Predicting Green Infrastructure Maintenance Needs Using Remote Sensing and Machine Learning

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***Abstract*—This paper explores the challenges posed by municipalities rapid increased adoption of green infrastructure stormwater management systems. Green infrastructure (GI) poses a sustainable option to reliving stress from traditional sewerage systems. However, limitations in on the ground inspections for maintenance have caused a decrease in green infrastructure functionality. This paper poses a technological approach to addressing GI maintenance needs. The potential use of remote sensing and machine learning technologies are explored. Sensors on drones and satellites can capture a wide range of data that can be analyzed and manipulated. The use of ArcGIS Pro's mapping and machine learning software was used to create a more efficient model. This study suggests that utilizing these technologies could mitigate personnel and resource constraints while providing continuous monitoring, ultimately advancing remote sensing methods in urban water management practices.**

***Index Terms*—green infrastructure, stormwater, remote sensing, satellite imagery, multi-spectral imagery**

I. Introduction

Historically, urban development uses impervious surfaces like concrete and asphalt, reducing vegetated areas. When it rains, impervious surfaces prevent stormwater infiltration, resulting in polluted water runoff due to the mobilization of particles on the ground [1]. To reduce flooding, municipalities must build "grey infrastructure" systems like underground sewerage pipes that divert water away from communities to treatment plants or local waterways. Cities like Milwaukee continue to deal with outdated combined sewer systems, which combine sewage and stormwater pathways to a treatment facility or an outfall, preventing groundwater recharging [2]. Municipalities can often find themselves overwhelmed with managing these systems during large storms, resulting in flooding and burdened treatment facilities. If the burden is large enough, untreated sewage can be released into local waterways, decreasing water quality.

Green infrastructure (GI) uses natural processes by integrating vegetated systems to absorb and filter water, decrease water velocity, reduce sediment inflow, and store stormwater [3]. Vegetation is crucial to the success of these best management practices (BMPs) because of these various functions. Past studies have shown that plant selection and health determine the long-term functionality of GI [4]. Plant stressors like poor soil or climate conditions can be an indicator of incorrect plant selection or a need for more frequent maintenance. Without proper maintenance GI viability can be further reduced due to sediment or trash can buildup, preventing filtration and infiltration [5].

Maintenance still proves to be a significant challenge for wide-spread adoption of BMPs due to time, money, and resource costs. Inspection costs have been studied and predicted to be some of the highest costs of BMP programs [6]. Currently, maintenance needs are assessed through on-the-ground inspectors sent out due to calls from concerned residents or for routine check-ins. Maintenance inspections include recording the aforementioned indicators of GI viability and sending recommendations back to municipalities. Technologies like remote sensing and machine learning can help alleviate personnel and resource challenges while providing frequent and direct monitoring.

II. Literature Review

Satellite and drone imagery have long been used to survey land and gain perspectives normally invisible to humans through reflective multi-spectral imagery. Technologies like vegetation indices and machine learning algorithms can help extract even more information from imagery. As consistent with my own research, Amir et al. (2021) points out in "Remote sensing of urban green spaces: A review" that past research has heavily focused on identifying health of trees in large-scale projects using methods like leaf area indices and not as much on small-scale urban areas like GI [7]. More recently, best management practices have continued to grow in popularity due to an increased focus on sustainability and climate change mitigation. This has led to the rise of recent research utilizing satellite imagery to investigate GI in a variety of ways. Examples of such investigations are a study to determine GI's ecosystem service capacity (Dimitrov et. al, 2018) [8] or studies to determine GI's cooling capacities (Carlos et al., 2019; Fuentes et al., 2021) [9] [10]. However, specific research on vegetation monitoring is limited. One of the few papers with this focus by Prettyman et al. (2021) showed that vegetation monitoring can be done using remote sensing methods in GI by using vegetation indicies like NDVI [11]. Most remote sensing work has been done only using satellite data; however, satellite imagery poses spatial and temporal constraints when compared with unmanned aircraft systems (UAS) like drones. Dimitrov et al. (2018) conducted research with both UAS and in-situ (on the ground) data in their paper, but they did not compare or analyze the results together [8]. This lack of comparison is consistent knowledge gap found in other research using both methods. Moreover, research involving GI investigations has stopped at streamlining the actual classification of imagery when there is significant potential to go further.

Machine learning models (MLMs) can be used to produce maintenance suggestions to municipalities using classified imagery from remote sensing. MLMs have already been implemented in other applications such as in agriculture to identify crop stress and produce detailed management suggestions [12]. We can learn from these applications in other fields and implement approaches using growing knowledge from current GI investigations to push research boundaries.

Utilizing drone and satellite, this study aims to create a machine learning model that can be implemented by municipalities to identify the highest priority green infrastructure locations in need of maintenance based on their average NDVI.

III. Proposed Solution

Utilizing classified drone, satellite, and in-situ data, this study aims to create a python model that can be used by municipalities to identify the highest priority green infrastructure locations in need of maintenance based on GI health indicators.

Remote sensing will enable municipalities to monitor multiple sites continuously and from a distance. By using drones and satellite data, sensor outputs could enable municipalities to retrieve a lot of usable information for further analysis. Some outputs are RGB images or NDVI rasters, which are the most important images for modelling maintenance needs. NDVI rasters can be created using a simple equation adding, subtracting, and dividing near infrared and RGB values. NDVI values range from -1 to 1, where -1 represents a bright red and 1 is a bright green. The more negative a value is, the more likely it is not a plant. Average NDVI values obtained from the raster will be used in the model to calculate sparse vegetation (low NDVI values for the entire swale) and unhealthy vegetation (low NDVI of just the plants), which can both be indicators of poor functionality in a BMP.

By using a coded model, municipalities will only have to edit simple parameters to get their outputs after obtaining their data. This coded method makes the maintenance recommendations more accessible. By using drone and satellite imagery, we are also able to better understand what possibilities are available through different methods.

A. Satellite vs. Drone Imagery

Comparing satellite and drone imagery accuracy has not been a focus of past research; often researchers analyze one method at a time. However, a long-term objective of this project is to produce the most accurate, accessible, and usable model. Therefore, comparing the advantages and disadvantages of both methods is one of the most important objectives in producing research that will be helpful in analyzing GI and in applications beyond vegetation health.

1) Spatial Resolution: Spatial resolution is the physical area of a surface represented by each pixel in an image. As technology advances for satellite images, resolution quality gets higher. EarthCache, the service used to obtain satellite images for this project, can produce up to 30 cm per pixel resolution, which for satellite imagery, is very high. However, a lower resolution was used from EarthCache because higher resolution is much more expensive. Lower resolution means each pixel represents a larger area of the earths surface. The satellite images then have greater averages and combinations of radiation reflectance from multiple objects in the area. This makes it hard to see finer details like a single tree or plant. On the contrary, drones are able to get much higher spatial resolution given that they can take images from a drastically closer range than satellites orbiting the earth. Satellites still provide a wide range view of dozens of BMPs at a time, whereas drones can only capture at most a few at a time. This means that municipalities would be able to run a model on multiple BMPs at a time using satellites. Additionally, it would take considerably less time and resources to obtain the image.

2) Temporal Resolution: Temporal resolution refers to how often an image is able to be taken of a specific location. Drones, weather permitting, can be flown at any time, whereas satellites have to wait to orbit to the same location. Currently, satellites have a revisit period of about 2-16 days. It is unclear of whether it is more important for a municipality to have a more passive data collection system or to have the ability to collect data more often.

3) Spectral Resolution: Spectral resolution is determined by the ability of a sensor to distinguish between finer electromagnetic spectral bands and therefore more wavelengths. Hyper spectral imaging is a type of imagery that provides a continuous spectrum of wavelengths from a sensor. Because hyper-spectral imagery requires better sensors, it's more expensive. Instead, we used the cheaper multi-spectral imaging option that provides single bands of specific wavelength ranges. Through the drone and satellite images we were able to obtain Red, Green, Blue (RGB), Near Infrared (NIR), and Red Edge bands. These bands are used to create RGB images and NDVI indexes and are often used in analysing vegetation health. Figures 1 shows the spectral characteristics of healthy vs. stressed plants. NDVI is used because it essentially measures the amount of green light reflectance. Figure 2 shows how green, leafy plants are most healthy when they reflect a lot of green and near infrared light. Satellites may be able to obtain more information from various sensors than drones, but considering there are drone cameras that can collect the needed amount of bands, both methods are useful for spectral resolution needs.

Overall there are many advantages and disadvantages to using satellites or drones for monitoring of BMPs. Satellites

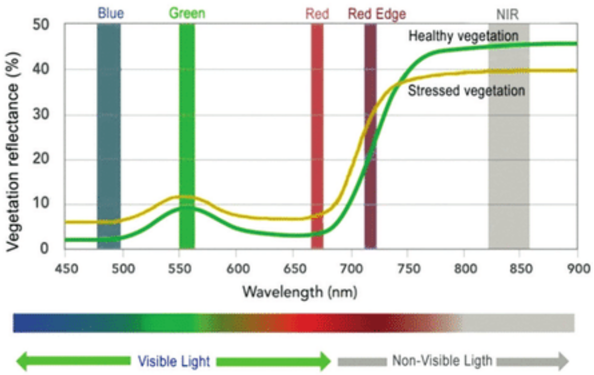

Figure 1. Percent vegetation reflectance on electromagnetic spectrum. [13]

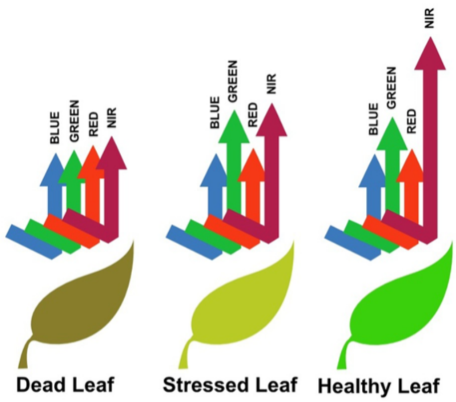

Figure 2. Types of reflectance for healthy, green, leafy plants. [14]

can passively provide consistent data on a large area whereas drones have limited coverage and require an operator. Drones can also provide more frequent and higher resolution imagery than satellites. Weather could also force satellite images to take longer than expected when drones are easy to deploy when weather clears. Because of these reasons drones and satellites can be used by municipalities in tandem. However, this cost-benefit analysis is irrelevant if future research suggest that one method is more precise and accurate than the other. This assessment is not the focus of this paper, but is a long-term goal for the research project and will be further analyzed in future papers.

IV. Methods

Much of the preliminary methodology and results were conducted and obtained by Matt Dupasquier. This section will discuss that preliminary work along with more recent work. Remote sensing methods alter the workflow for GI maintenance programs by reducing the need for site to site travel and manual observations. With these methods, the workflow would be reduced to obtaining the data from either online services or field collection, uploading the data, and then enabling the model to produce an automated maintenance recommendation.

A. Choosing BMP Sites

BMPs were chosen based on their vegetation content and lack of surrounding obstructions. Bioswales are the primary focus of this study, although some green roof were also analyzed. Bioswales work with a combination of natural and engineered systems. Figure 3 shows a cross section of a bioswale with native planting on top followed by soil and a series of rock and gravel with a perforated pipe as an underdrain outlet. Bioswales collect and filter rainwater with the plants uptaking pollutants to further increase water quality. Because of how large and complex these systems can be, bioswales were overall chosen over other types of green infrastructure because there are man problems that can decrease the functionality of the system. This means that there would be many different factors that could be possibly analysed for maintenance recommendations like weeds, overgrowth, and dead plants.

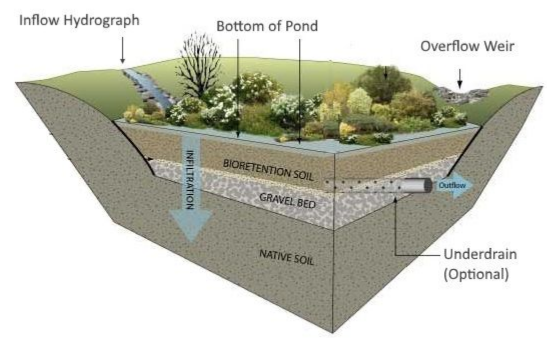

Figure 3. A cross section of a bioswale. [15]

B. Collecting Imagery

1) Satellite Imagery: The satellite data was taken using EarthCache satellites. An image is requested from EarthCache for a specific, defined area for a range of time. The imagery came in 0.22 m resolution and the bands that were captured were RGB and NIR. The satellite images can take some time to process, but then are able to be exported for use. These images were manipulated in ArcGis Pro to cut out only the areas where BMPs are. This would drastically reduce the size of the raster and therefore the computing time when classifying the image and running it through the model.

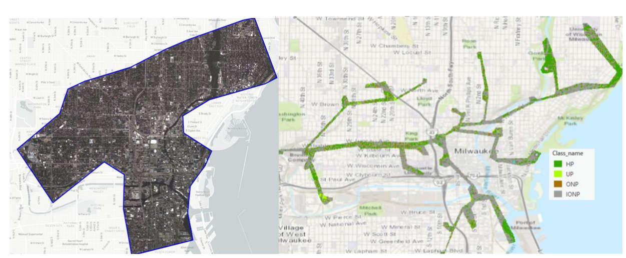

Figure 4. Left image shows the third round of satellite data and the right image shows the classified satellite image that was cut to fit the BMP area.

2) Drone Imagery: The drone was a DJI Matrice 100 drone (Figure 5) with an attached MicaSense RedEdge-M camera (Figure 6). The flight path, altitude, speed, and image settings can all be controlled in the DJI Go app that connects to the drone's controller. Through a ground sampling distance equation, the maximum altitude allowed for the used camera was calculated to be 4.2m cm per pixel. The drone was flown in mostly clear, non-cloudy weather. To prevent shadows from obstructing good view of the surface, all flights except for one, were taken near solar noon (between 10 AM and 2 PM). Shadows can affect the accuracy of data detected by a sensor, disrupting classifications, and giving false outputs from models.

Figure 5. Image of DJI Matrice 100 Drone. [16]

Figure 6. Image of MicaSense RedEdge-M camera used on the drone. [17]

To confirm the accuracy of drone NDVI imagery outputs, in-situ point were taken after each drone flight. The in-situ data was taken using a GPS and the FieldScout CM 1000 NDVI Meter. The GPS ensured that when NDVI value points were uploaded to the ArcGIS project map, they would appear at the exact locations where the NDVI was recorded in the field. A buffer analysis was done to compare the average NDVI of pixels where the in-situ data was taken to average of pixels on the drone NDVI raster output. Figure 7 displays the clear trend line between the drone and sample NDVI showing that the drone imagery was producing a relatively accurate NDVI raster. This positive correlation meant that drone imagery could be considered for the project.

C. Classifying Data

Originally, five classes were chosen to represent the different possible areas within a BMP: healthy plant, unhealthy plant, dead plant, organic material (i.e., soil), and inorganic material (i.e., trash, rocks, or cement). These classes can help identify and represent various BMP indicators. A smaller number of distinct classes allows for a smaller number of samples of training data needed. Figure 8 shows an example of classifying data.

Two methods were used to classify the data: classification wizard and classifier raster tool in arcgis pro. Training data is created by creating feature classes from manually drawn polygons that are identified as one of the five classes. For the classification wizard, inputs are training samples along with the composite RGB raster that overlaps with the training samples. A support vector machine algorithm is used as the machine learning classification method and the classification type is object or pixel based. This method outputs a new raster with the classifications applied. The other method is through the classify raster tool. To create the training data for this tool, polygons are again drawn manually. This time, the data under the polygons is extracted from the composite images and creates a classifier definition file. The classifier definition file is then applied to the input raster that is being classified. A raster is outputted with the classifications applied. This tool is better overall to match the end goal of the project because it applies training data to an unused raster.

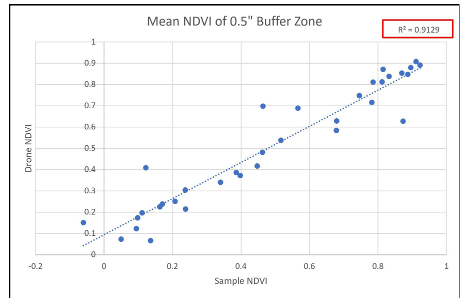

Figure 7. Line graph of NDVI accuracy buffer check.

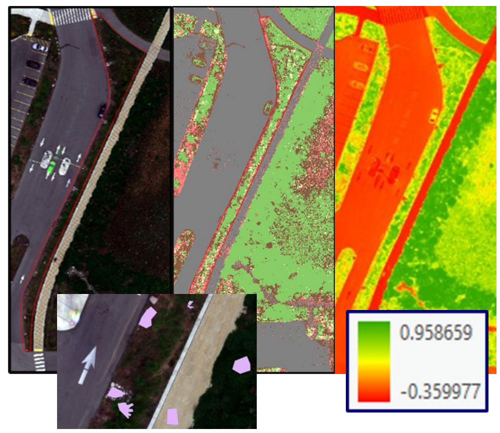

Figure 8. Left image shows an example of a BMP area. The lower left image shows an example of training data polygons. The middle image shows an example of a classified BMP area. The right images show an example of the NDVI of a BMP area and its scale.

For the classification wizard there is an option to further specify pixel or objected based classification. Pixel based classification assigns each pixel to a certain class based on its spectral characteristics and no neighboring pixel's characteristics. Object based classification segments pixels into groups based on similar spectral characteristics. The segments are further grouped into something that appears similar to real world objects based on color and shape. Pixel-based classification is simple and therefore widely used in much remote sensing software because each pixel has its own class. However, object-based classification may be more useful with vegetation analysis because it operates based on group assignments. For example, when vegetation, soil, rocks, or other materials overlap, object-based classification contextualizes neighboring pixels to determine a better classification rather than categorizing each pixel in an isolated environment. However, object-based classifications are complex in their segmentation and mistakes could lead to a wide area of pixels being incorrectly categorized. To determine which method is better, we will be comparing the results from the field with each classification type for each model produced. This could display sufficient comparisons on which type is better for this application (this comparison is not the topic of this paper).

D. Building a Model

The model was created using python through the Spyder IDLE. The code consists of a function called Model with various parameter to define inputs and outputs for the model and some lines that hold the directories for the outputs. Inputs consists of the NDVI raster from either the drone or satellite image, the classified raster outputted from the classification process, and the BMP polygon folder that holds all of the GI sites being analyzed. An output parameter is an output geodatabase that holds the overall maintenance determination table with all BMPs listed and a table for each BMP with different calculations listed. The second output parameter is a scratch geodatabase called "intermediate geodatabase" that holds all of the temporary data that is used to make calculations, but does not need to be presented in the final output. To connect the python model to ArcGIS Pro, a python package called ArcPy is used. ArcPy streamlines model building and geoprocessing tools that can be done in ArcGIS through its collection of modules that mimic those tools as functions within python. Without ArcPy, the model would not be a viable accessible option for mass distribution because all of the modelling would have had to be done in ArcGIS itself.

V. Results and Discussion

A. Model 1.0

The first model focused on understanding the quantity and quality of information that could be extracted from various imagery. It used five classes to classify imagery and it used the first and second round of satellite data requested from EarthCache. Through the arcpy library, different geoprocessing tools were used to create functions and perform various calculations. Some of these calculations included the area of the BMP, percentage of dead plants, average NDVI of the swale, and average NDVI of just the plants. To create the recommendations, conditional statements using standard thresholds were applied to the calculated average NDVIs and percentage of dead plants. These thresholds for average NDVI and percentage of dead plants have been researched and calculated in the past to determine the correct averages needed for a healthy BMP. If the the average NDVI or percentage of dead plants was found to be below the acceptable threshold, the model would populate a 'Y' for *yes maintenance is needed*. Model 1.0 produced clear classifications and an overall maintenance recommendation table successfully. A significant finding was that dead plants have spectral characteristics very close to organic non-plant material like soil, which is understandable since dead plants are decomposing into soil. Because of this observation, Model 2.0 will have four classes (see Figure 9) instead of five by merging dead plants into the organic non-plant material class.

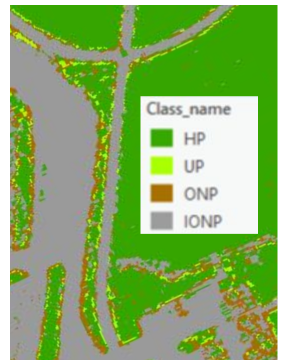

Figure 9. This image shows the new four class model. It is visibly more simple than the five class classification.

B. Model 2.0

The second model's main focus is on producing the most accurate and useful maintenance recommendation table. To produce a more accurate recommendation, four classes will be used instead of five considering the findings of the dead plant class. Additionally, with those four classes, object and pixel based classification methods will be tested. Lastly, more research will go into defining the best thresholds that should be used to identify failures in GI functionality.

Increasing the usefulness of the recommendation table means identifying what outputs for the table are most useful to municipalities. Furthermore, identifying if sparsity, average NDVI, or percentage of stressed plants should be seen as more important for triggering a maintenance recommendation. As of now, Model 2.0 will be a ranked list model, outputting the most unhealthy BMPs at the top of the table. Ranking the BMPs will enable municipality to further target resources to the BMPs that need attention the most. In addition to ranking, an extent statement was added to Model 2.0 to ensure that BMPs outside of the input raster are not included in calculations.

I was able to test two different models: a simple vegetation ranking model and a more complex NDVI ranking model. The vegetation ranking model ranked BMPs based on their vegetation rank, a new field created. The number of 'Y' for each health indicator field (sparsity and plant stress) were counted for each BMP. This number was then populated into the new vegetation indicator rank field with the highest rank being 2 and the lowest rank being 0. A BMP with rank 2 has been flagged for both vegetation health indicator fields and a

BMP with rank 0 appears healthy to the model. A sort function was then used to create a new re-ordered output table with the BMPs ranking 2 at the top. This model provided a simple and easy way for inspectors to see the top unhealthy BMPs, how unhealthy they are, and why they were flagged. The second and final model created was more complex. The NDVI ranking model ranked BMPs by their average swale NDVI and then their average plant NDVI. The swale NDVI was chosen as the more important sorting determinant because a low swale NDVI could mean sparsity. Sparsity could be an indicator that there are not enough plantings or that many plants have died off. The vegetation indicator rank was still calculated and populated into the table as additional information, but not as the overall table ranking determination. This model was also successful in outputting a ranked maintenance recommendation table (see Figure 10). The NDVI ranking model was chosen over the vegetation ranking because it included the most useful information. It showed both the amount of vegetation health indicators a BMP failed and the amount of overall green vegetation.

OBJECTID *	Polygon_Name	Sparsity	Stressed_Plants	Avg_NDVI_Swale	Avg_NDVI_Plants	Veg_Indicator_Ran
1	BMP82	Y	Y	0.409146556547413	0.484166783006321	
2	BMP122	Y	Y	0.418677375533545	0.452657745579794	
3	BMP9	Y	Y	0.436923598649565	0.451790558020664	
49	BMP79	N	Y	0.543798038815542	0.545143845640774	
50	BMP17	N	N	0.546402719758218	0.556134876072301	
51	BMP57	N	Y	0.548614510597418	0.53017289322293	
90	BMP75	N	N	0.70716200849654	0.70716200849654	
91	BMP124	N	N	0.715542777038224	0.736280314339782	
92	BMP87	N	N	0.765164292496048	0.76523719317671	

Figure 10. This is a cropped image of the model output table.

C. Model Accuracy

Although the model was able to output a populated maintenance table, the results of the model had to be confirmed. To do this, field inspections were conducted. Inspection standards vary between states. So, state inspection sheets available online were analysed to identify trends in inspection standards. Those standards were then compiled on an excel sheet to create a comprehensive inspection sheet to be used to confirm the results of the model. The inspection sheet, shown in Figure 11, included both vegetation health indicators like amount of dead plants or plant coverage and non-vegetation based functionality indicators like evidence of drainage blockage or erosion.

OVERALL NOTES FOR SITE

Location Description: WAR MEMORIAL BMP Identifier: 5 BMP Type: (Bioswale/ Green Roof/ Rain Garden/ Native Plant Area/ Other)

Vegetation Condition

Inspection Item	Satisfied	Unsatisfied	Other Notes
Plant Coverage = > 50% (Closer to 100% coverage for swales)	X		
Dead plants, brush, and leaves removed (No buildup)	X		
Existing plants are healthy	X		
Existing plants are alive (>75% survival rate)	X		
Minimal Weeds and Invasives Present		X	LARGE TREE WEEDS
Sum of S/U:			

Other Items

Inspection Item	Satisfied	Unsatisfied	Other Notes
No evidence of blockage of inlets or outlets(Leaves or sediment)		X	SEDIMENTATION
Overflow inlet functioning/ No water ponding	X		
No evidence of errosion/ channelization		X	CHANNELIZATION
No garbage buildup	X		
No evidence of expansive bare spots	X		
Sum of S/U:			

OVERALL NOTES FOR SITE GOOD FLOWERING

Figure 11. This figure shows an example of a filled out inspection sheet.

After obtaining a third round of satellite data, the average NDVI ranking model was run. All of the BMPs that were included in this model's table were mapped out. The BMPs that were closer to the research lab were more likely to be selected for a field inspection, however, a wide radius of BMPs were inspected. At each site, an inspection table was filled out in detail by one person and checked by another person. Inspection was all conducted visually. Some BMPs were not accessible due to private ownership and had to be skipped.

To compare the results of the field inspection and the model, a color-coded map was created as shown in Figure 12. A BMP was labelled as green if both indicators matched results in the model and inspection. For example, if the model flagged a BMP for both sparsity and stressed plants and the field inspection showed that the BMP was in fact sparse and stressed, then the BMP is marked as green. Another example is if the model flagged a BMP for only sparsity, but field inspection shows that the BMP was sparse and stressed then the BMP is marked yellow. Red means that the model flagged the BMP completely incorrectly. Only the vegetation related inspection fields were considered for this. The plant coverage, buildup, and survival rate fields in the inspection sheet were compared with the sparsity field of the model and the existing plants are healthy field was compared with the stressed plant field of the model. Out of 27 sites inspected, 3 sites were red, 8 yellow, and 16 green. This shows that the model flagged BMPs completely correctly about 60 percent of the time. For the BMPs that were flagged incorrectly, there were some observations as to why. One crucial observation was that two of the red BMPs were green roofs with succulent plants. These succulents were both small and appearing more reddish/purple than green. This showed that if a BMP does not contain bigger, green, leafy plants, it is more likely to be flagged by the model because the plant type does not work well with NDVI's green reflectance measures. This means that another model may need to be considered for different plant types or different types of BMPs.

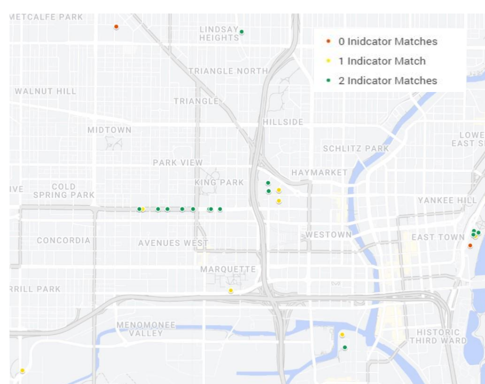

Figure 12. This map shows the results of the field inspection compared with those of the model.

Unrelated to the vegetation field comparisons, there was another discovery of a possible issue with the model. Some BMPs were completely healthy with vegetation. However, they may have shown signs of decreased functionality or lack of maintenance from the non-vegetation field inspections. These included drainage blockage, channelization, erosion, sedimentation, ponding or garbage build-up. These issues could cause a decrease in vegetation health in the future as well as further decreased BMP functionality. Recognizing these non-vegetation issues could be a possible area of research for future work.

Figure 13. Upper left image shows ponding, which could indicate outlet blockage or low infiltration rate. The upper right image shows erosion, which can deteriorate plant life and cause sediment build up. The lower left image shows blockage of outlet drain due to brush. This could cause flooding if water inflow is too fast. The lower right image shows abandoned construction materials knocking over plants and causing trash buildup.

VI. Conclusion

Maintenance needs are crucial to the success of sustainable green infrastructure and best management practices. With technological aids, the burden of increased maintenance could be drastically decreased. Paired with machine learning, drones and satellite's could use remote sensing methods with different cameras and sensors to act as a technological aid. By testing different programmed python models, it was found that this method would in fact work to monitor vegetation health. There is still further research that can be done to extract even more information from remote sensing technology to create more efficient models. Overall, more research is needed to expand the use of machine learning and remote sensing in green infrastructure, although, it has proven useful.

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