Predicting impacts of weather-driven urban disasters in the current and future climate

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Effective city operations depend on local weather conditions at the scale of critical urban infrastructure such as power and water distribution systems. This includes both routine and severe weather events. For example, with precipitation events, local topography and weather influence water runoff and infiltration, which directly affect flooding as well as drinking water quality and availability. The impact of such events creates issues of public safety. Thus, the availability of highly localized weather model predictions focused on public safety and operations of infrastructure can mitigate the impact of severe weather. This is especially true if the lead time for the availability of such predictions enables proactive allocation and deployment of resources to minimize recovery time from severe events. Typically, information at such a scale is simply not available. Hence, the ability of municipalities to proactively respond to these events is limited. Available continental- or regional-scale weather models are not appropriately matched to the temporal or spatial scale of such operations. While near-real-time assessment of observations of current weather conditions may have the appropriate geographic locality, by its very nature it is only directly suitable for reactive response. To address this gap, we use state-of-the-art physical weather models at the spatial scale of the city's infrastructure to avoid this mismatch in predictability. Model results are coupled to data-driven stochastic models to represent the actionable prediction of weather (business) impacts. In some cases, an intermediate physical model may be required to translate predicted weather into the phenomena that lead to such impacts. We have applied these ideas to several cities with a diversity of impacts and weather concerns and show how this coupled model methodology enables prediction of storm impacts on local infrastructure. We also discuss how this concept can be extended to a climate scale in order to evaluate the potential localized impacts of a warming planet and the effectiveness of strategies being used to mitigate such impacts.

1 Introduction

Reliable, efficient operations of urban infrastructure (i.e., electric, communications and water utilities, transportation, etc.) are critical for cities and their citizens to be safe and resilient. In many urban areas, such operations are highly dependent on the local weather conditions, especially at the scale of such critical infrastructure. This includes both routine and severe weather events such as tropical storms, tornadoes, snowstorms, damaging winds, and hail. For example, with precipitation events, local topography and weather influence water runoff and infiltration, which directly affect flooding as well as drinking water quality and availability.

Frequently, reports are published in the popular press of major flooding events impacting urban areas (e.g., [1, 2]). For example, from January 1, 1980 to July 9, 2019, there

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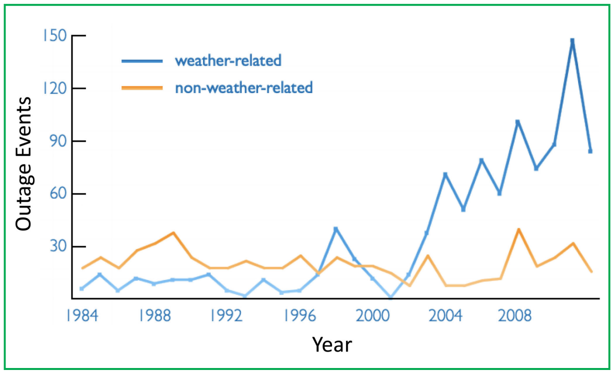

Figure 1

Weather-related power outage events (blue curve) in the United States have increased dramatically in the 2000s compared with those from nonweather causes (dark yellow curve) [5].

have been 31 flooding events with losses exceeding one billion CPI-adjusted U.S. dollars each across the United States without including those driven from tropical cyclones. In aggregate, those 31 events had a loss of $126 billion and 554 lives [3]. They are often influenced by increases in precipitable water in the atmosphere [4]. The impact of such events creates issues of public safety for both citizens and first responders.

Public services in the United States such as electricity delivery have seen a rise in the number of customer outages by a factor of ten in the 2000s, compared with the previous two decades [5]. Weather is increasingly becoming a significant factor that municipal services must include in their emergency planning activities. **Figure 1** illustrates how this increase compares with outages that are not caused by weather. These services often find that currently available information and tools are not delivering what they need to make critical decisions with adequate lead time to prepare appropriately.

Specifically, information at the required highly localized scales is rarely available, or what is available does not adequately address the concerns or the requirements of the stakeholder decision-maker. Presently, whatever optimization applied to these processes to enable proactive efforts utilizes either historical weather data as a predictor of trends or the results of continental- or regional-scale weather models. Neither source of information is appropriately matched to the temporal or spatial scale of many such operations, which often leaves large gaps in which highly localized weather events are occurring that have a significant impact on a local level but are not addressed in the broader response strategy of the stakeholder. While near-real-time assessment of observations of current weather conditions may have the appropriate geographic locality, by its very nature it is only directly suitable for a reactive response.

Access to highly localized weather model predictions focused on municipal public safety and operations of infrastructure has the potential to mitigate the impact of severe weather. This is especially true if the lead time for the availability of such predictions enables proactive allocation and deployment of resources (people and equipment) to minimize the time for restoration of damage from severe events.

2 Approach

The initial step to address the aforementioned gap is the application of the state-of-the-art physical weather models at the spatial scale of the city's infrastructure, calibrated to avoid this mismatch in predictability. The results of such a model are then coupled to a data-driven stochastic model to represent the actionable prediction of weather (business) impacts [6]. In some cases, an intermediate physical model may be required to translate predicted weather into the phenomena that lead to such impacts. We have applied these ideas to several cities with a diversity of impacts and weather concerns. It should be noted that in many cities the effect of weather events has been exacerbated by a combination of an aging and more vulnerable infrastructure as well as increased urban population growth that applies greater stress on infrastructure such as higher electricity demand [6].

This coupled model methodology has enabled operational prediction of storm impacts on local infrastructure, as well as the measurement of the model error associated with such forecasts. We have defined a flexible approach for such a one-way coupling that includes an abstraction of the weather forecasting component. We present the implementation of these urban weather impact predictions and the ongoing challenges they represent. We then discuss how we can extend this concept to a climate scale in order to evaluate the potential localized impacts of a warming planet and the effectiveness of strategies being used to mitigate such impacts.

For impacts that affect electric utilities, we employ data-driven techniques based upon statistical and machine learning methods to enable probabilistic forecasts for two primary reasons. Forecast uncertainty that needs to be quantified is derived not only from weather predictions, but also from impact data such as anecdotal storm damage reports. In addition, some of the physical forcings may be at a spatial or temporal scale not resolved by the computational grid used for the weather model. In some cases, such as flooding, this can be addressed by intermediate physical models (e.g., hydrological). In other cases, it could include explicit modeling of turbulence that drives strong winds that can down trees or break branches that damage power lines. In addition, a model at that level would be prohibitively expensive to produce operational forecasts, and there would be a lack of data to enable comprehensive verification. The two classes of components are discussed in Sections 2.1 and 2.3 with applications of the methods outlined in Section 3.

2.1 Atmospheric forcing for tailored weather forecasts

We build upon our earlier efforts at IBM to implement and apply an operational meso-γ-scale weather-model-based prediction system to business problems, dubbed "Deep Thunder," which has been tailored to the localized needs of decision-makers in urban environments, among others [7–9].

In this context, to predict localized storm impact, we need weather forecasts with high spatial and temporal resolution that are customized for the relevant geography as determined by decision-making stakeholders that work in urban settings. The computational grid should be sufficiently fine to resolve features required as input to a coupled impact prediction model. As outlined in [8], a convective-resolving configuration is typically required (e.g., 1–2 km, horizontally, and tens of meters vertically in the lower part of the atmospheric boundary layer). The further customization of the forecasting system for a specific application comprises: (a) the choice of a regional domain, constructed with topographic, meteorological, and land surface features in mind; (b) the choice of model physics (radiation, boundary layer, microphysical, land surface, and urban canopy); (c) pre-processing of ingested data; and (d) post-processing of forecast data. Diverse datasets may be leveraged in (c) via data assimilation techniques to improve weather forecast accuracy. Such datasets and example configurations are discussed in [7] and [9].

The Deep Thunder weather model is based, in part, on the advanced research core of the community Weather Research and Forecasting model [10]. To support diversity of coupled models for impact and damage prediction, models for other domains and visualization of the weather model output (i.e., a coupled geometric model), there is a standard set of weather variables that are included in an abstraction of the weather model output. It is designed to be standalone to drive the coupled models. Some of the fields are direct model output, whereas others are derived via post-processing as diagnostic variables. They include, but are not limited to, instantaneous precipitation rate and type (snow, rain, ice, or graupel), snow density, composite reflectivity (as a proxy for storm intensity), lightning potential, convective available potential energy, lifted and K-indices (indicative of convective potential), mean sea level pressure, turbulence-based wind gusts and visibility, as well as volumetric cloud properties and three-vector winds. The details of how this is addressed are discussed in [7].

The weather model configuration should be carefully constructed based on retrospective analysis, using a technique known as "hindcasting." Nominally, the intended application would drive the identification of several historical events, across multiple seasons, that had an impact on the region of interest but were missed or underforecasted by private and/or publicly available forecast services, resulting in underpreparedness or false alarms. These can include "blue sky," high wind cases, winter and convective season storms, large-scale extra-tropical events, etc. It is also important to identify blue sky (non-event) days to ensure that the weather model is producing realistic output. In order to determine the optimal configuration (customized to meet the application requirements), the historical cases are simulated as hindcasts, using only input data that would have been available at the time that a forecast would have been created. The results are validated against available observations, both quantitatively and qualitatively, to show improved skill compared to other forecasts. Operationally, the same comparisons are performed resulting in a consistent methodology [11].

2.2 Model coupling

To enable the coupling of downstream impact models driven by weather, the results of a weather-model-based forecast are abstracted to include the aforementioned key variables at the appropriate temporal and spatial resolution. The abstraction is presented through a consistent application programming interface (API) and data model, both of which preserve the underlying computational grid, coordinate systems, and semantics of the weather model. The open-source data model, Network Common Data Form (netCDF), has been adapted for this purpose, following its climate and forecast (CF) conventions [12]. The API is supported within the most common programming and scripting languages. In addition, access to the data within this data model is supported in a number of open-source and commercial data visualization and analysis software packages (e.g., [13]). netCDF is also used for the output of other coupled models for similar reasons as the weather model.

The generation of this abstracted weather model output applies to operational predictions as well as retrospective hindcasting. Hence, this approach supports the creation of training sets for the data-driven models via hindcasts or historical operational forecasts. Given the consistency in the output, it enables the coupled models to operate in an automated fashion, including the generation of visualizations of the weather model. An ancillary capability of the system is the ability to automatically generate a large history of such hindcasts, including the ingest and assimilation of the appropriate datasets [7].

The data flow associated with the model coupling is illustrated in **Figure 2**. The weather model, which includes physical modeling of the urban canopy and the land surface, is shown at the top with the ingest of local observations via data assimilation. The output of the models in netCDF is shown between the models, including where the

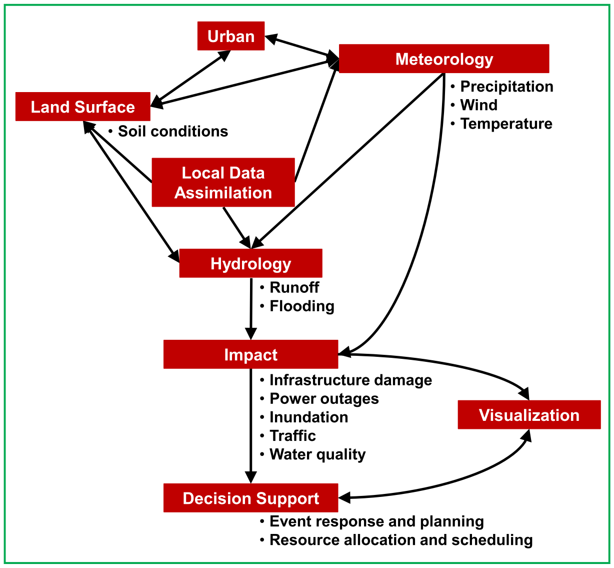

Figure 2

Data flow for coupled models to enable predictions of weather-driven impacts.

meteorology is sufficient to drive an impact model or where intermediate physical models like hydrological ones are required. Specific examples of the output required for such coupling are outlined in Section 3. The use cases for decision-makers are driven with the impact models, associated with the use of visualization to aid in the interpretation and communication. In most situations, there is no need to visualize meteorological data directly.

3 Case studies

To illustrate the applications of these ideas, we outline two example impacts on urban areas that are of current and growing concern by those that provide municipal services as well as citizens and businesses that rely on them. The first considers storm-driven electricity outages. The second examines urban-scale flooding from significant precipitation events.

3.1 Utility outages and emergency operations

Weather-induced power outages are increasing across the United States [5]. According to research by Climate Central, the number of power outages caused by weather has increased significantly from 1980 to 2012 (by a factor of ten), and their impact is widening. Weather caused 80% of the reported outages, which cumulatively affected 300–500 million people in the United States during that period. Aspects of increased electricity demand and vulnerability of aging infrastructure are also factors [14, 15].

Among weather-related outages, 59% of the weather-related outages analyzed were caused by storms and severe weather. Nearly 19% occurred during the winter (i.e., low temperatures and ice storms), and 18% of the outages were driven by hurricanes and tropical storms. Only 3% were due to tornadoes, and 2% by a combination of extreme heat and wildfires. More recently, beyond that study period, the United States has had a significant number of outages related to wildfires, especially in California, although not yet with a significant impact on urban areas. Many of these outages were planned by the local utility companies to reduce the risk of starting fires [16].

Utility companies spend a large amount of money on preparation and response, and utility managers want to use every rate-payer dollar wisely. For example, in 2010, one U.S. East Coast utility spent an estimated $30 million in preparation for Hurricane Earl, a storm that passed hundreds of kilometers out to sea and had no impact on its infrastructure [17]. Expenditures incurred by such an inefficient storm response could have been allocated elsewhere. Utilities also suffer the softer costs of customer sentiment and reputation, which typically are manifested as unhappy regulatory bodies, increased scrutiny and reporting, as well as fines, which can lead to loss of license or financial failure [18, 19].

In today’s constantly connected digital world, customers have little patience and high expectations about an electric utility’s ability to restore power to an area quickly and efficiently [15, 20]. Hence, it is critical for utility managers to have timely and specific information that is relevant to them. As discussed in Section 2, many free, publicly available, and/or commercial weather sources provide some level of warning that adverse weather is coming, but often fall short of the specificity required for utility managers to appropriately assess if the incoming weather will indeed impact their system. Once the question of “if” is answered, the next is “how” it will impact the system. The answer is a critical one as it will dictate the level of response, and thus the level of preparedness a utility will have to restore customers. Therefore, a highly customized weather modeling solution specific to the utility territory is required. Ideally, that weather model will be coupled to a decision support tool that can interpret the incoming weather conditions and predict with some certainty the level of impact on the utility infrastructure.

For example, a publicly available weather forecast may provide information that says 90-km/h winds and 15 cm of snow are predicted to impact a utility service territory. That information may be sufficient for the public who may be concerned about their commute to work the next morning. For the utility manager, it lacks key information required to decide if those conditions will be impactful to the infrastructure such as an overhead electric distribution network. Consider how quickly this simple example becomes complex for a utility manager who needs to consider the damage to trees that can lead to power outages because they are in close proximity to wires and poles. Since it is winter, there are no leaves on the trees, and therefore, winds of that magnitude may not be as significant as they would be during the summer when there is full foliage to capture the energy from high winds. On the other hand, during the winter in regions like the U.S. northeast and upper midwest, the root systems of deciduous trees may be retracted and less securely anchored in the ground, making them more vulnerable to damage from strong winds. Another element in this consideration is soil moisture in the volume that includes the root system of trees. If the soil is saturated due to antecedent rainfall or snowmelt, then anchoring of trees will be further weakened. Typical public and commercial weather forecasts include no information about soil moisture, soil saturation, or the status of foliage.

Such a forecast of 15 cm of snow adds further complexity for a decision-maker at a utility because it provides no information on the characteristics of the snow. Snow that is "light and fluffy" with low water content may have large impacts on transportation systems (e.g., road closures and airport delays). Since such snow will not adhere to trees and infrastructure, it therefore will have a negligible effect on an overhead distribution network. However, if the snow is denser with higher water content, then it will adhere to the trees and infrastructure. The weight of accumulated snow will increase the vulnerability for potential damage. If that factor is combined with strong winds, the aggregated impact the utility may encounter is much greater than simply adding the independent impacts of wind and heavy snow.

Several groups examined the quantitative relationship of these weather and non-weather factors that can lead to outages during the same period that utilities were recognizing an increase in the number of weather-driven impacts on their overhead infrastructure. Initially, the focus of these groups was on the analysis of historical events (e.g., [20]). This led to early work to create predictive models that can consider the winter situation described in the previous example and enable a utility manager to make more informed decisions. These efforts included only weather information [21], whereas others considered the aforementioned non-weather factors that were also executed operationally [22]. The latter was the first effort to function as a coupled modeling system where a targeted weather model that was focused on the utility service territory drove a statistical model for outage prediction. A damage forecast model for each substation was developed using historical weather and outage data as well as infrastructure and environmental data by building a hierarchical Poisson regression model. A generalized extreme value distribution was used to model daily gust maxima to bridge limitations in the weather model to the Poisson regression. This led to further advancement to include not only operational predictions of outages at different levels of aggregation, but of the resources necessary to restore power and the optimal scheduling for their deployment [23]. The Poisson regression was used with a decision tree classifier as well as a more advanced weather model. In addition, customized visualizations were deployed, consistent with the notion of cascading coupled models as shown in Figure 2. Given the increased incidences of outages, other independent efforts have revisited these ideas more recently (e.g., [24]).

Independently of the statistical or machine learning methods used, these classes of outage prediction models are trained on a large set of diverse historical data. They require a utility's records of outages, which can include where and when they occurred as well as information about specific damage (e.g., poles or wires down, transformer failure), weather conditions, and the type of restoration effort required (i.e., people and equipment). Historical weather data from observing systems are needed, and depending on the fidelity of the model, data about soil conditions and vegetation will be required. As discussed in [22–24], when the outage prediction is run as a coupled system, the training set must include historical predictions of the forcing weather model. These can be provided via hindcasts or archived forecasts. Typically, several years of such historical data are required to appropriately train an outage model. This is to ensure seasonal variations in outage events (e.g., winter versus summer) and statistically significant samples for relatively rare events. Such training should be revisited at least yearly to reflect updates to the infrastructure (i.e., upgrades, repairs, or aging) and improvements to the weather model.

Therefore, such outage prediction models should run in an automated fashion as a post-process to a high-resolution weather model focused on the utility service territory. This enables a utility manager to focus on the job they know best—preparing the electrical system and personnel for the impact of a pending event. A properly trained outage model will output the predicted outages, customers, restoration effort, and/or devices/infrastructure that will be affected by the incoming weather. A utility manager can use this information to determine and optimize the level of response required or simply give utility operations the evidence to mobilize or not.

Lead time is incredibly important to this decision-making process. This is often another limitation in typical public and commercial weather forecasts. A customized weather model coupled to an outage prediction model can provide the minimum 3-day lead time on incoming weather and the potential impact on the utility system that is often required for effective planning. It is assumed that even at 3 days out from a potential event, the forecast will vary, and thus the resulting impact predictions will as well. Longer lead times enable response personnel to be alerted that impactful weather is approaching, and storm preparations can be initiated. As the weather and resulting impact predictions are refined, so can the response.

Storm preparation is a huge undertaking even if a utility company is only mobilizing internal resources. Regular work is often put on hold, and schedules of personnel are changed to either arrive earlier or stay later, compared to their routine schedule. Both of these lead to additional expenses, which can be tens of thousands of U.S. dollars per day. Opening an emergency management center for a large urban utility can cost $1 million [25].

Most utilities are affected by several weather events per year that would cause them to mobilize internal resources. Hence, the total annual costs can easily reach several million dollars on the more routine weather events.

If the incoming storm is sufficiently large that a utility's internal resources cannot perform a timely recovery, then it will rely on its peers via mutual assistance networks to provide supplementary personnel and equipment. These resources are not unlimited and can be difficult to access in response to a storm that may span a large region with multiple utilities requesting additional resources. Furthermore, they are typically available on a first-come, first-serve basis. After major tropical systems that impacted the northeastern United States like Sandy (October 2012) and Irene (August 2011), utilities requested resources sooner and in greater numbers just to be prepared for subsequent events. An outage prediction model can provide the lead time that can help make the mobilization decision sooner, and thus, enable the request for mutual assistance to be addressed faster. In terms of cost, one storm of this magnitude can cost a utility of the order of $1 million per day [26].

To illustrate these ideas in the context of an operational deployment, consider the IBM outage prediction model derived from [23]. Specifically, this is with Hydro One, Ontario's largest distribution utility (a service territory of approximately 800,000 km^2 in area). In April 2017, a major storm hit the region, bringing torrential rain, an inch of ice, and wind gusts up to nearly 100 km/h. More than half a million people lost power. **Figure 3** illustrates the capabilities available to Hydro One prior to that storm. Two of the three maps show Hydro One's service territory decomposed by service districts, colored by the number of outages, following the color legend on the left. Map (a) shows the operational outage prediction 72 hours before the event. For comparison, map (b) depicts the distribution of actual outages that occurred. To illustrate the skill of the prediction, map (c) shows the mean absolute error (MAE) between maps (a) and (b). The service districts are colored by the MAE in the outage prediction following the legend to the lower left. Following the lead time requirements discussed earlier, these forecasts enabled Hydro One to position 1,400 front-line personnel, who were needed to restore power and to handle the nearly 130,000 customer

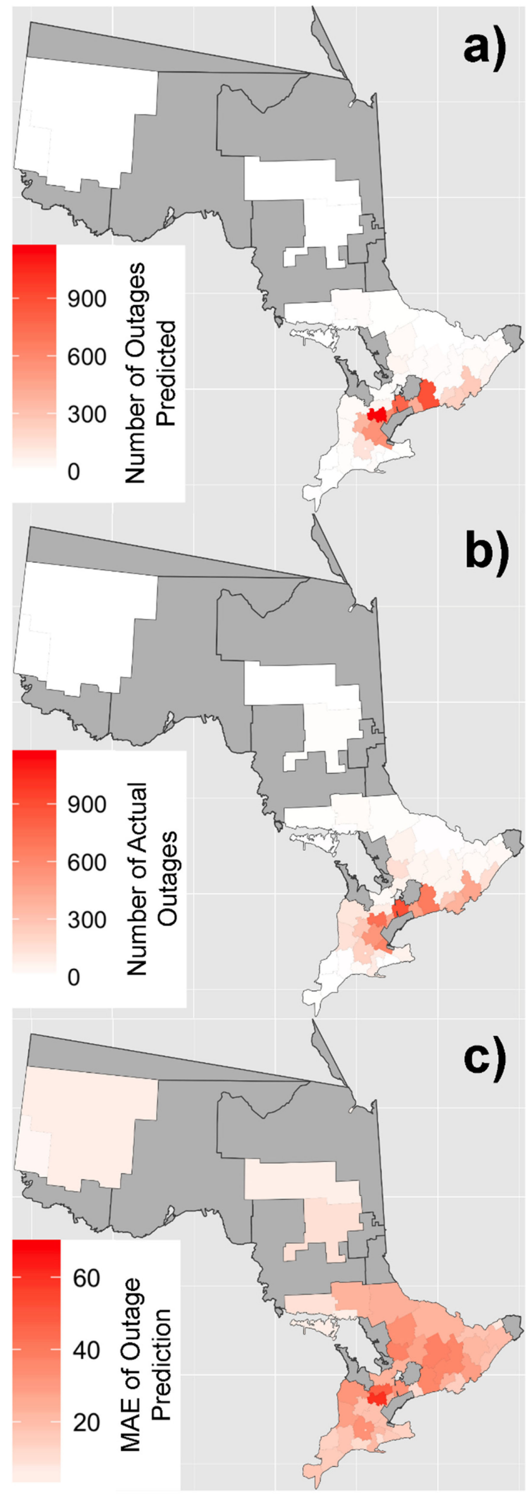

Figure 3

Example outage prediction for the Hydro One service territory in southern Ontario. (a) 72-h lead time. (b) Actual outages. (c) MAE for the outage prediction.

calls during the event. The utility was able to restore power to its customers' homes and businesses within 4 days. By contrast, after a major storm in 2016, it took 6 days to restore power because there was no outage prediction model in place at Hydro One in 2016 [27]. Operators at the time likely did not have the advance warning such a predictive tool could provide and, therefore, were not able to make the same preparation decisions in sufficient time to materially improve the restoration process prior to the 2016 event.

3.2 City emergency operations and flooding

Flooding impacts in many regions have increased in frequency in recent years, including underestimation of the ongoing risk (e.g., [28]). In 2018 alone, southern California experienced heavy rains, whereas Hurricanes Florence and Michael impacted the Gulf Coast, southeast, and mid-Atlantic regions of the United States. In many regions, urban flooding and associated impacts are a growing source of significant economic loss and social and infrastructure disruption. Suburban development has created increased flooding into urban areas along with aging and frequently undersized infrastructure in many communities, coupled with an inability to maintain existing drainage systems and uncoordinated watershed management [29].

Major urban regions can be affected by flooding, especially in coastal areas. A notable example is post-tropical cyclone Sandy, which impacted much of the eastern United States from coastal regions to the Midwest in October 2012. Urban centers in the northeastern United States suffered significant overland flooding and wind-driven storm surge [30].

When Sandy came ashore near Atlantic City, NJ, USA, with roughly 130-km/h winds, it drove catastrophic flooding into many communities north of the landfall along the New Jersey shore and New York City to Long Island, NY, and coastal Connecticut. Sandy's size brought tropical-storm-force winds nearly 800 km from the center of the storm. The size of the wind field combined with the angle of approach to the northeastern United States piled storm surge waters into the shorelines of these areas, causing historical flood levels that had not been seen in recent times, or ever in some locations. The storm surge impact was exacerbated by arriving near or at the time of high tide in some locations like New York City, where 2.7 m of storm surge waters contributed to the already high astronomical tides. The all-time record tidal maximum at the NOAA reporting gauge at the Battery (i.e., the southern tip of Manhattan) the evening of October 29, 2012 was 4.23 m, far surpassing the previous record of 3.41 m during the great hurricane of 1821 [31].

Storm surge flood waters rushed into lower Manhattan and the outer New York boroughs, infiltrating utility systems, most of which are underground. Although preparations were made prior to landfall, the magnitude of the storm and its eventual impact were underestimated. In some situations, the dire predictions made with a few days of lead time were not fully believed. The electric utility, Consolidated Edison, had plans to preemptively shut down parts of its underground network in lower Manhattan to reduce damage when flooding from storm surge infiltrated the system. However, the impact was greater than expected, including parts of the city that had not flooded previously. In addition, many of the flood wall barriers established at power plants were overtopped by the surge waters, causing impact in places that were believed to be adequately protected [32].

The city of Rio de Janeiro, Brazil, often faces the consequences of intense rainfall, which include landslides and flooding. In early April 2010, the city endured the worst rainstorms compared with the previous 48 years. This was considered one of the most significant global weather events of 2010 [33]. These storms led to flooding, including flash floods and mudslides. As a result, there was a significant loss of life, and tens of thousands lost their homes [34, 35]. There was little advance warning of the storms and their characteristics and, hence, no opportunity for an effective response. To assist in planning for such events in the future, the city's leaders enabled sophisticated capabilities for the coordinated management of disasters, emergencies, or planned events of importance. This would lead to the ability to provide lead time on flooding with a significant impact on the city infrastructure and citizens [36]. Unfortunately, some of the capabilities deployed in response to the April 2010 floods lapsed in the intervening years. As a result, there have been recent events with similar impacts as those in 2010 (e.g., [37, 38]). As part of any such effort to provide warnings, the integration of advances in hydrometeorological research is a key prerequisite. For cities like Rio de Janeiro, there are a number of challenges, which were first effectively addressed for operational forecasts by Treinish et al. [9].

This approach to flood impact prediction follows the methodology outlined in Section 2.2. Considering Figure 2 as a guide, the meteorological model (Deep Thunder) is tailored to the Rio de Janeiro metropolitan area. Predictions of accumulated rainfall, instantaneous rainfall rate, runoff from the land surface model, etc., are used to drive a two-dimensional (2-D) surface runoff model. Water levels and flood risk are derived from that model, also described in [9]. The availability of reliable local data, especially in real time, was a significant constraint on the fidelity of the models. No observations were available for data assimilation. Furthermore, there were no detailed data of land use, soil, drainage, etc. Only LIDAR-derived digital elevation data could be used for the runoff model. In contrast, very good historical flooding data were available. That required an assumption of an impervious surface. Since the gravity-driven flow is to first order the primary driver for flood risk in

Rio de Janeiro, this was an acceptable approximation since subsurface vertical effects are negligible. This leads to a solution of the two-dimensional shallow water equations. Since this is one equation with one unknown, depth, it can be solved implicitly with a linear system. In addition, there was an evaluation of other methods to assess storm impact, including using the predicted water level as an input to a simulation of traffic.

An example of these ideas is shown in **Figure 4**. Each portion of the figure is from the end of a 48-hr hindcast animation sequence (frames every 10 minutes). The top portion (a) shows one output from Deep Thunder as a hindcast for the aforementioned April 2010 strong convective event in Rio de Janeiro. It is a snapshot with both 2-D and 3-D features at 1-km horizontal resolution. The forecasted accumulated precipitation is used to color a 3-D map (extruded surface) of the weather model topography, following the color legend in the upper right. Additional overlays include coastal boundaries, rivers, and other features. The other 3-D feature is white, translucent surfaces that illustrate boundaries of dense clouds.

Although Figure 4 shows results of a hindcast, visualizations like these and others derived from the forecast models were disseminated operationally via a web portal that supports the display of and interaction with model outputs [9]. The middle portion (b) also shows an extruded 3-D surface of terrain derived from a 1-m-resolution digital elevation map of the city and rendered via Google Earth. It has been colored by the predicted water level from the aforementioned runoff model. Isolated areas of high water are seen in red, following the color legend in the lower left. The bottom portion (c) shows the output of an agent-based traffic simulator for predicting the effects of high water on the flow of vehicles in part of the city. Streets are colored by the traffic speed overlaid on standard maps within Google Earth. The behavior of individual drivers of vehicles is learned from probe-car data (e.g., route selection considering travel time and distance and the number of turns). This can be used by decision-makers in the city government to determine prior to a flood what roads to close and where and when to reroute traffic to avoided traffic jams caused by floods [39].

While such coupled capabilities have rarely been deployed on an operational basis for planning responses to urban floods, there are opportunities to advance the fidelity of such models, assuming the current availability of reliable environmental observations to be assimilated into meteorological and hydrological models. In addition to the aforementioned improvements in the meteorological models, there have been significant efforts in enabling more realistic urban flood prediction models [40].

4 Impacts of a future climate

In 2007, half of the world's population lived in urban areas, and by 2050, it is estimated that 66% of the world's

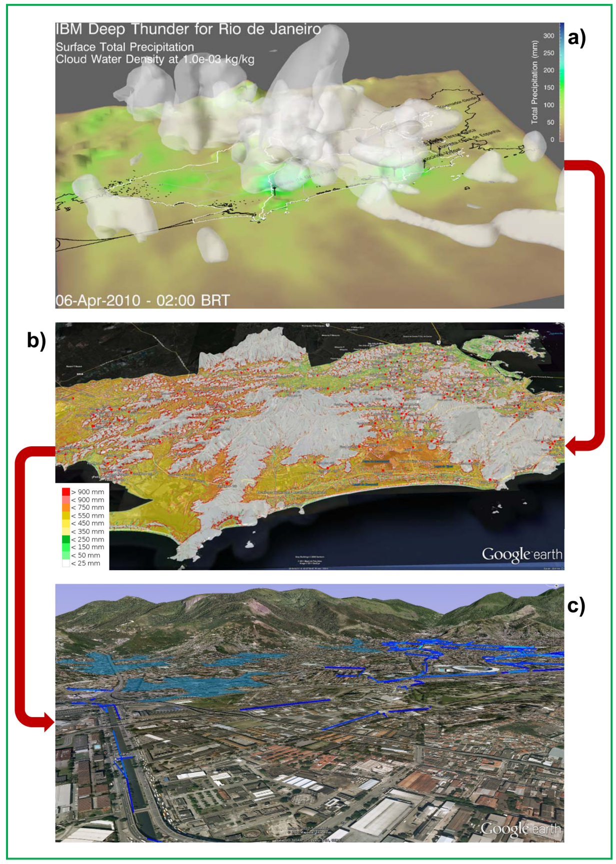

Figure 4

Coupled model example from precipitation prediction in Rio de Janeiro to impacts of flooding on traffic. (a) Clouds and precipitation. (b) Water level. (c) Traffic flow rate.

population will live in urban areas [41]. The effect of climate change will be experienced to a greater extent in cities compared with the surrounding rural areas given expected increases in temperature and the vulnerability of the environment to more extreme weather events. In a recent article, Tewari et al. studied the interaction of urban heat island and heat waves under current and future climate conditions and found that urban heat island intensity during heat-wave periods and in a warmer climate gets amplified in two large and growing U.S. metropolitan areas [42]. Specifically, they found that the intensity is increased by 21% in Phoenix, AZ, USA, and 48% in New York City for the 2070–2090 period.

Alfieri et al. studied the changes in the observed climate extremes in global urban areas [43]. Using observed station data for 217 urban areas across the globe, they showed that these areas have experienced a significant increase in the number of heat waves during the period 1973–2012, whereas the frequency of cold waves has declined.

Furthermore, the changing climate is leading toward an increase in the frequency of flood peaks. Estimates point toward an average doubling of severe flood peaks with a return period of 100 years within Europe by 2045 [44]. Among many examples, consider that in December 2015, there was unprecedented flooding in the Chennai region of India as a result of heavy rainfall. The lack of warning had a significant impact on the population, especially for those with disabilities [45].

Portions of Houston, TX, USA, were submerged in more than 1.5 m of water after Hurricane Harvey's landfall in August 2017. Trenberth et al. [46] showed that before the beginning of the northern hemisphere summer in 2017, ocean heat content (OHC) was the highest on record globally and in the Gulf of Mexico. The high OHC increased energy in the atmosphere via ocean evaporative cooling, which was available to sustain and intensify Hurricane Harvey. It also increased the rainfall as observed on land due to Harvey. They attributed this large amount of rain to a warmer climate.

Given what occurred in Houston due to Harvey, Shapiro et al. [47] analyzed the vulnerability associated with four other low-lying U.S. cities: New Orleans, LA; Tampa, FL; New York; and Miami, FL. Shortly after its publication, Hurricane Irma battered parts of the U.S. mainland and the Caribbean. It was a Category 5 storm when it made landfall on Barbuda on September 6, 2017. Its winds were 220 km/h for 37 h. Tropical-storm-force winds extended 220 km from the center. Its coastal storm surges were 6 m above normal tide levels [48].

One such catastrophic event, Phailin, and its modulation under climate change in the Bay of Bengal was studied by Mittal et al. [49]. Phailin, which made a landfall around 18:00 UTC on October 12, 2013, was the most intense cyclone to make landfall in India since 1999 (equivalent to a Category 5 Atlantic storm). It caused $700 million in damage in the state of Odisha. Mittal et al. [49] found that Phailin (in a future climate) will have a deeper core and expanded size. This would lead to a higher damage potential compared with the present day.

When such large tropical systems make landfall in coastal urban regions, they amplify the vulnerabilities of a population living there. Thus, coastal areas and the infrastructure required for their safety and livelihoods need more attention in the light of climate change and increased urbanization. In their work on future intensification of hourly precipitation extremes, Prein et al. [50] showed that precipitation is increasing with temperature in moist, energy-limited environments and decreases abruptly in dry, moisture-limited, environments. Frequencies and intensities of extreme weather events directly affect settlement vulnerability. When combined with rapid urbanization, these factors also influence urban resilience to climate-related hazards. Chow [51] examined how urban resilience can be maximized in the context of extreme hydroclimatic events (i.e., droughts and floods), with a specific case for Singapore. Willems et al. [52] provided a review of the state-of-the-art methods for assessing the impacts of climate change on precipitation at the urban catchment scale. In their work, they discussed the need for downscaling from global circulation models or regional climate models to urban catchment scales. For urban drainage studies, climate models are not able to accurately describe the rainfall process because the information is needed at a very high temporal and spatial resolution. They also discussed some of the difficulties of climate change impacts at these local scales, such as 1) the inaccuracies of climate model simulation results for short-duration extreme rainfalls at a local scale; 2) the necessity of empirical statistical downscaling methods, and the uncertainties involved in this process; and 3) the difficulties of identifying climate change trends in historical series of rainfall extremes because of short- and long-term persistence.

Some of these challenges in modeling the future climate and its impacts can be addressed by using the pseudo-global warming (PGW) method, where one can dynamically downscale from the climate models by adding a climate signal to the current high-resolution analysis of the atmosphere for the future period of interest. As discussed in [53], the climate perturbation's primary impact is on the large-scale planetary waves and associated thermodynamics, whereas the weather patterns entering the domain boundary remain structurally identical in simulations in terms of frequency and intensity. The weather events, however, can evolve within the regional model domain due to the altered planetary flow and thermodynamics as demonstrated in [42] and [49]. Since this approach resolves relevant physical processes (e.g., precipitation, orographic, or urbanization influences), it helps to address limitations with other downscaling techniques or using bias-corrected global climate models. Other issues with the inherent biases of climate models can also be addressed, to some extent, by generating the perturbation from ensemble means derived from several climate models.

Figure 5 illustrates how we can combine the approach used for operational prediction of severe weather impacts on urban environments to estimate potential impacts in a future, warming climate via the PGW method as well as to evaluate mitigation and resiliency strategies. Historic weather events provide the appropriate context. In step 1, a climate signal (i.e., as perturbations) is derived from global climate model(s) and combined with reanalysis to force a regional or local weather model for the event of interest. In this case, we apply the approach used for Deep Thunder in urban applications. To evaluate the quality of the model, the same configuration is used without the climate signal in

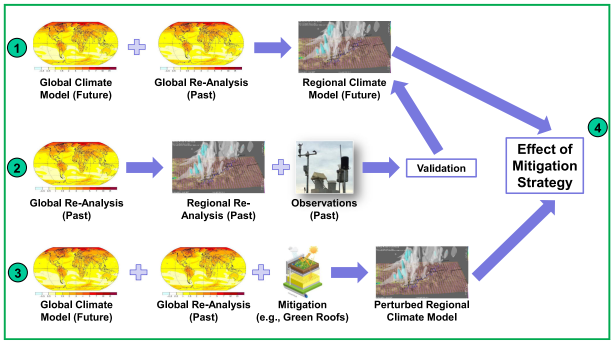

Figure 5

Data flow and processes to apply the pseudo-global warming (PGW) method to estimate future climate states.

step 2 and verified against historical observations. To evaluate the effectiveness of proposed changes to the urban environment to reduce the intensity of an urban heat island, step 3 is taken. The changes are imposed in the specification of land use and the urban canopy, for example, for the model run in step 1. In step 4, the results from steps 1 and 3 are compared to evaluate the effect of the mitigation strategy.

As a step toward such objectives, consider the discussion in Section 3.2 concerning the devastating impacts of post-tropical cyclone Sandy. The risks from such severe events are expected to increase due to climate change, which could result in more frequent infrastructure impacts, including water and transportation systems and power grids. Yates et al. [54] used a scenario-based approach to examine the impact of warmer atmospheric, soil, and sea surface temperature to investigate how these parameters would affect a Sandy-like storm in a future, warmer climate. A 2090 scenario showed that such a storm could make landfall in western Long Island, where there is more widespread rainfall, up to 4 cm for the 24-h period of the simulations. In their study, they performed a storm surge analysis and found that maximum water levels computed for future simulations of Sandy are significantly higher than the actual levels recorded in some areas of the New Jersey and Long Island coasts with significant damage to electric utility infrastructure. Lackmann [55] studied structural changes to Sandy for past and future climates by developing a dynamically downscaled ensemble. Wanik et al. [56] also revisited Sandy's impact in Connecticut, leveraging their outage prediction work referenced earlier [29]. They included estimations of population growth for a 2100 scenario, but did not assume any changes to the distribution system infrastructure. They found significant increases in power outages due to changes in intensity from a Sandy-like storm in a future, warmer climate.

5 Conclusion and future work

Given the increased risk over time and higher frequency of major environmental events, it is of utmost importance for those organizations responsible for critical services in urban population centers to proactively manage and recover quickly from environmental impacts. Cities in the twenty-first century are facing a growing challenge due to climate change because of the expected increase of urban disasters [57]. A critical aspect of meeting this challenge in planning and response is stakeholder communication. Expected actions must be communicated proactively and well in advance so that planners, responders, the general public, and other stakeholders can adequately prepare. That is only possible with the availability of highly localized and accurate environmental (weather, hydrological, and impact) forecasts coupled with decision support tools. While these actions tend to be relatively short-term and tactical, the capability to support them is a long-term goal because of the impacts of a warming planet, especially in urban areas.

The use of coupled predictive environmental models can be a critical asset for improving the efficiency and effectiveness of planning and response to urban weather and climate impacts. This includes weather predictions focused on metropolitan areas coupled to data-driven, stochastic, and other impact models to forecast the environmental impacts. We have presented the rationale for an integrated approach to such coupled modeling, and the issues that need to be addressed for a viable implementation. This includes the design of the systems and the underlying numerical weather prediction that support both hindcasting and forecasting. The approach also addresses methods to extract key spatial–temporal features to drive the coupled models such as an abstraction of the weather forecasting component. While we have focused on only a few use cases whose relevance is increasing due to changing climate, namely flooding [45, 50–52] and disruption of the electrical grid [58], the methodology applies to other applications in the urban environment. From a deployment perspective, characterization of issues such as calibration of data and quantifying uncertainty as well as the challenges for broader scalability must be addressed.

Future work will focus on the integration of coupled models and computing systems to meet the growing need for more effective urban planning and response to environmental impacts, and to enable advanced approaches as outlined above to be deployed. These approaches must necessarily leverage a diversity of models, data, and applications along with increased spatial and temporal fidelity in a scalable framework in order to meet current and future needs.

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