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Machine Learning-Based Disaster Modeling and High-Impact Weather Event Forecasting

Abstract

Machine learning-based disaster modeling and high-impact weather event forecasting are provided herein. Embodiments herein provide a flexible machine-learning platform for providing skillful forecast of severe weather (tornadoes, damaging wind gusts, and hail), tropical cyclone activity, and precipitation, with skill, extending to multiple months or more.

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Background/Summary

CROSS-REFERENCE TO RELATED APPLICATION(S) [0001] This application is a continuation-in-part of U.S. non-provisional application Ser. No. 17/746,845 filed on May 17, 2022, and claims the benefit and priority of U.S. application Ser. No. 17/728,858, filed on Apr. 25, 2022, is also a continuation of U.S. patent application Ser. No. 16/455,121, filed Jun. 26, 2019, now U.S. Pat. No. 11,315,046, issued on Apr. 26, 2022, which also claims the benefit and priority of U.S. Provisional Application Ser. No. 63/442,578, filed on Feb. 1, 2023, U.S. Provisional Application Ser. No. 63/612,857, filed on Dec. 20, 2023, U.S. Provisional Application Ser. No. 63/189,319, filed on May 17, 2021, which also claims the benefit and priority of U.S. provisional application Ser. No. 62/691,462, filed on Jun. 28, 2018; U.S. provisional application Ser. No. 62/702,547, filed on Jul. 24, 2018; U.S. provisional application Ser. No. 62/703,380, filed on Jul. 25, 2018; U.S. provisional application Ser. No. 62/703,387, filed on Jul. 25, 2018; U.S. provisional application Ser. No. 62/744,028, filed on Oct. 10, 2018; and U.S. provisional application Ser. No. 62/797,261, filed on Jan. 26, 2019, each of which are each hereby incorporated by reference herein in their entireties, including all references and appendices cited therein, for all purposes.

TECHNICAL FIELD
[0002] The present disclosure relates to machine learning, and in some embodiments, to machine learning-based methods of disaster modeling, high-impact weather event analysis, including extended range forecasting of the same.

BACKGROUND
[0003] Skillful and accurate extended-range forecasts of severe weather are currently unavailable and may potentially provide value to a wide range of professions (e.g., insurance, reinsurance, and underwriting) and government agencies (e.g., U.S. Military, Federal Emergency Management Agency). Professionals in these fields generally use long-term averages of severe weather frequency to assess risk and plan for disasters. For the insurance industry, this approach potentially exposes these industries to losses in excess of billions of dollars in the event of extreme weather conditions that deviate from those longer-term averages (i.e. hail storms, tornado outbreaks, tropical cyclone landfalls, extreme rainfall, ice storms, etc.). Many severe weather forecasts are skillful through three to seven days, although this doesn't provide enough time for professionals to properly alter their risk management strategy in advance of unusually severe or extreme weather conditions. These limited time frames also complicate federal disaster preparation efforts, and endanger the lives of countless individuals.

[0004] Extended-range predictions of severe weather (to monthly and even yearly timescales) do not exist at this time. Sparrow and Mercer (2015) used El Niño Southern Oscillation and

geopotential height variability, stepwise multivariate linear regression, and support vector regression to diagnose predictability of U.S. winter tornado seasons. Nath et al. (2015) also developed and described a model using neural networks to predict seasonal tropical cyclone activity over the North Indian Ocean.

Description

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] The detailed description is set forth with reference to the accompanying drawings. The use of the same reference numerals may indicate similar or identical items. Various embodiments may utilize elements and/or components other than those illustrated in the drawings, and some elements and/or components may not be present in various embodiments. Elements and/or components in the figures are not necessarily drawn to scale. Throughout this disclosure, depending on the context, singular and plural terminology may be used interchangeably.

[0006] FIG. **1** depicts an illustrative architecture in which techniques and structures for providing the systems and methods disclosed herein may be implemented.

[0007] FIG. **2** is a map comprising an example forecast for a spatial domain, generated using the machine learning processes disclosed herein.

[0008] FIGS. **3**A-**3**B collectively illustrate a flowchart of an example method of the present disclosure.

[0009] FIG. **4**A-**4**C collectively illustrate example two-dimensional domains.

[0010] FIG. **5** graphically illustrates the use of a spatial filtering routine.

[0011] FIG. **6** illustrates a forecast generated for two separate two-dimensional domain spaces.

[0012] FIGS. **7**A and **7**B collectively illustrate maps generated using the machine learning processes disclosed herein, specifically illustrating active and inactive severe weather periods.

[0013] FIGS. **8** and **9** both illustrate underlying grids for creating composite overviews as illustrated in FIGS. **7**A and **7**B.

[0014] FIGS. **10** and **11** each illustrate different long-range forecasts that can be provided in a map format, the forecasts being generated using the machine learning processes disclosed herein.

[0015] FIG. **12** is a map of an example tropical cyclone forecast generated using the machine learning processes disclosed herein.

[0016] FIG. **13**A illustrates a map of a seasonal forecast for a specific type of weather event, the map being generated using the machine learning processes disclosed herein.

[0017] FIG. **13**B illustrates a map of a year-long for a specific type of weather event, the map being generated using the machine learning processes disclosed herein.

[0018] FIG. **14** is a flowchart describing the process of using model backtests and statistical models to generate forecasts.

[0019] FIG. **15** illustrates forecast departures of sea level pressure (SLP) from longer-term climatological averages.

[0020] FIG. **16** illustrates weak surface boundaries and potential cyclone development may occur across the southern tier of the continental U.S. (from Texas to the Carolinas) during a period.

[0021] FIG. **17** illustrates forecast departures of geopotential height from longer-term climatological averages.

[0022] FIG. **18** illustrates forecast departures of surface wind speeds from longer-term climatological averages.

[0023] FIG. **19** illustrates forecast departures of surface temperature from longer-term climatological averages.

[0024] FIG. **20** illustrates domain centerpoints for the irregular domain used to develop a visual representation of monthly forecasts of severe thunderstorm activity.

[0025] FIG. **21** illustrates additional example domain centerpoints.

[0026] FIG. **22** illustrates an example forecast having a probability of 40+thunderstorm wind reports within 75 miles of a point.

[0027] FIG. **23** illustrates an example forecast of 1-1.99 inch hail instances within 75 miles of a point along and east of the Rocky Mountains.

[0028] FIG. **24** illustrates an example spring 2017 seasonal tornado outlook (valid April-June 2017).

[0029] FIG. **25** illustrates an example year-long 2017 tornado outlook (valid January-December 2017).

[0030] FIG. **26** illustrates an example seasonal tornado outlook (valid June-August 2020).

[0031] FIG. **27** illustrates potential customized regions of tropical cyclone forecasts (shaded variously).

[0032] FIG. **28** illustrates additional example potential customized regions of tropical cyclone forecasts (shaded variously).

[0033] FIG. **29** illustrates a forecast spanning multiple latitude bands.

[0034] FIG. **30** illustrates a forecast and feature track of a hail storm with pathcasts that highlight forecast locations of hail in the next hour(s) in increments of minutes.

[0035] FIG. **31** illustrates another example feature track related to a tornado event.

DETAILED DESCRIPTION

[0036] The systems and methods disclosed herein implement machine/deep learning tools to provide skillful weather forecasts around the world. These severe weather outlooks forecast the following severe weather perils at time ranges extending out to 12-13 months: (1) tornadoes (F0-F1) and significant tornadoes (F2-F5); (2) hail (one to two inches in diameter) and significant hail (two+inches in diameter); and thunderstorm wind gusts exceeding severe thresholds (50 knots or greater)—just to name a few. Additional embodiments enable forecasts of any weather for which (1) there is a reliable historical record of occurrence or (2) their occurrence can be implied through the use of weather observations or dynamical models. These include tropical cyclones, precipitation (such as rainfall, ice accumulation, and snowfall), dust storms, and heatwaves, surface wind, temperature, derivatives of temperature (such as heating degree days, cooling degree days), model radar reflectivity, and radar observations—just to name a few. While specific examples of weather events of importance have been described in examples herein, the present disclosure is not specifically limited to these example weather events. Moreover, when example attributes of weather events such as tornado strength are referenced, these are merely examples of weather event attributes that can be selected for analysis according to the present disclosure. For example, if a use case references forecasts for tornadoes having up to F1 strength, other example could include forecasts for tornadoes of any of F0 to F5 strength, inclusive.

[0037] Embodiments of the present disclosure extend the predictability of weather forecasts with demonstrated skill through 13 months and even further in some instances. Machine and deep learning models generally require past data in order to identify patterns and relationships in that data before predicting outcomes. The present disclosure identifies relationships between historical atmospheric and oceanic observations and extreme weather events and subsequently uses those relationships to forecast occurrence, frequency, and concentrations of various extreme weather events through the use of machine or deep learning. These relationships are utilized to create meaningful and practical disaster models and provide long-term prediction of significant weather events into the future.

[0038] In one embodiment, the systems and methods herein are configured to generate an L-model, which identifies relationships between historical atmospheric and oceanic data and historical severe weather reports to generate forecasts of tornadoes, hail, and severe thunderstorm wind gusts. In another embodiment, relationships between tropical cyclone frequency and historical atmospheric and oceanic conditions are identified and used to create tropical cyclone forecasts. In yet another

embodiment, relationships between precipitation and historical atmospheric and oceanic conditions are used to create precipitation forecasts. The forecasts developed using the systems and methods disclosed herein can span various timeframes ranging from a few minutes to one year or more. In various embodiments, forecasts can be created for meta-time periods, such as seasons, years, or even decades.

[0039] The present disclosure can be configured to predict various hazards which include, but are not limited to, sea ice development, sea ice melt, dust storms, fire weather, surface wind, and open-water wave activity. These and other advantages of the present disclosure are provided in greater detail herein.

[0040] Turning now to the drawings, FIG. **1** depicts an illustrative architecture **100** in which techniques and structures of the present disclosure may be implemented. The illustrative architecture **100** may include a machine learning service **102**, a user terminal **104**, and a plurality of data resources **106**A-**106**N, which are coupled through a network **108**. The network **108** may include any one or a combination of multiple different types of networks, such as cable networks, the Internet, wireless networks, and other private and/or public networks. In some instances, the network **108** may include cellular, Wi-Fi, or Wi-Fi direct.

[0041] In various embodiments, a user of the user terminal **104** can create and execute machine learning models (such as the L-model) through use of the machine learning service **102**. In general, the machine learning service **102** leverages big weather data available through the plurality of data resources **106**A-**106**N, based on the weather related data required to power the machine learning models created by the machine learning service **102**. In one or more embodiments, the machine learning service **102** is implemented in a cloud-based resource, while other embodiments allow for the machine learning service **102** to be executed at a server level. FIG. **2** illustrates an example predictive model **110** created by the machine learning service **102**. The predictive model **110** is provided on a graphical user interface in the form of a map that comprises F1 tornado outlook data, generated using the systems and methods disclosed herein, to create an outlook or forecast valid for April of 2017. The forecasts are concentrations of tornadoes within roughly 75 miles of a point of reference along and East of the Rocky Mountains.

[0042] Generally, the systems and methods herein are used for creating forecasts of high-impact weather phenomenon, including temperature, tornadoes, hail, thunderstorm wind gusts, tropical cyclones, and precipitation (hereafter referred to as predictands), as well as predicting and modeling disasters. Some embodiments are also provided to aid in detailed description of the processes disclosed herein, although the plurality of embodiments are not limited to the embodiments disclosed.

[0043] FIGS. **3**A and **3**B are flowcharts of example modeling methods for creating a predictive forecast and/or a disaster model in accordance with the present disclosure. Initially, the method includes a step **302** of specifying a spatial domain of for creating a desired forecast using machine learning. In various embodiments, a two-dimensional domain is selected for forecast output. This selection is may depend on a desired forecast and can vary in size. These sizes can range from a 0.25° latitude by 0.25° longitude bounding box to an entire country (i.e., the United States) or ocean basin (i.e., the Atlantic basin). FIG. **4**A illustrates an example map **402** that includes an example two-dimensional domain **404**. Another example two-dimensional domain **406** is illustrated on map **408**. Yet another example two-dimensional domain **410** is illustrated on map **412**. Thus, a two-dimensional domain can include any bounded area. While some embodiments contemplate developing forecasts over an entire ocean basin, certain embodiments/forecasts can also expand to entire continents or even in localized areas as fine-scale as 1 km by 1 km (precipitation) or a single point.

[0044] In some embodiments, two-dimensional domain sizes ranging from three degrees latitude by three degrees longitude bounding box to a five degrees latitude by five degrees longitude bounding box can be used for severe weather. It will be understood that the bounding box may have

any desired shape or size. The bounding box can be any polygonal shape. In certain embodiments, forecasts can be created for a specific point instead of a domain, specified region (i.e., city or state), or bounding box. In other embodiments, forecasts can be created along the path of a specific weather event (i.e., tornado, hail swath, wind swath, or tropical cyclone). For tropical cyclone forecasts, varying sizes of spatial domains can be employed depending on the desired forecast output. For instance, in tropical cyclone landfall forecasts, the spatial domain may encompass regions near a specific coastline (see map **412**) or specified over oceanic regions or for entire ocean basins. For precipitation forecasts, a two-dimensional domain may encompass much smaller regions (i.e., 0.25° latitude by 0.25° longitude bounding box).

[0045] Referring back to FIG. **3**, the method includes a step **304** of determining historical atmospheric and oceanic data. This process can be performed by the machine learning service **102** by obtaining data from the plurality of data resources **106**A-**106**N (see FIG. **1**).

[0046] Examples of weather data that can be obtained from the plurality of data resources **106**A-**106**N are provided herein. For example, historical atmospheric and oceanic observations and reanalyses can be used to train machine learning models to generate forecasts. Atmospheric reanalyses developed during the NCEP/NCAR Reanalysis project (as described in Kalnay et al., 1996) can be utilized. This global dataset is defined on a 2.5° longitude by 2.5° latitude grid with 28 vertical levels. These reanalyses are available dating back to 1948. Specific variables retrieved and/or derived from these analyses for model development include but are not limited to: geopotential heights, geopotential height variance, v-component wind, v-component wind variance, u-component wind, u-component wind variance, specific humidity, specific humidity variance, precipitable water, precipitable water variance, temperature, and temperature variance.

[0047] In another embodiment of the invention, atmospheric reanalyses created by the European Center for Medium-Range Weather Forecasts (ERA-interim, ERA5; website at cds.climate.copernicus.eu, web page at confluence.ecmwf.int/display/CKB/ERA5%3A+data+documentation) can be utilized for training models and generating forecasts. In another embodiment of the invention, NCEP/DOE reanalysis data (web page at psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html) can be utilized for training models and generating forecasts.

In another embodiment of the invention, data from the 20th Century Reanalysis project (web page at psl.noaa.gov/data/20thC_Rean/) can be utilized for training models and generating forecasts. In another embodiment of the invention, data from the North American Regional Reanalysis (web page at psl.noaa.gov/data/narr/) may be utilized for training models and generating forecasts.

[0048] Sea surface temperature reanalyses can be retrieved from the National Oceanic and Atmospheric Administration's Extended Reconstructed Sea Surface Temperature analysis (ERSST v.4; Huang et al. 2014) in a similar manner as atmospheric data described earlier in this step. The monthly analyses are available on a 2° longitude by 2° latitude grid over ocean areas dating back to 1854. In another embodiment, both atmospheric and sea surface temperature information can also be used simultaneously for developing models and generating forecasts. In other embodiments, larger-scale oscillations influencing global weather could also incorporated for training models. These larger-scale oscillations include the El Niño Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), Arctic Oscillation (AO), Pacific-North American teleconnection pattern (PNA), Madden-Julian Oscillation (MJO), Global Atmospheric Angular Momentum (GLAAM), Global Wind Oscillation (GWO), East Atlantic Pattern (EA), West Pacific Pattern (WP), East Pacific/North Pacific Pattern (EP/NP), East Atlantic/West Russia Pattern (EA/WR), Scandinavia pattern (SCA), Tropical/Northern Hemisphere Pattern (TNH), Polar/Eurasia Pattern (POL), and Pacific Transition Pattern (PT). Standardized indices characteristic of these larger-scale atmospheric and oceanic oscillations are archived online by the NOAA Climate Prediction Center (website at www.cpc.noaa.gov) and NOAA Earth Systems Research Laboratory (web page at www.esrl.noaa.gov/psd/). Monthly Global Atmospheric Angular

Momentum (GLAAM) and Global Wind Oscillation (GWO) indices can be made available via Climate Prediction Center and Earth Systems Research Laboratory archives and also calculated using reanalyses from the NCEP/NCAR Reanalysis project. A few of these large-scale oscillations have known influences on severe weather in the United States, including ENSO (Cook and Schaefer 2008, Allen et al. 2015, Cook et al. 2017), GWO (Gensini and Mariano 2015), PNA, PDO, and NAO (Muñoz and Enfield 2006), and MJO (Barrett and Gensini 2013). Four separate ENSO indices can be incorporated for use in this study: Nino 1+2, Nino 3, Nino 3.4, and Nino 4 (located at: ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/tele_index.nh). In other embodiments of the invention, ENSO can be described using the Oceanic Nino Index, Multivariate Index, the Southern Oscillation index, or any combination of these indices.

[0049] In certain embodiments of the invention, atmospheric and oceanic variables can be derived directly and/or indirectly from radar (i.e., WSR-88D Doppler Radar Level II and Level III data; National Research Council 2002), satellite observations, surface observations (i.e., Automated Field Observations and Services), or any combination thereof. These types of observations are particularly helpful in embodiments where very-high-resolution modeling and/or detection of weather phenomenon is being conducted (e.g., 1 km by 1 km grid resolution or forecasts at a given point.)

[0050] In other embodiments, predictor variables can be explicitly calculated by performing statistical dimensionality reduction (via principal component analysis, canonical correlation analysis, or singular value decomposition) to determine atmospheric and oceanic modes of variability that influence predictor variables. These types of predictor variables are very similar to the large-scale oscillations described above, but can be customized to specific geographic domains known to influence desired predictands. Atmospheric and oceanic data as disclosed above can be used to train models and create forecasts are collectively referred to as "reanalysis data". In more detail, the method includes a step **306** of determining dynamical model forecasts. In some embodiments, dynamical model forecasts may be utilized for training models and creating forecasts in a similar manner to reanalysis data as described above. Examples of model forecasts (hereafter referred to as "dynamical data") include (but are not limited to) output from the following forecast systems: NOAA Climate Forecast System Operational Forecasts (Saha and Coauthors 2010, 2014); Global Forecast System (web page at www.emc.ncep.noaa.gov/index.php?branch=GFS); Global Ensemble Forecast System (Zhu et al., 2018; website at www.emc.ncep.noaa.gov/emc/pages/numerical_forecast systems/gefs.php); Rapid Refresh (RAP) and High Resolution Rapid Refresh (HRRR) model (Benjamin et al. 2016); and Weather Research and Forecasting Model (Skamarock et al. 2008)

[0051] North American Mesoscale Forecast System (web page at ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-mesoscale-forecast-system-nam); North American Multi-Model Ensemble (Kirtman et al., 2014); and General Circulation Models, including The Community Climate System Model (CCSM4), Community Earth System Model (CESM1), The Canadian Coupled Climate Model (CanCM4)—all available at the National Center for Environmental Information (web page at ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-multi-model-ensemble). Additional examples include General Circulation Models archived as part of the World Climate Research Programme's Coupled Model Intercomparsion Project (CMIP). Various phases of CMIP include models data with experiments designed to assess the influence of varied degrees of greenhouse gas concentrations on climate while also assessing model accuracy and adding and/or removing various forcings (i.e., sea surface temperatures (web page at esgf-node.llnl.gov/projects/cmip5/; esgf-node.llnl.gov/projects/cmip6/). These models are also referred to as Community Climate System Model experiments in later steps.

[0052] Additional output from dynamical models can also be leveraged for generating forecasts in various embodiments of the invention and are publicly available at the NOAA Operational Model Archive and Distribution System (NOMADS; web page at nomads.ncep.noaa.gov). These forecast

systems include the High Resolution Ensemble Forecast (HREF; web page at nomads.ncep.noaa.gov/txt_descriptions/HREF_doc.shtml), Short Range Ensemble Forecast (SREF; web page at nomads.ncep.noaa.gov/txt_descriptions/HREF_doc.shtml), Real Time Mesoscale Analysis (RTMA; web page at werp-climate.org/WGNE/BlueBook/2015/individual-articles/01_Pondeca_Manuel_etal_RTMA.pdf), Unrestricted Mesoscale Analysis (URMA; web page at wcrp-climate.org/WGNE/BlueBook/2015/individual-articles/01_Pondeca_Manuel_etal RTMA.pdf), Canadian Global Ensemble Prediction System (web page at nomads.ncep.noaa.gov/txt_descriptions/CMCENS_doc.shtml), Fleet Numerican Meteorology and Ocenaography Ensemble Forecast (web page at nomads.ncep.noaa.gov/txt_descriptions/FENS_doc.shtml), MetOffice Numerical Weather Prediction Models (web page at metoffice.gov.uk/research/modelling-systems/unified-model/weather-forecasting), Near-Surface Sea Temperature (NSST; web page at nomads.ncep.noaa.gov/txt_descriptions/NSST_doc.shtml), Real-Time Ocealn Forecast System (RTOFS; web page at nomads.ncep.noaa.gov/txt_descriptions/RTOFS_global_model_forecast_doc.shtml), Storm Surge and Tied Operational Forecast System (STOFS; web page at nomads.ncep.noaa.gov/txt_descriptions/STOFS_doc.shtml), Probabilistic Hurricane Storm Surge model (P-Surge; web page at nomads.ncep.noaa.gov/txt_descriptions/PSURGE_doc.shtml), Extra-Tropical Storm Surge model (ETSS; web page at nomads.ncep.noaa.gov/txt_descriptions/ETSS_doc.shtml), Probabilistic Extra-Tropical Storm Surge model (P-ETSS; web page at nomads.ncep.noaa.gov/txt_descriptions/PETSS_doc.shtml), sea ice behavior (web page at nomads.ncep.noaa.gov/txt_descriptions/SEA_ICE_doc.shtml), and others. While each of these datasets are not directly relevant to each embodiment of the invention, their importance is influenced by a couple of important factors. First, each of these datasets may be important for detecting, predicting, and forecasting weather, climate, and their impacts to specific locales, and each of these datasets provide additional insights on the behavior of weather and climate on nearly all temporal and spatial scales, ultimately resulting in models that may provide accurate predictions of the same.

[0053] Forecast output from these systems may exist in the form of daily analyses, monthly (time-averaged) analyses, hourly, daily forecasts, or monthly (time-averaged) forecasts. These forecasts may also comprise similar atmospheric and oceanic variables as those contained in reanalysis datasets (described above) and can also contain calculations of convective available potential energy, vertical wind shear, and storm relative helicity, which can be important for embodiments involving shorter-term forecasts of tornadoes, hail, and damaging wind gusts.

[0054] In cases where a combination of both reanalysis data and dynamical data are used by the machine learning service **102** for generating forecasts in accordance with the present disclosure, output from dynamical data may: (1) generally include; or (2) provide an ability to derive similar atmospheric and oceanic variables as those contained within reanalysis data. In certain embodiments, reanalysis data as generated in step **304** and dynamical data may be interpolated to a similar grid (e.g., 2.5° latitude by 2.5° longitude, or 1 kilometer by 1 kilometer) to ensure proper identification of predictor variables, which are described in greater detail infra. The longer timeframes of certain dynamical models (i.e., general circulation models with forecasts of future climates beyond 2100), enable forecasts of a variety of weather fields in future climates.

[0055] Atmospheric and oceanic data contained in reanalyses of step **304**, large-scale oscillation indices, and dynamical data are collectively referred to as "predictors" or "predictor variables". In other embodiments, predictors may comprise any combination of reanalysis data and dynamical data or may consist solely of one of these types of predictors (e.g., only reanalysis data, or only dynamical data) for the purpose of generating forecasts.

[0056] According to some embodiments, the method can include a step **308** of determining historical severe weather, tropical cyclone, and/or precipitation datasets of interest, generally

referred to herein as predictands. In various embodiments, an example method and system disclosed herein can be applied to any weather phenomenon as long as sufficiently strong relationships exist between a phenomenon of interest and larger-scale atmospheric and oceanic conditions. As a result, embodiments of this disclosure involve the use of varying historical weather datasets for use in creating forecasts. In one embodiment (e.g., the L-model of the present disclosure), the NOAA Storm Prediction Center severe weather database (Schaefer and Edwards 1999) can be used to for model calibration and forecasts of tornadoes, thunderstorm wind gusts, and hail—just to name a few. The NOAA database contains historical information on tornadoes, including starting and ending latitude/longitude coordinates, time and date of occurrence, and Fujita scale rating (Fujita 1971, McDonald and Mehta 2006). The NOAA database also contains hail information (e.g., latitude/longitude location, diameter, and date and time of occurrence) and information on thunderstorm wind gusts (e.g., wind magnitude, date, and time of occurrence). In another embodiment, historical tropical cyclone information contained in the "International Best Track Archive for Climate Stewardship" (IBTrACS, Knupp et al. 2010) was retrieved from the NOAA National Centers for Environmental Information, used for calibrating machine learning models, and generating forecasts of tropical cyclone activity. In another embodiment, historical precipitation information archived by the NOAA Earth Systems Research Laboratory (web page at www.esrl.noaa.gov/psd/) are used to calibrate machine learning models and generate precipitation forecasts. Other examples of historical databases of extreme weather events exist and may be utilized for creating forecasts, including "Storm Data" archived at the National Centers for Environmental Information (web page at www.ncdc.noaa.gov/stormevents/), surveyed tornadoes by the U.S. National Weather Service (web page at apps.dat.noaa.gov/StormDamage/DamageViewer/), and precipitation rates developed as part of the NOAA Precipitation Reconstruction Dataset (archived at the NOAA Earth Systems Research Laboratory). The data contained in the "Storm Data" database enables predictions of a number of weather hazards (e.g., snow, winter storms, lightning, heat waves) and their respective impacts (e.g., estimated property losses, crop losses, casualties). These weather hazards are listed and archived on the National Centers for Environmental Information website: (web page at ncdc.noaa.gov/stormevents/details.jsp?type=eventtype) In another embodiment, duststorms can be indirectly identified through locating areas of sufficiently windy and dry surface conditions in dynamical data or reanalyses occurring in areas of bare soil. In another embodiment, areas of enhanced fire-weather conditions (i.e., atmospheric conditions at the surface characterized by less than 15% relative humidity, temperatures greater than 60 degrees Fahrenheit, and wind speeds>15 knots) can be identified in dynamical data, observations, or Reanalyses. In another embodiment, energy demand can be gauged via the calculation of heating degree days or cooling degree days using temperature information contained in Reanalyses, dynamical datasets, or observations. In another embodiment, unusually active or inactive weather patterns, extreme temperatures, and above or below normal wind speeds can be identified through examination of geopotential height, atmospheric pressure, temperature, and/or wind data in Reanalyses or weather observations. Again, these databases mentioned above are included in the plurality of data resources **106**A-**106**N (see FIG. **1**A) and any atmospheric or oceanic variable contained in observations or model output specified in prior steps may be utilized as a predictand in later model steps.

[0057] According to some embodiments, the method includes a step **310** of determining time frames of desired prediction and aggregate appropriate predictands. Varying aggregations of predictands (i.e., severe thunderstorm reports, tropical cyclone tracks, and precipitation) within the domain specified in step **302** may be performed based on desired forecast timeframes. These timeframes are flexible and vary from a few minutes to one year or more. These predictands can be stored in an array for later use by the service provider system **102**. Examples embodiments are provided as follows. If a 15-day forecast of significant (F2+) tornadoes valid for Apr. 15-30, 2018 is desired, an annual count of significant tornadoes for each April 15-30 period from 1965-2017 can

be stored in an array by the machine learning service **102** for use in later steps.

[0058] In another embodiment, if a monthly forecast of hail (one inch or greater in diameter) valid for September 2018 is desired, then an annual count of hail reports for each September period from 1975-2017 can be stored in an array by the machine learning service **102** for use in later steps. In an embodiment related to tropical cyclone forecasts, if a seasonal forecast of tropical cyclone frequency (valid June-November 2018) is desired, annual counts of tropical cyclones for each June-November period from 1960-2017 can be stored in an array by the machine learning service **102** for use in later steps.

[0059] In another embodiment: if a monthly forecast of hurricane activity (valid August 2018) is desired, annual counts of hurricane activity in each August period from 1960-2017 can be stored in an array by the machine learning service **102** for use in later steps. In an embodiment related to generating precipitation forecasts: if a three-month forecast of precipitation (valid January-March 2018) is desired, annual accumulated precipitation totals from each January-March period (from 1960-2017) can be calculated and stored in an array by the machine learning service **102** for use in later steps. While this example uses hurricane activity as an example predictand, other predictands could be used such as tropical cyclone predictands, tropical depression predictands, and so forth. Thus, in general, tropical storm related predictands could include storms of varying strength/intensity.

[0060] In an embodiment related to seasonal forecasts of tornadoes: if a three-month forecast of F1 or greater tornadoes (valid January-March 2018) is desired, annual accumulated tornado counts from each January-March period (from 1960-2017) can be calculated and stored in an array by the machine learning service **102** for use in later steps.

[0061] In an embodiment related to year-long forecasts of tornadoes: if a 12-month forecast of F1 or greater tornadoes (valid January-December 2018) is desired, annual accumulated tornado counts for each January-December period (from 1970-2017) can be calculated and stored in an array by the machine learning service **102** for use in later steps.

[0062] In an embodiment related to identification of relatively active or inactive weather patterns: if a monthly forecast of sea level pressure tendency (valid June 2020) at a specified point is desired, average annual sea level pressure for each June period (from 1950-2017) at the specified point were calculated and stored in an array by the machine learning service **102** for use in later steps.

[0063] In an embodiment related to prediction of fire weather conditions: if a daily forecast of at least one hour of fire weather conditions in the next 24 hours and within a specified 0.25° by 0.25° domain is desired, the presence of fire weather conditions in the specified domain was determined during each 24 hour period (from 1950-2021) and stored in an array for use in later steps. Fire weather conditions may be defined using a combination of atmospheric surface conditions (i.e., temperature, relative humidity, and wind speeds), and dryness of surface vegetation.

[0064] In an embodiment related to identification of abnormally strong surface winds: if a monthly forecast of surface wind (valid July 2020) at a specified point is desired, average surface wind for each July period (from 1950-2017) at the specified point were calculated and stored in an array by the machine learning service **102** for use in later steps.

[0065] In an embodiment related to identification of abnormally cold temperatures: if a monthly forecast of surface temperature (valid June 2020) in a specified 1° by 1° domain is desired, annual averages of surface temperature within each valid point in the domain during each June period (from 1950-2017) were calculated and stored in an array by the machine learning service **102** for use in later steps.

[0066] In an embodiment related to hourly temperature fluctuations: if a forecast of temperature change between 3:00 pm and 4:00 pm local time is desired at a given point is desired, accumulated temperature change data from past observations (usually derived from data sources in Steps **2-4**) are calculated and stored in an array by the machine learning service **102** for use in later steps.

[0067] In an embodiment related to changes in RAP composite reflectivity between 8:00 am and

9:00 am local time at a given point, accumulated changes in composite reflectivity values from past RAP data are calculated and stored in an array by the machine learning service **102** for use in later steps.

[0068] In an embodiment related to forecasting changes in radar reflectivity at a given point, changes in composite reflectivity values between radar scans across multiple cases are accumulated and stored in an array by the machine learning service **102** for use in later steps.

[0069] In an embodiment related to "feature tracking", if a forecast of movement of a tornado within the next 5 minutes is desired, movements of tornadoes (in five-minute increments) identified either via historical severe weather databases, past radar data, observations, and/or dynamical data was calculated and stored in an array by the machine learning service **102** for use in later steps.

[0070] In an embodiment related to "feature tracking" if a forecast of estimated path length of a tornado (start to end) is desired, path lengths of tornadoes were retrieved from historical severe weather databases were calculated and stored in an array by the machine learning service **102** for use in later steps.

[0071] In an embodiment related to "feature intensification", if intensity fluctuation of a tropical cyclone within the next 24 hours is desired, 24-hour intensity fluctuations can be derived from prior observations of tropical cyclone intensity and stored in an array by the machine learning service **102** for use in later steps.

[0072] In an embodiment related to tornado detection, observations of tornadoes can be archived and stored in an array by the machine learning service **102** for use in later steps. The tornadoes can be identified by identifying areas of azimuthal shear in radar data, then identifying peak "outbound" and "inbound" velocities to determine rotational velocity (Smith et al. 2015). These rotational velocities and nearby environmental information derived from dynamical data (i.e., instability, shear, significant tornado parameter) and radar characteristics (i.e., reflectivity, radial velocity, correlation coefficient) can also be assessed to determine tornado occurrence.

[0073] In an embodiment related to "feature tracking", if forecast movement of a tornado is desired, attributes of paths of tornadoes could be identified via the use of radar data, environmental information derived from dynamical data, and/or observations (i.e., surveyed tornadoes by the National Weather Service) and stored in an array by the machine learning service **102** for use in later steps.

[0074] In an embodiment related to short-term forecasts of tornadoes, if a forecast of tornado potential in a given domain (i.e., 40 km by 40 km) in the next six-hour period is desired, dynamical data and/or observations within six-hour antecedent and/or concurrent periods of historical tornado data can be stored in an array by the machine learning service **102** for use in later steps.

[0075] According to some embodiments, the method includes a step **312** of developing one or more classes of the predictands. The array of predictands developed in step **310** can be converted to an array of classes based on annual predictand frequency. The decision on thresholds for determining these classes can be determined and relates to one or more of: (1) needs of potential end users and (2) relative sample sizes of the classes. Examples of classes are listed in Tables 1-11 below:

TABLE-US-00001 TABLE 1 Classes F2+ Tornadoes 0 0-1 1 2-3 2 4-5 3 6-8 4   9-11 5 12+

TABLE-US-00002 TABLE 2 Classes Tornadoes 0 Below annual mean 1 At or above annual mean

TABLE-US-00003 TABLE 3 Classes Tropical Cyclones 0 0 1 1 2 2 3 3 4 4 5 5

TABLE-US-00004 TABLE 4 Classes Thunderstorm Wind events 0 0-1 1   2-10 2 11-19 3 20-39 4 40-59 5 60-99 6 100-149 7 150-299 8 300-499 9 500+

TABLE-US-00005 TABLE 5 Classes Preciptation 0 0-0.25 inch 1 0.26-0.75 inch 2 0.76-1.5 inch 3 1.51-3 inches 4 3.01-6 inches 5 6.01-12 inches 6 12.01+ inches

TABLE-US-00006 TABLE 6 Classes Tornadoes Percentiles 0 Much Below Normal   0-10th 1 Below Normal 11th-34th 2 Near Normal 35th-65th 3 Above Normal 66th-89th 4 Much Above Normal   90th-100th

TABLE-US-00007 TABLE 7 Classes Tropical Cyclones 0 0 1 1 or more

TABLE-US-00008 TABLE 8 Deviations of 500 hPa Geopotential Height Classes between timesteps 0 −70 dm 1 −60 dm 2 −50 dm 3 −40 dm 4 −30 dm 5 −20 dm 6 −10 dm 7 0 dm 8 10 dm 9 20 dm 10 30 dm 11 40 dm 12 50 dm 13 60 dm 14 70 dm

TABLE-US-00009 TABLE 9 Latitudinal change of feature of interest Class from prior timestep 1 −0.501° or less 2 −0.5° to −0.401° 3 −0.4° to −0.301° 4 −0.3° to −0.201° 5 −0.2° or −0.101° 6 −0.1° to −0.001° 7 .sup.   0° to 0.099° 8 0.1° to 0.199° 9 0.2° to 0.299° 10 0.3° to 0.399° 11 0.4° to 0.499° 12 0.5° or greater

TABLE-US-00010 TABLE 10 Deviation of rotational velocity intensity from Class prior time step 5 30 m/s or greater 4 15-30 m/s 3 −15 to 15 m/s 2 −15 to −30 m/s 1 30 m/s or lower

TABLE-US-00011 Observed hourly change in Class relative humidity 0 −5 1 0 2 3 3 5 4 10 5 12 6 16

[0076] In Table 1, example significant tornado classes (left) and report counts associated with those classes (right) are provided. In Table 2, classes can be separated into above and below normal tornado counts. In other embodiments, the "below" and "at or above" annual mean thresholds can be applied for any predictand. In Table 3, a number of tropical cyclones can be directly converted to classes as a one-to-one relationship. In Table 4, a number of wind reports can be converted to classes based on thresholds in the above table and later used for creating predictions. In Table 5, precipitation accumulations can be converted to classes based on thresholds in the above table and later used for creating predictions. In Table 6, classes of predictands can be created based on where a particular annual predictand falls within the percentile ranges specified in the above table and used for creating predictions.

[0077] In Table 7, classes of predictands can be created based on the occurrence of at least one tropical cyclone in a specified region. In other embodiments, classes can be created based on occurrence of at least one tropical cyclone of specified maximum intensity (e.g., 70 knots or 90 knots). In certain embodiments, classes may also involve deviations of certain atmospheric and oceanic variables from prior timesteps (example given in Table 8). For instance, if geopotential height at 500 hPa fell from 5520 to 5490 from August 23 to August 24, the difference between those two variables (30 hPa) can be treated as a class and compared to other measured deviations (based on methods described in Step **5**). These deviations can be derived for any variable and any timestep based on the desired forecast. In certain embodiments involving forecasts of precipitation and/or radar echoes may utilize classes describing deviations of precipitation rate and/or radar reflectivity, respectively. In certain embodiments, classes of predictands may also be derived to describe spatial displacement of specific atmospheric features or weather hazards (i.e., tropical cyclone center, tornado, or hailstorm; Table 9). These classes can include (but are not limited to) displacement measured in meters, latitude/longitude coordinates, grid point coordinates, or entire path lengths for tornadoes. In additional embodiments, classes of predictands may also be derived to describe intensification or weakening of specific atmospheric features or weather hazards (Table 10. These classes can include (but are not limited to) intensification of rotational velocity of mesocyclones or tornadoes identified by radar or intensity fluctuations of tropical cyclones. In an embodiment related to feature tracking and tornado prediction, binary classes (0 verses 1) can be utilized to determine if a tornado is detected (0=no, 1=yes), or whether a tornado will occur in the next 5 minutes (0=no, 1=yes), or whether a tornado will occur in the next hour (0=no, 1=yes). Binary classes can also be applied to forecast whether tornado movement will occur to the left of mean flow or right of mean flow (French and Kingfield, 2019). Additionally, binary classes can be applied to detections of downburst winds or large hail prediction. In certain embodiments, each individual observation or predictor variable can be assigned to a unique class. In addition, these classes can be organized by magnitude of predictor variable (Table 11). It is important to note that some predictands are organized by binary (0 versus 1, or yes versus no) classes while others are organized into continuous classes (tied more directly to frequency of the specific hazard or weather phenomenon being predicted; Tables 1 and 3-6). These binary and continuous classes are referred

to in later steps.

[0078] In certain embodiments related to prediction of temperature derivatives (i.e., heating demand via heating degree days), classes of predictands may be generated based on heating degree day counts for prior time periods (as derived from observations, Reanalyses, and/or dynamical data) in a manner similar to that described in Table 6. These classes of predictands may also be generated for cooling degree days, growing degree days, and temperature. The defining of these classes is quite flexible and dependent on the needs of the end users.

[0079] In additional embodiments related to the prediction of energy production (in a given season, for instance), classes may also be developed for predictands derived from atmospheric observations, Reanalysis data, and/or dynamical data that include fractional cloud coverage, surface wind speed, and relative humidity. Predictands may also be derived to directly predict energy production from solar panels, wind turbines, and other renewable energy sources with data sourced from a variety of public or private data sources (including, but not limited to datasets hosted by the U.S. Energy Information Administration: web page at eia.gov).

[0080] In additional embodiments, classes may also be developed for predictands derived from historical crop production data. This data may be sourced from a variety of public and private data sources (including, but not limited to the National Agricultural Statistics Service hosted by the USDA: web page at nass.usda.gov/index.php).

[0081] Lastly, predictands may include stock prices of publicly traded companies and their tendency (averaged over a range of timeframes spanning seconds, minutes, hours, days, weeks, months, seasons, or years). Predictands may also include commodity futures price tendency (i.e., 1 for increasing price tendency, 0 for decreasing price tendency; or 2 for price tendency increasing beyond 5% in a given timeframe, 1 for price remaining within 5% of its value in a given timeframe, or 0 for price falling more than 5% in a given timeframe).

[0082] In some embodiments, the method can include a step **314** of aggregating predictor variables based on desired lead times (e.g., time frame for desired forecast). To be sure, varying aggregations of predictor variables (i.e., atmospheric and oceanic variables) may be performed based on desired forecasts (described above) and desired lead times. These aggregations are performed by the machine learning service **102** via the use of instantaneous or time-averaged (i.e., monthly, biweekly, ten-day, seven-day) periods. Decisions on selecting appropriate, time-dependent aggregations of these data usually depended on the specific phenomena being predicted (e.g., predictands) and timeframes during which those predictands can be accumulated. Examples outlined below provide further clarity on this step. If lead times of one month are desired for the example described above, then instantaneous atmospheric and oceanic reanalysis data valid on March 15 (one month prior to the start of the 15-day period of desired timeframe prediction) can be aggregated annually from 1965-2018 and stored in an array for later processing.

[0083] In a separate embodiment, monthly averages of reanalysis data can be used as an alternative to instantaneous reanalysis data for the example described above. In that corresponding example, averages of each reanalysis variable (from February 15-March 15) can be calculated annually (from 1965-2018) and stored in an array for later processing by the machine learning service **102**.

[0084] In another embodiment, monthly averages of reanalysis data can be used in conjunction with monthly large-scale atmospheric and oceanic indices can be aggregated in a manner similar to that described above. An average of February and March indices and averages of each reanalysis variable (from February 15-March 15) can be calculated annually (from 1965-2018) and stored in an array of predictors for later processing by the machine learning service **102**.

[0085] For monthly, seasonal, or yearly forecasts of severe weather, monthly averages of each reanalysis variable are stored in an array based on desired lead time of forecasts. For instance, for a three-month forecast of September 2018 hail (as described above), monthly averages of reanalysis variables and monthly large-scale atmospheric and oceanic indices for the June prior to each September period (between 1975-2018) can be calculated and stored in an array for later processing

by the machine learning service **102**. If a seasonal forecast of January-March 2018 tornadoes is desired with one month of lead-time, monthly averages of reanalysis variables for the December prior to each January-March timeframe (between 1965-2018) was calculated and stored in an array for later processing by the machine learning service **102**. Similarly, for year-long forecasts of tornadoes (i.e., January-December 2018), monthly averages of reanalysis variables for the one-month period prior to the forecast timeframe (i.e., December 1964-2017) can be calculated and stored in an array for later processing by the machine learning service **102**. It will be understood that the time frame(s) selected for analysis may vary according to the forecast(s) desired as outputs from the systems and methods disclosed herein. Thus, the time frames disclose above are merely examples.

[0086] Similarly for tropical-cyclone-related embodiments, monthly averages of each reanalysis variable are stored in an array based on desired lead times of forecasts. For instance, for creating a forecast of August 2018 tropical cyclone occurrence with one month of lead time (as described above), monthly averages of each reanalysis variable for the prior July period (calculated annually between 1960 and 2018) may be stored in an array for later processing by the machine learning service **102**.

[0087] Likewise, instantaneous, weekly, and monthly periods preceding desired forecast time frames for precipitation (outlined above) can be aggregated and stored for later processing by the machine learning service **102**. In other embodiments, dynamical data can be used as an alternative to, or in conjunction with, reanalysis data. For example, monthly averaged reanalysis data from each April between 1965 and 2017 can be stored in an array for forecasting April 2018 tornado activity, while dynamical forecasts of monthly averages of variables derived from the NOAA Climate Forecast System for April 2018 can also be added to that same array for later processing by the machine learning service **102**. In another embodiment, year-long forecasts from dynamical models (i.e., Community Climate System Model or CMIP5) can be combined with year-long or monthly reanalysis data averages and stored in an array for later processing by the machine learning service **102**.

[0088] Hourly periods preceding desired forecast time frames for temperature deviations (outlined in Step **5**) can be aggregated and stored for later processing.

[0089] In additional embodiments, monthly averaged reanalysis data from one particular month (e.g., for each April between 1965 and 2017) can be combined with data stored from one or more prior months (e.g., for each March between 1965 and 2017) to forecast May 2018 tornado occurrence. Although this specific embodiment can result in a one-month forecast of tornado occurrence, the use of additional prior data can assist in creating more robust, accurate predictions by 1) incorporating additional data for learning and 2) incorporating important atmospheric or oceanic predictor variables into arrays for later processing and predictions.

[0090] In an embodiment related to prediction of publicly traded stock price tendency, reanalysis data valid the day before a specific 15-day period of pricing tendency may be collected and stored in an array for later processing.

[0091] Alternatively, reanalysis data valid two days before a specific 15-day period of pricing tendency may be collected and stored in an array for later processing in an additional embodiment. The temporal periods of data collection are primarily tied to the timeframes that afford the most predictive capability.

[0092] Lead times for storing predictor variables are not always needed for embodiments related to detection of tornadoes, hail, or wind damage via radar and/or satellite. Instead, predictor variables concurrent to tornado occurrence, hail occurrence, or damaging wind occurrence may be stored in an array for later processing in conjunction with dynamical data, observations, reanalyses, radar, current satellite imagery, and/or past satellite imagery.

[0093] In embodiments related to feature tracking for tornadoes, nearby radar reflectivity and velocity data can be combined with nearby environmental data (i.e., convective available potential

energy, vertical wind shear, storm relative helicity) for each reported tornado and stored into arrays for later processing. Nearby data can be selected within a specific range from the feature being detected (i.e., 1 kilometer, or 20 kilometers, or at the same location).

[0094] According to some embodiments, there are a few additional considerations in deciding upon antecedent timeframes of averaging predictor variables for the subsequent processing outlined in later steps. These timeframes are not static and can be customized to a) implicitly encapsulate the behavior of specific predictor variables and/or certain larger-scale atmospheric and oceanic oscillations known to influence weather conditions around the world (i.e., El Nino Southern Oscillation, Pacific Decadal Oscillation, North Atlantic Oscillation, Pacific/North American teleconnection pattern, Global Wind Oscillation, Madden-Julian Oscillation, and others listed above) and/or b) explicitly encapsulate the behavior of the aforementioned large-scale oscillations via the use of archived indices from sources listed in step **304**. These timeframes can range from less than two weeks (for predictor variables that vary rapidly) to multiple months or more (for oceanic oscillations that evolve slowly).

[0095] Variance of specific predictor variables (as described in **304** and **306**) may only be available in instances where specified timeframes (spanning multiple days to a month or more) of predictor variable averaging is being employed. Variances may not be calculated for instantaneous predictors in some embodiments.

[0096] As indicated previously, the accumulation of train/test data need not be tied specifically to a specific annual timeframe (i.e., monthly averaged reanalysis data from 1965-2018), but can apply to multiple time periods (i.e., biweekly, or even daily) within a given set of years. They can also apply to individual cases (i.e., radar-based tornado detections in individual cases occurring between December 2016 and May 2020). They can also apply to current and/or future datasets (i.e., monthly averaged April reanalysis data utilized to forecast April tornado activity), which is useful in embodiments that leverage NMME, CCSM, and/or CMIP5 data for generating forecasts.

[0097] In one or more embodiments, the method can include a step **316** of dividing data obtained from the plurality of data resources **106**A-**106**N into segments. In various embodiments, the segments can include training, testing, and validation datasets. Once desired predictands and associated predictor variables are aggregated (as outlined in step **310** and step **312**, respectively), these data are separated into three subsets: a first portion for training (roughly 60% of all data), a second portion for validation (roughly 20% of all data), and a third portion for testing (roughly 20% of all data). The individual compositions of these portions, relative to one another, may vary according design requirements (e.g., based on desired forecast outcomes and the phenomenon that is being predicted). For example, in some embodiments, rather than 60/20/20 the ratio may be 63/38/2, or 70/20/5, as other examples. A test subset is not required in certain embodiments, and up to 100% of the data can be utilized for training and validation if needed.

[0098] Segmentation can be performed in any desired manner although in certain embodiments, a few criteria can be employed by the machine learning service **102** in order to address limitations in prior predictand datasets (particularly the non-meteorological trends in NOAA Storm Prediction Center severe weather database as described in Verbout et al. 2006). These criteria area as follows. The testing dataset may contain both recent (e.g., 2017-2018) and early year (e.g., 1965-1970) predictor variables and may be treated independently of the training and validation datasets. The validation dataset may also contain both recent (e.g., 2012-2016) and early year (e.g., 1970-1975) datasets. In additional embodiments of the present disclosure, linear and non-linear detrending of predictands can be applied to address potential biases and other aforementioned limitations in historical reports databases.

[0099] According to some embodiments, the method can include a step **318** of determining regions where a strongest relationship or relationships exist(s) between predictor variables and predictands. In some embodiments, the machine learning service **102** utilizes the training dataset to create a series of arrays containing correlations between each predictor variable (outlined in steps **304** and

306) and predictand (outlined in steps **308** and **310**). The machine learning service **102** can create a correlation array for each predictor variable. Locations of extrema in each of those correlation arrays can be identified via spatial filtering routines applied by the machine learning service **102** (see FIG. **5** as an example of spatial filtering). In more detail, in FIG. **5**, a map **500** comprises shaded areas represent magnitudes of positive (red such as area **502**) and negative (blue such as area **504**) correlations between January annual hail reports in Mississippi (1985-2015) and November monthly 500 hPa geopotential heights two months prior to the hail occurrences (1984-2014). The stars, such as star **506** represent local extrema. 500 hPa geopotential height data located at each local extreme from each November monthly period can be stored and later evaluated for potential use in generating forecasts as disclosed below.

[0100] Corresponding predictor variables at each local extreme (identified in each correlation array as noted above) can be selected for potential incorporation into subsequently developed models and stored into an array for further processing by the machine learning service **102**. For instance, if a local correlation extrema (relating November monthly mean 500 hPa geopotential height and January monthly hail instances in Mississippi) was identified at 35° N, 75° W, then November monthly mean 500 hPa geopotential height values at that location (identified through reanalysis and/or dynamical data) can be stored for each year in the training dataset and later used by the machine learning service **102** to create models and predictions as outlined infra. This process can be repeated for predictor variables in the validation and testing datasets using locations of correlation extrema identified in arrays correlating predictor variables in the training dataset and predictands. That data was also stored in separate arrays for creating models and predictions as disclosed below. Magnitudes of corresponding correlations can be also stored in a separate array to assist in variable selection as follows.

[0101] In one or more embodiments, time frames for identifying locations of correlation extrema between predictor variables and predictands can differ from time frames selected for identifying predictors in the training dataset. These timeframes are not static and can be customized to implicitly encapsulate the behavior of specific predictor variables and/or certain larger-scale atmospheric and oceanic oscillations. In certain embodiments, locations of correlation extrema (e.g., relating January variance of 300 hPa v-component wind concurrent and predictands) can be combined by the machine learning service **102** with locations of correlation extrema from a different timeframe (e.g., relating November monthly mean 500 hPa geopotential height values and predictands). Ultimately, a choice of time frames for identifying locations of correlation extrema may dependent on which combinations of variables maximize forecast accuracy.

[0102] Other methods for selection of predictor variables (as described in Step **9***c* and **9***d*) can be utilized. In other embodiments, atmospheric variables nearest the domain or point of interest specified in Step **1** may be collected and stored and used for models in Steps **10**-**12**. Or, the selection of variables can be chosen based on the magnitude of correlation between predictors and predictands, but only spatially filtered variables with a specified range of the domain or point of interest (i.e., within 5 degrees latitude and/or longitude or within 2 km) can be selected and stored for later use. In certain embodiments, weights can also be assigned based on proximity of selected variables to the domain or point of interest (as described in Step **11**), with greater weight being given to closer variables. This "nearest-neighbor" approach is often utilized in many popular dynamical weather models (i.e., GFS, CFS, etc.) where data near each grid point and a series of governing equations and/or algorithms are utilized to make predictions.

[0103] In other embodiments, all available predictor data may be selected (irrespective of distance from point of interest or spatial filtering routine) and stored for later use. In other embodiments, all available predictor data with a predetermined radius near features of interest (i.e., tornadoes) for detection and/or prediction as outlined in prior steps.

[0104] In one or more embodiments, weighting of variables may be used when those variables have a correlation magnitude greater than 0.5. In additional embodiments, predictor variables can be

added randomly (without any regard to geographical location or correlation magnitude), or within a restricted geographical domain (i.e, to exclude polar regions, or regions less likely to exhibit meaningful predictors). In other embodiments, variables may be weighted depending on their distance from the domain or point of interest for creating forecasts. In some embodiments, only certain machine learning algorithms (i.e., support vector machines) are utilized to create models.

[0105] In one or more embodiments, the method can include a step **320** of normalizing stored predictor variables. Predictor variables (identified in steps **304** and **306** above) can be normalized to values between 0 and 1. In additional embodiments, variables may also be scaled to values between −1 and 1 or standardized by the machine learning service **102**.

[0106] According to some embodiments, the method can include a step **322** of generating or creating a series of machine learning models. Multiple models are created iteratively by the machine learning service **102** using the training dataset. Each model can test a separate combination of the following: machine learning algorithms (support vector machines for classification, support vector machines for regression, decision trees, random decision forests, neural networks for multilayer perceptron classification, artificial neural networks, convolutional neural networks [including, but not limited to neural networks for multilayer perceptron classification, neural networks for multilayer perceptron regression, and restricted Boltzmann machines], K-Nearest Neighbors, K-means clustering, and Bayesian networks [including, but not limited to Naïve Bayes classification and Bayesian regression]), machine learning architectures for (for neural networks, including [but not limited to], U-net, V-net, ResNet, DenseNet, MobileNet, InceptionV3, InceptionResNetV2, EfficientNet, Long Short-Term Memory, Gated Recurrent Unit, Generative Adversarial Networks, Markov Chain, Liquid State Machine, Radial Basis Network, Deep Belief Network, Extreme Learning Machine, Echo State Network), kernels (for support vector machines, including radial basis functions, linear, and polynomial kernel types), solvers (for neural networks, including stochastic gradient descent and quasi-Newton methods), hidden layers, hidden layer sizes (for neural networks) such as, attention layers, recurrent layers, feed-forward layers, bidirectional layers, and activation layers, tuning and penalty parameters (increased incrementally and tested for improved model predictions), activation functions (for for neural networks, including [but not limited to] rectified linear unit ['relu'], softmax, and sigmoid), pooling layers, solvers or optimization parameters (for neural networks, including [but not limited to] stochastic gradient descent, quasi-Newton methods, Adam, AdamW, RMSprop, Adadelta, Adagrad, Adamax, Adafactor, Nadam, Follow The Regularized Leader), dropouts (for hidden layers in neural networks to prevent overfitting), early stopping options (also for preventing overfitting in embodiments leveraging neural networks algorithms and architectures), output layer sizes, tuning and penalty parameters (increased incrementally and tested for improved model predictions, including [but not limited to] epochs, learning rates, and batch sizes), dimensions (including, but not limited to 2-dimensional and 3-dimensional layers), and quantities and combinations of predictor variables. In some embodiments, predictor variables can be added in sequential order, with most strongly correlated variables added first. In other embodiments, large-scale oscillation indices (described in step **304**) can be exclusively used to create models or combined with other predictor variables (i.e., reanalysis data). In a separate embodiment, weights can also be applied subjectively to individual subsets of predictor variables. Given the number of unique combinations of machine learning algorithms, kernels, tuning parameters, numbers of variables, and weights of variables to be incorporated, over 6000 models can be created and evaluated in any given forecast creation process by the machine learning service **102**. In other embodiments, variables may be weighted depending on their distance from the domain or point of interest for creating forecasts. In some embodiments, only certain machine learning algorithms (i.e., support vector machines) are utilized to create models. In additional embodiments, machine learning algorithms, kernels, tuning parameters, numbers of variables, and weights of variables can be derived from prior forecast creation processes.

[0107] According to some embodiments, the method can include a step **324** of evaluating results of the series of machine learning models. For each model or a subset thereof, created in step **322**, a series of predictions may be created by the machine learning service **102** for each year in the training dataset (each of the predictions can be expressed as classes as described in step **310**). Then, errors can be calculated by counting a total number of classes each model forecast deviated from the classes that can be actually observed. An idealized example is contained in Table 7 below: TABLE-US-00012 1979 prediction: 5; actual: 5.0 1980 prediction: 5; actual: 5.0 1981 prediction: 1; actual: 1.0 1982 prediction: 1; actual: 1.0 1983 prediction: 2; actual: 2.0 1984 prediction: 1; actual: 1.0 1985 prediction: 3; actual: 3.0 1986 prediction: 2; actual: 2.0 1987 prediction: 1; actual: 1.0 1988 prediction: 2; actual: 3.0 1989 prediction: 3; actual: 3.0 1990 prediction: 0; actual: 0.0 1991 prediction: 0; actual: 0.0 1992 prediction: 1; actual: 1.0 1993 prediction: 1; actual: 1.0 1994 prediction: 0; actual: 0.0 1995 prediction: 2; actual: 2.0 1996 prediction: 1; actual: 1.0 1997 prediction: 1; actual: 1.0 1998 prediction: 5; actual: 5.0 1999 prediction: 1; actual: 1.0 2000 prediction: 0; actual: 0.0 2001 prediction: 1; actual: 1.0 2002 prediction: 5; actual: 5.0 2003 prediction: 4; actual: 4.0 2004 prediction: 3; actual: 3.0 2005 prediction: 3; actual: 3.0 2006 prediction: 0; actual: 0.0 2007 prediction: 2; actual: 2.0 2008 prediction: 5; actual: 4.0 2009 prediction: 1; actual: 1.0 2010 prediction: 2; actual: 2.0 2011 prediction: 2; actual: 2.0 2012 prediction: 1; actual: 1.0 2013 prediction: 1; actual: 1.0 2014 prediction: 2; actual: 0.0 2015 prediction: 1; actual: 1.0 Absolute error: 4.0

[0108] Table 7 comprises an example list of model class predictions in each year of a sample training dataset (prediction column) and actual observed classes (actual column). The absolute error of these predictions is four (4) due to prediction errors in 1988 (1), 2008 (1), and 2014 (2). In the example outlined in Table 7, 37 would be a perfect score (zero forecast errors in 37 years of training data). The actual score is 33, however (a penalty of four based on the total number of classes each model forecast deviated from the actual observed classes during the years of 1988, 2008, and 2014). When expressed as a ratio, the score of the example in Table 7 is 89.2% (33=37). The above example is not all-encompassing, and training, testing, and validation subset sizes can change in additional embodiments.

[0109] In various embodiments, the method can include a step **326** of selecting a best-performing model and generating forecasts based on the best-performing model. In one or more embodiments, a two-step process was employed for selecting the best-performing model. In a first process, the machine learning service **102** can determine models that scored 75% or higher (based on the scoring process described in step **324**) may be retained for further testing by the machine learning service **102**. Each retained model is used to determine predicted classes for each year of the validation dataset by the machine learning service **102**. The model containing the least amount of error in predicting classes from the validation dataset (based on scoring in step **324**) can then be selected to make predictions using independent data not contained in the training or validation datasets (i.e., the testing dataset). In additional embodiments, the best performing model can be determined by identifying one or more models containing the greatest skill across both testing and validation datasets. That is, one or more thresholds may be associated with one or more different levels of skill. By way of example, a first threshold may be associated with a sufficient skill level, while a second threshold may be associated with a higher skill level than the sufficient skill level.

[0110] In other embodiments, multiple model configurations were selected for generating forecasts based on their ability to skillfully predict the test dataset. The skill for generalizing the test dataset may comprise of assessing model skill in predicting the test dataset or assessing the correlation of model predictions and the classes observed in the test dataset. In this example, models that correctly predicted at least 75% of outcomes of the test dataset were included for generating forecasts. Alternatively, models that were well correlated with outcomes from the test dataset (0.5 or greater) were also included in generating forecasts.

[0111] It will be understood that the testing dataset contains predictor variables at the timeframes of

desired forecasts (i.e., April 2018 significant tornadoes). Forecasts based on predictor variables for the testing dataset are the basis for example forecasts shown in FIG. **2** and also a subsequent step disclosed below. In other embodiments, step **326** can be completed using lower scoring thresholds (i.e., 50%) to identify potentially useful models for generating forecasts. These thresholds assist in identifying models that may generalize to new data and do not over-fit to training predictors. To be sure, skill scores as mentioned and described through the disclosure can be used as a basis for model selection, and can include, but are not limited to bias, false alarm, or other similar skill scores that would be known to one of ordinary skill in the art. These skill scores can apply across all training, testing, and/or validation subsets.

[0112] In other embodiments of the invention, skillful models may be selected based on their performance (accuracy, correlation, etc.) in predicting the validation dataset. Ideally, these highly skilled models are generalizing the predictands well while mitigating the risk of overfitting. In embodiments where multiple models are being utilized for generating forecasts, predictions on the test dataset may be averaged to make a final prediction. Additionally, the most-frequent prediction across the entire set of collected models can also be utilized as a final prediction.

[0113] In one or more embodiments, the method can include an optional step **328** of establishing probabilities, as well as repeating the steps of the method in step **330** to process additional domains (if desired). In more detail, probabilities of a particular classification (based on support vector machines for classification, and random forests by the machine learning service **102**) can be generated using the predict_proba algorithm within scikit-learn in Python. These probabilities are automatically generated by the machine learning service **102** when generating predictions via scikit-learn and tensorflow algorithms in Python. Other similar computing languages can be utilized by the machine learning service **102**.

[0114] Referring now to FIG. **3**B, backtests are an important aspect of assessing performance of models and verifying appropriate model selection methods. In one embodiment, various steps are repeated while leaving one or more subsets of collected data (atmospheric data, oceanic, data, and predictands; hereafter referred to as removed data) out of the model generation and forecast process. The remaining is then used data to generate and select models and use those models to make predictions using the removed data. For example, in the idealized example presented in Table 7, data and predictions from 1986 can be removed entirely from the process of generating models and predictions. That removed data can then be used to create an independent prediction of the 1986 period. Removed data subsets can be any size (one month, one year, two months, etc.) as long as there is enough remaining data to complete the processes disclosed above. Ultimately, a collection of independent backtests spanning multiple periods and/or cases can be created and stored for later use (often referred to as cross-validation). Optionally, the independent backtests should include each period included in the training and validation datasets.

[0115] As noted above, the modeling methods can be repeated across a variety of predictands for creating robust predictions. In one embodiment, initial backtests can be created for predicting all monthly tropical cyclones within a specified domain while a separate set of backtests can be created for all monthly tropical cyclones with maximum sustained wind speeds of greater than 60 knots. Another set of backtests can be created for all monthly tropical cyclones with maximum sustained wind speeds greater than 70 knots.

[0116] In one embodiment forming the basis of EWS (Early Warning System for Tropical Cyclone Landfalls (EWS)) forecasts, model backtests for a variety of predictands are created with the primary intent of forecasting maximum tropical cyclone intensity in a specified region. These predictands can include (but are not limited to): all tropical cyclones within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 20 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 30 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 40 knots within the specified domain; all tropical cyclones with maximum sustained

wind speeds of greater than 50 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 55 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 60 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 63 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 70 knots within the specified domain; all tropical cyclones with maximum sustained wind speeds of greater than 80 knots within the specified domain; and all tropical cyclones with maximum sustained wind speeds of greater than 96 knots within the specified domain.

[0117] In another embodiment forming the basis of L-model forecasts, model backtest for a variety of predictands are created with the primary intent of assessing potential tornado concentrations. These predictands can include (but are not limited to): two or more tornadoes within the specified domain, five or more tornadoes within the specified domain, ten or more tornadoes within the specified domain, and days (24-hour periods) with five or more tornadoes within the specified domain.

[0118] In one embodiment, backtests of predictands from varied hazards and/or weather conditions can be collected and stored for later use. These predictands can include (but are not limited to): all tropical cyclones within the specified domain, all tropical cyclones with maximum sustained wind speeds of greater than 20 knots within the specified domain, all tropical cyclones with maximum sustained wind speeds of greater than 30 knots within the specified domain, 50th percentile of geopotential heights (spatially averaged within a specified domain), two or more tornadoes within a specified domain, and 50th percentile of surface wind speeds (spatially averaged within a specified domain).

[0119] The backtests for varied predictands are not necessarily limited to the same domain. In certain embodiments, backtests involving tropical cyclones can be restricted to Gulf of Mexico tropical cyclone predictands only while backtests involving geopotential height predictands can be restricted to a separate geographic area entirely (i.e., the southeastern U.S., or Florida, or another 3° by 3° domain). Rationale for domain choice is highly dependent upon desired predictand (i.e., likelihood of tropical cyclone impact to a specified domain or region).

[0120] More specifically, backtests of predictands in Table 7 can be compared to backtests of predictands in Table 3 in certain embodiments. Additionally, correlations calculated above can be calculated between binary (yes or no; 0 or 1) predictands (e.g., Table 7) and atmospheric conditions in certain embodiments. In other embodiments, correlations can be calculated between continuous predictands (e.g., Table 3) that are more directly tied to the frequency of a given hazard in the domain and atmospheric conditions. Each of these backtests can be calculated and stored for later processing.

[0121] Once backtests are created, the method can include a step of comparing results of each backtest to any predictand of choice (hereafter referred to as "designated predictand") and scored for accuracy using skill scores typically used for objectively assessing weather forecast skill (Wilks 2006). For instance, if a prediction of June 2020 tropical storms with maximum intensities of greater than 40 knots in the Gulf of Mexico, yearly frequency of June tropical storms with greater than 40 knot maximum intensities are the predictands that are compared to backtests created above. It is important to note that designated predictands utilized in this step are not necessarily the same as predictands utilized in prior steps for generating models and backtests. The predictands can vary by hazard and/or binary versus continuous classification as described in above with regard to Tables 1-11. Correlations between backtests and designated predictands can be used for assessing forecast skill in this step, although in other embodiments, the following skill scores may be used (not exclusive): accuracy, BIAS, critical success rate, false alarm rate, probability of detection, threat score, equitable threat score, Pierce's skill score, Heidke skill score, or any combination thereof. Models can also be subjectively scored and/or weighted based on the ability of backtests to capture and independently forecast specific events of significance to the user (i.e., a major

landfalling hurricane, a series of significant tornadoes, or a major hail storm). Scores for each model are stored for later use.

[0122] In certain embodiments, the top five (other data volumes can be used) performing backtest methods (these can be based on skill score of choice) are selected and stored for later use. In other embodiments, the top three backtest methods can be selected and stored for later use. Additionally, weights can be applied to rely more on the best performing models while still incorporating information from less skillful models that are still useful for making predictions. In additional embodiments, models with negative skill can be selected and stored for later use in addition to models with positive skill. The number of backtest methods selected is not limited and can be tied to the number of well-performing models for forecasting the desired predictand. Backtest methods can also be subjectively chosen or based on ability of individual methods to predict weather or desired predictands of interest.

[0123] In certain embodiments, the method can include fitting statistical models to backtest results chosen and desired predictands to create forecasts. The following steps describe this process in greater detail, but do not encapsulate the plurality of embodiments of the invention. Initially, results from backtests and desired predictands are stored in arrays (see Table 8). Statistical models, including (but not limited to) multiple linear regression, logistic regression, and support vector regression, can then be utilized to fit backtest results to desired predictands. Additionally, backtest results and desired predictands that inform model development can be separated into training, testing, and validation datasets. Thereafter, statistical models can be applied to model forecasts of independent data (from timeframes not included in the process of creating models). For example, data from monthly periods listed in Table 7 can inform model and forecast generation as specified above. Additional data from outside of those monthly periods (i.e., 2016-2020, or 1970-1979) can be collected and applied to models generated to generate forecasts. These forecasts are derived from methods disclosed above; After independent forecasts are created and stored, statistical models developed in can be applied to generate model forecasts for the independent timeframes and utilized to create additional forecasts.

[0124] FIG. **14** is a flowchart describing the process of utilizing model backtests and statistical models to generate forecasts (also described above). In some embodiments, a series of forecasts can be utilized with varied skill to generate forecasts of impactful weather conditions while concurrently providing an indication of model performance via independent forecasts.

TABLE-US-00013 TABLE 13

	Model 1	Model 2	Model 3	Model 4	Model 5	Predictand	Average
2000	0	0	0	0	0	0	0
2001	0	0	0	1	0	1	0.2
2002	0	0	0	0	0	0	0
2003	0	0	0	0	0	1	0
2004	0	0	0	0	0	0	0
2005	1	1	1	1	1	1	1
2006	0	1	0	1	0	1	0.4
2007	0	0	0	1	0	1	0.2
2008	0	0	0	0	0	0	0
2009	0	1	0	0	0	0	0.2
2010	0	1	0	0	0	1	0.2
2011	0	1	0	0	0	1	0.2
2012	0	1	0	0	0	1	0.2
2013	0	0	0	0	0	1	0
2014	0	0	0	0	0	0	0
2015	0	1	0	0	0	1	0.2

[0125] In general, Table 13 illustrates idealized backtest results for predicting incidence of tropical cyclones in the Gulf of Mexico in June. Models **1** through **5** are subjectively chosen, best-performing models. Desired predictands are corresponding tropical cyclone occurrence during respective backtest periods. The "Average" column corresponds to the average of backtest results from selected models. In one embodiment, results from backtests can be averaged to develop objective thresholds for forecasting desired predictands. For instance, in Table 13 (above), averages of backtest results equaling 0.2 or greater generally correspond to tropical cyclone occurrence in the Gulf of Mexico in June.

[0126] Using this information, probabilities of tropical cyclone occurrence can be empirically calculated. For instance, backtests in Table 13 indicate that when selected model results average 0.2 or greater, there is an 88.9% chance of tropical cyclone occurrence in the Gulf of Mexico during June. When selected model results are less than 0.2, there is a 33% chance of tropical cyclone occurrence in that same time period and location.

[0127] As noted, the methods and sub-methods herein can be repeated for multiple domains and

multiple time periods to provide insights into regional severe weather activity (e.g., FIGS. **1** and **6**); discriminate between active and inactive severe weather periods (FIGS. **7**A and **7**B); and highlight regions of active or inactive weather patterns (FIGS. **15-17**); abnormally high wind speeds (FIG. **18**); extreme temperatures (FIG. **19**) and/or heating/cooling demand; heightened tropical cyclone potential (FIG. **12**); changes in radar reflectivity over time; and feature tracking for tornadoes, hail swaths, and thunderstorm wind gusts (not all inclusive). Two examples of underlying grids for creating these types of composite overviews are described and illustrated in FIGS. **21** and **22**. In different embodiments, these grids can be adjusted for smaller, larger, and/or multiple customized regions around the world (see FIGS. **2**, **27**, and **28** for examples). Additional sample forecasts are located in FIGS. **22-26** and FIGS. **29** and **30**. An embodiment resulting in probabilistic tropical cyclone landfall forecasts is also provided in FIG. **12**.

[0128] In another embodiment informing the EWS, forecasts of tropical cyclone activity in various, customizable domains can be combined with forecasts of a number of atmospheric variables, including sea level pressure, geopotential height, surface wind, and tornado activity in nearby domains to assess landfall potential in specific geographic regions. These processes can be completed objectively (as alluded to and described above, with combinations of desired predictands) or subjectively through visualization of concurrent forecasts of aforementioned variables.

[0129] FIGS. **24-26** illustrated and describe a specific embodiment of this process. Tornado activity forecasted in southern Louisiana in the June-August 2020 period will most likely be attributed to landfalling tropical cyclone activity. Additionally, areas of minimized sea level pressure expected in the Jun. 3-18, 2020 timeframe can be attributed to the presence of tropical cyclones—particularly in the Gulf of Mexico during summer months (FIG. **9**). Also, basin-wide forecasts of tropical cyclone activity in the Gulf of Mexico (not shown) indicated potential for a tropical cyclone with intensity of 60 knots in June 2020. Each of these forecasts suggest potential for a landfalling tropical system in southern Louisiana, and the EWS forecast valid for June 2020 indicated this potential. Tropical Storm Cristobal eventually made landfall on Jun. 7, 2020 in southeastern Louisiana.

[0130] Again, EWS forecasts are often created using a combination of objective and subjective inferences based on the most recent forecast information available and past model performance. The forecasts can include a written discussion explaining aspects of the forecast process along with potential impacts on local areas.

[0131] In certain embodiments methods disclosed herein can be utilized to develop regional and/or global weather prediction model with a few additional embodiments described in the following steps. Models can be generated utilizing predictor variables and predictands aggregated from multiple individual points and/or chosen domains within latitude 'bands' or specified geographical regions (examples shown in FIG. **29**). In certain embodiments, these predictor variables and predictands can then be combined and used to identify a single skillful model to create predictions at each point or domain within the band or region. The process can be repeated for multiple bands and/or regions as needed in certain embodiments. Alternatively, a single band or geographical region can encompass the entire desired forecast domain.

[0132] In additional embodiments, machine learning configurations (i.e., long short-term memory neural networks and others as specified in Step **15**) may enable simultaneous predictions within an entire specified domain (or multiple points within that domain) rather than at one or more individual points. These configurations may aid in predicting evolution of radar, satellite, atmospheric variables (i.e., geopotential height, temperature), thunderstorm wind swaths, tornado paths, or other variables as specified in Steps **2-4**.

[0133] In certain embodiments, once predictions are created, the resulting predictions can be utilized as predictands that can be used by models to create new predictions for subsequent timesteps; or as predictor variables to create predictions of atmospheric and/or oceanic

phenomenon created within each 'band' or specified geographical region (i.e., CAPE, or tornado occurrence, or precipitation, or even composite reflectivity); or as predictands that can be ingested into entirely new models.

[0134] In embodiments related to feature tracking, output from a series of models generated above can be utilized to describe recent and future evolution of tornado activity, including length of forecast tornado path, movement of tornado (left-moving or right-moving), and tornado intensification trends (increase, remain steady, or decrease). Additional embodiments of the invention involve forecasting movement of tornadoes, wind swaths, or hail swaths based on right-moving storm motion derived from dynamical models (i.e., RAP analyses and/or forecasts) or observations (i.e., near-storm upper air soundings). Other embodiments may also include forecasts of hail swaths or wind swaths, with wind swath detections made by identifying areas of high reflectivity (i.e., greater than 50 dBz) in areas of in atmospheric instability (i.e., convective available potential energy greater than 100 J/kg) and hail swath detections made by identifying areas of high radar reflectivity (i.e., greater than 55 dBz) or by utilizing Level III radar data for hail size estimates. In certain embodiments, as illustrated in FIG. **31**, tornado paths can be determined by identifying rotational velocity signatures that are consistent in space and time (i.e., two or more rotational velocity signatures greater than 20 m/s along a consistent path that are separated in time by less than 10 minutes). These embodiments underlie the development of a hyper-localized weather forecasting system that can pinpoint precise areas of impending hailfall, downburst winds, and tornadoes with very fine resolution (i.e., overlaid on streets, municipal boundaries, buildings, and/or critical infrastructure). Hyper-local temperature prediction is also enabled by the models—especially those that incorporate radar data (Level II and Level III), observations, and dynamic models.

[0135] Example significant tornado forecasts valid January 2017 (FIG. **7**A) and January 2018 (FIG. **7**B). Forecasts are of concentrations of significant tornadoes within roughly 75 miles of a point along and east of the Rockies. Tornadoes resulted in 20 fatalities and over 380 injuries in January 2017 across the southern United States. January 2018 was markedly less active. The underlying grid used to create this information is illustrated in FIG. **8**.

[0136] Two examples of underlying grids for creating these types of composite overviews are described and illustrated in FIGS. **8** and **9**. FIG. **8** illustrates domain centerpoints for an irregular domain used to develop a visual representation of monthly forecasts of severe thunderstorm activity. Each point is centered on a domain that is roughly 5° latitude by 5° longitude (except for regions near coasts and international borders). The domain is designed to overlap such that multiple forecasts are created for any given point in the Continental United States (along and east of the Rocky Mountains). FIG. **9** is similar to FIG. **8** but includes a domain that is roughly 3° latitude by 3° longitude.

[0137] In different embodiments, these grids can be adjusted for smaller, larger, and/or multiple customized regions. Additional sample forecasts are located in FIGS. **10** and **11**. FIG. **10** illustrates a probability of 40+thunderstorm wind reports within 75 miles of a point (valid May 2011 (5 month forecast)). The underlying grid used to generate this forecast is shown in FIG. **8**. FIG. **11** illustrates a forecast of 1-1.99 inch hail instances within 75 miles of a point along and east of the Rocky Mountains (also valid May 2011 (5 month forecast)). The underlying grid used to generate this forecast is shown in FIG. **8**.

[0138] An embodiment resulting in probabilistic tropical cyclone landfall forecasts is also provided in FIG. **12**, which illustrates 2017 tropical cyclone landfall forecast probabilities. Domains (color-shaded polygons) can be customized in order to assess probabilities of landfalls in particular regions of the U.S. Percentages are color-coded to correspond with each domain and express the likelihood of at least one tropical cyclone occurring within each domain in 2017. For instance, the region surrounding the Texas coastline had a 79% chance of one or more tropical cyclones occurring in the region, while regions surrounding the Florida coastline had an 88% chance of one

or more tropical cyclones. The probabilities can be created by repeating the steps of the method of FIG. **3**A for each domain. In additional embodiments of the present disclosure, probabilities of a major hurricane occurring in a given domain can be provided. Greater time resolution (i.e., hurricane landfall forecasts occurring in August 2017, etc.) can also be produced in other embodiments.

[0139] FIG. **13**A illustrates a map of an example spring 2017 seasonal tornado outlook (valid April-June 2017). Forecasts are of above normal, much above normal, below normal, much below normal, and near normal F1+tornado activity during the April-June 2017 period. FIG. **13**B illustrates a map of an example year-long 2017 tornado outlook (valid January-December 2017). Forecasts are of above normal, much above normal, below normal, much below normal, and near normal F1+tornado activity during the April-June 2017 period.

[0140] According to some embodiments, the systems and methods disclosed herein can utilize an ensemble of model output to generate a forecast or prepare a disaster model. In some embodiments, rather than running a single model for a plurality of rounds relative to a single domain, the systems and methods herein can be adapted to execute models with various predictands and parameters over more than one domain. In some embodiments, these domains may slightly overlap in their geographical boundaries relative to one another. For example, domain **1** and domain **2** may each have geographical boundaries that overlap by ten percent. For example, a northernmost portion domain **1** may overlap a southernmost portion of domain **2**.

[0141] In another example, multiple model types can be created in accordance with the embodiments disclosed herein. In one example, a first model may include a first set of predictands and/or parameters, whereas a second model may include a second set of predictands and/or parameters that are different from the first model. The first model may be executed against a first domain. The second model may be executed against a second domain. As noted above, these domains may be geographically independent, or may overlap geographically. A resulting forecast or disaster model/prediction may include an ensemble of these two model outputs. In some embodiments, the ensemble can include an average or other statistical calculation or operation performed on the model outputs. In one example, the systems and methods may determine a weighted average, where one or more of the model outputs for one or more of the domains are weighted. In one embodiment, the systems and methods could apply weighting to models based on proximity to a specific area of interest. For example, a domain that is closest to a desired area of prediction may have its model output weighted higher than areas that are farther away or geographical areas having general climatological differences that are distinct from the domain of interest. To be sure, any number of different models can be executed against any number of overlapping or non-overlapping domains.

[0142] Referring now to FIG. **3**B, which illustrates additional aspect that can be used alone or in combination with the methods disclosed above. For example, steps **332-338** can be used in replacement of various forecast selecting steps in the method of FIG. **3**A, such as steps **332-330**. In some embodiments, the method includes a step **332** of generating a plurality of backtest models, as well as a step **334** of comparing forecasts from each of the plurality of backtest models to one another to test designated predictands. The method can include a step **336** of scoring each of the forecasts using skill scores. In some instances, correlations between backtests and designated predictands are used for assessing the skill scores of the forecasts.

[0143] The method can include a step **338** of selecting a forecast of the forecasts with the highest skill score, and generating at least one of a map or a weather model from the forecast. In one embodiment, the atmospheric variables are obtained based on a magnitude of correlation between the predictor variables and the predictands in step **342**. One embodiment may include a step **344** of assigning weights based on proximity of the predictor variables to the spatial domain, where the weights are increased as the distance from the spatial domain is reduced.

[0144] The method can also include a step **346** of removing a portion of the training dataset, the

testing dataset, or the validation dataset and repeating the method to produce a second weather model. In one embodiment, the method includes a step **348** of comparing the weather model to the second weather model, and a step **350** of selecting the second weather model when the skill score of the second weather model is higher than the skill score of the weather model.

[0145] As noted above, weights can be assigned randomly. In other instances, weights are assigned when the predictor variables have a correlation magnitude above a threshold. In some instances, a best-performing model is determined by identifying a series of machine learning models having the greatest skill across both testing and validation datasets.

[0146] In various embodiments, the method can include removing a portion of the training dataset, the testing dataset, or the validation dataset and repeating the method to produce a second weather model, comparing the weather model to the second weather model, and selecting the second weather model when the skill score of the second weather model is higher than the skill score of the weather model.

[0147] In some instances, the following examples may be implemented together or separately by the systems and methods described herein. One embodiment is directed to machine learning method, comprising: specifying a spatial domain of for creating a desired forecast using machine learning; determining historical atmospheric and oceanic data from a plurality of data resources; determining predictands for a weather event of interest from the historical atmospheric and oceanic data; determining one or more time frames for a desired prediction, the one or more time frames being up to approximately a year in advance; determining dynamical model forecasts; aggregating predictor variables from the dynamical model forecasts based on the one or more time frames; dividing the predictands and the predictor variables into segments that include a training dataset, a testing dataset, and a validation dataset; determining regions in the spatial domain where a strongest relationship or relationships exist(s) between predictor variables and predictands; generating or creating a series of machine learning models using the training dataset; selecting a best-performing model of the series of machine learning models; generating forecasts based on the best-performing model; automatically generating probabilities for the forecasts; selecting a highest probability forecast of the forecasts; and generating at least one of a map or a disaster model from the forecast.

[0148] Another embodiment includes aggregating one or more of the predictands based on the weather event of interest, while some embodiments include generating an array of the predictands; converting the array of the predictands into one or more classes of predictands based on annual predictand frequency; standardizing the stored predictor variables; and normalizing stored predictor variables.

[0149] Various embodiments include wherein the spatial domain is a geographical region defined by a range of 0.25 degrees latitude by 0.25 longitude, to 5 degrees latitude by 5 degrees longitude, inclusive. In one embodiment, the training dataset comprises a ratio comprising a first portion of the predictands and the predictor variables, the testing dataset comprises approximately 20 percent a second portion of the predictands and the predictor variables, and the validation dataset comprises a third portion of the predictands and the predictor variables.

[0150] According to some embodiments, a method can include generating a series of arrays comprising correlations between each of the predictor variables and each of the predictands.

[0151] Some embodiments comprise determining extrema in each of the correlations via spatial filtering, as well as selecting predictor variables associated with the extrema and incorporating the same into the series of machine learning models.

[0152] Some embodiments include wherein each of the series of machine learning models includes at least one of a combination of one or more machine learning algorithms, one or more kernels, one or more solvers, one or more hidden layer sizes, one or more tuning and penalty parameters, and one or more quantities and combinations of the predictor variables.

[0153] In one or more embodiments, the predictor variables can be added in sequential order in

such a way that most strongly correlated variables are added first, further wherein at least a portion of the predictor variables can be weighted. In some instances, the predictor variables are further determined from large-scale oscillation indices. In additional embodiments, predictor variables can be added randomly (without any regard to geographical location or correlation magnitude), or within a restricted geographical domain (i.e, to exclude polar regions, or regions less likely to exhibit meaningful predictors).

[0154] In one or more embodiments, the series of machine learning models includes at least thousands of machine learning models. Some methods include evaluating results of the series of machine learning models; and generating a series of predictions for each year in the training dataset.

[0155] Various embodiments include calculating errors by determining a total number of classes of each of the series of machine learning models of the forecasts which deviated from classes that can be actually observed.

[0156] One or more embodiments include selecting the machine learning model of the series of machine learning models with a least amount of errors; and obtaining independent datasets, as well as applying the machine learning model with the least amount of errors to the independent datasets.

[0157] In various embodiments, the independent datasets include only portions of the historical atmospheric and oceanic data and the dynamical model forecasts that can be not used to generate the training dataset.

[0158] In some embodiments, a method can comprise specifying a spatial domain of for creating a desired forecast for a weather event of interest using machine learning; determining predictands for the weather event of interest from historical atmospheric and oceanic data; determining dynamical model forecasts or large-scale oscillation data; determining predictor variables from the dynamical model forecasts; dividing the predictands and the predictor variables into segments that include a training dataset, a testing dataset, and a validation dataset; determining regions in the spatial domain where a strongest relationship or relationships exist(s) between the predictor variables and the predictands; generating a series of machine learning models using the training dataset; and generating forecasts based on a best-performing model of the series of machine learning models.

[0159] In various embodiments, the method comprises automatically generating probabilities for the forecasts; selecting a highest probability forecast of the forecasts; and generating at least one of a map or a disaster model from the forecast.

[0160] In the above disclosure, reference has been made to the accompanying drawings, which form a part hereof, which illustrate specific implementations in which the present disclosure may be practiced. It is understood that other implementations may be utilized, and structural changes may be made without departing from the scope of the present disclosure. References in the specification to "one embodiment," "an embodiment," "an example embodiment," etc., indicate that the embodiment described may include a particular feature, structure, or characteristic, but every embodiment may not necessarily include the particular feature, structure, or characteristic. Moreover, such phrases are not necessarily referring to the same embodiment. Further, when a particular feature, structure, or characteristic is described in connection with an embodiment, one skilled in the art will recognize such feature, structure, or characteristic in connection with other embodiments whether or not explicitly described.

[0161] Implementations of the systems, apparatuses, devices, and methods disclosed herein may comprise or utilize a special purpose or general-purpose computer including computer hardware, such as, for example, one or more processors and system memory, as discussed herein. Implementations within the scope of the present disclosure may also include physical and other computer-readable media for carrying or storing computer-executable instructions and/or data structures. Such computer-readable media can be any available media that can be accessed by a general purpose or special purpose computer system. Computer-readable media that stores computer-executable instructions is computer storage media (devices). Computer-readable media

that carries computer-executable instructions is transmission media. Thus, by way of example, and not limitation, implementations of the present disclosure can comprise at least two distinctly different kinds of computer-readable media: computer storage media (devices) and transmission media.

[0162] Computer storage media (devices) includes RAM, ROM, EEPROM, CD-ROM, solid state drives (SSDs) (e.g., based on RAM), flash memory, phase-change memory (PCM), other types of memory, other optical disk storage, magnetic disk storage or other magnetic storage devices, or any other medium which can be used to store desired program code means in the form of computer-executable instructions or data structures and which can be accessed by a general purpose or special purpose computer.

[0163] An implementation of the devices, systems, and methods disclosed herein may communicate over a computer network. A "network" is defined as one or more data links that enable the transport of electronic data between computer systems and/or modules and/or other electronic devices. When information is transferred or provided over a network or another communications connection (either hardwired, wireless, or any combination of hardwired or wireless) to a computer, the computer properly views the connection as a transmission medium. Transmission media can include a network and/or data links, which can be used to carry desired program code means in the form of computer-executable instructions or data structures and which can be accessed by a general purpose or special purpose computer. Combinations of the above should also be included within the scope of computer-readable media.

[0164] Computer-executable instructions comprise, for example, instructions and data which, when executed at a processor, cause a general purpose computer, special purpose computer, or special purpose processing device to perform a certain function or group of functions. The computer-executable instructions may be, for example, binaries, intermediate format instructions such as assembly language, or even source code. Although the subject matter has been described in language specific to structural features and/or methodological acts, it is to be understood that the subject matter defined in the appended claims is not necessarily limited to the described features or acts described above. Rather, the described features and acts are disclosed as example forms of implementing the claims.

[0165] Those skilled in the art will appreciate that the present disclosure may be practiced in network computing environments with many types of computer system configurations, including in-dash vehicle computers, personal computers, desktop computers, laptop computers, message processors, handheld devices, multi-processor systems, microprocessor-based or programmable consumer electronics, network PCs, minicomputers, mainframe computers, mobile telephones, PDAs, tablets, pagers, routers, switches, various storage devices, and the like. The disclosure may also be practiced in distributed system environments where local and remote computer systems, which are linked (either by hardwired data links, wireless data links, or by any combination of hardwired and wireless data links) through a network, both perform tasks. In a distributed system environment, program modules may be located in both the local and remote memory storage devices.

[0166] Further, where appropriate, the functions described herein can be performed in one or more of hardware, software, firmware, digital components, or analog components. For example, one or more application specific integrated circuits (ASICs) can be programmed to carry out one or more of the systems and procedures described herein. Certain terms are used throughout the description and claims refer to particular system components. As one skilled in the art will appreciate, components may be referred to by different names. This document does not intend to distinguish between components that differ in name, but not function.

[0167] It should be noted that the sensor embodiments discussed above may comprise computer hardware, software, firmware, or any combination thereof to perform at least a portion of their functions. For example, a sensor may include computer code configured to be executed in one or

more processors and may include hardware logic/electrical circuitry controlled by the computer code. These example devices are provided herein for purposes of illustration and are not intended to be limiting. Embodiments of the present disclosure may be implemented in further types of devices, as would be known to persons skilled in the relevant art(s).

[0168] At least some embodiments of the present disclosure have been directed to computer program products comprising such logic (e.g., in the form of software) stored on any computer-usable medium. Such software, when executed in one or more data processing devices, causes a device to operate as described herein.

[0169] While various embodiments of the present disclosure have been described above, it should be understood that they have been presented by way of example only, and not limitation. It will be apparent to persons skilled in the relevant art that various changes in form and detail can be made therein without departing from the spirit and scope of the present disclosure. Thus, the breadth and scope of the present disclosure should not be limited by any of the above-described exemplary embodiments but should be defined only in accordance with the following claims and their equivalents. The foregoing description has been presented for the purposes of illustration and description. It is not intended to be exhaustive or to limit the present disclosure to the precise form disclosed. Many modifications and variations are possible in light of the above teaching. Further, it should be noted that any or all of the aforementioned alternate implementations may be used in any combination desired to form additional hybrid implementations of the present disclosure. For example, any of the functionality described with respect to a particular device or component may be performed by another device or component. Further, while specific device characteristics have been described, embodiments of the disclosure may relate to numerous other device characteristics. Further, although embodiments have been described in language specific to structural features and/or methodological acts, it is to be understood that the disclosure is not necessarily limited to the specific features or acts described. Rather, the specific features and acts are disclosed as illustrative forms of implementing the embodiments. Conditional language, such as, among others, "can," "could," "might," or "may," unless specifically stated otherwise, or otherwise understood within the context as used, is generally intended to convey that certain embodiments could include, while other embodiments may not include, certain features, elements, and/or steps. Thus, such conditional language is not generally intended to imply that features, elements, and/or steps are in any way required for one or more embodiments.

Claims

1. A machine learning method, comprising: specifying one or more points in a spatial domain for creating a desired forecast using machine learning; determining predictor variables from a plurality of data resources including at least one of historical atmospheric data, historical oceanic data, radar data and dynamical models; determining predictands for a weather event of interest from a plurality of data resources for a weather event of interest from the historical atmospheric, the historical oceanic data, the radar data, or any combination thereof; determining one or more time frames for a desired prediction; aggregating predictor variables from at least one of the dynamical models based on the one or more time frames; dividing the predictands and the predictor variables into segments that include a training dataset, a testing dataset, and a validation dataset; generating a series of machine learning models using the training dataset; selecting at least one of the models of the series of machine learning models, wherein the selected model is associated with a skill level above a selected skill threshold; and generating the desired forecasts based on the selected model for each point of the one or more points in the spatial domain.

2. The method of claim 1, wherein the selected skill threshold is one of: a first threshold that is associated with the skill level that is sufficient; or a second threshold that is associated with the skill level that is higher than sufficient.

3. The method of claim 1, further comprising aggregating one or more of the predictands based on the weather event of interest.

4. The method of claim 1, further comprising determining regions in the spatial domain where a strongest relationship or relationships exist(s) between predictor variables and predictands and incorporating one or more predictor variables therefrom into the series of machine learning models.

5. The method of claim 1, further comprising simultaneously generating the forecasts based on the selected model for each point of the one or more points in the spatial domain.

6. The method of claim 1, further comprising: generating an array of the predictands; converting the array of the predictands into one or more classes of predictands based on annual predictand frequency; standardizing the stored predictor variables; and normalizing stored predictor variables.

7. The method of claim 1, wherein the spatial domain is a geographical region defined by a range of 0.25 degrees latitude by 0.25 longitude, to 5 degrees latitude by 5 degrees longitude, inclusive.

8. The method of claim 1, wherein the training dataset comprises a ratio comprising a first portion of the predictands and the predictor variables, the testing dataset comprises approximately 20 percent a second portion of the predictands and the predictor variables, and the validation dataset comprises a third portion of the predictands and the predictor variables.

9. The method of claim 6, further comprising generating a series of arrays comprising correlations between each of the predictor variables and each of the predictands.

10. The method of claim 9, further comprising determining extrema in each of the correlations via spatial filtering.

11. The method of claim 10, further comprising selecting predictor variables associated with the extrema and incorporating the same into the series of machine learning models.

12. The method of claim 11, further comprising adding the predictor variables a in sequential order such that most strongly correlated variables are added first, wherein at least a portion of the predictor variables are weighted.

13. The method of claim 1, wherein each of the series of machine learning models includes at least one of a combination of one or more machine learning algorithms, one or more kernels, one or more solvers, one or more hidden layer sizes, one or more tuning and penalty parameters, and one or more quantities and combinations of the predictor variables.

14. The method of claim 1, wherein the predictor variables are further determined from large-scale oscillation indices.

15. The method of claim 1, wherein the series of machine learning models comprises at least thousands of machine learning models.

16. The method of claim 1, further comprising: evaluating results of the series of machine learning models; and generating a series of predictions for each year in the training dataset.

17. The method of claim 16, further comprising calculating errors by determining a total number of classes of each of the series of machine learning models of the forecasts which deviated from classes that are observed.

18. The method of claim 17, further comprising: selecting the machine learning model of the series of machine learning models with a least amount of errors; and obtaining independent datasets; and applying the machine learning model with the least amount of errors to the independent datasets.

19. The method of claim 18, wherein the independent datasets include portions of the historical atmospheric and oceanic data and the dynamical model forecasts that are not used to generate the training dataset.

20. The method of claim 1, further comprising generating at least one of a map or a disaster model from at least one of the forecasts.

21. The method of claim 1 wherein the predictands comprise tornado events, hail storm events, thunderstorm events, a seasonal average of temperature, or any combination thereof.

22. The method of claim 1 further comprising generating probabilities of event occurrence or categorical prediction.

23. The method of claim 1, wherein the determining one or more time frames for a desired prediction is for time frames being up to one or more years in advance.