Cyber–Physical–Social Model of Community Resilience by Considering Critical Infrastructure Interdependencies

Jaber Valinejad, *Member, IEEE*, and Lamine Mili, *Life Fellow, IEEE*

***Abstract*—Each year, several disasters occur, resulting in enormous human, infrastructural, and economic losses. To minimize losses and ensure an adequate emergency response, it is vital to prepare the community for greater shock absorption and recovery after an occurrence. This raises the concept of community resilience and also demands appropriate metrics and prediction models for improved preparedness and adaptability. While a community is impacted in three main ways during a disaster, namely social, physical, and cyber there are currently no tools to model their interrelationship. Thus, this article presents a multiagent cyber–physical–social model of community resilience, taking into account the interconnection of power systems, emergency services, social communities, and cyberspace. To validate the model, we used data on two hurricanes (Irma and Harvey) collected from Twitter, GoogleTrends, FEMA, power utilities, CNN, and Snopes (a fact-checking organization). We also describe methods for quantifying social metrics, such as the level of anxiety, risk perception, and cooperation using social sensing, natural language processing, and text mining tools. We examine the suggested paradigm through three different case studies: 1) hurricanes Irma and Harvey; 2) a group of nine agents; and 3) a society comprised of six distinct communities. According to the results, cooperation can positively change individual behavior. Relationships within a community are so crucial that a smaller population with greater empathy may be more resilient. Similar dynamic changes in social characteristics occur when two empathetic communities share resources after a disaster.**

***Index Terms*—Community resilience, critical infrastructures, cyber–physical–social system, fake news, natural language processing, power systems, social media, urban computing.**

I. Introduction

SEVERAL calamities occur throughout the world each year, resulting in varying losses. Disasters wreak havoc on infrastructures and impair operation [1], [2]. They result in death and affect people's mental and physical health. Additionally, fake news spread throughout the disaster can lead to a community taking harmful actions based on incorrect information. These physical, social, and cyber impacts of a disaster can result in significant economic losses, as demonstrated by the $ 423 billion loss in 2011 in Tohoku, Japan, and the $ 133 billion loss in hurricane Harvey, U.S.A. To mitigate losses, we must strengthen communities' readiness, flexibility, and resilience. Before strengthening community resilience, we need to have appropriate techniques for forecasting a community's capacity and functionality in the face of impending crises. Before enhancing and predicting resilience, we should establish suitable community resilience metrics and identify how to quantify the proposed metrics.

Numerous measures and frameworks have been presented to quantify and predict community resilience. Generally, we can categorize these frameworks as index-based or output-oriented. While output-oriented methods quantify a community's degraded functionality over time following a crisis, capacity-based assessments conduct a static examination of community resilience. Early works on community resilience, such as BRIC [3], RAPT [4], [5], and CDRI [6] are capacity-based in nature. COPEWELL [7], and Zobel'model [8] recently proposed output-oriented assessment methods. Bruneau et al. [9] presented a comprehensive framework for assessing and enhancing the seismic resilience of communities, emphasizing the importance of a holistic approach that considers social, economic, and institutional factors in addition to traditional engineering-based approaches. Rinaldi et al. [10], [11] discussed the importance of critical infrastructure interdependencies and their impact on the functioning of essential services. They define critical infrastructure and interdependencies and highlight their importance in modern society. They also describe the different types of interdependencies that exist among critical infrastructure systems, including physical, cyber, and logical interdependencies. While these works are excellent starts, they do not: 1) look at the interconnection of a community's cyber, physical, and social components in their model; 2) account for the dynamic changes in resilience-related characteristics that occur during a disaster; 3) account for the flexibility, cooperation, learning, fake news, and availability (functionality) of critical infrastructures, such as emergency services and power systems; 4) account for the role of individuals and their connections in community resilience; 5) address the effect of a disaster severity's dynamic change on behavioral change and community resilience while developing their model; 6) look at the network-based feature of community resilience; and 7) provide exhaustive metrics.

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Jaber Valinejad is with the Data and System Science Lab, Harvard University, Cambridge, MA 02138 USA (e-mail: JValinejad@mgh.harvard.edu).

Lamine Mili is with the Bradley Department of Electrical and Computer Engineering, Virginia Tech, Northern Virginia Center, Falls Church, VA 22043 USA (e-mail: lmili@vt.edu).

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Fig. 1. Physical, cyber, and social layers of a community resilience.

As a result, we present an output-oriented cyber–physical–social model of community resilience in this work. We develop the proposed model using a multiagent framework based on social science and psychological theories. Fig. 1 illustrates the physical, cyber, and social layers of community resilience and their interdependence. When a cyber, physical, or social characteristic is changed, it may affect the other features, either positively or negatively. For instance, electricity outages can exacerbate people's worries during a disaster. Additionally, negative news can heighten this worry. Although fear is regarded as a negative characteristic of society, it is necessary to increase a community's risk perception during a disaster to take appropriate action. Overall, this work makes the following contributions.

1) We propose the multiagent cyber–physical–social model of community resilience. The physical component of disasters consists of two major vital infrastructures: power systems and emergency services. With cyber, we examine the impact of released news, information, and fake news during a disaster on community resilience. We discuss the social characteristics of a community in the social section. Additionally, in this work, we also model the interdependence between these different components.
2) The following measures are proposed: a) cyber: news positivity and amount of fake news; b) social: fear, physical health, risk perception, information-seeking behavior, cooperation, adaptability, and learning; and c) physical: utility-provided electricity, distributed energy resources (DERs) and microgrids (MGs) electricity, and emergency services availability (functionality).
3) We present a method for quantifying each indicator of the cyber, physical, and social components by using natural language processing, text mining, data analytics, and social sensing. Specifically, we suggest quantifying a community's social behaviors through linguistic inquiry and word count (LIWC).
4) We validate the model using data sets from hurricanes Irma and Harvey. We collected data from FEMA, Snopes (a fact-checking organization), CNN, and power utilities, as well as Twitter and GoogleTrends, as two social sensing tools. We gathered the following information for each hurricane: a) hurricane Harvey: 279 news, 24 fake news stories (as recognized by Snopes), and 212 000 tweet IDs between 25 August 2017 and 9 November 2017 and b) hurricane Irma: 652 news, 16 fake news stories (as discovered by Snopes), and 275 000 tweet IDs between 1 September 2017 and 13 September 2017.

In this article, we use an output-oriented and index-based method to measure community resilience. In the output-oriented methods yielding accurate information about the trend and dynamic change of functionality, we can use community functionality to assess resilience. We define community resilience as our community's ability to absorb the shock and hardship caused by a specific type of disaster, bounce back to its original community functionality, and recover from it. Community functionality refers to a community's ability to provide necessary services to its residents. In the index-based method, we consider various dimensions of community resilience. Each dimension may consist of various metrics that are time independent. In case, we measure functionality, its capacity shows the time-weighted overall functionality.

In this article, we consider the energy infrastructures and emergency services as two physical infrastructures. For example, transportation disruption during disasters, e.g., flooded/damaged roads, traffic systems, etc., is a critical component of physical resilience that affects social and cyber resilience. While we have 16 critical infrastructures in the U.S. [12], for comprehensive study, we should consider the interdependence of all of them together and with social and cyber spaces. Note that in the context of different countries, it is important to acknowledge that other listings of Critical Infrastructure may exist, which would require careful consideration when transferring the approach utilized in this study to these contexts.

A. Related Works

Given the continuing occurrence of unanticipated events around the world, cities are undergoing rapid transformations. Cities must be resilient to maintain their fundamental functions; they must be able to return to their original state following extreme events. Due to the interdependence of their constituent infrastructure systems, the behavior of cities is unfortunately complicated. Therefore, modeling the risk and resilience of critical infrastructure necessitates the incorporation of their interdependencies and dependencies. Here, we offer a general review of community resilience, covering the cyber, physical, and social dimensions both individually and in combination. It should be noted that the scope of related literature in this field is broader than what is presented here. The search term for each of the related sections is based on their respective titles.

1) *Physical Systems Resilience:* Haggag et al. [13] provided a critical review of research on the resilience of the critical infrastructure systems of cities. Sharma et al. [14] modeled the post-disaster recovery of the power infrastructure while taking into account the dependence on the transportation infrastructure. Eldosouky et al. [15] discussed the resilience of critical infrastructures, such as dams and power grids.
2) *Cyber Systems Resilience:* kott and Linkov [16] provided an overview of the concepts, principles, and practices of

cyber resilience in the context of systems and networks. Jakubowicz et al. [17] explored the harmful effects of online racism and discrimination while also highlighting the potential for technology to promote social justice and community resilience. Hausken [18] discussed the importance of cyber resilience for organizations and society as a whole, and proposes a framework for building and assessing cyber resilience.

3) *Social Systems Resilience:* Davidson [19] examined both the promises and challenges of using resilience as a framework for understanding and addressing complex social problems. Fath et al. [20] outlined a set of strategies for navigating the different phases of the adaptive cycle and enhancing the resilience of social systems in the face of changing conditions and challenges. Lyon and Parkins [21] examined the role of social systems, cultural systems, and collective action in fostering resilience in communities undergoing transitions.
4) *Physical–Social Systems Resilience:* Marasco et al. [22] assessed seismic resilience and vulnerability of critical infrastructures at the urban level, such as the built environment, power grid, and socio-technical network, taking into account their interdependence. Sony and Naik [23] suggested a design mechanism for three types of integration mechanisms in Industry 4.0, namely, vertical, horizontal, and end-to-end integration, by considering the socio-technical systems' impact on people, infrastructure, technology, processes, culture, and objectives.
5) *Cyber–Physical Systems Resilience:* DiMase et al. [24] presented a framework for designing, developing, and evaluating cyber–physical systems with a focus on security and resilience. Scalco and Palmer [25] provided a discussion on novel technologies and cyber innovations applied to physical control system infrastructures, such as power, water, wastewater, and dams, not only for short-term profits but also in the interest of the greater good of society.
6) *Cyber–Social Systems Resilience:* Doostmohammadian et al. [26] proposed a framework for modeling and analyzing cyber–social systems, which are systems that integrate cyber and social components. The framework includes methods for inference and optimal design, and it can be applied to various domains, such as smart cities, social networks, and online marketplaces. Valinejad et al. [27] proposed a framework for measuring cyber–social community resilience during the COVID-19 pandemic.
7) *Cyber–Physical–Social Systems Resilience:* Khan et al. [28] discussed smart cities in detail, including its key technologies, challenges, and future development through the use of cyber–physical and social systems. Zhou et al. [29] treated the smart city as a cyber–physical–social System by analyzing the characteristics of information diffusion, its application to the smart city field, and the critical technologies of information diffusion modeling and analysis. Patriarca et al. [30] investigated knowledge creation and knowledge conversion within cyber-socio-technical systems. Lombardo et al. [31] provided a survey on the adoption of social media in socio-technical systems.

II. Cyber–Physical–Social Model of Community Resilience

We develop a multiagent-based dynamic model to capture the dynamic change in community behaviors in response to a disaster. This cyber–physical–social paradigm is advantageous for capturing emerging processes and studying the multifaceted characteristics of output-oriented community resilience. Before describing the suggested model, we will explain the threshold model with a logistic function frequently used in sociology, medicine, biology, ecology, and neural networks to consider the cyber–physical–social effect [32], [33].

A. Threshold Model Using Logistic Function

The logistic function-based threshold model enables us to define thresholds for behavior change [34], [35]. For example, if the power outages surpass a certain threshold $\phi(X)$, consumer panic can ensue during a crisis. Each factor's logistic value $\psi(X)$, on the resilience-related characteristic X, is given as follows:

$$\psi(X) = \frac{1}{1 + e^{-\sigma^X (X_{ti} - \phi^X)}}. \tag{1}$$

Additionally, we define $\psi'(X) = 1 - \psi(X)$.

B. Multiagent Cyber–Physical–Social Model

Equations (2)–(12) describe the dynamic changes in resilience-related behaviors. Note that all variables and functions defined take values between 0 and 1. There are two kinds of features: 1) diffusional and 2) nondiffusional [36], [37]. It is worth noting that C, P, and S represent the cyber, physical, and social characteristics, respectively. For instance, S^E_{ti} denotes the intensity of fear as a social feature (S) experienced by agent i at time t.

1) Diffusion-Based Features: Social diffusion-based features, i.e., θ_{ti} consist of fear (S^E_{ti}), information-seeking behavior (S^I_{ti}), and flexibility (S^F_{ti}). The level of each feature can be affected by another agent if they are connected. Hence, we should consider panic diffusion, information mirroring, and flexibility contagion in the related equations. According to $\theta_{ti} = \{S^E_{ti}, S^I_{ti}, S^F_{ti}\}$, the dynamic change of θ_{ti} is determined by the following:

$$\Delta(\theta_{ti}) = \alpha'^{\theta}_{ti}\left(f\left(\hat{\theta}_{ti}, \theta_{ti}\right) - \theta_{ti}\right)\Delta t, \alpha'^{\theta}_{ti} = \frac{\sum_j \alpha^{\theta}_{ij}\theta_{tj}}{\sum_j \alpha^{\theta}_{ij}}. \tag{2}$$

$$\begin{aligned} f\left(\hat{\theta}_{ti}, \theta_{ti}\right) = \ & \eta^{\theta}\Big[S^R_{ti}\Big(1 - (1 - \theta_{ti})\Big(1 - \hat{\theta}_{ti}\Big)\Big) \\ & + \ \big(1 - S^R_{ti}\big)\hat{\theta}_{ti}\theta_{ti}\Big] + \big(1 - \eta^{\theta}\big)\hat{\theta}_{ti}. \end{aligned} \tag{3}$$

Equation (2) yield the incremental change, $\Delta(\theta_{ti})$. We regard the peace of dynamic change to be equivalent to the social diffusion of related characteristics, i.e., α'^{θ}_{ti}. Additionally, α^{θ}_{ij} is proportional to the intensity of the connection between agents i and j. Equation (3) illustrates the amplification and absorption effects of the event [38] on the feature, where S_{ti}^R denotes the level of risk perception. Based on Fredrickson's broaden-and-build theory, the amplification effect (the term with the coefficient of η^θ) is made up of two parts: 1) upward spirals (the term with the parameter of S_{ti}^R) and 2) downward spirals (the term with the parameter of $(1-S_{ti}^R)$) [39]. According to the Fredrickson theory, positive emotion can offer resources and expand the mind's capacity, a process referred to as spirals upward. On the other side, negative emotions can narrow the mind's ability resources, a phenomenon known as downward spiral. On the other hand, the absorption effect (the phrase with the coefficient of $(1-\eta^\theta)$) is related to the level of collective behavior, which is based on Barsade theory' bottom–up approach [40]. Note that $\hat{\theta}ti$=$\{\hat{S}_{ti}^E, \hat{S}_{ti}^I, \hat{S}_{ti}^F\}$. The level of $\hat{\theta}ti$ for each of the diffusion-based features is derived using the following:

$$\hat{S}_{ti}^E = \iota^{\theta_1}\left(\frac{\sum_j \alpha_{ij}^E S_{tj}^E}{\sum_j \alpha_{ij}^E}\right) + \iota^1\psi'\left(S_{ti}^C\right) + \iota^2\psi'\left(S_{ti}^P\right) + \iota^3\psi'\left(P_{ti}^E\right) + \iota^4\psi\left(P_{ti}^S\right) + \iota^4\psi'\left(S_{ti}^F\right) + \iota^5\psi'\left(S_{ti}^L\right) + \iota^6\psi'\left(C_t^+\right). \quad (4)$$

$$\hat{S}_{ti}^I = \iota^{\theta_2}\left(\frac{\sum_j \alpha_{ij}^I S_{tj}^I}{\sum_j \alpha_{ij}^I}\right) + \iota^7\psi'\left(S_{ti}^L\right) + \iota^8\psi\left(S_{ti}^R\right) \quad (5)$$

$$\hat{S}_{ti}^F = \iota^{\theta_3}\left(\frac{\sum_j \alpha_{ij}^F S_{tj}^F}{\sum_j \alpha_{ij}^F}\right) + \iota^9\psi'\left(S_{ti}^C\right) + \iota^{10}\psi'\left(S_{ti}^E\right) \quad (6)$$

where $\hat{\theta}_{ti}$ is composed of two components: 1) social diffusion (the term with parameters $\iota^{\theta_{1,2,3}}$) and 2) the impact of external factors, i.e., influential features of Agent i. The external factors of fear, S_{ti}^E, as defined in (4), consists of cooperation S_{ti}^C, [41], physical health S_{ti}^P, [42], and accessibility to electricity P_{ti}^E [43], the severity of a disaster P_{ti}^S, flexibility S_{ti}^F [44], learning S_{ti}^L [44], and news positiveness C_t^+ [45]. Additionally, the information-seeking behavior S_{ti}^I as defined in (5) is influenced by external factors, i.e., learning S_{ti}^L [46], [47], and risk perception S_{ti}^R [45]. Furthermore, the external factors of flexibility S_{ti}^F, as defined in (6) consists of cooperation S_{ti}^C [48], and fear S_{ti}^E [49]. Note that $\iota^{1,\ldots,10}$ are parameters.

2) Nondiffusional Features: Equations (7)–(10) provide the dynamic change of physical health, risk perception, cooperation, and learning, respectively

$$\Delta\left(S_{ti}^P\right) = \eta^P\psi'\left(S_{ti}^E\right)\left[\frac{\iota^{11}\psi\left(P_{ti}^M\right)+\iota^{12}\psi\left(P_{ti}^E\right)+\iota^{13}\psi'\left(P_{ti}^S\right)}{3} - S_{ti}^P\right]\Delta t. \quad (7)$$

$$\Delta S_{ti}^R = \eta^R\psi\left(S_{ti}^E\right)\psi'\left(S_{ti}^C\right)\psi'\left(S_{ti}^I\right)\left[\frac{\iota^{14}\psi'\left(P_{ti}^E\right)+\iota^{15}\psi'\left(P_{ti}^M\right)+\iota^{16}\psi\left(P_{ti}^S\right)+\iota^{17}\psi\left(S_{ti}^E\right)+\iota^{18}\psi'\left(C_t^+\right)}{5} - S_{ti}^R\right]\Delta t. \quad (8)$$

$$\Delta\left(S_{ti}^C\right) = \eta^C\psi\left(S_{ti}^E\right)\psi\left(S_{ti}^F\right)\left[\frac{\iota^{19}\psi'\left(P_{ti}^E\right)+\iota^{20}\psi\left(P_{ti}^S\right)+\iota^{21}\psi\left(S_{ti}^E\right)+\iota^{22}\psi\left(S_{ti}^I\right)}{4} - S_{ti}^C\right]\Delta t. \quad (9)$$

$$\Delta S_{ti}^L = \eta^L\psi\left(S_{ti}^F\right)\left[\frac{\iota^{23}\psi\left(S_{ti}^C\right)+\iota^{24}\psi\left(S_{ti}^I\right)+\iota^{25}\psi'\left(C_t^F\right)}{3} - S_{ti}^L\right]\Delta t. \quad (10)$$

The dynamical changes in physical health $\Delta(S_{ti}^P)$, as defined by (7) is affected by the level of panic [42], the availability of emergency services P_{ti}^M, the access level to electricity P_{ti}^E [50], and the severity of a disaster X_{ti}^S. The dynamic changes in risk perception, $\Delta(S_{ti}^R)$, as defined by (8) are influenced by the level of panic [45], [51], cooperation, [52], information-seeking behavior, [53], the availability of emergency services, the access level to electricity, the severity of a disaster, and news positivity. The dynamical changes in cooperation $\Delta(S_{ti}^C)$, as defined by (9) are affected by the level of panic [41], flexibility [48], information-seeking behavior [54], the severity of a disaster, and the access level to electricity. The dynamical changes in learning $\Delta(S_{ti}^L)$ as defined by (10) are affected by the level of flexibility [55], cooperation [56], information-seeking behavior [57], and the amount of fake news C_{ti}^F [58]. Note that $\Xi = \{\eta^P, \eta^R, \eta^C, \eta^L\}$ denotes the coefficient of related features. In addition, the relationship between the level of experience S_{ti}^X and the level of learning is given by $S_{ti}^L = (\Delta S_{ti}^X/\Delta t)$. The dynamic change of electricity provided by DERs, and MGs, $\Delta(P_{ti}^D)$, as well as the total accessibility to electricity P_{ti}^E are obtained by

$$\Delta\left(P_{ti}^D\right) = \alpha_{ti}^D\left(\alpha_{ti}^D - P_{ti}^D\right)\Delta t, \alpha_{ti}^D = \frac{\sum_j \alpha_{ij}^D S_{tj}^C P_{tj}^D}{\sum_j \alpha_{ij}^D S_{tj}^C}. \quad (11)$$

$$P_{ti}^E = \varpi P_{ti}^D + (1-\varpi)\psi\left(P_{ti}^S\right)P_{ti}^U. \quad (12)$$

Electricity demand can be met primarily by DERs and MGs, P_{ti}^D, as well as by power utilities, P_{ti}^U. Depending on the intensity of a disaster, the utility's functionality may be compromised. End users who own DERs, known as prosumers, may desire to share their power with consumers and critical loads that are not linked to the grid but are connected to them in this situation, α_{ij}^D, depending on their level of cooperation, S_{tj}^C. In (12), ϖ denotes the fraction of end users total electricity consumption that DERs supply.

III. Metrics of Community Resilience and Their Measurements

This section addresses the cyber–physical–social metrics that characterize community resilience and how they can be quantified using real-world data on hurricanes Harvey and Irma.

A. Psychologically Based Text Mining Analysis

Modern text analysis has roots in early psychology [59]. Daily words reflect who we are and our social relationships. Language is the most common and reliable way to communicate internal thoughts and emotions. Psychology and communication rely on words and language. They help cognitive, personality, clinical, and social psychologists understand humans. High-speed computers, the Internet, and new statistical strategies have ushered in a new era of language psychology. As an example, content word categories show where people are focusing. Personal pronouns reflect attentional allocation. Painful people tend to focus on themselves and use more first-person singular pronouns [60]. Various dictionary-based sentiment analysis tools have already been

TABLE I
DEFINITION OF THE RESILIENCE METRICS AND THE MEANING OF THEIR NUMERICAL VALUES. THE SOCIAL FEATURES FOR COMMUNITY FEATURES ARE ASSUMED TO FOLLOW A GAUSSIAN DISTRIBUTION WITH A MEAN OVER THE INTERVAL [0 1]

Tweets	Cleaned tweets	Social	Joy	Family	Fear	Politeness	Respect	Trust	Failure	Wellbeing	Economy	Certainty
We are providing live updates on Hurricane Harvey as it surges toward the Texas Coast. https://t.co/VvJXqvTxsj	provid live updat hurrican harvey surg toward texa coast	0	0	0	0	0.267	0	0	0	0	0	0
White House warns Hurricane Harvey is a ”serious” and ”dangerous” storm. President Trump was briefed by his team on storm.	white hous warn hurrican harvey seriou danger storm presid trump brief team storm	0.16	0	0	0	0.28	0	0	0	0	0.36	0.038
i literally just had to evacuate my town cause of hurricane harvey @99_goonsquad :/	liter evacu town caus hurrican harvey 99goonsquad	0.051	0	0.186	0	0.058	0	0	0	0	0	0
APOD: Hurricane Harvey, Seen From the Cupola of the International Space Station via NASA https://t.co/8SrRaaBkoi https://t.co/A2tsljswlP	apod hurrican harvey seen cupola intern space station via nasa	0	1.773	0.654	0.905	0.235	0.136	0.42	0.12	0	0.68	0.094
RT @axios: Hurricane Harvey could cause gas prices to surge due to the oil and natural gas infrastructure in the region. https://t.co/Ts3FCâ€¦	hurrican harvey could caus ga price surg due oil natur ga infrastructur region	0.176	0	0.26	0	0	0.096	0.054	0	0.17	0.27	0

used to capture personality, and social behavior, such as leading lexicons provided by National Research Council Canada (NRC) [61], sentiment analysis and cognition engine (SEANCE) [62], [63], the LIWC framework [64], [65], WordNet [66], [67], [68], and expressions of opinions and emotions in the language (MPQA) [69], [70]. As examples of employing Psychologically based Text mining analysis of tweets, Table I displays some SÉANCE outputs, such as fear, respect, trust, well-being, economy, respect, and politeness.

In this study, LIWC, which counts words in psychologically significant categories, was utilized. LIWC can detect meaning in a variety of experimental contexts, such as attentional focus, emotion, social relationships, thinking styles, and individual differences. LIWC provides leisure, achievement, health, anxiety, anger, sadness, family, friends, money, religion, etc. LIWC has two main components: 1) processing and 2) dictionaries. The program itself processes text files—essays, poems, blogs, novels, etc.—word by word. LIWC's dictionaries are its core. A dictionary contains words that define a category. Each word in a text file is compared to the dictionary file to calculate the percentage of positive and negative emotion words. For all subjective categories, dictionaries, thesauruses, questionnaires, and research assistant lists were consulted. Three judges rated whether each word candidate fit the category. The final rating phase had 93% to 100% judge agreement. LIWC has been utilized frequently to assess social behavior in [71], [72], [73], [74], [75], [76], [77], [78], [79], and [80]. Utilizing LIWC to analyze social behavior based on tweets has also been utilized in numerous works [45], [81], [82], [83], [84], [85], [86].

B. Cyber Layer Metrics and Their Measurement

We consider the positivity of news and the spread of fake news as cyber layer indicators that affect community resilience. To gather news on the event, we relied on CNN. Additionally, several fact-checking organizations, such as Snopes, examine, and disseminate false information throughout various events. As a result, we used a Web scraper and manually verified news and fake news from CNN and Snopes. From 25 August 2017 to 9 November 2017, we gathered 279 news and 24 fake news about Hurricane Harvey. Additionally, from 1 September 2017 to 13 September 2017, we gathered 652 news and 16 fake news about Hurricane Irma.

1) *News Positiveness:* We scraped the headline and text of CNN news regarding hurricanes Irma and Harvey using the Google Chrome Extension "Web Scraper—Free Web-Scraping." Then, we used LIWC to assess the news's positivity over time.
2) *Fake News:* Several fact-checking organizations, such as Snopes, Politifact, and Factcheck, conduct investigations into the news validity. Snopes provides a variety of news types, including real, mostly true, half true, mostly false, and false news. We classified all of the following categories as fake news: half true, mostly false, and false news.

Note that this study only considered fake news released by politicians, celebrities, and other prominent public figures when collecting data sets related to fake news. Based on analysis done by Brennen et al. [87], top–down misinformation from them accounted for only 20% of claims in their sample but 69% of total social media engagement.

C. Physical-Layer Metrics and Their Assessment

As Physical layer measures of community resilience, we evaluate the availability of power provided by DERs, MGs, and utilities, as well as the availability of emergency services. Specifically, for Hurricane Harvey and Hurricane Irma, we acquired data on emergency services and power systems from FEMA and power utilities. Emergency services indicators include response staff, meals, water, blankets, hygiene kits, rescue teams, and medical deployment teams. In the United States, numerous organizations, including the American Red Cross (ARC), the Corporation for National and Community Service (CNCS), the U.S. Department of Defense (DOD), the U.S. Army Corps of Engineers (USACE), the U.S. National Guard Bureau (NGB), the U.S. Department of Homeland Security (DHS), the U.S. Immigration and Customs Enforcement (ICE), and the U.S. Department of the Interior (DOI), collaborate to address a disaster. We quantified the availability of emergency services by analyzing open-access data given by FEMA. For Hurricane Harvey, we utilized HQ-17-59 to HQ-17-79 reports, and for Hurricane Irma, we used HQ-17-85 to HQ-17-120 reports.

D. Social Layer Metrics and Their Assessment

We explore and suggest the following social indicators for assessing community resilience: mental health, physical health, risk perception, information-seeking behavior, adaptability, cooperation, and learning. Measuring these characteristics during a disaster can be difficult. Psychologists and researchers in conventional social science typically use surveys to assess social behavior. However, surveys have several disadvantages, such as high cost, limited sample size, and the possibility of response bias. To overcome these obstacles, we can use various social sensing tools, such as Twitter, Facebook, and GoogleTrends, to quantify and assess social behaviors and responses. In contemporary social science, we can evaluate and analyze text, such as tweets, from a social and phycological perspective using the phycological meaning of the words and natural language processing [65]. For social sensing tools, we use Twitter and GoogleTrends. To ascertain the community's social behavior during a disaster, we collected two samples of tweets from hurricanes Irma and Harvey (275 000 and 212 000 IDs). Additionally, we used GoogleTrends to identify information-seeking behavior associated with these occurrences. We explore how each feature of social resilience can be quantified using the psychological meaning of the words and computerized text analysis as follows.

1) *Fear:* We measure the fear of the social community based on the level of anxiety of the community during a disaster. By using the categories of the LIWC, the level of fear is obtained by

$$S^E = LIWC['anx']/LIWC[`WC']$$

where $LIWC['anx']$ means the category of *anx* from outputs of LIWC.

2) *Physical Health:* According to a psychological study of language, higher usage of first-person singular pronouns can signify physical discomfort and more attention to oneself [88]. Also, positively using phrases associated with physical activities such as "motion," "work," "leisure," "health," and "body" can indicate physical health [89], [90], [91], [92]. By using the categories of the LIWC, the level of physical health is obtained by $S^P = (-LIWC['i'] + LIWC['\text{health}'] + LIWC['\text{leisure}'] + LIWC['\text{work}'] + LIWC['\text{body}'] + LIWC['\text{motion}'])/LIWC[`WC']$.

3) *Cooperation:* Increased use of complicated words and terms with more than six letters is known to be inefficient for communication, cooperation, and social interaction from a psychological standpoint [93]. Conversely, the frequent use of the first person pronoun implies group engagement and cohesion [94]. According to language behavior research, assent-related languages (e.g., "agree," "OK," and "yes") are known in psychological linguistics to convey group consensus, interaction, and collaboration [95]. Finally, increased use of social process terms, such as "social," "friend," and "family" imply increased social interaction, involvement, and collaboration [96], [97]. Hence, the level of cooperation is obtained by $X_C = (LIWC['WC'] - LIWC['Sixltr'] + LIWC['we'] + LIWC['\text{social}'] + LIWC['\text{family}'] + LIWC['\text{friend}'] + LIWC['\text{assent}'])/(LIWC['WC'])$.

4) *Risk Perception:* Increased ambiguity is associated with an increase in risk perception. According to the psychological analysis of the words, the more the present tense is used, the more undisclosed an event is. In contrast, the more that past tense is used, the lower the level of ambiguity [65]. Also, increased use of certain related language can bolster assurance. The use of tentative language (e.g., maybe, perhaps, and guess) and additional filler words (blah, I mean, and you know) indicates that the speaker is unsure about the subject [65]. Additionally, phrases denoting discrepancies (e.g., should, would, and could) should incorporate the degree of uncertainty [65] $XR = (LIWC['risk'] + LIWC['\text{tentat}'] - LIWC['\text{certain}'] + LIWC['\text{filler}'] + LIWC['\text{focuspresent}'] + LIWC['\text{discrep}'] - LIWC['\text{focuspast}'])/(LIWC['WC'])$.

5) *Adaptability:* Respect, empathy, trust, and optimism are the main characteristics of adaptation and flexibility. Languages associated with assent (e.g., "agree," "OK," and "yeah") indicate agreement and flexibility, [65]. Pronouns are critical in language psychology study. The use of second-person pronouns denotes a lower-quality relationship and flexibility. When people are lying, they employ a greater degree of negative emotion and motion language (arrive, car, and go), reducing trust and adaptability. Increased use of negation-related phrases (e.g., no, not, and never) indicates that the individual is less adaptable $X_f = (LIWC['\text{posemo}'] - LIWC['\text{negate}'] + LIWC['\text{assent}'] - LIWC['\text{you}'] - LIWC['\text{motion}'])/(LIWC['WC'])$.

6) *Learning:* The level to which people pay attention demonstrates their desire to learn. Cognitive mechanisms (e.g., cause, know, and ought) and prepositions imply that the subject is informed. The abstracts and introductions of published journal articles contain more complicated language and prepositions. The use of casual language ("because, effect, and hence") and insight terminology (e.g., think, know, and consider) demonstrates the learning process. $X_L = (LIWC['\text{insight}'] + LIWC['\text{cause}'] + LIWC['\text{prep}'] + LIWC['\text{cogproc}'])/(LIWC['WC'])$.

7) *Information-Seeking Behavior:* The volume of tweets sent by individuals over time and throughout the disaster demonstrates their information-seeking behavior. Along with Twitter, GoogleTrends can be used to detect social trends. For instance, the number of searches for the terms "Hurricane Irma" and "Hurricane Harvey" demonstrates the extent of information-seeking behavior. We combine the two data sets obtained by Twitter and GoogleTrends to derive a more precise measure of information-seeking behavior.

E. Normalization and Dealing With Missing Values

We have two types of data sets, i.e., nonpolarity and polarity-based data sets, which are normalized as follows.

1) *Nonpolarity Values:* We normalize all values between the interval [0, 1] using a min–max normalization.

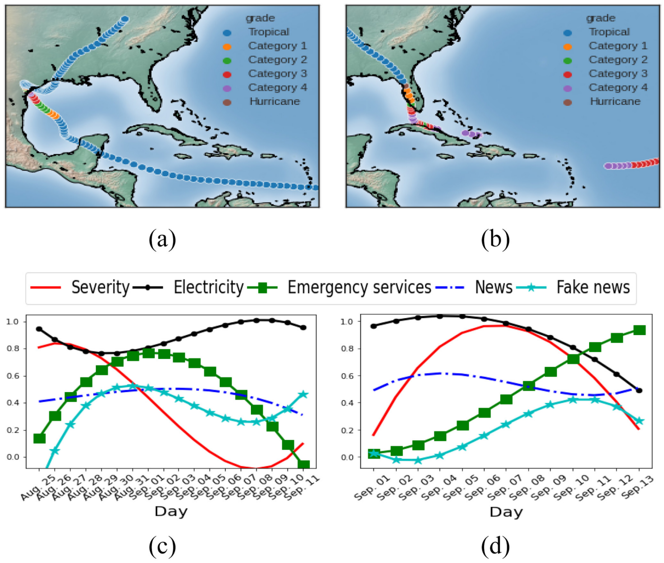


Fig. 2. Hurricane tracks, in-hurricane power plants, hurricane severity, availability of electricity and emergency services, propagation of fake news, and news positivity. (a) Harvey track. (b) Irma track. (c) Harvey features. (d) Irma features.

2) *Polarity-Based Values:* L^+ and $L-$ denote the length of the range of positive and negative values, respectively. The following two cases are considered.

a) *If $L^- < L^+$:* The positive values are normalized between the interval [0.5, 1]. By using $X^{\min} = 0.5 - [L^- * 0.5]/[L^+]$, we determine the intervals for the negative values, i.e., $[X^{\min}, 0.5]$. Then, we use a min–max normalization to standardize the values inside the intervals $[X^{\min}, 1]$.

b) *If $L^- > L^+$:* Here, we normalize the negative values between intervals [0, 0.5]. By using $X^{\max} = 0.5 + [L^+ * 0.5]/[L^-]$, we can determine the intervals for positive values, i.e., $[0.5, X^{\max},]$. Then, we normalize values within intervals $[0, X^{\max}]$ using min–max normalization.

After normalization, we deal with missing values via an interpolation approach.

Soft validation, simulation, real data sets, and statistical tests were used to validate the approach. Because social behavior is subjective, no single method of validation has been identified in the literature. The investigation of word use as a reflection of psychological state and the measurement of social behavior via social media is in its early stages. This article does not aim to provide a robust method for measuring each social behavior. In this article, the method's reliability is limited to comparing text mining results with simulation results obtained by the model, which is built using psychological and social science theories and verified using basic models. We provided an r-square and ran a number of statistical tests. It is worth noting that we can keep the definition of each variable based on how we measured it, while it is not unique due to its subjective nature.

IV. Case Study 1: Hurricanes Harvey and Irma

We validate the suggested model by examining data sets related to hurricanes Harvey and Irma. For validation purposes, We retrieved tweets from Hurricane Harvey's 18 336 283 and Hurricane Irma's 17 227 935 tweets via Twitter's streaming application programming interface (API). Specifically, We collected the tweets ids related to hurricanes Harvey and hurricane Irma using the TweetSets provided by the gwu library. The detail of the id collection can be found at [98]. Given a tweet id, we retrieved the text of tweets from the Twitter API using DocNow's Hydrator. We also leveraged GoogleTrends for social sensing. Hurricane Harvey and Irma's paths, in-storm power plants, hurricane severity, electricity and emergency services availability, the spread of fake news, and news positivity are represented in Fig. 2. Hurricane Harvey struck Texas and the ERCOT territory between 25 August 2017 and 11 September 2017. It was upgraded to Category 4 on 25 August 2017. As was the case with Hurricane Katrina, this hurricane is the most expensive tropical cyclone to strike the United States. Hurricane Irma made landfall largely in Florida and to a lesser extent in Georgia and South Carolina between 1 September 2017 and 13 September 2017. This storm was a Category 5 hurricane from 6 September 2017 to 8 September 2017. The electricity system's restoration began on 11 September 2017 and lasted 12 days.

To obtain a normalized index for measuring the intensity of a hurricane, category 5 is used as the base value. Therefore, a Category 4 hurricane has a severity of 0.8. For example, Hurricane Irma between 6 September 2017 and 8 September 2017 was a Category 5 storm (severity of 1). Before making landfall in Florida on 9 September 2017, Hurricane Irma was downgraded to a Category 3 storm (severity: 0.6). On 10 September 2017, however, it was upgraded to a Category 4 hurricane (severity of 0.8). On 11 September 2017, Hurricane Irma was downgraded to Category 1 status (severity of 0.2).

1168 MW of wind and 5679 MW of solar capacity in ERCOT during Hurricane Harvey became unavailable in Texas, reducing energy production by 21%. Between 8/25 and 8/29, ERCOT's power systems went down, leaving many without power or water. Maximum outages reached 309 204, affecting AEP Texas North Company (#20404) and AEP Texas Central Company (#3278). These utilities have 1 028 900 m, smart and nonsmart. The customer outage data set has missing values between 2:00 P.M. and 11:00 P.M. on 30 August 2017 due to a website outage. On the other hand, between 9 September 2017 and 11 September 2017, power systems faced outages due to Hurricane Irma. It damaged several utilities, including the City of Tallahassee (TAL#18445), the Jacksonville Electric Authority (JEA#9617), Gainesville Regional Utilities (GVL#6909), the City of New Smyrna Beach (NSB#13485), Florida Power Corporation (FPC#6457), Tampa Electric Company (TEC#18454), Seminole Electric Cooperative (SEC), Florida Municipal Power (FMPP#19804), and Florida Power and (SOCO).

The Cyber–Physical–Social-systems Data Analytics Package [99] contains the data sets, data processing, and analytics used in this article to make it easier for other researchers who are interested in continuing the research. This package contains in-depth descriptions of the related algorithms, API, NLP methods, and Python packages.

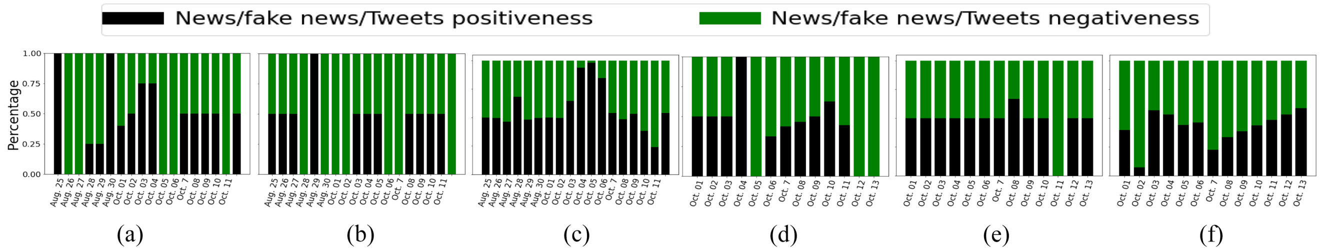


Fig. 3. Positiveness and negativeness of the news, fake news, and tweets for hurricanes Harvey and Irma over time. (a) News (Harvey). (b) Fake news (Harvey). (c) Tweets (Harvey). (d) News (Irma). (e) Fake news (Irma). (f) Tweets (Irma).

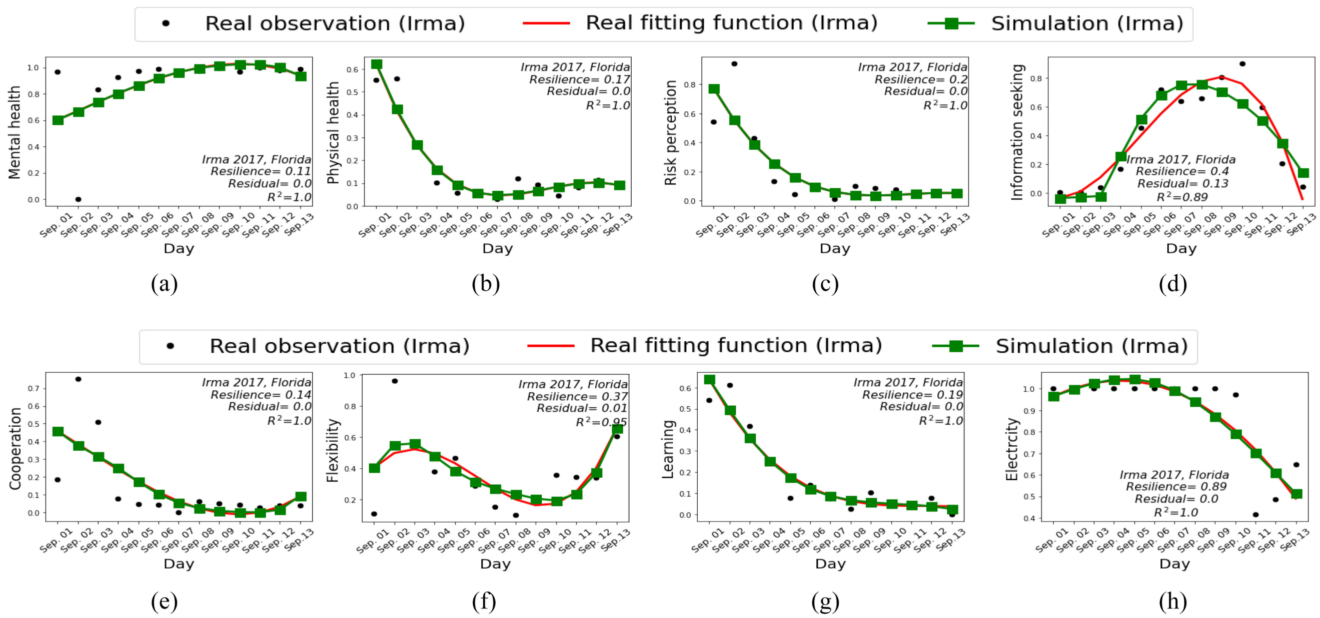


Fig. 4. Results for hurricane Irma by using the cyber–physical–social model of community resilience over time. (a) Mental health. (b) Physical health. (c) Risk perception. (d) Information seeking. (e) Cooperation. (f) Flexibility. (g) Learning. (h) Electricity.

TABLE II
TOP 5 1-GRAM AND 2-GRAMS FOR NEWS, FAKE NEWS, AND TWEETS ABOUT HURRICANES HARVEY AND IRMA

Analysis		1-gram	2-grams
Tweets	Harvey	power, harvey, hurrican, weather, annisepark	power weather, annisepark darn, darn thought, weather annisepark, without power
	Irma	power, irma, hurrican, florida, puerto	hurrican irma , power outag, categori 4, power florida, climat chang
News	Harvey	harvey, texa, irma, rescu, katrina	thing august, thing septemb, hurrican irma,hurrican harvey, lost everyth
	Irma	irma, florida, septemb, caribbean, trump	hurrican irma, thing septemb, catch day, irma path, irma relief (3)
Fake	Harvey	harvey, houston, presid, rescu, trump	hurrican harvey, church houston, harvey flood, victim hurrican (2), categori 6
	Irma	hurrican, irma, florida , pet, shark	hurrican irma, categori 6, show hurrican,irma project, becom categori

A. Analysis of Cyber–Social Layer

Sensing social impacts due to community disruptions when a disaster strike is an unexplored aspect of disaster response [100], [101]. It is crucial for emergency management to accurately record human emotional and behavioral responses via social media [102], [103]. The emotional signals in social media posts reflect the experience and hardship of residents affected by disruptions [104]. Table II displays the top five 1- and 2-grams for news, fake news, and tweets on hurricanes Harvey and Irma. For both events, the most often used term in people's Tweets is "power." This demonstrates that they are concerned about the state of electricity at that time period. Similarly, among the 2-grams, one of the most frequently repeated terms is "power outage." Interestingly, during hurricane Irma, the term "climate change" was constantly used. On the other hand, the phrase "category 6" is repeated for both incidents in fake news. Fig. 3 illustrates the positivity and negativity (affect aspect) of hurricanes Harvey and Irma over time associated with news, fake news, and tweets (representative of community behavior). Generally, news for both events is more negative than positive. Similarly, fake news is negative. Additionally, while those affected by Hurricane Harvey had a higher level of positive emotions, those in Florida had a higher level of negative emotions. This is consistent with the fact that people in Irma are more anxious than people in Harvey at the start of the hurricane.

B. Daily-Based Validation and Analysis

Fig. 4 illustrates real-world observations, related fitting curves, and simulation results for Hurricane Irma using a cyber–physical–social model of community resilience over time. The provided characteristics include the level of mental and physical health, risk perception, information-seeking

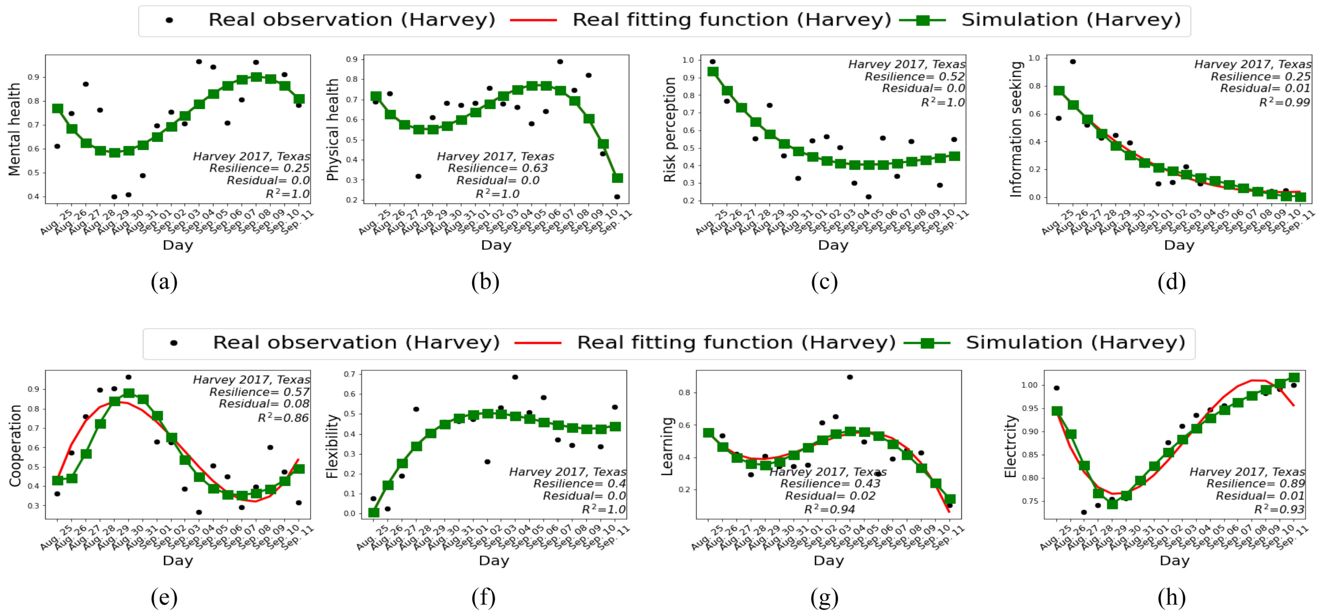
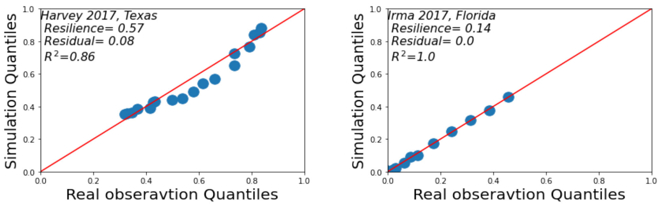


Fig. 5. Results for hurricane Harvey by using the cyber–physical–social model of community resilience over time. (a) Mental health. (b) Physical health. (c) Risk perception. (d) Information seeking. (e) Cooperation. (f) Flexibility. (g) Learning. (h) Electricity.

behavior, cooperation, adaptability (flexibility), learning, and the level of electricity that is cooperative/severity-dependent. For each subfigure, we show the information related to the type of event, capacity-based level of resilience (area under curve), residuals, and value of statistical $R^2 = 1 - (RSS/TSS)$, where $RSS = \sum(y - \tilde{y})^2$, and $TSS = \sum(y - \bar{y})^2)$.

Although Irma arrived in Florida later than Puerto Rico, it affected Floridians immediately on 1 September. Human behavior is subjected mainly to heterogeneous perceptions of events rather than objective information. Prior knowledge (e.g., past experiences) also influences perceptions. The real world and social networks are heterogeneous spatially due to this diversity of prior experiences [105]. Due to the occurrence of previous hurricanes, such as Andrew (1992), Charley (2004), and Wilma (2005), people's risk perception at the onset of Hurricane Irma was elevated. The level of fear fell till 8 September. Following that, by intensifying power interruptions, the level of fear increased. Other community disruptions include casualties, people in danger, and evacuation orders, which are closely related to physical infrastructure systems [104]. Then, with a high level of risk perception and an increase in the severity of Irma, people's information-seeking behavior increased until 7 September, at which point it declined. Note that According to the U.S. Geological Survey, people can also get their first event-related information from social media [106], which can spread unreliable information [107]. This ambiguous and often conflicting information can increase anxiety and fear due to event uncertainty [108]. Fear, social diffusion, and risk perception all contributed to a high level of cooperation at the start. It first stimulates a high level of learning. By gradually reducing fear and risk perception, the level of cooperation decreased. As a result of the decline in cooperation and the proliferation of fake news over time, the level of learning declined. After the first surge, the level of flexibility decreased until 8 September. After 8 September, due to the power outage and increased panic, the level of cooperation and flexibility increased. Physical infrastructure disruptions cause most community impacts. Understanding the societal impacts of infrastructure disruptions would help prioritize disaster response and resource allocation [109].

Fig. 5 illustrates real-world observations, fitting curves, and simulation results for hurricane Harvey using the proposed cyber–physical–social model of community resilience. At first, as the intensity of Harvey and the power loss increased, the level of worry increased, and physical health declined. Texas has the highest annual expected losses, with hurricane damage estimated at $1.5 billion. The occurrence of previous hurricanes, such as Rita (2005), Ike (2008), and Hermine (2010) causes people's risk perception to be the highest at the beginning of Hurricane Harvey and even higher than that of Hurricane Irma. Additionally, the initial level of information-seeking behavior was high. Note that in a survey of 761 European emergency service workers, over 60% found "general situational updates" and "information about the public mood" useful or very useful [110]. By reducing fear and increasing access to emergency services, both risk perception and information-seeking behavior gradually declined. Cooperation increased until 30 August and then diminished. Similarly, people's level of adaptability increased initially. At first, due to the prevalence of fake news and the decrease in information-seeking behavior, the level of learning reduced and then increased as the prevalence of fake news declined. Take note that while this study focuses on a single event occurring at a single moment, these traits can also be impacted by events other than Hurricane Harvey. The multi-hazard assessment of community resilience can be researched in the future.



(a) (b)

Fig. 6. *QQ*-plot for Hurricane Harvey and Irma's level of cooperation. (a) Cooperation (Harvey). (b) Cooperation (Irma).

TABLE III
GOODNESS RESULTS, I.E., RESIDUAL AND R^2 FOR DAILY-BASED, 3 HOURLY, AND HOURLY-BASED ANALYSIS FOR HURRICANES IRMA AND HARVEY

Residual and R^2			S^E	S^P	S^R	S^I	P^E	S^C	S^F	S^L
3 Hourly	Irma	R	0	0	0	0	0.05	0	0	0.01
		R^2	1	1	1	1	0.98	1	0.99	0.94
	Harvey	R	0	0	0	0.14	0.07	0	0.03	0.06
		R^2	1	1	1	0.97	0.94	1	0.95	0.9
Hourly	Irma	R	0	0	0	1.15	0.18	0	0	0.02
		R^2	1	1	1	0.9	0.98	1	0.94	0.94
	Harvey	R	0	0	0	1.07	0.19	0	0	0.02
		R^2	1	1	1	0.9	0.95	1	1	0.92

Fig. 6 depicts the *QQ*-plot for Hurricane Harvey and Irma's level of cooperation. It illustrates that the distributions of the simulated and real data sets are similar.

C. 3 Hourly- and Hourly-Based Analysis

Depending on the requirement and type of study, the time step can be every hour or every 3 h rather than every day. Table III provides the goodness results, i.e., residual and *R*2, for 3 hourly- and hourly-based assessments of all community-resilience-related features for both hurricanes Irma and Harvey. The residuals are insignificant, and statistical R^2 is close to 1. Table IV contains the findings of a statistical analysis conducted on real-world and simulated data sets for 3 hourly and hourly studies of all community-resilience-related features following hurricanes Irma and Harvey. The Shapiro–Wilk normality test indicates that not all cases conform to the normal distribution. Additionally, Pearson and Kendall tau correlations reveal a strong correlation between the simulation and the real data sets for all 3 hourly and hourly-based studies. Furthermore, the *p*-values of the Student's *t*-test and the Mann-Whitney U test (as parametric and nonparametric statistical hypothesis tests, respectively) show that the distribution of community resilience-related features obtained from the real data set and simulation outputs are similar in all cases, with the exception of information-seeking behavior during Hurricane Harvey for the hourly-based case. Note that we can enhance this outcome by improving the precision of the parameter estimation.

V. CASE STUDY 2: GROUP OF NINE AGENTS

This section analyzes the performance of the proposed dynamic model of a community (group) of nine agents experiencing a hurricane. This community consists of three areas. Each area involves three individuals who are empathetic to each other. The individuals of each area do not have any communication with those of another area. Fig. 7 shows the dynamic changes in human response for different levels of connection, α_{ij}^{θ}, among individuals. To clarify the importance of α_{ij}^{θ} on community resilience, the resilience-related features of 3 agents inside each area are assumed to be 0%, 0.5%, and 1%, respectively. The results are presented for two different levels of α_{ij}^{θ}, 0.1 and 1. Less α_{ij}^{θ}, among individuals plus other characteristics, including fear, information-seeking behavior, flexibility, and cooperation, all tend to converge at the same level. Also, agents share their electricity later than when α_{ij}^{θ}, is 1. As a result, when the α_{ij}^{θ} is high, the average level of physical well-being and mental well-being for the whole time interval [0 300] is more than that when individuals are not close-knit. During an event, sensitive people and those with few social connections (i.e., few friends in their social networks) should receive more supportive, event-specific information [105]. These individuals are more anxious and prone to unhelpful response behaviors [108], [111].

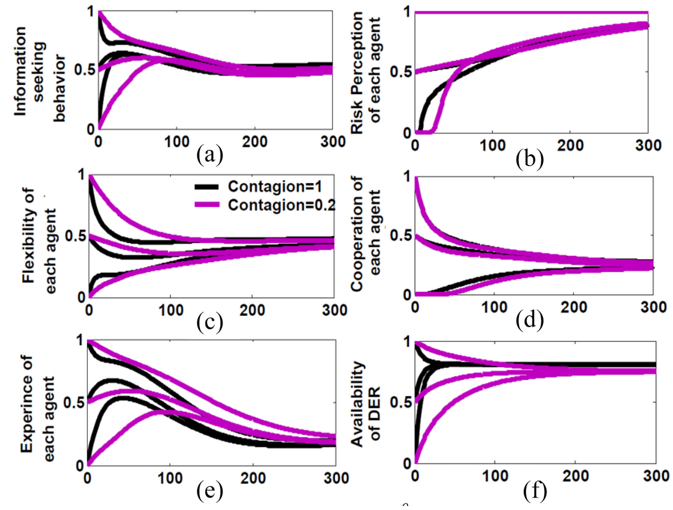


Fig. 7. Effects of different values of α_{ij}^{θ} (contagion), on collective behavior. (a) Information-seeking behavior. (b) Risk perception. (c) Flexibility. (d) Cooperation. (e) Experience. (f) Availability of DER.

VI. CASE STUDY 3: SIX SEPARATE COMMUNITIES

In this case study, the society consists of six communities with different characteristics and populations. Communities 1 and 2 are assumed to be extremely close-knit. As a result, the connection among these communities is assumed to be 0.9. Regarding the other communities, it is assumed there is no connection between them. Additionally, there are two potential places where the disaster occurs directly (i.e., in Communities 1 and 5).

A. Effects of the Occurrence of Disasters at Different Times in Separate Communities on Human Response

One disaster occurs in Community 1 at time step 0, while another occurs in Community 5 at time step 100. Because of severe hazards, emergency services and the power utility are inaccessible in community 1, but the individuals in this community can still use on-site generation. The disaster in community 5 causes a power outage at time step 100. Fig. 8

TABLE IV
RESULTS OF THE STATISTICAL ANALYSIS OF RESILIENCE METRICS, INCLUDING SHAPIRO–WILK NORMALITY TEST, PEARSON CORRELATION, KENDALL TAU CORRELATION, STUDENT'S t-TEST, AND MANN–WHITNEY U TEST

	Event	Hurricane Irma								Hurricane Harvey							
	Features	S^E	S^P	S^R	S^I	P^E	S^C	S^F	S^L	S^E	S^P	S^R	S^I	P^E	S^C	S^F	S^L
3 hourly-based outputs	P-value for real dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	P-value for simulation dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Pearson correlation	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.97	1.00	1.00	1.00	0.99	0.97	1.00	0.98	0.95
	Dependent	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	kendalltau correlation	0.94	1.00	1.00	0.98	0.99	0.96	0.84	0.79	0.99	1.00	1.00	0.46	0.84	0.96	0.85	0.75
	Student's t-test p value	0.98	1.00	1.00	0.99	0.96	0.98	1.00	0.91	0.99	1.00	1.00	0.87	0.94	0.99	0.72	0.96
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Mann-Whitney U Test p value	0.49	0.50	0.50	0.49	0.23	0.49	0.46	0.22	0.43	0.50	0.50	0.29	0.38	0.46	0.22	0.24
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hourly-based outputs	P-value for real dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	P-value for simulation dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Pearson correlation	1.00	1.00	1.00	0.95	0.99	1.00	0.97	0.97	1.00	1.00	1.00	0.96	0.97	1.00	1.00	0.96
	Dependent	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	kendalltau correlation	0.95	1.00	0.99	0.90	0.98	0.97	0.85	0.81	0.99	1.00	1.00	0.63	0.86	0.99	0.96	0.77
	Student's t-test p value	0.98	1.00	0.99	0.97	0.95	0.98	0.98	0.83	1.00	1.00	1.00	0.95	0.88	0.99	0.93	0.87
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Mann-Whitney U Test p value	0.41	0.50	0.48	0.45	0.09	0.46	0.13	0.08	0.46	0.50	0.50	0.02	0.32	0.48	0.49	0.08
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓

*Note that after the P-value results of each test, we bring the related descriptions in the next row.

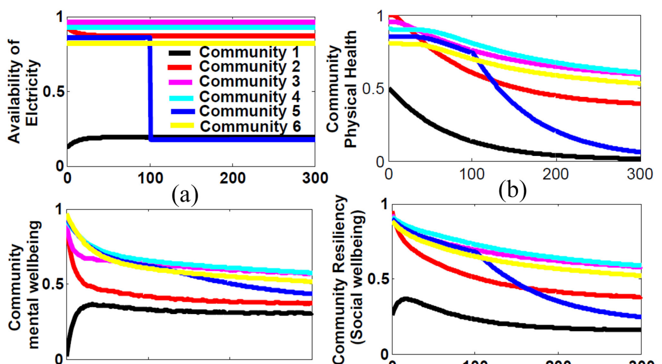


Fig. 8. Dynamic change of the availability of electricity, physical health, mental well-being, and community resilience for the six communities. (a) Availability of electricity. (b) Community physical health. (c) Community mental health. (d) Community resilience.

shows the average dynamic change of collective behavior for the six communities during the disasters. As expected, the physical health of Community 5 is sharply lower at time step 100. Understandably, because of the event's occurrence during this time interval, the level of fear of Community 5 is high. Individuals in this community perceive a high level of risk and seek information. As a result, they obtain experience. Despite living in a connected world with modern information channels, people can be grouped by nationality, culture, or location [112]. Such groups react differently to the same events [45]. Note that close connections between communities can increase the emotional impact of an extreme event. Through new communication channels like mobile and social media, extreme events may also raise concerns in unaffected regions [105].

B. Effects of Different Population on Community Resilience

An increase in the population size with the same level of α_{ij}^{θ} is associated with an increase in the level of experience and mental well-being. Moreover, a society with more experience induces higher physical well-being. If the level of cooperation and experience during and after a disaster is raised, then the level of panic among people is lowered, while mental well-being is increased. The larger the number of individuals with connections in a community, the more resilient that community is. When the population is the same (50), a community with more empathetic individuals ($\alpha_{ij}^{\theta} = 0.9$) is more resilient than a community with less empathetic individuals ($\alpha_{ij}^{\theta} = 0.2$). The relationship among the individuals of a community is an essential characteristic of community resilience. A community with a smaller population (20) and more α_{ij}^{θ} (0.9) is more resilient than a community with a larger population (60) and less α_{ij}^{θ} (0.2).

VII. CONCLUSION

We proposed a multiagent cyber–physical–social model of community resilience. Fear, risk perception, information-seeking behavior, physical health, cooperation, flexibility, and learning are all social indicators of community resilience. We tracked these indicators using data from Twitter and GoogleTrends. Physical indicators of community resilience include the availability of electricity via DERs, MGs, and utilities, as well as the accessibility of emergency services. We quantified the physical characteristics using data provided by FEMA and the electric utility company. Cyber layer metrics include the news positivity and the propagation level of fake news during events. We evaluated the cyber metrics using data from CNN and fact-checking organizations. The proposed model provides various advantages that compensate for the literature's shortcomings. It considers the cyber–physical–social interdependence of metrics in order to model their dynamic behavior. It can be used to simulate a variety of situations that are either prohibitively expensive or impossible to test in the real world. We further confirmed our cyber–physical–social model using natural language processing and text mining methods.

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Jaber Valinejad (Member, IEEE) received the master's degree in computer science and the Ph.D. degree in electrical and computer engineering from Virginia Tech, Blacksburg, VA, USA, in 2021 and 2022, respectively.

He is currently a Postdoctoral Researcher with the Data and System Science Lab, Harvard Medical School, Harvard University, Cambridge, MA, USA. He was a Fellow of the following NSF-sponsored interdisciplinary programs while earning the Ph.D. degree at Virginia Tech: 1) disaster resilience and risk management and 2) urban computing. He is the Founder of the Communitycomput incubated with Harvard Innovation Lab through the venture program and is supported by MIT i-corps and Harvard. His research focuses on community resilience, computational social science, energy, and socio-technical systems through the use of network science, data science, natural language processing, social sensing tools (such as Twitter and Google), machine learning, and optimization techniques.

Lamine Mili (Life Fellow, IEEE) received the Ph.D. degree from the University of Liège, Liège, Belgium, in 1987.

He is a Professor of Electrical and Computer Engineering with Virginia Tech, Blacksburg, VA, USA. He has five years of industrial experience with the Tunisian electric utility, STEG, Sousse, Tunisia. At STEG, he worked in the Planning Department from 1976 to 1979 and then at the Test and Meter Laboratory from 1979 to 1981. He was a Visiting Professor with the Swiss Federal Institute of Technology in Lausanne, Switzerland; Grenoble Institute of Technology, Grenoble, France; the École Supérieure D'électricité, Gif-sur-Yvette, France; and the École Polytechnique de Tunisie, Carthage, Tunisia, and did consulting work for the French Power Transmission company, RTE. His research has focused on power system planning for enhanced resiliency and sustainability, risk management of complex systems to catastrophic failures, robust estimation and control, nonlinear dynamics, and bifurcation theory.

Prof. Mili is a recipient of several awards, including the U.S. National Science Foundation (NSF) Research Initiation Award and the NSF Young Investigation Award. He is the Co-Founder and the Co-Editor of the *International Journal of Critical Infrastructure*. He is the Chairman of the IEEE Working Group on State Estimation Algorithms and the Chair of the IEEE Task Force on Power System Uncertainty Quantification and Uncertainty-Aware Decision-Making.