an additional measure of income with the capability to capture income disparities between high and low income communities. Like poverty measures, income provides an indication of the capacity of a community or household to access resources and services that can improve recovery outcomes.

### Unemployment
Unemployment can indicate how much disposable income is available to an individual to assist in recovery efforts. In addition, it may also indicate social connectedness. Employed individuals have access to a social network of coworkers and employers who can provide recovery assistance or information about resources. Unemployed individuals do not have the same degree of access to this kind of network.

### Education less than high school
An individual's educational attainment is an important indicator of economic earning potential. In addition, educational attainment may also play a role in the likelihood of an individual to prepare for a disaster. Both of these factors can impact the success and speed of recovery following a disaster

### Speaks English less than well
This variable indicates how accessible information materials including disaster preparedness publications, and emergency messages are to people in an area. Understanding this social characteristic can help to direct resources and information in a language other than English to a particular area or region.

### Households without a car
The availability of a vehicle can determine whether or not a household is able to evacuate in the event of a major disaster. Additionally, having a vehicle available may also influence whether or not a household is able to return to their home following a disaster.

### Internet Access
Having a secure and reliable internet connection can improve the accessibility of disaster related information such as preparedness tips and emergency warnings. In addition, there is a growing trend amongst organizations to communicate with residents and members via social media and/or email. Therefore, households without internet may struggle to receive the most up-to-date information regarding a disaster.

### Over 65 living alone
Elderly populations, especially those living alone, are particularly vulnerable to poor recovery outcomes due to limited mobility and reliance on a fixed income. In addition, we heard from community partners in the New Orleans region that elderly populations often view themselves as a burden to their families and communities and frequently suffer from social isolation.

### Children under 5
Young children and infants often have different needs than adults particularly in regards to nutritional and sheltering requirements. Households with young children may have a more difficult time finding resources and facilities able to accommodate their varied needs following a disaster. Therefore, households with young children may experience slower recovery.

### Single Parents
Single parent homes are uniquely vulnerable to disaster situations due to the need to provide for disaster preparedness and recovery for not only themselves but also for children without the support of second parent.

### Mobile Homes
Mobile homes are more susceptible to physical damage during natural disaster events and are a greater risk of being completely destroyed. The market value of mobile homes can be relatively low, which may limit the amount of recovery funds available to households living in mobile homes. Our team of researchers heard from community partners in the New Orleans region that this often traps households in the disaster recovery cycle and inhibits their abilities to either relocat to a safer area, or purchase a sturdier home.

### Renter occupied units
Many disaster recovery programs and damage assessments focus on owner occupied structures. Therefore, current disaster recovery models leave out renters and underprovide assistance to these residents.





### Fewer than four years spent in home
Research suggests that the longer amount of time a household is in their home, the faster that household is likely to recover. This is because that household is able to form more connections with neighbors and local service providers to help them through the recovery process.

### Crowded
Households with greater than two people are more likely to have slower recovery times due to the need to provide for several people. In addition, crowded homes (defined as having more than 1.5 people per room) may indicate non-traditional housing arrangements, and lower income households.

### Group Quarters
Individuals living in group quarter arrangements, such as nursing homes and incarceration facilities, may lack strong social ties within their living arrangements and may not have the same level of access to information as residents living outside of group quarters. This makes this subsection of the population more vulnerable to disasters.

### Disabled Population
Impaired mobility and additional medical needs limit the number of facilities and resources accessible to disabled individuals which slows down the time of recovery. Disabled populations may also prioritize medical expenses and needs over sheltering expenses.

### Non-white population
Racial minorities and marginalized communities face additional barriers to receiving aid and resources following a disaster. Some of this is due to a lack of institutional knowledge created as a result of historic disinvestment. These systemic barriers slow down the time of recovery and makes these populations more vulnerable to displacement. This can have the further effect of damaging the existing social ties within the community leading to further vulnerability in future disasters.

### Multi-Unit Apartments
Households living in apartment buildings (defined as any residential building with more than 10 units) are often not included in traditional damage assessments and may have fewer resources available to them for recovery aid. In addition, resident turnover in apartment units is higher than in single-family neighborhoods making it more difficult to form strong social ties that can provide resources after a disaster.

## PARCEL SPECIFIC VARIABLES

The following variables were included in the parcel level recovery vulnerability index. Data for each variable was obtained from the St. Charles Parish government.

### Market value of home
Higher home value indicates less vulnerability. Rationale is two-fold: higher home value indicates wealth, and some recovery programs are based on value of the structure damaged meaning that residents are more likely to get a larger sum of recovery assistance dollars.

### Zoning
R1A-M, R1-M zones allow mobile homes on the structure, households living in mobile homes are more likely to sustain greater amounts of damage, and more likely to be displaced from the community. R13, multi-family housing, households living in apartment buildings are more likely to be disconnected from community and less likely to be targeted by recovery programs which often focus on homeowners. Zoning was incorporated as a binary variable in the rSVI.

### Flood Zones
Special Flood Hazard Areas (SFHA) are those within the 1-percent flood area. Zones included in the SFHA are Zones A, AO, AH, A1-A30, AE, A99, AR, AR/AE, AR/AO, AR/A1-A30, AR/A, V, VE, V1-V30. Areas of moderate flood hazard are listed as Zone B or Zone X. Zone C has minimal flood risk. A binary variable is used for the vulnerability assessment with SFHA zones receiving a value of one, and all other zones receiving a value of zero.

Our parcel rSVI compares the vulnerability of 13,924 individual parcels in St. Charles Parish. This sample represents approximately 31% of the total 45,059 parcels in the parish. The sample does not include parcels that did not have a Hurricane Ida Damage Assessment report or parcels for which property market values could not be matched to existing records. Duplicate parcel identification codes were also excluded from this sample.

## DATA CALCULATIONS

**Tract rSVI**

Similar to the CDC's SVI, our rSVI relies on ranking census tracts on each variable to create a composite vulnerability score. For our process, the census tracts in St. Charles were compared to only the census tracts in that parish. This differs from the CDC process which compares each census tract to all census tracts in the nation. By comparing the census tracts to tracts within their county or parish, a more specific and localized comparison can be made which better enables the NDPTC and local emergency managers to draw conclusions about vulnerability in areas expected to experience natural disasters.

For each variable, percent of population (or households) is calculated by dividing the estimated value by the population or number of households. For simplicities sake, margin of errors are not accounted for in these measurements. After percentages are calculated for each variable, percentile rankings are calculated by using the percentile.inc function in Microsoft Excel. Once each census tract has been ranked across all variables, rankings are summed for each tract to provide an overall ranking of vulnerability. These summed rankings are categorized based on the 25th, 50th, 75th, and 100th percentiles of summed totals and given a recovery vulnerability score of 1-4 with 1 being least vulnerable and 4 being the most vulnerable. By ranking census tracts on the vulnerability variables, we are able to get a sense of how vulnerable a census tract is relative to all other census tracts in the study area. This makes comparisons—and by extension, prioritization— between census tracts easier.

Due to the large number of variables and the nature of indices, regression analyses were not run to determine the significance of each variable in determining the vulnerability score of each tract. However, simple scatterplots were created to get an indication of any possible relationship in the data. To eliminate any possible error or bias that could be introduced through variable significance analyses, variables were left unweighted. While this method may not be statistically rigorous, it does allow for greater interpretation of values. This can provide opportunities for community members to participate and weigh in on which variables they feel are most impactful to the community.

After calculations are complete, the rSVI data is visualized as a map in Esri ArcGIS. Visualizing data as a map allows planners and emergency managers to better understand the spatial distribution of vulnerability in the study area. Image 1 on the following page shows the tract level vulnerability index visualized for St. Charles Parish.

**Parcel rSVI**

To calculate the parcel level rSVI, a similar process was adopted. First, a spatial join between parcel and tract boundaries was performed in ArcGIS pro to determine which census tract each parcel belonged to. The information from this new feature layer was exported as a database file so that additional data calculation could be performed in excel. Each parcel is associated with a property identification number (PID) and all parcel related data including zoning information, market value of properties, and flood zone designation includes PID numbers. These values are then matched (using xlookup) to their associated parcels using PIDs and rankings are calculated for each parcel. These parcel rankings are added to the tract rSVI summed rankings of the tract associated with each parcel. Like with the tract rSVI, the summed rankings for each parcel are categorized based on the 25th, 50th, 75th, and 100th percentiles and parcels are assigned a rSVI score of 1-4 with 4 being the most vulnerable.

By calculating a parcel rSVI as well as the tract rSVI, greater nuances of vulnerability can be captured. While the tract level index captures a macro view of vulnerability and provides average values for certain social characteristics, the parcel level index is able to pinpoint specific households in a neighborhood that may be uniquely vulnerable to disasters due to aging or poor structural integrity of their home. In addition, parcel level zoning data is able to give a clearer indication of which households may be renter occupied and therefore more likely to be disconnected from community resources and assets.

Image 2 illustrates the parcel level rSVI for St. Charles Parish. The scale of the map has been decreased to improve legibility for print format. For an interactive





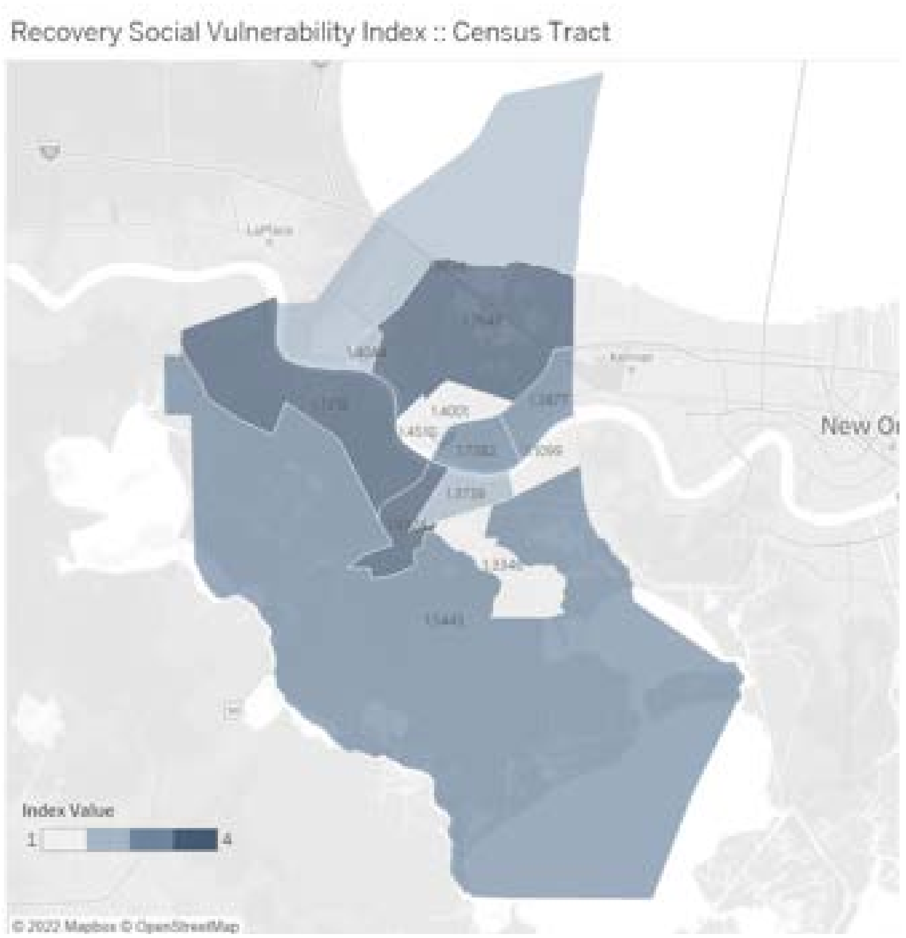


*Image 5.1: St. Charles Parish tract level rSVI. Most vulnerabile populations are shown in dark blue, while the least vulnerable are shown in white. Census tract level rSVI provides a macro view of vulnerability in a region. Best used for intitial prioritization. Graphic made with ArcGIS Pro and Tableau*

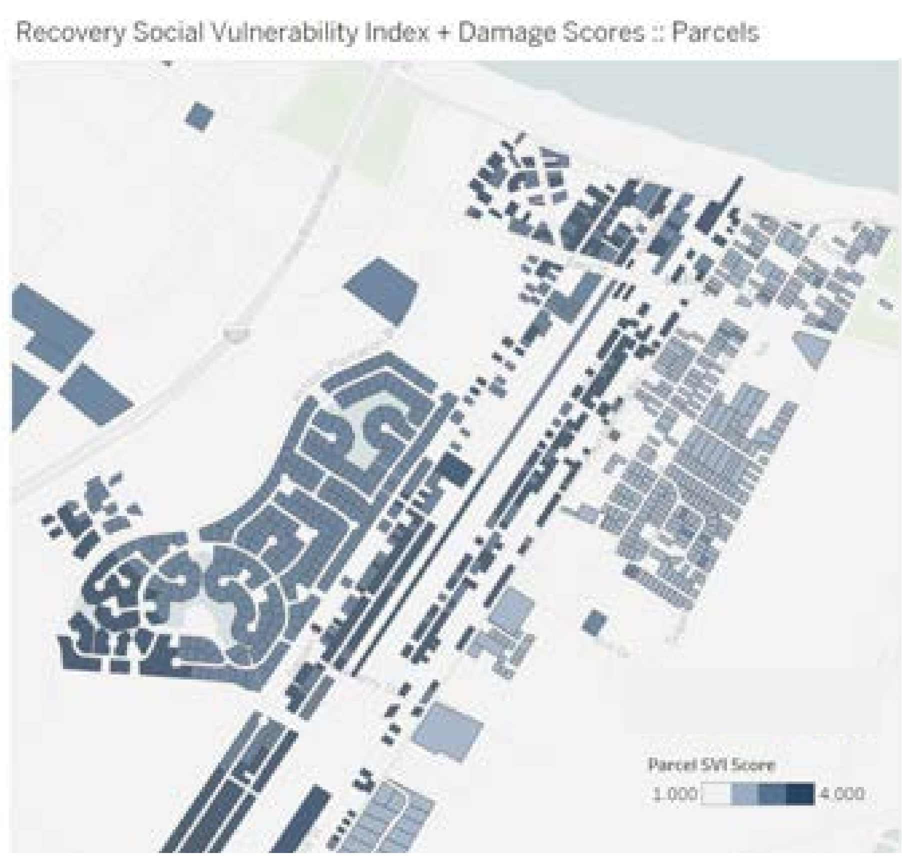


*Image 5.2: St. Charles Parish parcel level rSVI. Map is zoomed in to Luling, Louisiana near the Mississippi River. Similar to the tract level rSVI, more vulnerable parcels are shown in dark blue, while lighter blue parcels indicate less vulnerable parcels. Parcel level rSVI provides a greater level of nuance and helps planners and emergency managers better understand vulnerability in a community. Graphic made with ArcGIS Pro and Tableau*

version of this map that allows you to zoom and pan across the entirety of the parish, please go to our website.

## 5.3 Results

The following section disccuses the results of the rSVI analysis and offers ways to incorportate the rSVI into the RIDA+ model.

### COMPARISON TO CDC SVI

In general, the vulnerability index rankings for census tracts in St. Charles Parish, Louisiana increased when using the rSVI as compared to the CDC SVI. In total 5 out of 13 census tracts saw an increase in vulnerability rankings while only two decreased (see Image 4 for greater detail). It is most likely that the shift from comparing tracts nationally to regionally resulted in these changes in vulnerability assessments.

### RELATIONSHIP TO DAMAGE ASSESSMENTS

After calculating parcel rSVI scores for each of the 13,924 parcels with damage assessment data available, we can test the relationship between vulnerability and damage using St. Charles Parish Assessor's damage assessment data. This can help provide an understanding of how, if at all, the vulnerability of a household impacts the amount of damage sustained by the structure. If the relationship is strongly correlated in a positive direction (i.e. the greater the vulnerability score, the greater the amount of damage we can expect to see to the structure) our rSVI could be used as a predictive tool.

The damage assessment data that was provided from the St. Charles Parish Assessor's Office is based on a 0-4 scale. A damage assessment score of 0 indicates cosmetic damage only, 1 indicates minor damage (minimal shingle damage, damage to outbuildings), 2 indicates moderate damage (significant shingle loss, no structural damage to main building), 3 indicates major damage (visible structural damage, large portions of roof missing, likely water damage), and finally, 4 indicates complete structural damage (structure is unusable, significant sidewalls or roofing missing or destroyed). Damage assessments were determined based on aerial imagery taken shortly after Hurricane Ida made landfall. For tract level rSVI comparisons to damage scores, parcel damage scores were summed across the tracts and divided by the number of parcels in each tract that had damage scores available. While this is an imprecise way to calculate parcel damage averages, we determined that this was the best way given our data constraints and availability of parcel level damage assessments.

Figure 2 shows a scatterplot mapping the relationship between the tract rSVI and the tract average damage score. This plot shows a positive relationship at the tract level between our newly developed rSVI and average damage assessments. Census tracts with the highest level of vulnerability also have average damage scores at the high end of the scale. Further investigation of individual rSVI variables is necessary to understand which social variables have the strongest relationship to observed damage assessments.

This graphs and the supporting maps provide justification for the development of vulnerability indices as tools for prioritizing deployment of recovery resources since they show that there is a relationship between the two variables. Planners and emergency managers can use the rSVI to predict where damage is likely to be most severe and where community residents have the least amount of resources available to help with recovery efforts. This can help to make recovery more equitable and faster for those who are traditionally slow to receive help from disaster relief and recovery agencies.

## 5.4 RIDA+ Integration

The rSVI should be deployed in the earliest phases of the RIDA+ process. After determining the likely storm trajectory for a given storm, rSVI calculations should be made for all census tracts and parcels within that storm path. Deployment of aerial imaging tools (drones, planes, etc) should be based on the most vulnerable tracts in the study area. Within the most vulnerable and second most vulnerable tracts, deployment of street level imaging should be based on parcel level rSVI. This will help to prioritize perishable data capture and analysis of the most at risk communities first.

In addition, the rSVI should be revisited at the end of a disaster recovery cycle to assess its efficacy in predicting the amount of damage sustained by homes. Revisiting the rSVI regularly also allows for data to be updated as new data becomes available. Keeping data as up to date as possible (something that the CDC has not done with its SVI—it's currently drawing from 2018 data) will ensure that vulnerable populations are being targeted to the best of NDPTC's ability.

## 5.5 Next Steps

While our team has made significant innovations to the existing SVI used in the RIDA model by adding more specific disaster specific variables and introducing a parcel level rSVI, there is still additional work to be done to further improve on this new methodology. Most importantly, regression analyses should be performed on individual variables to see which variables included in the rSVI have the greatest level of statistical significance in predicting damage outcomes. In future iterations of the rSVI, variables or groups of variables could be weighted according to their significance to better estimate vulnerability and therefore disaster outcomes. This can help reduce the "noise" in the vulnerability index produced by having a large number of variables.

The second improvement that should be made to the rSVI is including information gathered from the asset mapping process recommended as part of the RIDA+ model. (See the working paper on community asset mapping and network analysis for more information on asset mapping.) Following asset mapping processes that indicate the number of resources available to each household, this information can be added to the parcel rSVI to better identify gaps between needs and resources available. The image below shows where clusters of households exist in St. Charles Parish that are both highly vulnerable to disasters and have the fewest number of resources available to them. This visualization shows the potential for combining our proposed rSVI and asset mapping processes to develop an overall measure of vulnerability and resource availability.


*Image 5.3: St. Charles Parish Needs + Resource Gaps. This map shows, in blue, where households exist that have the highest vulnerability ranking and lowest access to resources. After more comprehensive assett mapping processes, analysis like this one could contribute to the rSVI to further refine our identification of vulnerable households. Graphic made with ArcGIS Pro and Tableau*

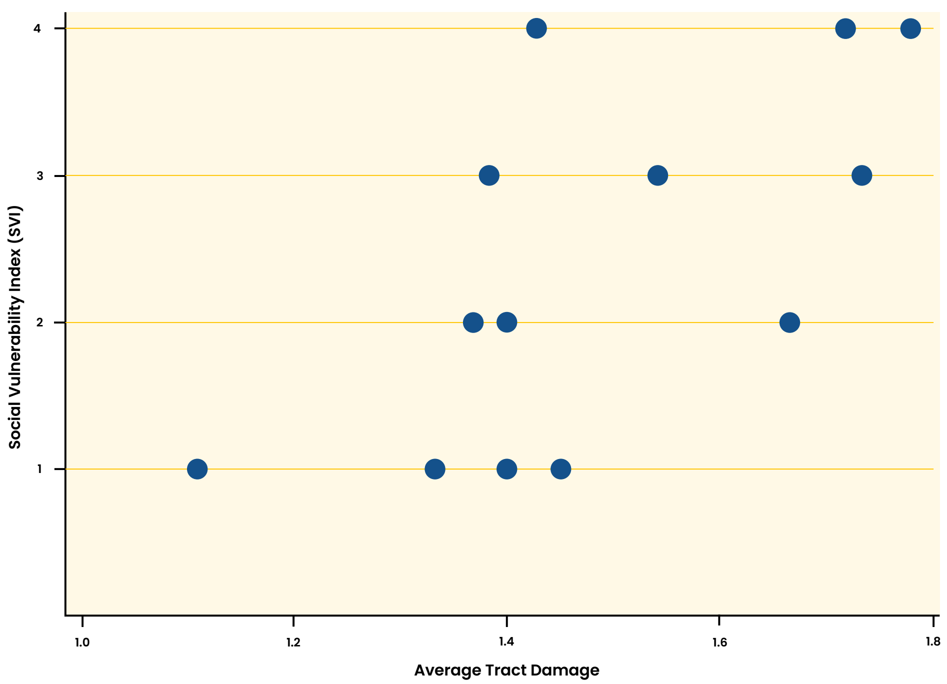


*Figure 5.2: Relationship between tract rSVI and average tract damage. This scatter plot shows a generally positive relationship between the rSVI and average damage scores. With a low n value of 13, further study is needed to determine if this relationship is strengthened or weakened by additional observations. Graph made with Stata*

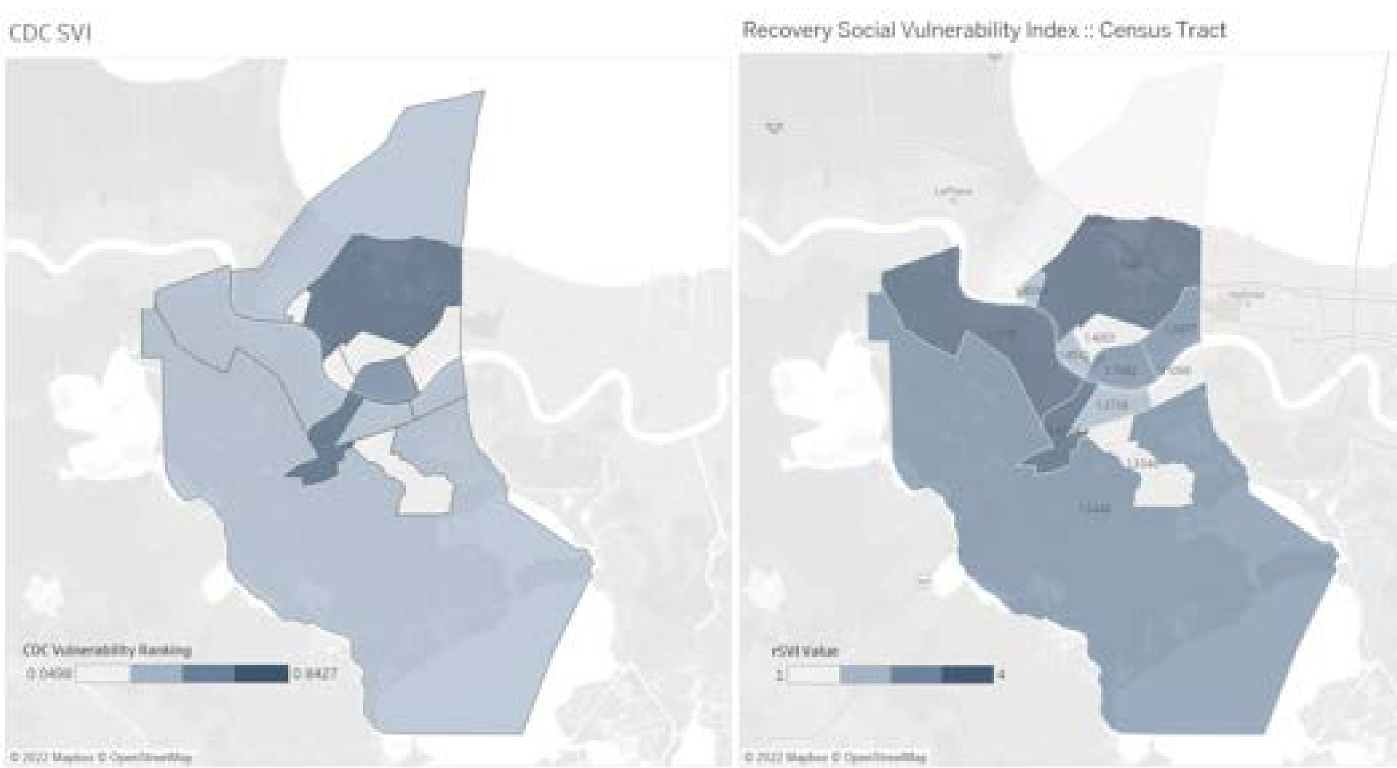


*Image 5.4: Map showing comparison between CDC SVI (left) and Deluge rSVI (right). In both maps, more vulnerable census tracts are shown in dark blue. The most significant changes occured in census tracts south of the Mississippi River. Graphic made with ArcGIS Pro and Tableau*

## 5.6 Conclusions

To increase the efficacy of the social vulnerability index (SVI), it is necessary to integrate additional measures that add nuance to our understanding of vulnerability. One way of accomplishing this is by using multiple units of analysis to capture both macro and micro perspectives of vulnerability. On the macro level, it is important to cater social vulnerability indices specifically to disaster contexts to capture the variables that speak directly to a household or individual's capacity to seek out recovery resources. These types of indicators, such as renter occupancy, and access to internet connections are widely available on the census tract level. Aggregating and averaging these types of variables across the census tract provide a sweeping overview of a large population and allow users of RIDA+ to make first level prioritizations for tool and resource deployment. For rural and sparsely populated regions where census tract level measurements are inadequate, parcel level SVIs provide a closer glimpse of vulnerability and enable us to identify clusters of at-risk households. This can further support the prioritization of RIDA+ deployment.

The method proposed in this working paper provides the NDPTC with a first step toward improving on the existing RIDA framework. This team believes that through our suggested improvements, RIDA+ has the potential to become a revolutionary tool for delivering recovery assistance in a timely and equitable manner.

RISING ABOVE THE DELUGE

# RECOVERY SOCIAL VULNERABILITY INDEX

## about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

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