

METHOD AND APPARATUS FOR FORECASTING WEATHER, ELECTRONIC DEVICE AND STORAGE MEDIUM THEREOF

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TECHNICAL FIELD

[0001] The present disclosure relates to the field of weather forecast, and in particular, relates to a method and apparatus for forecasting weather, and an electronic device and a storage medium thereof.

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BACKGROUND

[0002] Weather forecasting (prediction) or meteorological forecasting (prediction) is the application of modern science and technology to predict the conditions of the atmosphere for a given location and a given future time by using modern scientific technologies. Weather forecasts are made by collecting quantitative data about temperature, humidity, wind direction, wind speed, atmospheric pressure, and the like, and then by determining how the atmosphere will change at a given place based on current knowledge about meteorology using a qualitative or quantitative method.

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[0003] Among related technologies for forecasting weather in the future 0 to 3 hours, one is to acquire a movement trajectory and a movement law of cloud clusters based on analysis of a plurality of cloud cluster images in a past period of time by using a cloud extrapolation technology; and then acquire a predicted cloud cluster image result by speculating a trend of cloud clusters in the future.

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[0004] A forecast method in the related art is only based on processing and prediction of images, and thus a forecast result is inaccurate.

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SUMMARY

[0005] Embodiments of the present disclosure provide a method and apparatus for forecasting weather, and an electronic device and a storage medium thereof, which may achieve a more accurate weather forecast result.

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[0006] In one aspect of the embodiments of the present disclosure, a method for forecasting weather is provided. The method includes:

[0007] acquiring a model wind field at a second time point, the model wind field being a wind field acquired by using a numerical weather forecast model, the numerical weather forecast model including a calculation method for solving a future weather state by using a numerical method;

5 [0008] acquiring first radar data at a first time point, the first radar data including a geographic location and radar reflectivity data corresponding to the geographic location;

[0009] acquiring an extrapolated wind field at the second time point by inputting the first radar data into an extrapolation model, the extrapolation model being configured to output a predicted wind field by analyzing a change trend of radar data by an extrapolation method; and

10 [0010] acquiring an optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into a variational module.

[0011] In another aspect of the embodiments of the present disclosure, an apparatus for forecasting weather is provided. The apparatus includes:

15 [0012] an acquiring module, configured to acquire a model wind field at a second time point, the model wind field being a wind field acquired by using a numerical weather forecast model, the numerical weather forecast model including a calculation method for solving a future weather state by using a numerical method;

20 [0013] wherein the acquiring module is further configured to acquire first radar data at a first time point, the first radar data including a geographic location and radar reflectivity data corresponding to the geographic location;

[0014] an extrapolating module, configured to acquire an extrapolated wind field and second radar data at the second time point by inputting the first radar data into an extrapolation model, the extrapolation model being configured to output a predicted wind field and predicted radar data by analyzing a change trend of radar data by an extrapolation method; and

25 [0015] a variational module, configured to acquire an optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module.

[0016] In still another aspect of the embodiments of the present disclosure, a computer device is provided. The computer device includes: a processor, and a memory configured to store at least one instruction, or at least one program, at least one code set, or at least one instruction set therein. The processor, when loading and executing the at least one instruction, the at least one

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program, the at least one code set, or the at least one instruction set, is caused to perform the method for forecasting weather as described above.

[0017] In yet still another aspect of the embodiments of the present disclosure, a non-transitory computer-readable storage medium is provided. The storage medium stores at least one instruction, at least one program, at least one code set, or at least one instruction set therein. The at least one instruction, the at least one program, the at least one code set, or the at least one instruction set, when be loaded and executed by a processor of a computer device, causes the computer device to perform the method for forecasting weather as described above.

[0018] In yet still another aspect of the embodiments of the present disclosure, a computer program product is provided. The computer program product includes computer instructions stored in a non-transitory computer-readable storage medium. The computer instructions, when loaded and executed by a processor of a computer device, cause the computer device to perform the method for forecasting weather as described above.

[0019] In the technical solutions according to the embodiments of the present disclosure, an extrapolated wind field is acquired by inputting radar data into an extrapolation model, and an optimized wind field is acquired by inputting the extrapolated wind field and a model wind field into a variational module. The method combines the extrapolated wind field acquired by using an extrapolation model and the model wind field acquired by solving by a numerical method to acquire a final optimized wind field. The final optimized wind field combines a plurality of wind fields, such that a forecast result is more accurate.

BRIEF DESCRIPTION OF THE DRAWINGS

[0020] For clearer descriptions of the technical solutions in the embodiments of the present disclosure, the following briefly introduces the accompanying drawings required for describing the embodiments. Apparently, the accompanying drawings in the following description show merely some embodiments of the present disclosure, and a person of ordinary skill in the art may still derive other drawings from these accompanying drawings without creative efforts.

[0021] FIG. 1 is a schematic diagram of an implementation environment according to an embodiment of the present disclosure;

[0022] FIG. 2 is a flowchart of a method for forecasting weather according to an embodiment of the present disclosure;

[0023] FIG. 3 is a flowchart of a method for forecasting weather according to another embodiment of the present disclosure;

[0024] FIG. 4 is a flowchart of a method for forecasting weather according to another embodiment of the present disclosure;

5 [0025] FIG. 5 is a workflow diagram of an extrapolation model according to another embodiment of the present disclosure;

[0026] FIG. 6 is a workflow diagram of a variational module according to another embodiment of the present disclosure;

[0027] FIG. 7 is a workflow diagram of an adjusting module according to another embodiment
10 of the present disclosure;

[0028] FIG. 8 is a block diagram of an apparatus for forecasting weather according to an embodiment of the present disclosure; and

[0029] FIG. 9 is a block diagram of a computer device according to an embodiment of the present disclosure.

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DETAILED DESCRIPTION

[0030] In order to make the objectives, technical solutions and advantages of the present disclosure clearer, further detailed descriptions will be made to the embodiments of the present disclosure hereinafter with reference to the accompanying drawings.

20 [0031] Artificial intelligence (AI) is a theory, method, technology and application system which simulates, extends, and expands human intelligence by using a digital computer or a machine controlled by a digital computer; and acquires the best result by perceiving an environment, acquiring knowledge and using the knowledge. In other words, the AI is a comprehensive technology of computer science. The AI attempts to understand the essence of intelligence and
25 produce a new type of intelligent machine which can respond in a similar way to human intelligence. That is, the AI is to study design principles and implementation methods of various intelligent machines, such that the machines have functions of perception, reasoning and decision-making.

[0032] The AI technology is a comprehensive discipline, involving a wide range of fields,
30 including both hardware technologies and software technologies. Basic AI technologies generally include technologies such as sensors, dedicated AI chips, cloud computing, distributed

storage, big data processing technologies, operating/interaction systems , electromechanical integrations, and the like. AI software technologies mainly include a computer vision technology, a voice processing technology, a natural language processing technology, a machine learning (ML)/deep learning technology, and technologies in other major directions.

5 [0033] The ML is a multi-field interdisciplinary subject, involving multiple disciplines such as probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory, and the like. The ML acquires new knowledge or skills by specializing in the study of how a computer simulates or realizes human learning behaviors; and continuously improves its own performance by reorganizing an existing knowledge structure. The ML is a core of the AI and a
10 fundamental way to make a computer smart. Its application covers various fields of the AI. The ML and deep learning usually include an artificial neural network, a belief network, a reinforcement learning technology, a transfer learning technology, an inductive learning technology, a learning from demonstration technology and other technologies.

[0034] A neural network (NN) is a complex network system formed by widely connecting a
15 large quantity of simple processing units (called neurons) with each other. It reflects many basic features of human brain functions, and is a highly-complex nonlinear dynamic learning system. The NN has capabilities of large-scale parallelism or distributed storage and processing, self-organization, self-adaptation, and self-learning, thereby the neural network is especially suitable for processing imprecise and fuzzy information processing problems which need to
20 consider many factors and conditions at the same time.

[0035] Numerical weather prediction (NWP) provides a future state of atmosphere by simplifying and discretizing dynamics and thermodynamic equations which govern the atmosphere, based on an actual situation of the atmosphere, under conditions of certain initial and boundary values, , and performing solution and integration by using a numerical method.
25 Unlike a weather forecast which is generally made by synoptics method combined with experience, the NWP uses objective methods to give a quantitative forecast. Governing equations to be solved are composed of at least one of continuity equations, thermodynamics equations, water vapor equations, state equations and motion equations. Forecast variables in the governing equations are composed of at least one of variables which describe the conditions of the
30 atmosphere, such as wind direction, wind speed, temperature, humidity, atmospheric pressure, air density, different water-phases, and the like.

[0036] Referring to FIG. 1, a schematic structural diagram of a computer system according to an example embodiment of the present disclosure is illustrated. The computer system includes a terminal 120 and a server 140.

[0037] The terminal 120 and the server 140 are connected to each other via a wired or wireless network.

[0038] In some embodiments, the terminal 120 may include one of a laptop computer, a desktop computer, a smart phone, a tablet computer, a smart speaker, and a smart robot.

[0039] The terminal 120 includes a first memory and a first processor. The first memory stores a first program. The first program is invoked and executed by the first processor to implement a weather forecast method. The first memory may include but is not limited to the following: a random-access memory (RAM), a read-only memory (ROM), a programmable read-only memory (PROM), an erasable programmable read-only memory (EPROM), and an electric erasable programmable read-only memory (EEPROM).

[0040] The first processor may be composed of one or more integrated circuit chips. In some embodiments, the first processor may be a general-purpose processor, for example, a central processing unit (CPU) or a network processor (NP).

[0041] In some embodiments, the terminal 120 includes a display which displays forecast output of weather forecast.

[0042] The server 140 includes a second memory and a second processor. The second memory stores a second program. The second program is invoked by the second processor to implement the weather forecast method provided in this embodiment of the present disclosure. For example, the second memory stores an extrapolation model and an adjustment model. The extrapolation model and the adjustment model are invoked by the second processor to perform processes in the weather forecast method. In some embodiments, the second memory may include but is not limited to the following: a RAM, a ROM, a PROM, an EPROM, and an EEPROM.

[0043] In some embodiments, the second processor implements the foregoing weather forecast method by invoking the extrapolation model and the adjustment model which are stored in the second memory. In some embodiments, the second processor may be a general-purpose processor, for example, a CPU or an NP.

[0044] Referring to FIG. 2, a flowchart of a weather forecast method according to an embodiment of the present disclosure is illustrated. The method may be applied to the server in

FIG. 1.

[0045] The server acquires second radar data 203 and an extrapolated wind field 204 by inputting first radar data 201 into an extrapolating module 202.

[0046] The first radar data 201 includes: at least one of radar reflectivity data (precipitation rate), geographic location, time, and altitude. For example, the first radar data corresponds to a first time point. The second radar data corresponds to a second time point which is a future time point of the first time point. For example, radar data is acquired by processing original radar data which may be purchased from a meteorological bureau or a meteorological website. For example, the server performs data normalization processing on the original radar data in response to acquiring the original radar data; adjusts radar reflectivity data to new data with a mean value of 0 and a same variance; and determines a label according to the new data. The label is a classification result of classifying the radar reflectivity data. For example, the label includes heavy rain, moderate rain, and light rain. For example, the acquired original radar data is a radar reflectivity image. In the figure, different radar reflectivity data are distinguished by colors. The server corresponds colors to radar reflectivity values or precipitation rates. For example, dark blue corresponds to 10 dBZ and yellow corresponds to 1 dBZ. Then, the server uses labels to classify the radar reflectivity data, such that different labels are uniformly distributed. For example, in the original radar data, if radar reflectivity data in six samples are 1 dBZ, 2 dBZ, 5 dBZ, 10 dBZ, 30 dBZ, and 50 dBZ, respectively, and then radar reflectivity data of 0 to 4 dBZ is classified under label 1, radar reflectivity data of 5 to 10 dBZ is classified under label 2, and radar reflectivity data of 11 to 50 dBZ is classified under label 3, such that, there are two samples corresponding to each of the three labels, that is, the samples number is uniformly distributed in each label. The original radar data which is labeled is determined as the first radar data 201 which is input into the extrapolating module 202. For example, the input first radar data 201 includes a multiple sets of radar data in a period of time, such as radar data at 10:00, radar data at 10:10, radar data at 10:20, and radar data at 10:30. For example, the first radar data 201 is radar data in the last 2 to 3 hours. The extrapolating module 202 acquires the second radar data 203 and the extrapolated wind field 204 by performing prediction based on the first radar data 201. The extrapolating module 202 is a neural network model. For example, the extrapolating module 202 includes a feature extractor and a recurrent neural network. The second radar data 203 is predicted radar data acquired based on the first radar data 201. For example, the second radar

data 203 includes: at least one of radar reflectivity data (precipitation rate), geographic location, time, and altitude. The extrapolated wind field 204 is a predicted wind field acquired based on the first radar data 201. For example, if the first radar data 201 is radar reflectivity data of Beijing in the past two hours, the second radar data 203 is predicted radar reflectivity data of Beijing in the next two hours, and the extrapolated wind field 204 is a predicted wind field of Beijing in the next two hours.

[0047] For example, the server may also acquire the second radar data 203 and the extrapolated wind field 204 by inputting the first radar data 201 and an observed wind field 206 into the extrapolating module 202. The observed wind field 206 is the wind field data at the first time point observed in history. An optimized wind field and an optimized stability 208 are acquired by inputting the extrapolated wind field 204, a model wind field and model stability 207 into a variational module 205. For example, the model wind field and the model stability are a predicted wind field and an atmospheric stability at the second time point which are acquired by a numerical weather forecast method. For example, the model wind field is acquired from a meteorological data acquiring channel. For example, the model wind field is acquired from a weather forecast website. The variational module 205 comprehensive analyzes the extrapolated wind field 204, the model wind field and the model stability 207 to acquire an optimal optimized wind field and an optimized stability. For example, the stability is determined by at least one of factors: temperature, humidity, and atmospheric pressure. For example, the extrapolated wind field 204 includes a historical extrapolated wind field and a future extrapolated wind field, wherein the historical extrapolated wind field is a wind field historically predicted for a past time point or a current time point; and the future extrapolated wind field is a wind field currently predicted for a future time point. Whether the historical extrapolated wind field is accurate or not can be verified, but whether the future extrapolated wind field for the future time point is accurate or not cannot be verified. For example, the model wind field includes a historical model wind field and a future model wind field. For example, the variational module acquires the optimized wind field and the optimized stability 208 by applying analysis results of the historical model wind field and the historical extrapolated wind field to analysis and optimization of the future extrapolated wind field and the future model wind field by a three-dimensional variational assimilation technology.

[0048] Optimized radar data 210 is acquired by inputting the second radar data 203, the

optimized wind field and the optimized stability 208 into an adjusting module 209, wherein the adjusting module 209 is a neural network model. For example, the adjusting module 209 acquires the optimized radar data 210 by adjusting the second radar data 203 using the optimized wind field and the optimized stability 208. Final optimized radar data is acquired by combining
5 the second radar data acquired by an extrapolation method with the extrapolated wind field and the model wind field, such that a forecasted result is more accurate.

[0049] FIG. 3 is a flowchart of a method for forecasting weather according to an example embodiment of the present disclosure. The method can be performed by the server in the computer system shown in FIG. 1. The method includes the following processes.

10 [0050] In 301, the server acquires a model wind field at a second time point. The model wind field is a wind field acquired by using a numerical weather forecast model. The numerical weather forecast model includes a calculation method for solving a future weather state by using a numerical method.

[0051] In some embodiments, the model wind field is an NWP wind field acquired by a
15 numerical weather forecast method.

[0052] In some embodiments, the server acquires a model wind field at a future time point (the second time point) from a numerical weather forecast model. The numerical weather forecast model is any calculation method for solving a future weather state by a numerical method. The model wind field is a wind field at the future time point which is calculated by the numerical
20 weather forecast model. In some embodiments, the model wind field includes a wind field at the second time point which is calculated by the numerical weather forecast model.

[0053] In some embodiments, the model wind field may be acquired from a meteorological data acquiring channel such as at least one of a global forecasting system (GFS) of US National Meteorological Bureau and the European Centre for Medium-Range Weather Forecasts.

25 [0054] In 302, the server acquires first radar data at a first time point. The first radar data includes a geographic location and radar reflectivity data corresponding to the geographic location.

[0055] The server acquires the first radar data at the first time point.

[0056] In some embodiments, the first time point is a past time point, that is, the first time point
30 is a time point before the server acquires the first radar data at the first time point. In some embodiments, the first time point may be a time interval of the last 2 to 3 hours in which the

latest radar data is acquired.

[0057] The first radar data is radar reflectivity data of a rainfall acquired by a radar. The radar reflectivity data reflects a distribution state of raindrops in atmosphere. The larger the radar reflectivity data, the larger the amount of precipitation that may occur on the ground, and the larger the possibility of a rainfall. For example, the first radar data is historical data, which is the past radar reflectivity data that the radar acquired.

[0058] In some embodiments, it is assumed that the radar data at a time point is a group. The group of radar data includes the time point, a geographic location (latitude and longitude information), radar reflectivity data corresponding to the geographic location, and an altitude corresponding to the radar reflectivity data. In some embodiments, one radar image can be generated by using one group of radar data, for example, a radar reflectivity image of China at 10:00 on November 12, 2019. A radar reflectivity strength or precipitation rate at the time point of each region of China is marked on the image. In some embodiments, different colors on the radar image represent different radar reflectivity strengths, so as to mark radar reflectivity data of each region on a map. In some embodiments, the server can acquire a precipitation rate based on the radar reflectivity data by calculation.

[0059] In some embodiments, the first radar data is acquired from a meteorological data acquiring channel. The meteorological data acquiring channel is a department, an organization, a website, a store or a company which provides meteorological data to the public. In some embodiments, the meteorological data acquiring channel includes a meteorological bureau website, a meteorological research institute, a weather forecast service agency, or the like of each region.

[0060] In some embodiments, data acquired by the server from the meteorological data acquiring channel is original radar data, and the server needs to acquire the first radar data by processing the original radar data. In some embodiments, in response to acquiring the original radar data from the meteorological data acquiring channel, the server acquires the first radar data by processing the original radar data. In some embodiments, at first, the server removes meaningless data by denoising treatment, such as radar data reflected back from a building on the ground; then the server performs normalization processing on the data; and in response to acquiring radar reflectivity data of a group of radar data, the server adjusts the radar reflectivity data to values whose mean values are 0 and whose variances are equal to each other. In some

embodiments, the server acquires new radar reflectivity data by computing a mean value and a standard deviation of all pieces of radar reflectivity data, subtracting the mean value from each piece of the radar reflectivity data, and dividing results by the standard deviation. In some embodiments, in response to acquiring the new radar reflectivity data, the server marks labels according to the new radar reflectivity data.

[0061] In some embodiments, radar data acquired from meteorological data acquiring channels is radar data whose radar reflectivity data is marked based on the meteorological data acquiring channels. In some embodiments, the radar reflectivity data is classified into ten levels based on the meteorological data acquiring channels; and radar reflectivity data of each region is marked on the radar image by ten colors. In some embodiments, in response to acquiring the radar data from the meteorological data acquiring channels, the server reclassifies and marks the radar reflectivity data with labels based on its own radar reflectivity data classification rule. In some embodiments, the radar reflectivity data is reclassified into 20 levels; and 20 labels are used to mark the radar reflectivity data of each region. In some embodiments, the server performs relabeling in many fashions, such as a normalization method and a classification method.

[0062] In some embodiments, the server relabels the radar reflectivity data according to the classification rule, such that samples under different labels are uniformly distributed. In some embodiments, the server classifies the radar reflectivity data with three labels. Upon the classification, areas marked on the map by the three labels on the radar image are approximately equal to each other.

[0063] In some embodiments, the server performs 303 by using the foregoing radar data acquired upon data processing as the first radar data.

[0064] In 303, the server acquires an extrapolated wind field at the second time point by inputting the first radar data into an extrapolation model. The extrapolation model is configured to output a predicted wind field by analyzing a change trend of radar data by an extrapolation method.

[0065] The server acquires the extrapolated wind field at the second time point by inputting the first radar data into the extrapolation model.

[0066] In some embodiments, the first time point is a past or current time point; and the second time point is a future time point. For example, a difference between the first time point and the second time point is fixed. For example, a time interval between the first time point and the

second time point is fixed to one hour. In some embodiments, the first time point is a period of time or a time point. Accordingly, the second time point is a period of time or a time point. In some embodiments, when the first time point and the second time point are a period of time, duration of the first time point and duration of the second time point may be the same as or different from each other. For example, the first time point is the last three hours; and the second time point is the next two hours.

[0067] In some embodiments, the server acquires a predicted extrapolated wind field by inputting the known first radar data into the extrapolation model. In some embodiments, the extrapolation model is a neural network model. In some embodiments, the extrapolation model may output the predicted wind field at the second time point by inputting radar data at the first time point, wherein the difference between the first time point and the second time point is fixed. In some embodiments, in response to inputting the radar data of the last three hours, the server outputs a predicted wind field of the next one hour.

[0068] In some embodiments, the extrapolation model is acquired by training historical radar data and a historical wind field. In some embodiments, in the case that the neural network model is initialized, first output is acquired by inputting radar data of 0 to 3 hours; a distance between the first output and a wind field of 3 to 4 hours is computed by a loss function; network parameters of the extrapolation model are constantly updated by backward propagation and gradient descent, until the output of the extrapolation model fits the wind field of 3 to 4 hours to an ideal level. A trained extrapolation model can output wind field data of the next hour based on radar data of the last three hours.

[0069] In some embodiments, the extrapolation model provides the predicted wind field by analyzing radar data by the extrapolation method. In some embodiments, the extrapolation model performs feature extraction on the input radar data; analyzes a wind field change trend of the radar data; and outputs the extrapolated wind field based on the wind field change trend. In some embodiments, the first radar data includes radar reflectivity data which can reflect a gather state of cloud clusters. The extrapolation model can infer at least one piece of wind field information among wind direction and wind speed based on a change trend of the cloud clusters.

[0070] In some embodiments, wind field data includes a time point, a geographic location, and a wind speed and a wind direction corresponding to the geographic location.

[0071] In 304, the server acquires an optimized wind field at the second time point by inputting

the extrapolated wind field and the model wind field into a variational module.

[0072] The second time point is a future time point of the first time point. For example, the second time point may be the next 1 to 2 hours or 3 to 4 hours.

[0073] The variational module is configured to acquire the optimized wind field by combining the extrapolated wind field with the model wind field. For example, the variational module acquires an optimal result by processing the extrapolated wind field and the model wind field by a three-dimensional variational assimilation technology.

[0074] In summary, in the technical solutions according to the embodiments of the present disclosure, an extrapolated wind field is acquired by inputting radar data into an extrapolation model, and an optimized wind field is acquired by inputting the extrapolated wind field and a model wind field into a variational module. The method combines the extrapolated wind field acquired by using an extrapolation model and the model wind field to acquire a final optimized wind field. The final optimized wind field integrates multiple wind fields, such that a forecast result is more accurate.

[0075] FIG. 4 is a flowchart of a method for forecasting weather according to an example embodiment of the present disclosure. The method can be performed by the server in the computer system shown in FIG. 1. The method includes the following processes.

[0076] In 301, the server acquires a model wind field at a second time point. The model wind field is a wind field acquired by using a numerical weather forecast model. The numerical weather forecast model includes a calculation method for solving a future weather state by using a numerical method.

[0077] In some embodiments, the server may also acquire model stability corresponding to the model wind field by using the numerical weather forecast model. The model stability indicates atmospheric stability. The model stability is atmospheric stability acquired by using the numerical weather forecast model. That is, the server can acquire the model wind field and the model stability corresponding to the model wind field by using the numerical weather forecast model.

[0078] In 302, the server acquires first radar data at a first time point. The first radar data includes a geographic location and radar reflectivity data corresponding to the geographic location.

[0079] In 3031, the server acquires second radar data and an extrapolated wind field at the

second time point by inputting the first radar data into an extrapolation model. The extrapolation model is configured to output predicted radar data and a predicted wind field by analyzing a change trend of radar data by an extrapolation method.

[0080] In some embodiments, the extrapolation model may also output the predicted radar data.

5 In some embodiments, the second radar data is radar data acquired by prediction of the extrapolating module based on the first radar data.

[0081] In some embodiments, the extrapolation model includes a feature extractor and a recurrent neural network model. In some embodiments, the server acquires a feature extraction result by inputting the first radar data into the feature extractor; and acquires the extrapolated
10 wind field by inputting the feature extraction result into the recurrent neural network model.

[0082] In some embodiments, the server acquires a feature extraction result by inputting the first radar data into the feature extractor; and acquires the second radar data at the second time point by inputting the feature extraction result into the recurrent neural network model.

[0083] In some embodiments, the extrapolation model is composed of at least one feature
15 extractor–recurrent neural network model group. In some embodiments, the extrapolation model is composed of two feature extractor–recurrent neural network model groups. The first feature extractor–recurrent neural network model group is configured to acquire wind field information of the first radar data by performing wind field analysis on the input first radar data; and the second feature extractor–recurrent neural network model group is configured to acquire the
20 extrapolated wind field and the second radar data by prediction based on the first radar data and the wind field information.

[0084] In some embodiments, the feature extractor is a neural network model. The feature extractor includes multi-layer convolution which is configured to extract features of the first radar data. In some embodiments, the feature extractor includes a plurality of feature kernels.
25 Each feature kernel convolves radar data or an image. Data or an image acquired upon the convolution is the first radar data acquired upon feature extraction. The first radar data acquired upon feature extraction is input into the recurrent neural network model.

[0085] In some embodiments, the feature extractor may perform a plurality of layers of convolutions. Each layer includes a plurality of feature kernels. Each feature kernel learns
30 different information. For example, a lower-layer convolution involves at least one of edge information and color information; and a higher-layer convolution involves semantic information

and the like. A recurrent neural network (RNN) is a recursive neural network which inputs sequence data and performs recursion in an evolution direction of a sequence and in which all nodes (circulation units) are in chain connection.

[0086] In some embodiments, the server inputs the first radar data into the recurrent neural network chronologically. In some embodiments, the server inputs a first group of pieces of first radar data at a first moment into the recurrent neural network, to acquire a predicted wind field and a piece of predicted radar data; inputs the predicted wind field and a second group of pieces of first radar data into the recurrent neural network, to acquire a next predicted wind field and a next piece of predicted radar data; inputs the next predicted wind field and a third group of pieces of first radar data into the recurrent neural network; and finally acquires an extrapolated wind field and second radar data by repeating this procedure. For example, the recurrent neural network may be a long short term memory (LSTM) deep neural network.

[0087] In some embodiments, the server may also acquire an observed wind field at the first time point. The observed wind field is a wind field acquired by observation on the ground. The second radar data and the extrapolated wind field at the second time point are acquired by inputting the first radar data and the observed wind field into the extrapolation model. In some embodiments, the observed wind field may be acquired by observing a wind speed and a wind direction by at least one of an automatic meteorological ground station, a wind profiler, and a sounding balloon.

[0088] In 3041, the server acquires an optimized wind field at the second time point (future time point) by inputting the extrapolated wind field and the model wind field into a variational module for three-dimensional variational assimilation.

[0089] A variational assimilation method solves an initial-value problem through the minimization of an objective function. The method applies optimal control principle to adjust control variables (usually from initial fields), such that an optimal atmosphere state in terms of control variables can be reached. Herein, "optimal" means the distance of the optimal atmosphere state to initial field and to observations reaches the minimum or is smaller than a predetermined threshold. The variational assimilation method can provide a relatively reasonable initial fields which are smoother in thermodynamics and dynamics, thereby playing a very important role in improving forecast skill of a high-resolution numerical prediction model. Variational assimilation makes full use of meteorological observation data by a variational

method; and implements assimilation by nonlinear model solving and global adjustment of observational data sets at different time points and by different times.

[0090] In some embodiments, the model wind field further corresponds to model stability. The model stability indicates atmospheric stability of the model wind field. The server may also acquire the optimized wind field at the second time point and optimized stability corresponding to the optimized wind field by inputting the extrapolated wind field, the model wind field, and the model stability into the variational module for three-dimensional variational assimilation. For example, the server may acquire the optimized stability by updating the model stability by the optimized wind field.

[0091] In some embodiments, 3041 includes 3041-1 in which the optimized wind field is acquired by minimizing the objective function:

[0092] An objective function $J(x)$ of three-dimensional variation is shown by the following formula:

$$J(x) = \frac{1}{2}(x - x^b)^T \mathbf{B}^{-1}(x - x^b) + \frac{1}{2}(y - y^o)^T \mathbf{R}^{-1}(y - y^o)$$

[0094] In the formula:

[0095] $\mathbf{B}$ represents a predicted error of the numerical weather forecast model, which is acquired by historical forecast statistics of the numerical weather forecast model.

[0096] x^b represents a background field and a forecast from a global or limited-area numerical weather forecast model; and may be acquired directly by running the limited-area numerical weather forecast model on the Internet.

[0097] $\mathbf{R}$ represents an error of the extrapolated wind field, which is acquired by statistics on historical forecasts of the extrapolation model.

[0098] y represents the model wind field calculated based on forecasts of the numerical weather forecast model and is calculated based on interpolation operators $\mathbf{H}$ and x :

$$y = \mathbf{H}(x)$$

[00100] y^o represents the extrapolated wind field, has the same dimensionality as the model wind field y , and is provided by the extrapolation model.

[00101] x represents an optimized meteorological field which minimizes the objective function $J(x)$, and the optimized wind field is a subset of x . To determine the optimal wind field,

it should be determined that the optimized meteorological field x makes the objective function $J(x)$ minimum or meet certain iterative convergence conditions, for example, the objective function gradient descent to 1% of an initial value.

[00102] In some embodiments, the server may also acquire model stability corresponding to the model wind field. In this case, in 3041, the server also acquires the optimized wind field at the second time point and optimized stability corresponding to the optimized wind field by inputting the extrapolated wind field, the model wind field, and the model stability into the variational module.

[00103] In some embodiments, computation of the optimized stability includes the following processes.

[00104] In 3042, a convergence field D of the optimized wind field is computed according to the following formula. In the formula, U and V represent an east-west wind component and a south-north wind component of the optimized wind field respectively.

[00105]
$$D = \frac{\partial U}{\partial x} + \frac{\partial V}{\partial y}$$

[00106] In 3043, a total amount W of water vapor in a vertical column is computed according to the following formula. In the formula, q_v represents a ratio of water vapor mass to wet air mass, g represents gravitational acceleration, and p represents atmospheric pressure.

[00107]
$$W = -\frac{1}{g} \int q_v dp$$

[00108] In 3044, uplift stability information C is computed according to the following formula. In the formula, z_e and z_c represent a free convection altitude and an equilibrium altitude of atmosphere respectively, T_v represents a virtual temperature of moist adiabatic rising air mass, T_e represents a virtual temperature of ambient air, and g represent gravitational acceleration.

[00109]
$$C = -g \int_{z_c}^{z_e} \frac{T_v - T_e}{T_e} dz$$

[00110] The optimized stability S is a vector composed of D , W , and C .

[00111] In 305, the server acquires optimized radar data by adjusting the second radar data by using the optimized wind field.

[00112] In some embodiments, the server acquires the optimized radar data by inputting the optimized wind field and the second radar data into the recurrent neural network model. The

optimized radar data is acquired by adjusting a cloud cluster position in the second radar data based on a wind speed and a wind direction of the optimized wind field.

[00113] In some embodiments, in response to acquiring the optimized wind field, the server adjusts the second radar data by using the optimized wind field. In some embodiments, the adjusting fashion is using a neural network model. In some embodiments, the neural network model is a recurrent neural network model. In some embodiments, the neural network model in the adjusting module may be the same as the recurrent neural network model in the extrapolating module, or may be a new model. In some embodiments, the optimized radar data is output by inputting the optimized wind field and the second radar data into the neural network model of the adjusting module. In some embodiments, the optimized radar data is acquired by optimizing the second radar data based on the optimized wind field. In some embodiments, the optimized radar data is the radar data at the second time point. In some embodiments, the optimized radar data is predicted radar data at the second time point. In some embodiments, the server may also acquire optimized stability corresponding to the optimized wind field by the variational module based on the model stability corresponding to the model wind field. Further, in 305, optimized radar data is acquired by adjusting the second radar data by using the optimized wind field and the optimized stability.

[00114] That is, the neural network model may also acquire optimized radar data by adjusting and optimizing the second radar data based on the input optimized wind field and optimized stability.

[00115] In summary, in the technical solutions according to the embodiments of the present disclosure, an extrapolated wind field and second radar data are acquired by inputting first radar data into an extrapolation model; an optimized wind field is acquired by optimizing and processing the extrapolated wind field and a model wind field by using a three-dimensional variational assimilation technology; and optimized radar data is acquired by adjusting the second radar data by using the optimized wind field. Therefore, the optimized radar data which is acquired finally combines data which is in a plurality of aspects and collected by a numerical weather forecast method, an extrapolation method, and an actual observation method to make a forecasted result more accurate.

[00116] In the technical solutions according to the embodiments of the present disclosure, an extrapolated wind field is acquired by inputting radar data into an extrapolation model, and an

optimized wind field and optimized stability are acquired by inputting the extrapolated wind field and a reference wind field into a variational module. Finally, the adjusting module acquires final radar data by further modifying the second radar data by using the optimized wind field and the optimization stability. In this solution, a neural network, which describes a nonlinear relationship between main variables of a thermodynamic field, predicts radar data by processing a variety of data sources. Therefore, a predicted result is more accurate.

[00117] FIG. 5 is a workflow diagram of an extrapolation model according to an example embodiment of the present disclosure. The method can be performed by the server in the computer system shown in FIG. 1. The method includes the following processes.

[00118] The server inputs first radar data and an observed wind field into an extrapolation model as a radar image sequence and an observed wind field 401; in response to processing using a feature extractor 402 and a recurrent neural network 403 sequentially, the server acquires a wind speed analysis 404 of the first radar data and a predicted extrapolated wind field 405; and finally, the server outputs second radar data (predicted radar image 406).

[00119] FIG. 6 is a workflow diagram of a variational module according to an example embodiment of the present disclosure. The method may be performed by the server in the computer system shown in FIG. 1. The method includes the following processes.

[00120] The server acquires an optimized wind field and optimized stability 413 by inputting a model wind field and model stability 407, a model wind field background error 408, an extrapolated wind field background error 409, and an extrapolated wind field 405 into a variational module for variational analysis. In some embodiments, the model wind field background error 408 and the extrapolated wind field background error 409 are wind field forecasted errors from a numerical model and an extrapolating module respectively. The background errors are used to evaluate quantities of the model wind field and the extrapolated wind field. The model wind field background error 408 is acquired by analysis based on a model wind field historical forecast 414; and is measured based on a wind field error acquired by forecasting by a numerical weather forecast method. In some embodiments, the extrapolated wind field is a predicted wind field acquired by using an extrapolation model. The extrapolated wind field background error 409 is measured based on an error of a predicted wind field acquired by using an extrapolation model. The extrapolated wind field background error 409 is acquired by statistical analysis based on extrapolated wind field historical forecast 415.

[00121] FIG. 7 is a workflow diagram of an adjusting module according to an example embodiment of the present disclosure. The method can be performed by the server in the computer system shown in FIG. 1. The method includes the following processes.

[00122] In some embodiments, the server first acquires a predicted radar image 406 (second radar data) by inputting a radar image sequence 401 (first radar data) into a recurrent neural network model 417; and acquires an optimized predicted radar image 416 (optimized radar data) by inputting an optimized wind field and optimized stability 413 which are acquired by a variational module and the predicted radar image 406 into the recurrent neural network 417.

[00123] In summary, in the technical solutions according to the embodiments of the present disclosure, an extrapolated wind field and a predicted radar image are acquired by inputting a radar image sequence and an observed wind field into a recurrent neural network; an optimized wind field is acquired by optimizing and processing the extrapolated wind field and a model wind field by using a three-dimensional variational assimilation technology; and an optimized predicted radar image is acquired by adjusting the predicted radar image by using the optimized wind field. Therefore, the optimized predicted radar image which is acquired finally combines data which is in a plurality of aspects and collected by a numerical weather forecast method, an extrapolation method, and an actual observation method to make a forecasted result more accurate.

[00124] Referring to FIG. 8, a block diagram of an apparatus for forecasting weather according to an embodiment of the present disclosure is illustrated. The apparatus has the function of implementing the example weather forecast method above. The function may be implemented by hardware or by executing corresponding software by the hardware. The apparatus may be a computer device or may be arranged therein. The apparatus may include:

[00125] an acquiring module 501, configured to acquire a model wind field at a second time point, the model wind field being a wind field acquired by using a numerical weather forecast model which includes a calculation method, the numerical weather forecast model comprising a calculation method for solving a future weather state by using a numerical method;

[00126] wherein the acquiring module 501 is further configured to acquire first radar data at a first time point, the first radar data including a geographic location and radar reflectivity data corresponding to the geographic location;

[00127] an extrapolating module 502, configured to acquire an extrapolated wind field at

the second time point by inputting the first radar data into an extrapolation model, the extrapolation model being configured to output a predicted wind field by analyzing a change trend of radar data by an extrapolation method; and

[00128] a variational module 503, configured to acquire an optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module.

[00129] In some embodiments, the variational module 503 is further configured to acquire the optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module for three-dimensional variational assimilation.

[00130] In some embodiments, the model wind field corresponds to model stability, the model stability being atmospheric stability acquired by using the numerical weather forecast model.

[00131] The variational module 503 is further configured to acquire the optimized wind field at the second time point and optimized stability corresponding to the optimized wind field by inputting the extrapolated wind field, the model wind field, and the model stability into the variational module for three-dimensional variational assimilation.

[00132] In some embodiments, the apparatus further includes:

[00133] the extrapolating module 502 configured to acquire second radar data and the extrapolated wind field at the second time point by inputting the first radar data into the extrapolation model; and

[00134] an adjusting module 504 configured to acquire optimized radar data by adjusting the second radar data by using the optimized wind field.

[00135] In some embodiments, the acquiring module 501 is further configured to acquire an observed wind field at the first time point, the observed wind field including a wind field acquired by observation on the ground.

[00136] The extrapolating module 502 is configured to acquire the second radar data and the extrapolated wind field at the second time point by inputting the first radar data and the observed wind field into the extrapolation model.

[00137] In some embodiments, the optimized wind field corresponds to optimized stability, the optimized stability being intended to describe atmospheric stability. The apparatus further includes:

[00138] the adjusting module 504 configured to acquire the optimized radar data by adjusting the second radar data by using the optimized wind field and the optimized stability.

[00139] In some embodiments, the extrapolation model includes a feature extractor and a recurrent neural network model;

5 [00140] the extrapolating module 502 is further configured to acquire a feature extraction result by inputting the first radar data into the feature extractor; and

[00141] the extrapolating module 502 is further configured to acquire the extrapolated wind field by inputting the feature extraction result into the recurrent neural network model.

[00142] In some embodiments, the extrapolation model includes a feature extractor and a
10 recurrent neural network model;

[00143] the extrapolating module 502 is further configured to acquire a feature extraction result by inputting the first radar data into the feature extractor; and

[00144] the extrapolating module 502 is further configured to acquire the second radar data and the extrapolated wind field by inputting the feature extraction result into the recurrent neural
15 network model.

[00145] In some embodiments, the adjusting module 504 is further configured to acquire the optimized radar data by inputting the optimized wind field and the second radar data into the recurrent neural network model, the optimized radar data being acquired by adjusting a cloud cluster position in the second radar data based on a wind speed and a wind direction of the
20 optimized wind field.

[00146] It should be noted that division of all of the above functional modules of the apparatus provided by the embodiments of the present disclosure is described only as an example when the apparatus realizes its functions. In practical application, the above functions may be implemented by different functional modules as required. That is, an internal structure of the
25 apparatus may be divided into different functional modules to implement all or part of the functions described above. In addition, the apparatus according to the above embodiments is based on the same inventive concept as the method embodiments, and for specific practice thereof, reference may be made to the method embodiments, which is not described any further herein.

30 [00147] Please refer to FIG. 9, which is a block diagram of a computer device according to an embodiment of the present disclosure. The computer device can be used to realize the above

weather forecast method examples or the functions thereof.

[00148] Specifically, the computer device 800 includes a processing unit 801 (such as a central processing unit (CPU), a graphics processing unit (GPU) and a field programmable gate array (FPGA)), a system memory 804 including a RAM 802 and a ROM 803, and a system bus 805 connecting the system memory 804 and the central processing unit 801. The computer device 800 further includes a basic input/output system (I/O system) 806 which helps transmit information between various components within the computer device, and a high-capacity storage device 807 for storing an operating system 813, an application 814 and other program modules 815.

[00149] The basic input/output system 806 includes a display 808 configured to display information and an input device 809, such as a mouse and a keyboard, configured to input information by the user. Both the display 808 and the input device 809 are connected to the central processing unit 801 by an input/output controller 810 connected to the system bus 805. The basic input/output system 806 may also include the input/output controller 810 configured to receive and process inputs from a plurality of other devices, such as the keyboard, the mouse, or an electronic stylus. Similarly, the input/output controller 810 further provides output to the displays, printers, or other types of output devices.

[00150] The high-capacity storage device 807 is connected to the central processing unit 801 by a high-capacity storage controller (not shown) connected to the system bus 805. The high-capacity storage device 807 and a computer-readable medium associated therewith provide non-volatile storage for the computer device 800. That is, the high-capacity storage device 807 may include the computer-readable medium (not shown), such as a hard disk or a compact disc read-only memory (CD-ROM) driver.

[00151] Without loss of generality, the computer-readable medium may include a computer storage medium and a communication medium. The computer storage medium includes volatile and non-volatile, removable and non-removable media implemented in any method or technology for storing information such as a computer-readable instruction, a data structure, a program module or the other data. The computer storage medium includes a RAM, a ROM, an EPROM, an EEPROM, a flash memory or other solid-state storage technologies; a CD-ROM, a digital video disc (DVD) or other optical storage devices; and a cassette, a magnetic tape, a disk storage or other magnetic storage devices. It is known by those skilled in the art that the

computer storage medium is not limited to above. The above system memory 804 and the high-capacity storage device 807 may be collectively referred to as the memory.

[00152] According to the various embodiments of the present disclosure, the computer device 800 may also be run by a remote server connected to a network via a network, such as the Internet. That is, the computer device 800 may be connected to the network 812 by a network interface unit 811 connected to the system bus 805, or may be connected to other types of networks or remote server systems (not shown) with the network interface unit 811.

[00153] The memory includes at least one instruction, at least one program, at least one code set, or at least one instruction set stored therein. The at least one instruction, the at least one program, the at least one code set, or the at least one instruction set, when loaded and executed by a processor of a computer device, causes the computer device to perform the method for forecasting weather as described above.

[00154] An embodiment of the present disclosure further provides a non-transitory computer-readable storage medium. The non-transitory computer-readable storage medium stores at least one instruction, at least one program, at least one code set, or at least one instruction set. The at least one instruction, the at least one program, the at least one code set, or the at least one instruction set, when loaded and executed by a processor of a computer device, causes the computer device to perform the method for reforecasting weather as described above.

[00155] In some embodiments, the non-transitory computer-readable storage medium may include a ROM, a RAM, a solid state drive (SSD), an optical disk, or the like. The random-access memory may include a resistance random-access memory (ReRAM) and a dynamic random-access memory (DRAM).

[00156] An embodiment of the present disclosure further provides a computer program product. The computer program product includes computer instructions stored in a non-transitory computer-readable storage medium. The computer instructions, when loaded and executed by a processor of a computer device, cause the computer device to perform the method for forecasting weather as described above.

[00157] It should be understood that the term "a plurality of" refers to two or more, and the term "and/or" only describes an association relationship between associated objects and indicates three relationships. For example, A and/or B may indicate that there are three cases where A exists alone, A and B exist at the same time, and B exists alone. In addition, the symbol "/"

herein generally indicates an "or" relationship between contextual objects. In addition, the process numbers described in the present disclosure only show a possible execution sequence of the processes as an example. In other embodiments, these processes may not be performed according to the execution sequence. For example, two processes with different numbers are performed simultaneously, or two processes with different numbers are performed in a sequence opposite to the sequence shown in the drawings, which will not be limited in the embodiments of the present disclosure.

[00158] The foregoing descriptions are merely exemplary embodiments of the present disclosure, and are not intended to limit the present disclosure. Within the spirit and principles of the disclosure, any modifications, equivalent substitutions, improvements, and the like are within the protection scope of the present disclosure.

CLAIMS

What is claimed is:

1. A method for forecasting weather, comprising:

acquiring a model wind field at a second time point, the model wind field being a wind field acquired by using a numerical weather forecast model, the numerical weather forecast model comprising a calculation method for solving a future weather state by using a numerical method;

acquiring first radar data at a first time point, the first radar data comprising a geographic location and radar reflectivity data corresponding to the geographic location;

acquiring an extrapolated wind field at the second time point by inputting the first radar data into an extrapolation model, the extrapolation model being configured to output a predicted wind field by analyzing a change trend of radar data by an extrapolation method; and

acquiring an optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into a variational module.

2. The method according to claim 1, wherein acquiring the optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module comprises:

acquiring the optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module for three-dimensional variational assimilation.

3. The method according to claim 2, wherein

the model wind field corresponds to model stability, the model stability being atmospheric stability acquired by using the numerical weather forecast model; and

acquiring the optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module for three-dimensional variational assimilation comprises:

acquiring the optimized wind field at the second time point and optimized stability corresponding to the optimized wind field by inputting the extrapolated wind field, the model wind field, and the model stability into the variational module for three-dimensional variational assimilation.

4. The method according to any of claims 1 to 3, wherein

acquiring the extrapolated wind field at the second time point by inputting the first radar data into the extrapolation model comprises:

acquiring second radar data and the extrapolated wind field at the second time point by inputting the first radar data into the extrapolation model; and
the method further comprises:

acquiring optimized radar data by adjusting the second radar data by using the optimized wind field.

5. The method according to claim 4, further comprising:

acquiring an observed wind field at the first time point, the observed wind field comprising a wind field acquired by observation on the ground;

wherein acquiring the second radar data and the extrapolated wind field at the second time point by inputting the first radar data into the extrapolation model comprises:

acquiring the second radar data and the extrapolated wind field at the second time point by inputting the first radar data and the observed wind field into the extrapolation model.

6. The method according to claim 4, wherein

the optimized wind field corresponds to optimized stability, the optimized stability being intended to describe atmospheric stability; and

acquiring the optimized radar data by adjusting the second radar data by using the optimized wind field comprises:

acquiring the optimized radar data by adjusting the second radar data by using the optimized wind field and the optimized stability.

7. The method according to claim 1, wherein

the extrapolation model comprises a feature extractor and a recurrent neural network model; and

acquiring the extrapolated wind field at the second time point by inputting the first radar data into the extrapolation model comprises:

acquiring a feature extraction result by inputting the first radar data into the feature extractor; and

acquiring the extrapolated wind field by inputting the feature extraction result into the recurrent neural network model.

8. The method according to claim 4, wherein acquiring the optimized radar data by adjusting the second radar data by using the optimized wind field comprises:

acquiring the optimized radar data by inputting the optimized wind field and the second

radar data into a neural network model, the optimized radar data being acquired by adjusting a cloud cluster position in the second radar data based on a wind speed and a wind direction of the optimized wind field.

9. A apparatus for forecasting weather , comprising:

an acquiring module, configured to acquire a model wind field at a second time point, the model wind field being a wind field acquired by using a numerical weather forecast model, the numerical weather forecast model comprising a calculation method for solving a future weather state by using a numerical method;

wherein the acquiring module is further configured to acquire first radar data at a first time point, the first radar data comprising a geographic location and radar reflectivity data corresponding to the geographic location;

an extrapolating module, configured to acquire an extrapolated wind field at the second time point by inputting the first radar data into an extrapolation model, the extrapolation model being configured to output a predicted wind field by analyzing a change trend of radar data by an extrapolation method; and

a variational module, configured to acquire an optimized wind field at the second time point by inputting the extrapolated wind field and the model wind field into the variational module.

10. A computer device, comprising a processor, and a memory configured to store at least one instruction, or at least one program, at least one code set, or at least one instruction set therein, wherein the processor, when loading and executing the at least one instruction, the at least one program, the at least one code set, or the at least one instruction set, is caused to perform the weather forecast method as defined in any one of claims 1 to 8.

11. A non-transitory computer-readable storage medium storing at least one instruction, at least one program, at least one code set, or at least one instruction set therein, wherein the at least one instruction, the at least one program, the at least one code set, or the at least one instruction set, when loaded and executed by a processor of a computer device, causes the computer device to perform the weather forecast method as defined in any one of claims 1 to 8.