A Computational Framework for Modelling and Analyzing Ice Storms

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Abstract

Ice storms are extreme weather events that can have devastating implications for the sustainability of natural ecosystems as well as man made infrastructure. Ice storms are caused by a complex mix of atmospheric conditions and are among the least understood of severe weather events. Our ability to model ice storms and characterize storm features will go a long way towards both enabling support systems that offset storm impacts and increasing our understanding of ice storms. In this paper, we present a holistic computational framework to answer key questions of interest about ice storms. We model ice storms as a function of relevant surface and atmospheric variables. We learn these models by adapting and applying supervised and unsupervised machine learning algorithms on data with missing or incorrect labels. We also include a knowledge representation module that reasons with domain knowledge to revise the output of the learned models. Our models are trained using reanalysis data and historical records of storm events. We evaluate these models on reanalysis data as well as Global Climate Model (GCM) data for historical and future climate change scenarios. Furthermore, we discuss the use of appropriate bias correction approaches to run such modeling frameworks with GCM data.

1 Introduction

Ice storms are extreme weather events that can cause extensive and permanent devastation to ecosystems, infrastructure and life. They are characterized by freezing rain causing ice to glaze over exposed surfaces such as roads, power lines and tree branches. They are not necessarily high precipitation (rainfall) events; even small amounts of ice accumulation can increase the branch weight of trees by up to one hundred times its actual weight. The same applies to power lines and even larger communication towers. Ice deposited on tree branches can lead to severe destruction of local ecosystems, and fallen tree branches can damage life and property, as well as obstruct essential pathways and roads. Severed power lines have been responsible for extended power outages, with significant damage to infrastructure and in some cases even resulting in human casualties [Jones and Mulherin, 1998]. Accidents due to icy road conditions also contribute to property loss and the loss of human lives. Losses from the 1998 ice storm that affected north eastern USA and south eastern Canada were estimated at 6.2 billion U.S dollars with less than one half of the amount insured. More than four million people were left without power and about 40 people lost their lives due to icy roads and lack of essential services. Combined losses due to ice storms in recent years amount to billions of dollars in measurable losses [Gyakum and Roebber, 2001]. To plan and prepare for ice storm impacts, stakeholders need to understand how the prevalence, duration and intensity of storms may change in the future, which proves challenging for several reasons. First, there is insufficient scientific understanding of anything other than the basic physical atmospheric processes that cause ice storms [Kunkel et al., 2013]. We can study storms in the past to improve our understanding about storms, but historical storm record accuracy and availability vary according to factors such as population density and infrastructure distribution [Cutter and Finch, 2008]. For instance, ice accumulation information in sparsely populated or heavily forested areas may not be recorded with as much rigour as metropolitan areas. Furthermore, databases that record storms and other extreme events typically suffer from reporting biases, often resulting in incomplete and disparate information [Gall et al., 2009]. Finally, any information learned from past records will have to be considered in the context of future change to provide similar information about ice storms in the future.

1.1 Problem Definition

In this paper, we propose a holistic framework to address the challenges arising from inadequate ice storm data and domain expertise, and to provide relevant information about ice storm occurrences in the future. We use historical records of ice storms from storm databases and information about atmospheric variables (e.g., temperature, humidity etc.) on storm and non-storm days from gridded reanalysis data. Reanalysis is an approximation of observed weather data generated by a weather model constrained by observations, which we use to learn models that explain ice storm behaviour. We then use Global Climate Model (GCM) simulations to evaluate our
learned models and develop ice storm projections under future scenarios. Our framework addresses relevant aspects of ice storms and how they may change in the future as follows:

- **Ice storm prevalence, including frequency of occurrence**: we build a storm detector using historical storm data records and large scale, relatively coarse surface and upper atmospheric conditions accompanying the historical storms.

- **Ice storm intensity**: we characterize storm features such as intensity by matching salient features of objectively identified storms (in simulated GCM data) with those of historical storms using an hierarchical agglomerative clustering algorithm.

- **Ice storm information for the future**: we develop appropriate bias correction approaches to make any models learned on historical reanalysis data compatible with simulated GCM projections for the future.

- **Domain knowledge representation**: we develop a module that facilitates the incorporation of newly acquired domain knowledge to further refine our modelling outputs.

While we provide experimental results for a specific natural phenomenon (iceshocks) occurring in a particular region northeastern continental USA in this paper, our framework can be adapted for similar extreme weather events and different geographic locations. Furthermore, we illustrate the interdisciplinary nature of our work and show how machine learning and AI methods can be adapted to formulate and address a key problem in climate science and resilience planning.

## 2 Related Work

A study of the temporal and spatial distribution of freezing rain events associated with ice storms in the contiguous USA show that about half these events occur in the northeastern region [Changnon, 2003]. The national maximums were found to be in New York and Pennsylvania, as a result of storm-favorable weather conditions. [Rauber et al., 2001] study typical atmospheric patterns, including those associated with topography, that cause most storms in the north and southeastern regions of the USA. Their key findings include the fact that the vertical temperature profile and surface and upper air wind directions were characteristic of the overall archetypical storm patterns. [Castellano, 2012] studied the atmospheric conditions associated with northeastern ice storms, including synoptic scale movement of moisture and temperature. These analyses are all grounded in observational data at relatively high spatial and temporal resolutions. Currently, ice storm forecasts are calculated by feeding this data into computationally intensive weather models that produce composite maps which are then subjectively analyzed by domain experts. The necessity for both high resolution data and human subject experts is further compounded by the question of how these ice storms will be affected by changing climate patterns in the future. According to the Intergovernmental Panel of Climate Change’s recent report, milder winter temperatures in the future could cause an increase in freezing rain, especially if average daily temperatures fluctuate about the freezing point [Field et al., 2012]. Global Climate Models (GCMs) use the laws of physics to simulate atmospheric circulation patterns, and are capable of generating three-dimensional projections for different atmospheric variables under varied future climate scenarios [Taylor et al., 2012]. GCM simulations generate these projections at coarser spatial (250km vs 32km) and temporal (daily vs hourly) resolutions than observed data. [Cheng et al., 2011] use a process called statistical downscaling to combine observations with GCM output to generate higher resolution projections, and apply the resulting output fields to study changes in future occurrences of ice storms in Canada. More recently, advanced machine learning techniques such as deep networks have been used to understand extreme events such as tropical cyclones and weather fronts by studying large synoptic scale patterns [Liu et al., 2016] as well as for generating higher resolution data to study these extreme events [Vandal et al., 2017]. As far as we are aware, [Swaminathan et al., 2015] are the only others who attempt to objectively identify large synoptic scale patterns for ice storms using advanced machine learning algorithms. However, their choice of climate variables was incompatible with many GCMs and so cannot be used in ensemble model experiments for future scenarios. Furthermore, their experiments were restricted to historical reanalysis output, and do not discuss integrating domain knowledge or identifying other storm characteristics of interest.

## 3 Modeling Framework

We present an overview of our ice storm modelling framework in Figure 1. The framework includes an Input Preprocessing stage which includes (at the minimum) extracting dates from a storm data base, acquiring Global Climate Model and reanalysis data, and regridding the data to appropriate resolutions. The Storm Detection and Clustering modules are for finding ice storms and understanding storm characteristics. The Knowledge Based Reasoning module is currently linked only to the Storm Detection step but can potentially add information to the Clustering process too. We get two main outputs: storm projections and storm characteristics, which can be further analysed to get information such as storm frequency, duration and seasonality.

### 3.1 Ice Storm Detection

The first component of our ice storm modelling framework is a storm detector that learns from historical storm data to recognize patterns when presented with relevant atmospheric conditions. Our geographic region of interest is the northeastern continental USA from eastern Ohio across to Maine, and to Virginia in the south. To identify synoptic or large scale patterns that may indicate ice storms, we look at atmospheric variables between 55°N to 24°N and 50°W to 94°W for the winter months from October to April. We combined this information with historical records of storm events from the National Climatic Data Center’s Storm Data database [NCDC, 2018] to learn a storm detection model. We also included storm events from the U.S Army Corps of Engineers’ Damaging Ice Storm GIS database that records storm
footprints as storms progress through different states in the country [USAC, 2018]. A literature survey, as described in Section 2, yielded domain expertise that could then be applied to determine relevant near-surface and upper atmospheric (at various pressure levels above the earth) variables that could potentially indicate the presence of an ice storm in the region. The features we use in our model are: geopotential height or the gravity-adjusted height of pressure levels at 250mb, 500mb, 700mb and 850mb; temperature and specific humidity at the surface and at pressure levels 700mb and 850mb; and finally wind direction at the surface and at pressure level 850mb. We posed this as a classification problem where the chosen climate variables in a 3-dimensional space are features that interact with each other to either produce ice storm conditions (positive labels) or not (negative labels). Our training dataset consisted of all winter month days in the historical time period 1979-2008, which included both negative days as well as positive days as identified by either the Storm Data database or the Damaging Ice Storm database. Combining these two datasets gave a total of 493 individual days when storms were recorded, with many of the days being part of multi-day storm events; grouping together successive storm days, we find a total of 130 multi-day storm events in the thirty year period. It is important to note that the observational data sources contain known inconsistencies and inadequacies. It is possible that some storms were not recorded if the impacts were not experienced in a well populated zone. In the case of the storm footprint data, the days spanning a storm event may include days where the storm was actually felt in states outside the northeast USA. At this time, the available data does not provide any way to prune out or add to the current list of storms, but we consider these facts when we discuss our results. For the identified storm days, we would ideally use as feature values the actual recorded quantities for the different climate variables. However, since the balloon or radiosonde network that makes these observations is very sparse, we instead use reanalysis data from the NCEP North American Region Reanalysis (NARR) project. NARR was created by taking all observed recordings during the period 1979-2008 and assimilating them into high resolution numerical models to generate a dynamically consistent climate state at each time step [Mesinger et al., 2006]. NARR output is available at 3-hourly intervals each day and at a resolution of 32km, meaning that a single reading would apply to a 32kmx32km grid cell at a certain height or pressure level above the ground. With the number of variables and the geographical area (about 145x147 grid cells) selected for this analysis, this yielded over two million features. Since our models were to be applied to GCM simulations which typically have much coarser resolutions, we computed daily averages and smoothed the data with a 5x5 sub mask to arrive at ~10,000 features.

Ice storms are relatively rare events as reflected in the positive to negative sample ratio; even with using all the winter dates in the selected time period, we had very few training samples relative to the number of features, thereby rendering popular Neural Network [Gardner and Dorling, 1998] or Deep Learning [LeCun, Yann and Bengio, Yoshua and Hinton, Geoffrey, 2015] methods unsuitable for our task. We experimentally determined through cross-validation experiments on the reanalysis data that a Support Vector based classifier implementing a Sequential Minimal Optimization algorithm [Platt, 1998] and a polynomial kernel provided the best classification results.

### 3.2 Bias Correction for GCM Data

Once a storm classification model is learned using reanalysis data, we could potentially use this model to analyze the frequency of such storms in future climate scenarios. As mentioned earlier, Global Climate Model (GCMs) are the primary sources of future climate simulations. They generate consistent gridded output fields for variables and at pressure levels similar to reanalysis, at somewhat coarser spatial resolution, and at daily or sometimes even sub-daily resolution for time periods generally ranging from 1900 to 2100 or beyond. GCM simulations driven by future scenarios of human forcing provide the basis for assessing the potential impacts of human-induced climate change on a broad range of natural phenomena and geographic regions. However, GCMs also exhibit biases or systemic errors in their atmospheric circulation patterns compared to reanalysis, a result of their lower spatial resolution, simplified physics and ther-
modynamic processes, numerical schemes, and incomplete knowledge of physical climate processes [Navarro-Racines and Tarapuces, 2015]. Biases in GCMs relative to observations can be significant, emphasizing the need to bias-correct raw climate model outputs to better mimic observed patterns. Traditionally, standard bias correction methods are applied to a single variable such as temperature or precipitation. In our case, the data is high dimensional. Correcting along each dimension based on observed data will not necessarily result in a bias correction in the high-dimensional space. We therefore implemented bias correction with bootstrap aggregation or bagging on the output obtained by applying the storm detection model to the GCM output fields, rather than the GCM output fields themselves, and obtained final classification labels by consensus voting over all the bootstrap subsets [Friedman et al., 2001]. For comparison purposes, we also ran classification experiments on GCM data with standard bias correction along each dimension. This was done by calculating a six-week average around each individual winter date over a thirty year climatological period for both reanalysis and GCM data. Bias was then computed as $bias = \frac{model-reanalysis}{model}$ and subtracted from the model variable data for each date and each variable.

3.3 Determining Storm Characteristics with Hierarchical Agglomerative Clustering

One of the key pieces of information regarding ice storms that stakeholders care about is storm intensity, or how much of an impact an ice storm event will have. However, this measure tends to be very subjective and frequently unreliable as it depends on presence of infrastructure, type of ecosystem, and population distribution in the areas affected by the storm. The Damaging Ice Storm Data set has text narratives describing the effects of the storm in individual states and counties which makes for a rich depository but requires extensive natural language processing to extract this information in meaningful quantitative ways. We thus decided to focus on the climatological aspects of ice storm events as being a more objective measure of storm strength. We agree with [Rauber et al., 2001] that archetypal storm categories exist, but we do not necessarily know what they are at daily resolution and synoptic scales. We thus frame this as an unsupervised learning problem, where we neither have intensity (or category) labels for each storm event nor have the number of such categories, but are aware that they can be grouped. We cluster known storm features (using ground truth data for recorded historical storm events) with objectively detected storm day features (as obtained from classification experiments). This way we ensure that storm intensity is a scientifically measurable metric, independent of any specific impact analysis, but one that can still be matched to impacts of previously seen storms by looking at which reanalysis storm dates in the historical databases and which positively classified dates are together in each cluster. We use an hierarchical agglomerative clustering algorithm to cluster reanalysis storm day features with GCM projected features as described in [Duda et al., 1973]. From the dendrogram obtained from the clustering algorithm, we determine the optimal number of clusters or categories for the storm events under consideration. Since storm features encode temporal and spatial information, we believe that clustering can give us further insights into these aspects of storm events as well. This is by no means the only approach to clustering or grouping storms, but we use this algorithm to explore the extent to which clustering may improve our understanding about the diversity of ice storm types and impacts.

3.4 Domain Knowledge Representation

The overall goal of our modeling framework is to improve our knowledge and understanding of ice storm events occurring in the northeastern USA. However, as more research goes into studying ice storms, including our own work with this framework, domain expertise in the area continues to improve. We therefore introduced a module in the framework that enables us to add growing domain knowledge, and apply it to refine our outputs such as storm frequency and intensity projections. We draw on well-established knowledge representation and reasoning methods, and adapt them for our application [Brachman et al., 1992]. Our current framework incorporates one such aspect of domain information as a pilot study. Specifically, a visualization of composite maps for the variable geopotential height at pressure level 500 mb and domain knowledge about the influence of this geopotential height on storm conditions was encoded as a rule to detect closed loop contours for this particular variable on storm days. Such closed loop contours represent low pressure systems that are considered to be a strong indicator of storm conditions. In Section 4, we discuss the implications of this rule on analyzing the false positives in our storm detection results to illustrate how domain knowledge can have a significant role to play in climate science domains.

4 Experimental Results

This section summarises the experimental results for each component of our ice storm modelling framework. All GCM results are based on simulations by the GFDL HIRAM high-resolution climate model [Dixon et al., 2016] for the historical period between 1979 and 2008, and for two future time periods (2026-2035 and 2086-2095) under a higher future scenario (RCP8.5) for which the relevant climate variable data is available.

Storm Detection: Table 1 summarizes our ability to detect storms in the reanalysis data, raw GCM data and two kinds of bias corrected GCM data, and compares it to the historical number of storms in the 30 year historical period (which themselves contain known biases, as discussed previously). The two kinds of bias correction performed on the GCM data were the standard and bootstrap method, as discussed in Section 3.4. Bootstrap consensus labelling results in simulated historical storm count numbers very close to the actual storms identified in the reanalysis output, providing a baseline for GCM experiments. Note that standard bias correction does not apply to reanalysis data since there is no bias there to correct. It is also important to note that the storm detection model recognizes more storms in both historical reanalysis and GCM output than were identified in the databases. We attribute this bias to the fact that the ground truth data is known to be incomplete and subject to error and reporting bias.
Interestingly, the standard bias-corrected GCM simulations provide poor results. This indicates that traditional bias correction methods do not work well with the kind of high dimensional data used here, justifying the need for more advanced statistical methods. Table 2 shows results on historical and future GCM scenarios for a ten year period in comparison with the number of actual storms typically observed in a historical ten year period. The number of storm events in the future period are not significantly different from those observed in the past. However, this time period is too short to capture the uncertainty in natural variability and arrive at any definitive conclusions regarding the impact of human-induced warming on the frequency or temporal distribution of ice storms over the northeast USA. Instead, we propose to use an ensemble of multiple GCMs with longer and continuous time series to increase the sample size of the future projections [Tebaldi and Knutti, 2007].

Hierarchical Clustering: Examining the clustering results in Figure 2 also reveals that the cluster distribution of storms identified in the historical GCM simulation closely matches that of the reanalysis data. This suggests, once again, that the GCM is able to simulate a range of, or various types of, events that resemble real-world ice storms to a sufficient extent that the model trained on reanalysis is able to not only identify them but also to group them into similar types of events. We analyzed the cluster compositions in different ways such as the average length of storms in each cluster and the day of storm in each cluster (e.g., did all first days in storm events fall in a single cluster) but did not see strong patterns. However, we noticed that starting from 1979 to 2008, the number of storms shifted across clusters with Cluster 3 seeing an increase in storms. In the two future scenarios, we again notice that Cluster 3 has the highest membership, indicating that we will likely see more storms like the ones in Cluster 3. We then looked up some of the worst ice storms seen in the north eastern USA region from our records collected for this project and an online search. We found that in the list of worst storms to affect the region, almost all (March 1991, January 1998, Dec 2007, April 2003, January 2007, December 2007 and December 2008) were grouped in Cluster 3. We also noted that all the dates that the storm lasted over the northeast USA region were grouped under Cluster 3. In the case of storms with footprints (storm forms in a different region and moves to the northeast), we noticed a trend where the days when the storm was likely outside the region of interest got assigned to a different cluster. This leads us to conclude two things: (i) that we are able to successfully use our hierarchical agglomerative clustering model to capture storm intensity as a reflection of damages and impacts; and (ii) that future storms are likely going to be more intense or fall in the category of worst storms. As in the case of storm detection experiments, we propose to run ensemble runs with multiple GCMs to increase the certainty of our findings. We also noticed that none of the storm events occurring in the month of April were ever assigned to Cluster 1. This could mean that April storms have a specific characteristic that we have not yet been able to determine but we are investigating ways to get domain expert feedback on these storms to understand the significance of the cluster assignment.

Domain Knowledge Representation: Domain experts consider the presence of a low pressure system as a strong, but by no means exclusive, indicator of storm conditions. We conducted a simple experiment where we applied this rule, and found that while the majority of ground truth storm days did contain a closed low pressure system, there were many days that did not (likely because they were part of a multi-day storm footprint tracking event and the low pressure system had either not moved in or already moved out of the study area) and some days that did were not identified as ice storms (because the criteria for ice storms includes very specific surface conditions, notably a warmer layer of air overlying a cooler layer, that are not present in every winter storm). We also found that our storm detection system captured this hidden feature even though it was not explicitly specified and some of the false positives in our result were actually storm days with this low pressure system. By applying this rule to

| Data Set | Oct | Nov | Dec | Jan | Feb | Mar | Apr | Total |
|----------|-----|-----|-----|-----|-----|-----|-----|-------|
| Actual Storm Events | 1   | 6   | 24  | 39  | 28  | 30  | 2   | 130   |
| Raw Reanalysis Data | 3   | 14  | 34  | 54  | 46  | 37  | 5   | 193   |
| Reanalysis (bootstrap) | 1   | 6   | 21  | 39  | 27  | 29  | 4   | 127   |
| Raw GCM Data | 5   | 15  | 54  | 80  | 79  | 58  | 24  | 315   |
| GCM Data (standard) | 4   | 53  | 61  | 102 | 89  | 58  | 18  | 385   |
| GCM Data (bootstrap) | 0   | 8   | 32  | 57  | 53  | 39  | 9   | 198   |

Table 1: Storm events detected with the support vector based classification model for the period 1979-2008. Results are shown on GCM and reanalysis data with bias corrected data rows highlighted in grey. We show bias correction results using both standard and bootstrap methods with the GCM data.

| Data Set | Oct | Nov | Dec | Jan | Feb | Mar | Apr | Total |
|----------|-----|-----|-----|-----|-----|-----|-----|-------|
| Actual Storm Events (historical) | 0.33 | 2   | 8   | 13  | 9.33| 10  | 0.67| 43.33 |
| GCM Data (historical) | 0   | 2.7 | 10.67| 19  | 17.67 | 13  | 3   | 66   |
| GCM Data (2026-2035) | 1   | 1   | 8   | 15  | 27  | 12  | 2   | 66   |
| GCM Data (2086-2095) | 0   | 4   | 15  | 18  | 15  | 8   | 2   | 62   |

Table 2: Storm events detected with the support vector based classification model. Results are shown for historical GCM data averaged for a ten year period and two future ten year scenarios. All classification labels were bias corrected using bootstrap aggregation.
the output of the storm detection module, we were able to explain our so-called false positives. Adding more such rules can help prune out or add confidence to our classification outputs. We implemented this module as a pilot study and we see that it can be applied as a pre-processing step to improve the quality of ground truth data or as a post-processing step to further refine our framework outputs.

5 Contributions

The ice storm modelling framework described in this paper addresses a challenging and complex problem in environmental science that has significant sustainability implications to our society. We answer key questions regarding ice storms that are relevant to stakeholders who undertake impact analysis projects. Climate and environmental sciences offer novel and challenging problems in terms of data complexity, uncertainty quantification at never seen before scales of data. Our framework illustrates that successful solutions to such problems must involve the application of interdisciplinary domain expertise and carefully tailored solutions to different aspects of the whole problem by posing the right questions instead of simply applying standard machine learning approaches. This framework can also be readily generalized to other geographic locations in the world and even to understand similar synoptic scale weather events such as hurricanes. We show that important features of such events like the formation of a lower pressure system in ice storms can also be captured without being explicitly modelled. Finally, we also show that domain knowledge can be used in conjunction with statistical methods to add value to research solutions in such complex domains.

Threats to Validity The process of modelling complex weather phenomena and making future projections or predictions is made challenging by many factors. First, ground truth data used for training or learning models can be inaccurate, inadequate and incomplete. Second, models learned with high resolution observed and reanalysis data introduce a bias when applied on GCM data. Third, is the issue of non-stationarity where the relationship between historic climate model and observed variables will evolve over time and we do not have the ability yet to forecast this effectively. Finally, though GCMs are our primary source for future climate projections, they are only approximations of the physical equations representative of atmospheric processes and are further limited by computational constraints. Each stage in the process adds uncertainty and noise and it is therefore important for us to be aware of them when using the outputs of the framework.

5.1 Future Work

We believe that the work done so far on this project provides a broad-based platform to pursue further research in several directions. First, we need to integrate an ensemble of GCMs with such frameworks to reduce climate modelling uncertainties and capture the range of possibilities under various possible future scenarios. We would like to see if the knowledge representation module can be used to improve the quality of our ground truth so we can get better projections for the future. Our clustering results can be further explored to investigate different aspects of the storms such as geographic locations or length of storms which are all important factors to improve our understanding of ice storms. Finally, we would like to adapt this framework to study ice storms in other geographic regions and other similar weather phenomena.

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