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(54) **PREDICTING WILDFIRES ON THE BASIS OF BIOPHYSICAL INDICATORS AND SPATIOTEMPORAL PROPERTIES USING A LONG SHORT TERM MEMORY NETWORK**

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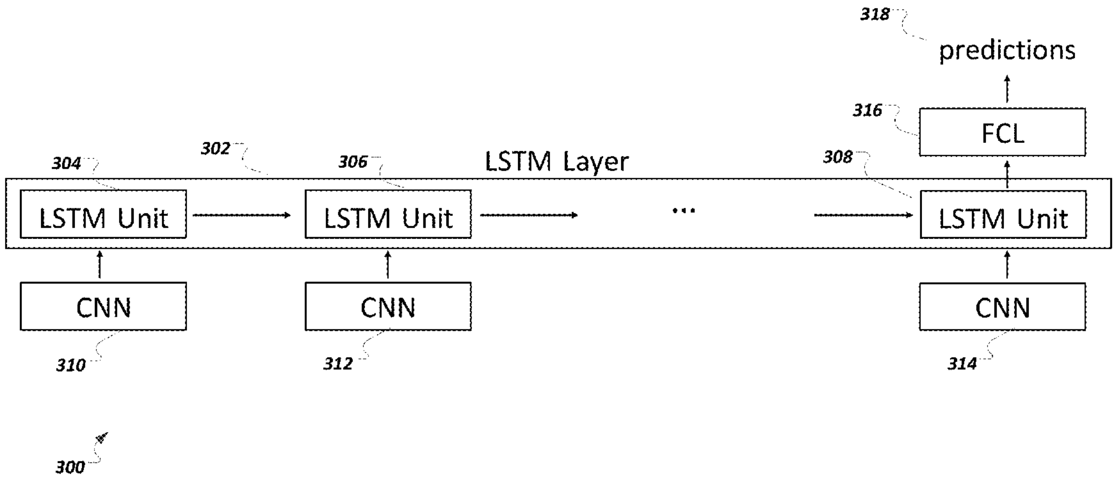
(57) **ABSTRACT**

The present disclosure involves systems, software, and computer implemented methods for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties. A method includes receiving a request for a wildfire prediction for at least one geographical area. At least one biophysical indicator is identified. Each biophysical indicator provides biophysical data for the at least one geographical area. The at least one biophysical indicator is provided to a long short term memory (LSTM) network. The LSTM network includes a convolutional neural network (CNN) for each of multiple LSTM units. Each LSTM unit and each CNN are associated with a historical time period in a time series. The LSTM is used to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period. The at least one prediction is provided responsive to the request.



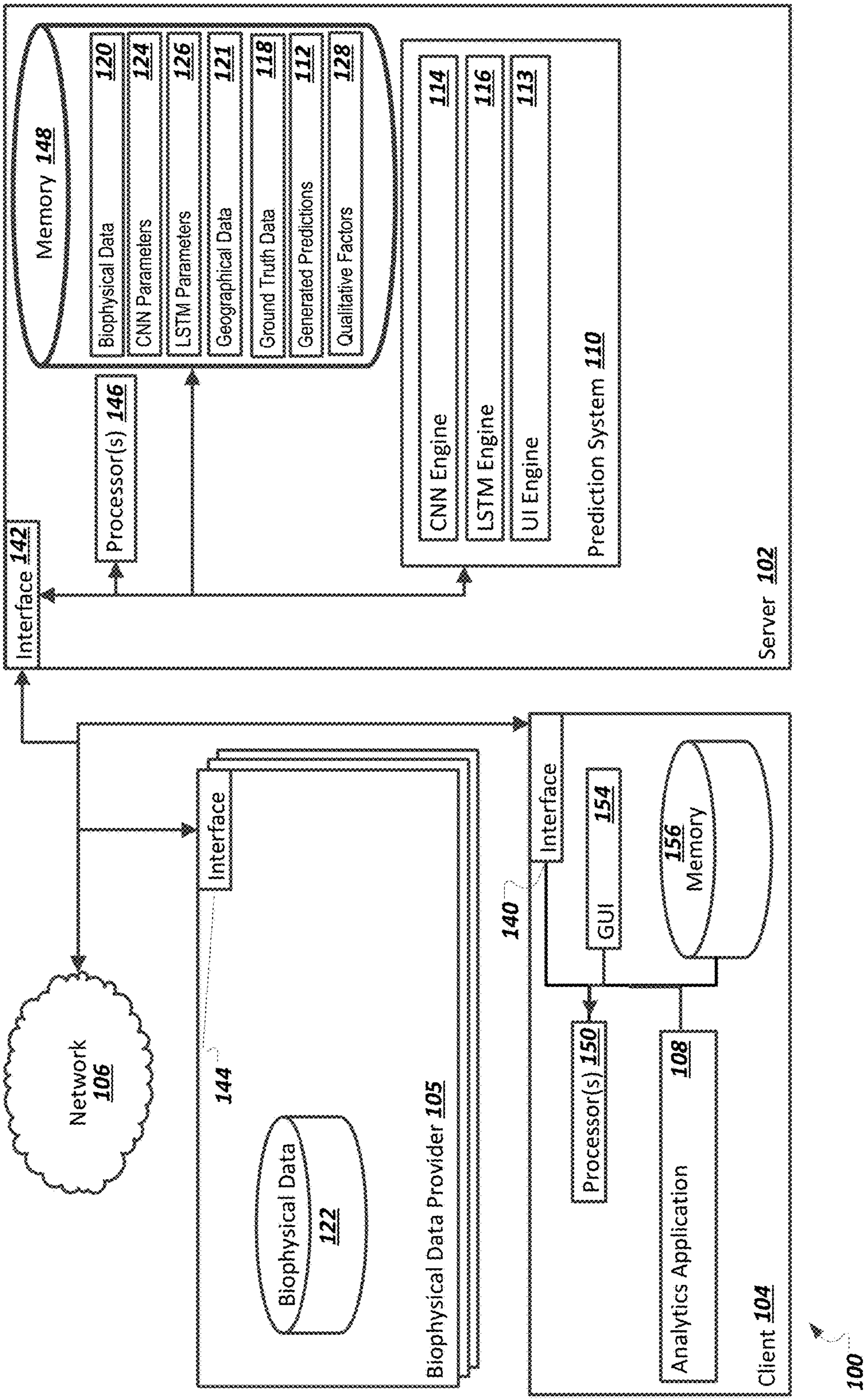

Interface 142
Processor(s) 146
Memory 148
Biophysical Data 120
CNN Parameters 124
LSTM Parameters 126
Geographical Data 121
Ground Truth Data 118
Generated Predictions 112
Qualitative Factors 128
CNN Engine 114
LSTM Engine 116
UI Engine 113
Prediction System 110
Server 102
Network 106
Interface
144
Biophysical Data 122
Biophysical Data Provider 105
Interface
140
GUI 154
156 Memory
Processor(s) 150
Analytics Application 108
Client 104
100

FIG. 1

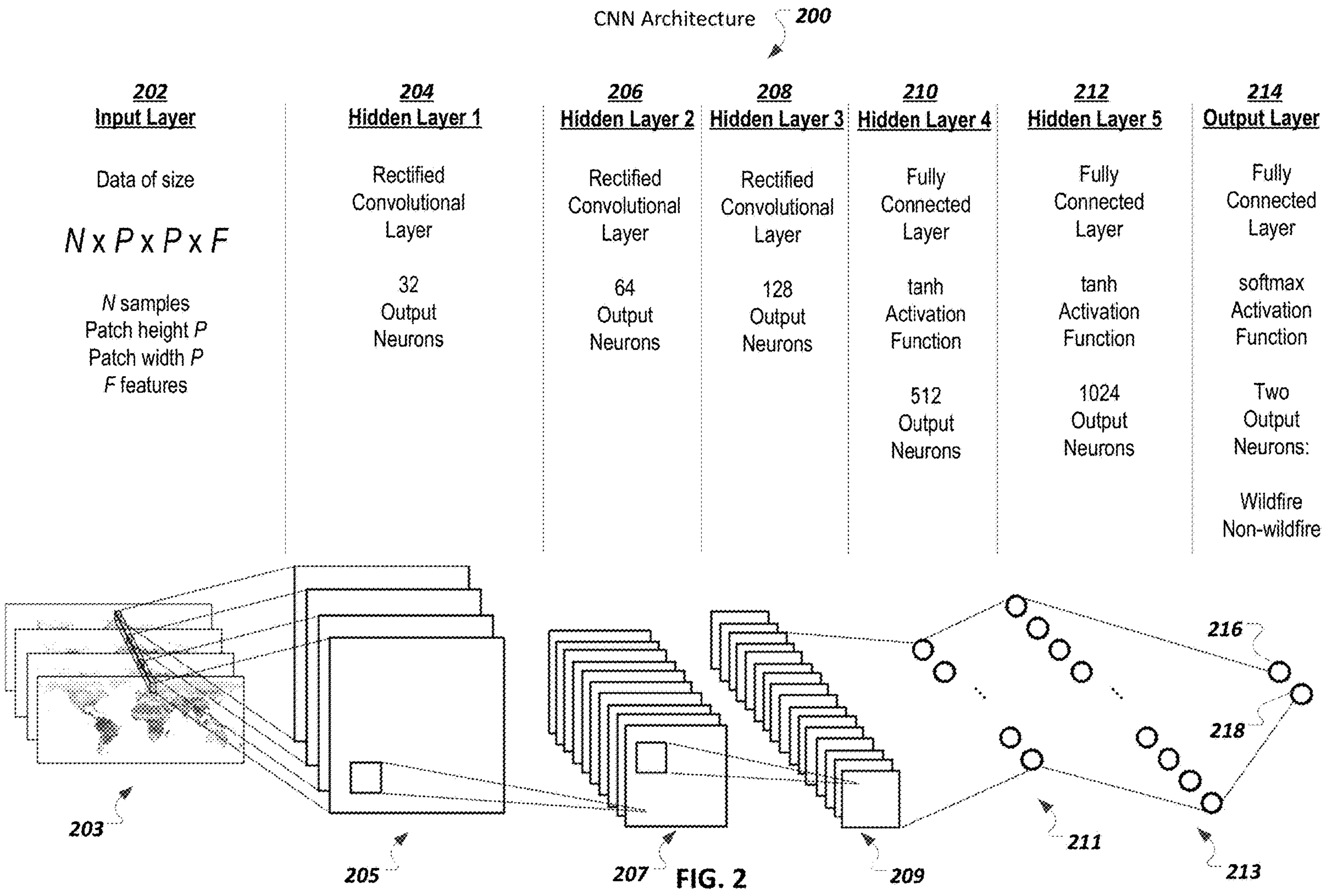

CNN Architecture
200
202
Input Layer
Data of size
$N \times P \times P \times F$
N samples
Patch height *P*
Patch width *P*
F features
204
Hidden Layer 1
Rectified
Convolutional
Layer
32
Output
Neurons
206
Hidden Layer 2
Rectified
Convolutional
Layer
64
Output
Neurons
208
Hidden Layer 3
Rectified
Convolutional
Layer
128
Output
Neurons
210
Hidden Layer 4
Fully
Connected
Layer
tanh
Activation
Function
512
Output
Neurons
212
Hidden Layer 5
Fully
Connected
Layer
tanh
Activation
Function
1024
Output
Neurons
214
Output Layer
Fully
Connected
Layer
softmax
Activation
Function
Two
Output
Neurons:
Wildfire
Non-wildfire
216
218
203
205
207
209
211
213

FIG. 2

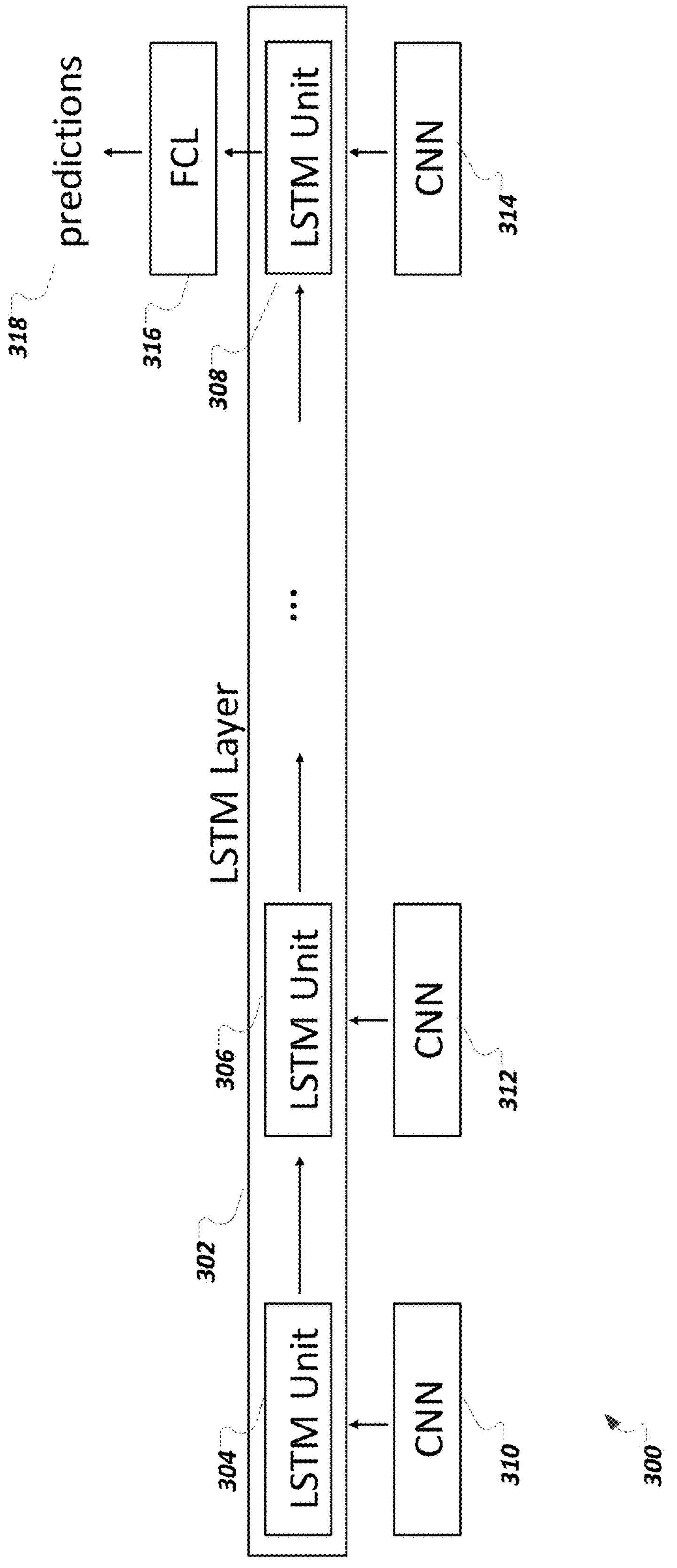

300
304
LSTM Unit
CNN
310
302
306
LSTM Unit
CNN
312
LSTM Layer
...
308
LSTM Unit
CNN
314
316
FCL
318
predictions

FIG. 3

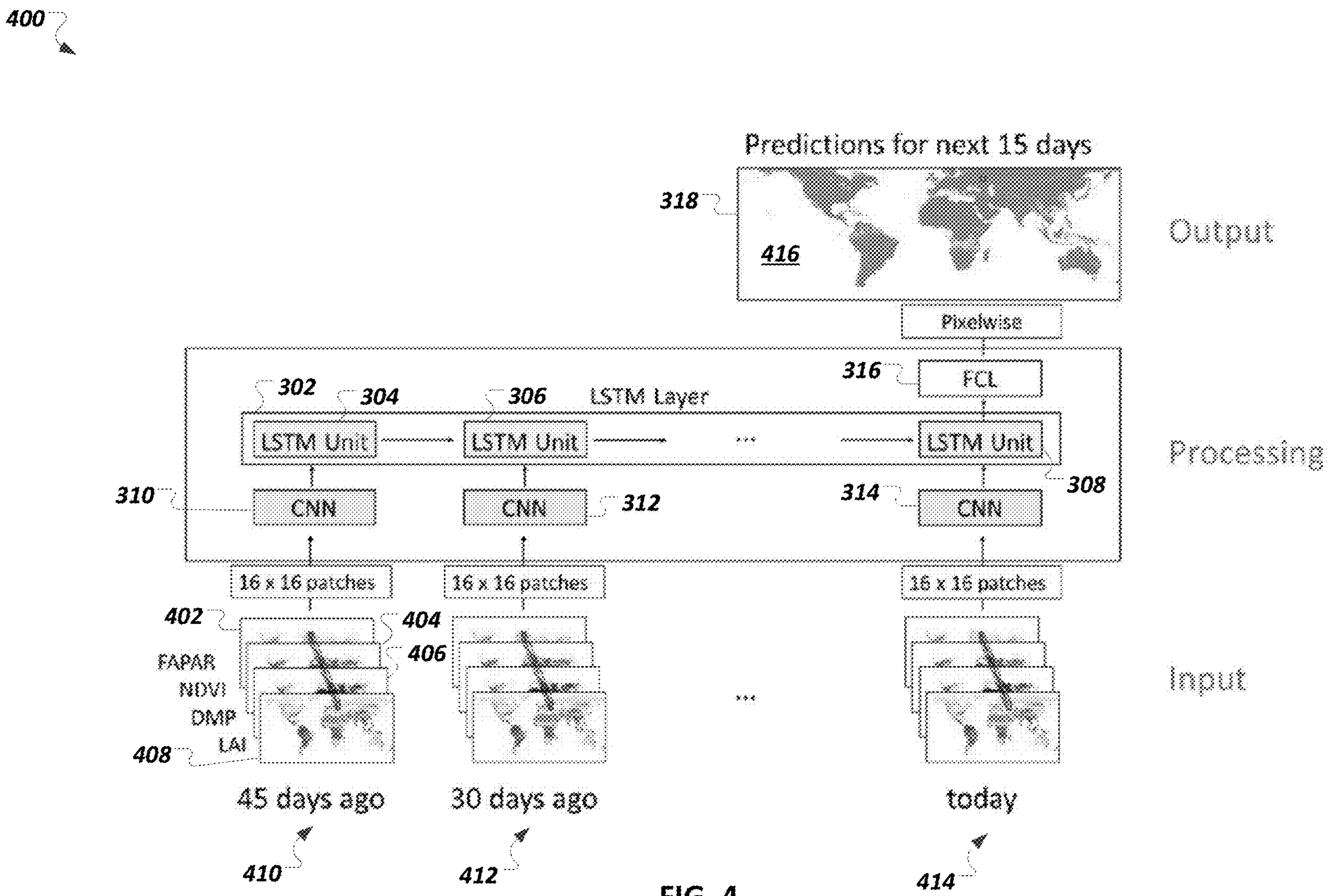

400
Predictions for next 15 days
318
416
Output
Pixelwise
316
FCL
302
304
306
LSTM Layer
LSTM Unit
LSTM Unit
...
LSTM Unit
Processing
310
CNN
CNN
312
314
CNN
308
16 x 16 patches
16 x 16 patches
16 x 16 patches
402
404
406
FAPAR
NDVI
DMP
LAI
408
...
Input
45 days ago
30 days ago
today
410
412
414

FIG. 4

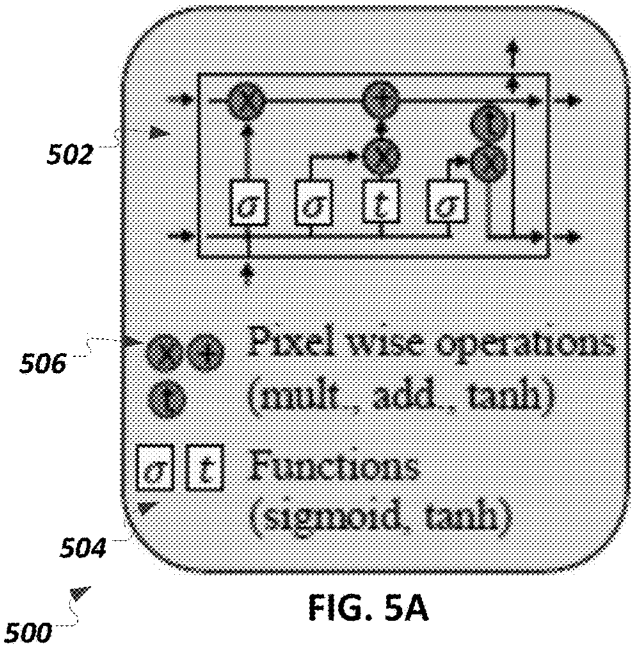

502
506
504
500
σ
σ
t
σ
Pixel wise operations
(mult., add., tanh)
σ t Functions
(sigmoid, tanh)

FIG. 5A

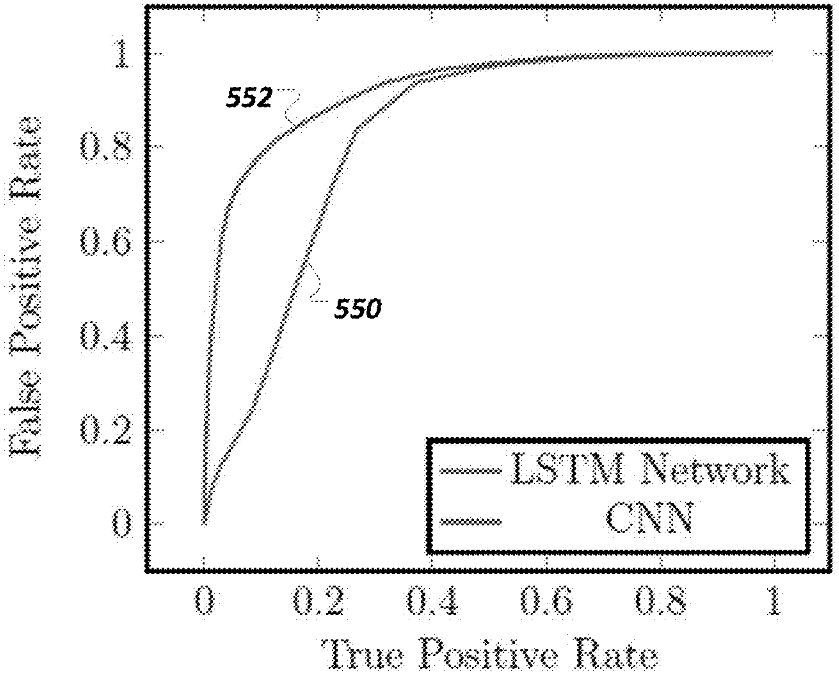

552
550
False Positive Rate
True Positive Rate
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
1
LSTM Network
CNN

FIG. 5B

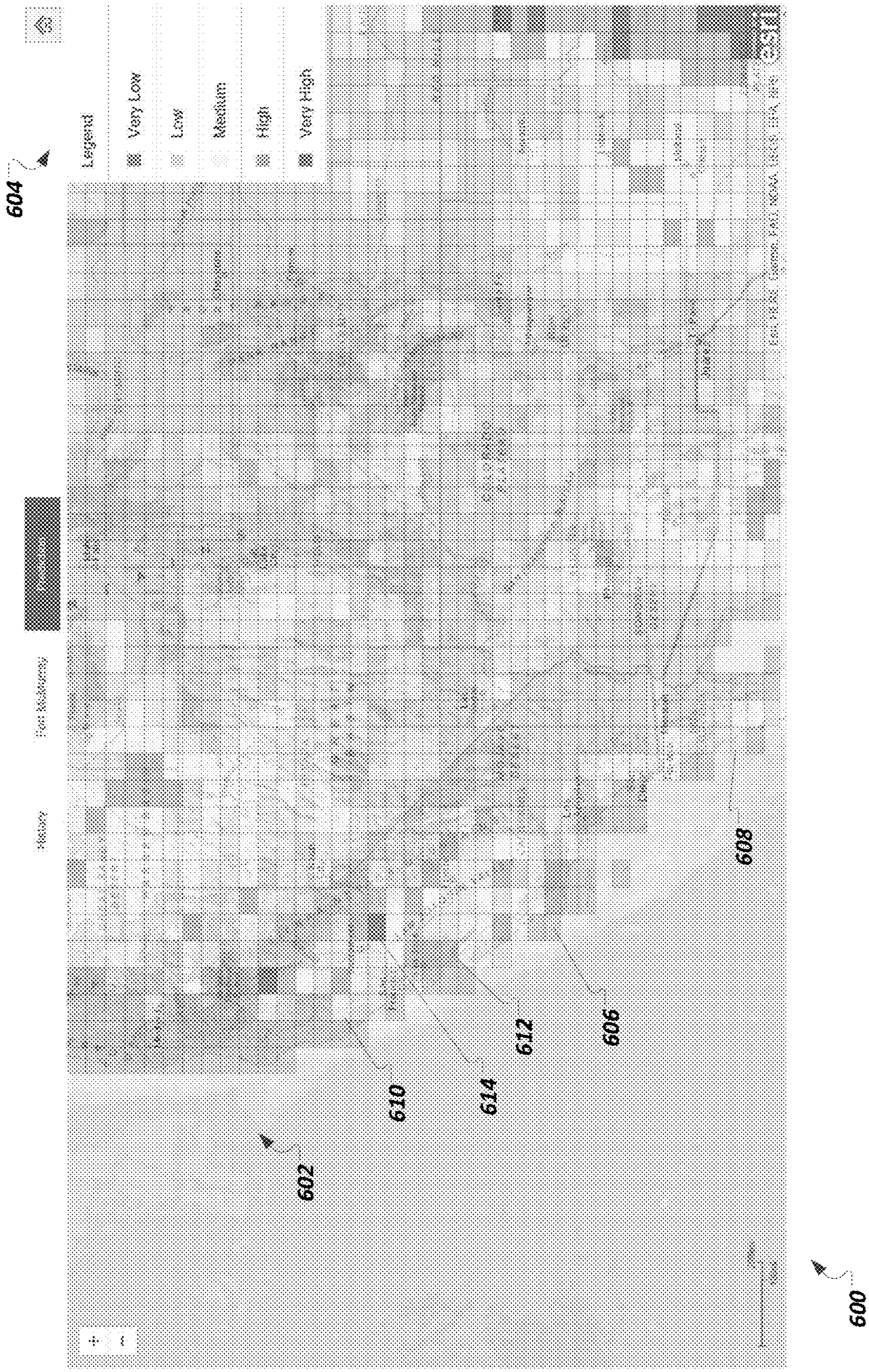

604
Legend
▨ Very Low
▨ Low
▨ Medium
▨ High
▨ Very High
History
Fort McMurray
Esri, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS
esri
602
610
614
612
606
608
600

FIG. 6

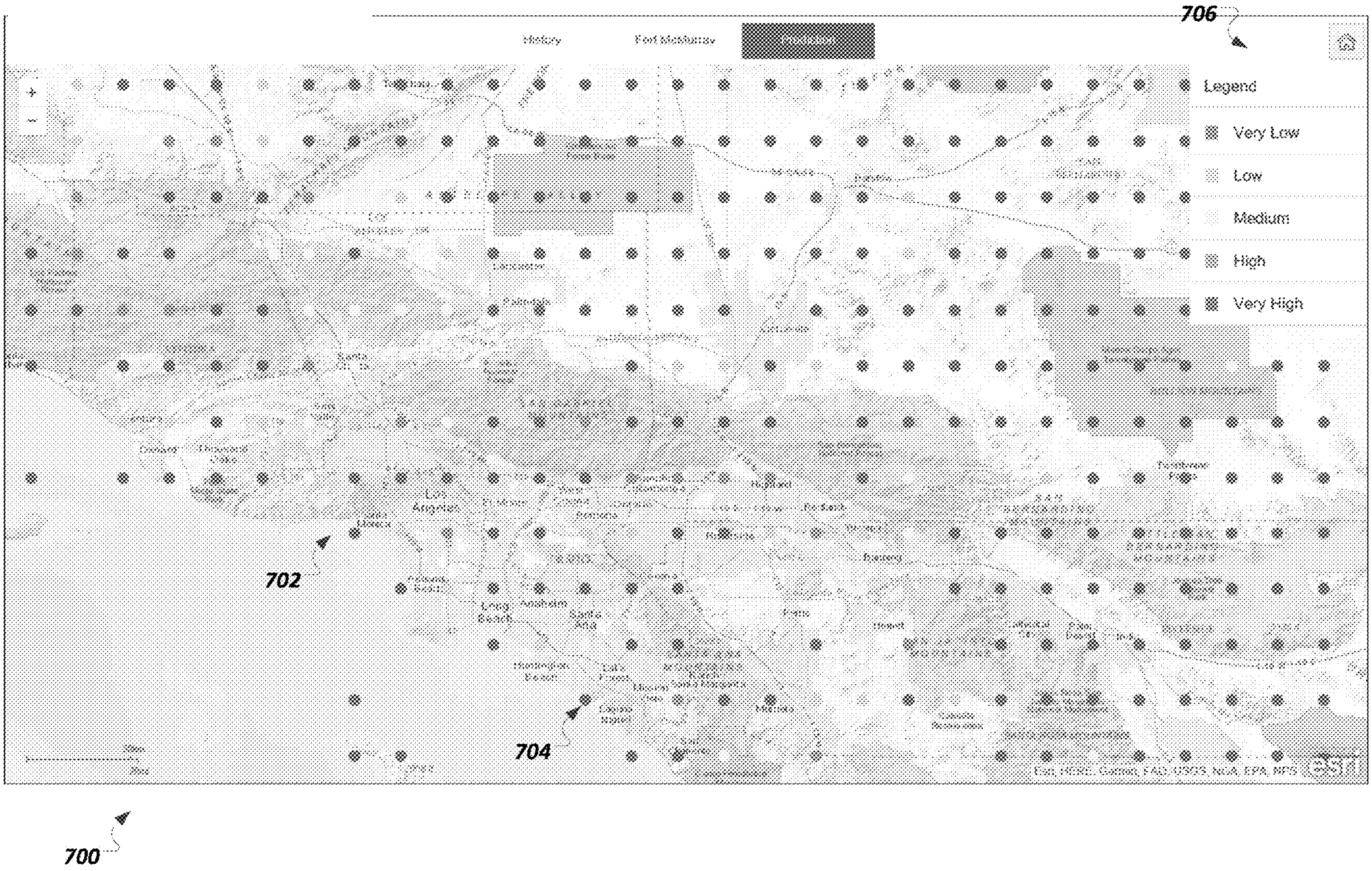
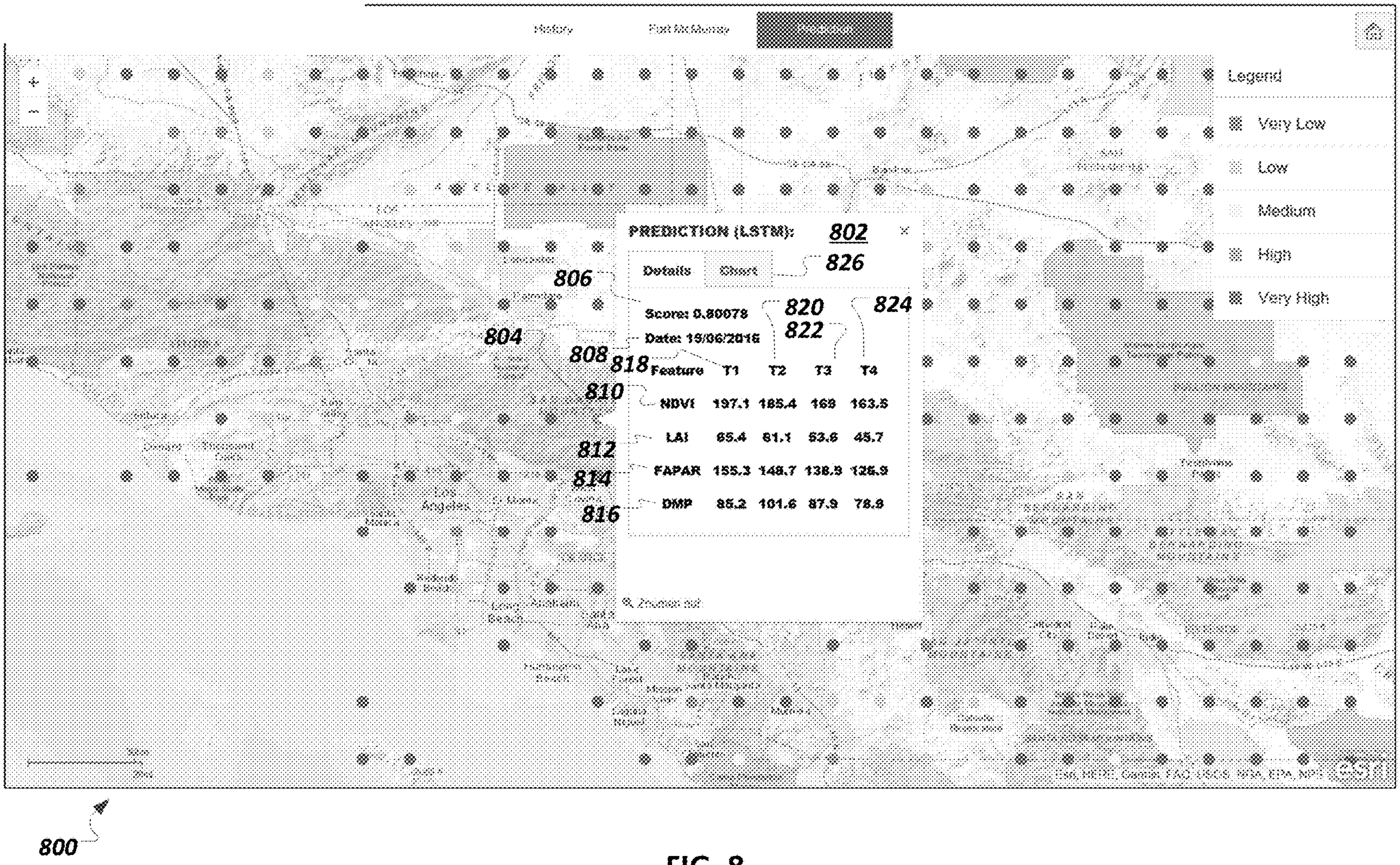

706
History
Fuel Moisture
Legend
▨ Very Low
▨ Low
▨ Medium
▨ High
▨ Very High
Lancaster
Palmdale
Oxnard
Thousand Oaks
Los Angeles
Long Beach
Anaheim
Santa Ana
Huntington Beach
Highland
Hemet
702
704
Esri, HERE, Garmin, FAO, USGS, NGA, EPA, NPS
esri
700

FIG. 7



PREDICTION (LSTM):

Score: 0.80078

Date: 19/06/2016

Feature	T1	T2	T3	T4
NDVI	197.1	185.4	169	163.5
LAI	65.4	61.1	53.6	45.7
FAPAR	155.3	148.7	138.9	126.9
DMP	85.2	101.6	87.9	78.9

FIG. 8

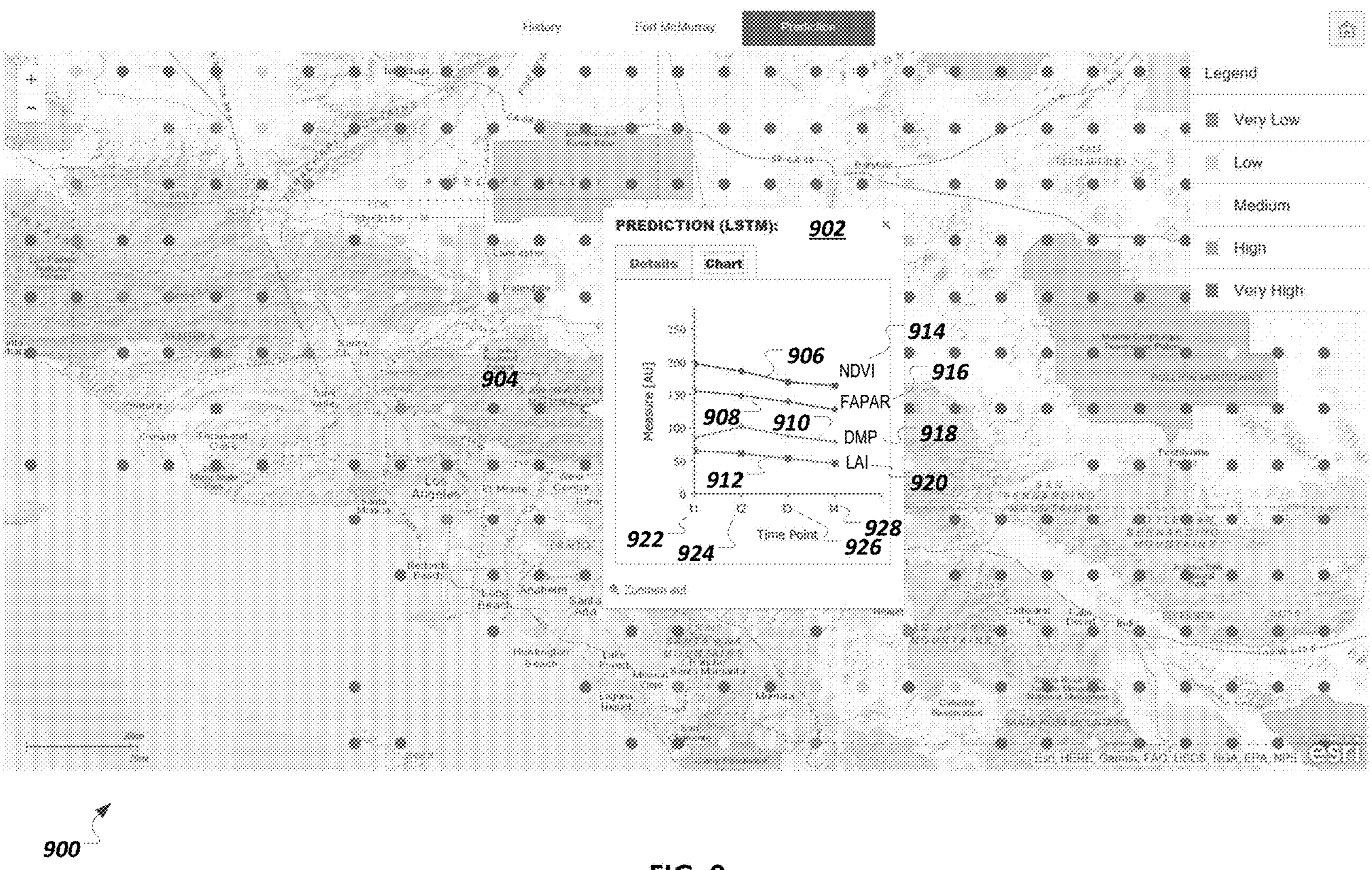

History
Fort McMurray
+
-
Legend
▩ Very Low
▩ Low
▩ Medium
▩ High
▩ Very High
PREDICTION (LSTM):
902
×
Details
Chart
Measure [AU]
250
200
150
100
50
0
t1
t2
t3
t4
Time Point
NDVI
FAPAR
DMP
LAI
906
908
910
912
914
916
918
920
922
924
926
928
Zoom to
904
Los Angeles
Long Beach
Anaheim
Esri, HERE, Garmin, FAO, USGS, NGA, EPA, NPS
900

FIG. 9

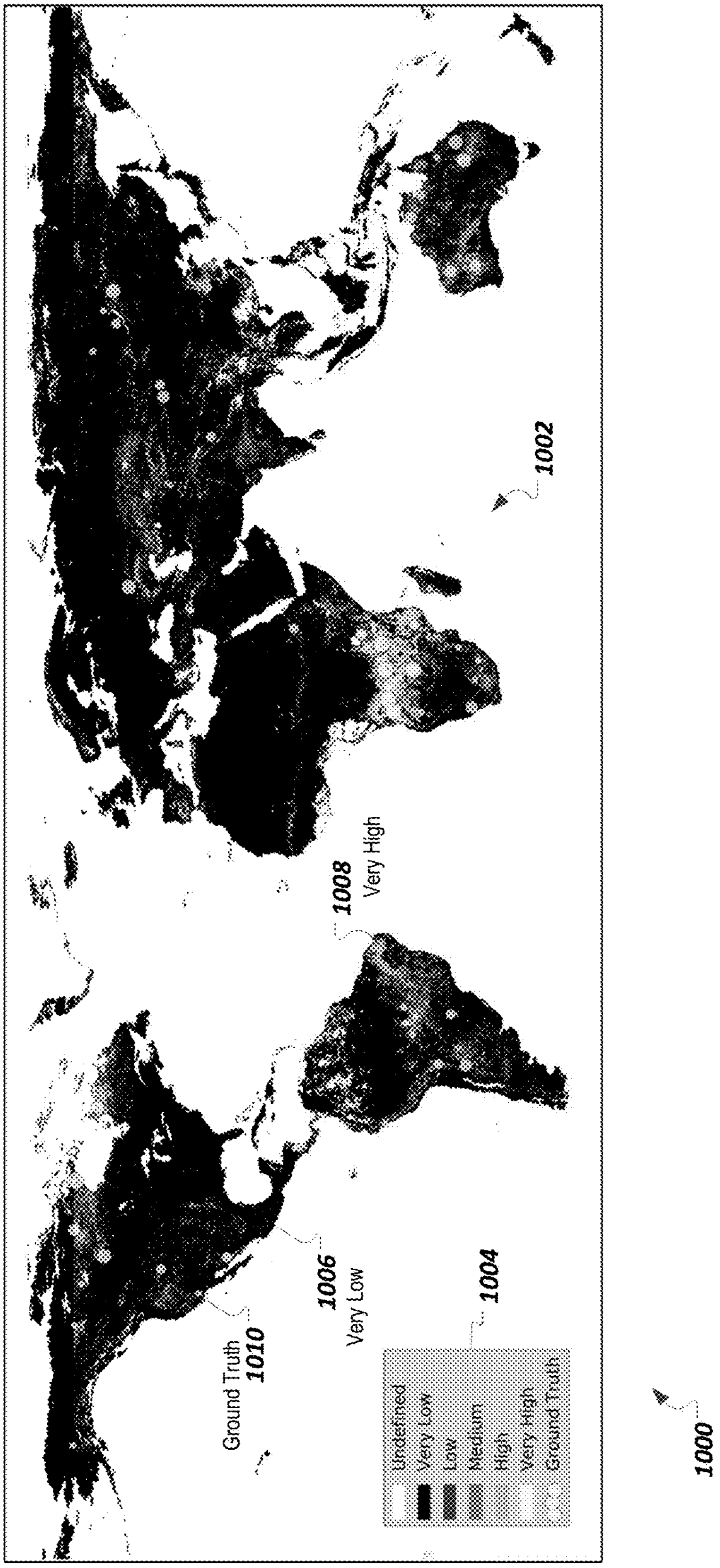
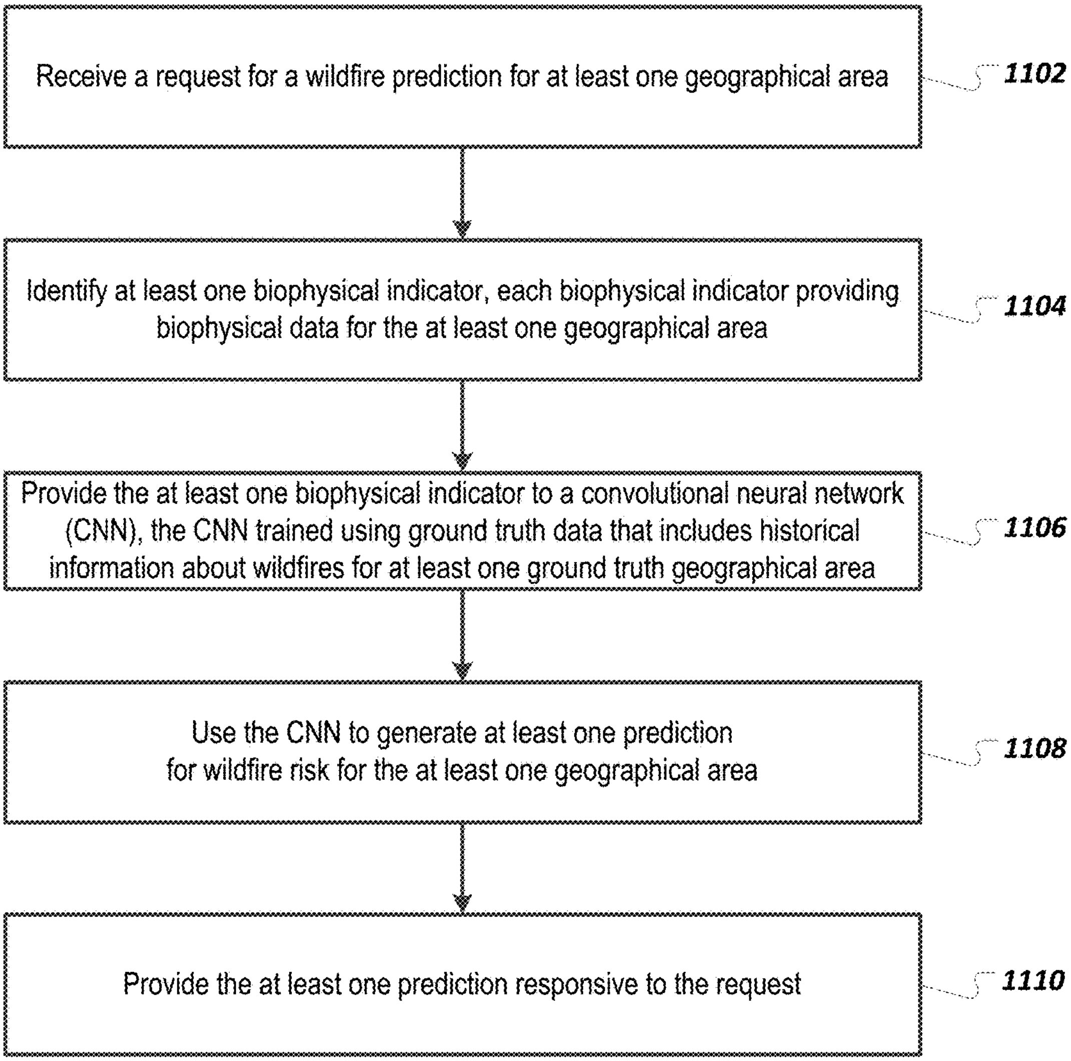

1002
1008
Very High
1006
Very Low
Ground Truth
1010
1004
Undefined
Very Low
Low
Medium
High
Very High
Ground Truth
1000

FIG. 10



Receive a request for a wildfire prediction for at least one geographical area

Identify at least one biophysical indicator, each biophysical indicator providing biophysical data for the at least one geographical area

Provide the at least one biophysical indicator to a convolutional neural network (CNN), the CNN trained using ground truth data that includes historical information about wildfires for at least one ground truth geographical area

Use the CNN to generate at least one prediction for wildfire risk for the at least one geographical area

Provide the at least one prediction responsive to the request

FIG. 11 1100

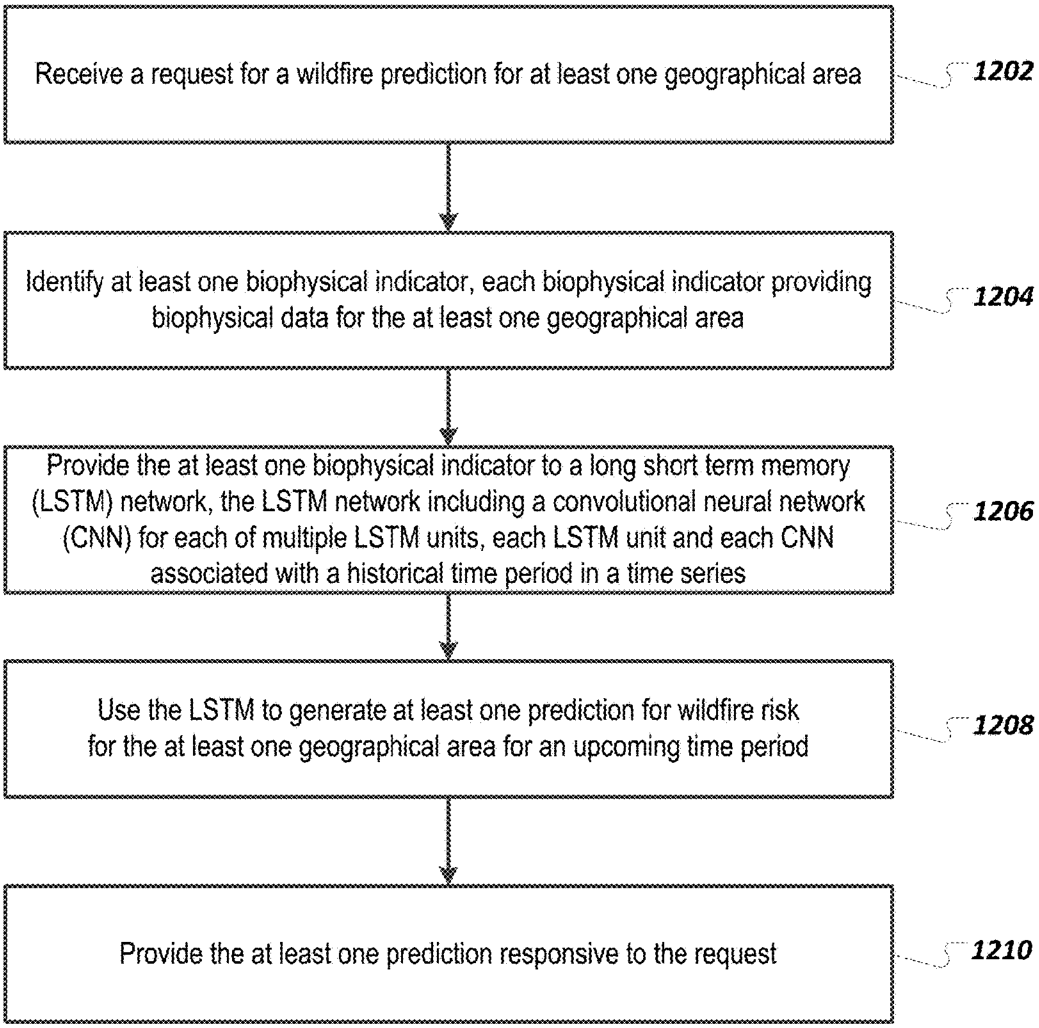

Receive a request for a wildfire prediction for at least one geographical area
1202
Identify at least one biophysical indicator, each biophysical indicator providing biophysical data for the at least one geographical area
1204
Provide the at least one biophysical indicator to a long short term memory (LSTM) network, the LSTM network including a convolutional neural network (CNN) for each of multiple LSTM units, each LSTM unit and each CNN associated with a historical time period in a time series
1206
Use the LSTM to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period
1208
Provide the at least one prediction responsive to the request
1210

FIG. 12 1200

PREDICTING WILDFIRES ON THE BASIS OF BIOPHYSICAL INDICATORS AND SPATIOTEMPORAL PROPERTIES USING A LONG SHORT TERM MEMORY NETWORK

BACKGROUND

[0001] An artificial neural network is a computational model based on a collection of artificial neurons which can be referred to as neural units. The artificial neural network can perform in a manner that is similar to the observed behavior of a biological brain's axons. Each neural unit can be connected to other neural units. In a recurrent neural network, connections between neural units form a directed cycle. In a feed-forward neural network, connections between neural units do not form a cycle.

[0002] A convolutional neural network (CNN) is a type of feed-forward neural network in which a connectivity pattern between neurons is based on the organization of the animal visual cortex. A CNN can be arranged into convolutional layers alternating with subsampling layers. A LSTM (Long Short-Term Memory) network is a type of recurrent neural network that includes LSTM units instead of, or in addition to, other network units. A LSTM unit is a recurrent network unit that is capable of remembering values for either long or short durations of time.

SUMMARY

[0003] The present disclosure involves systems, software, and computer implemented methods for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties. A method includes receiving a request for a wildfire prediction for at least one geographical area. At least one biophysical indicator is identified. Each biophysical indicator provides biophysical data for the at least one geographical area. The at least one biophysical indicator is provided to a long short term memory (LSTM) network. The LSTM network includes a convolutional neural network (CNN) for each of multiple LSTM units. Each LSTM unit and each CNN are associated with a historical time period in a time series. The LSTM is used to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period. The at least one prediction is provided responsive to the request.

[0004] While generally described as computer-implemented software embodied on tangible media that processes and transforms the respective data, some or all of the aspects may be computer-implemented methods or further included in respective systems or other devices for performing this described functionality. The details of these and other aspects and embodiments of the present disclosure are set forth in the accompanying drawings and the description below. Other features, objects, and advantages of the disclosure will be apparent from the description and drawings, and from the claims.

BRIEF DESCRIPTION OF DRAWINGS

[0005] FIG. **1** is a block diagram of an example environment for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties.

[0006] FIG. **2** illustrates layers of an architecture of a CNN.

[0007] FIGS. **3** and **4** illustrate example LSTM networks.

[0008] FIG. **5**A illustrates an example LSTM unit.

[0009] FIG. **5**B illustrates example curves for performance evaluation.

[0010] FIGS. **6** to **10** illustrate example user interfaces.

[0011] FIG. **11** is a flowchart of an example method for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties using a CNN.

[0012] FIG. **12** is a flowchart of an example method for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties using a LSTM network.

DETAILED DESCRIPTION

[0013] Wildfires can create substantial loss of property, life, income, and other damages. Considering these costs, an approach for assessing the wildfire risk for specific areas can be used to predict and plan for wildfire disasters. The ability to predict the risk of wildfires can be beneficial for helping safety services ensure public safety and for helping emergency services mitigate and reduce the impact of wildfires. Insurance companies can use wildfire predictions to improve estimates of insurance values and risks for specific areas.

[0014] Neural networks, including CNNs (Convolutional Neural Networks) and LSTM (Long Short-Term Memory) networks, can be utilized for prediction. A CNN can incorporate spatially local properties of wildfires. A LSTM network can include the architecture of a CNN and can account for the temporal properties of wildfires and vegetation states. Various biophysical indicators for geographical areas can be generated from satellite data, such as indicators for an amount of green and alive elements of the canopy, a thickness of a vegetation cover, an amount of visible and near-infrared light reflected by vegetation, or a dry biomass increase of the vegetation for a given geographical area.

[0015] A CNN and/or a LSTM neural network can be used to predict a wildfire risk for one or more geographical areas based on the generated biophysical indicators. The LSTM network can include multiple LSTM units that are associated with a time sequence. Each LSTM unit can use a CNN, with an output of a preceding CNN in the time sequence being used as an input for the next CNN. The CNNs can be trained using ground truth data that includes historical information about wildfires. A CNN and/or a LSTM network can output a set of wildfire predictions for the one or more geographical areas.

[0016] FIG. **1** is a block diagram illustrating an example system **100** for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties. Specifically, the illustrated system **100** includes or is communicably coupled with a server **102**, a client device **104**, one or more external biophysical data providers including an external biophysical data provider **105**, and a network **106**. Although shown separately, in some implementations, functionality of two or more systems or servers may be provided by a single system or server. In some implementations, the functionality of one illustrated system or server may be provided by multiple systems or servers.

[0017] A user can use an analytics application **108** on the client device **104** to request generation of wildfire predictions for one or more geographical areas for an upcoming time period. The request can be sent to a prediction system **110** running on the server **102**. The prediction system **110** can generate predictions **112**, and provide the predictions **112** to the client device **104**, for presentation in the analytics application **108**. The predictions can be presented using one or more map interfaces generated by a UI (User Interface) engine **113**, for example.

[0018] The prediction system **110** includes a CNN engine **114** and a LSTM engine **116**. One or both of the CNN engine **114** and the LSTM engine **116** can be used to generate predictions **112**. The LSTM engine **116** can use several CNN instances managed by the CNN engine **114**, as described below.

[0019] A given CNN instance can be trained using ground truth data **118**. The ground truth data **118** can include a Fire Occurrence Index (FOI). The FOI can be computed using two burned area maps BA_{t1} and BA_{t2} (where t1 and t2 are corresponding dates of measurement with t1<t2). If a pixel in a burned area map is not associated with a burned area in time step t=t1 but is associated with a burned area in a later time step t=t2 then a determination can be made that a fire occurred between t1 and t2 in the area. Thus, a true-value ($\mathrm{FOI}_{t2}=1$) can be assigned to the pixel, whereas a false-value can be assigned otherwise ($\mathrm{FOI}_{t2}=0$). Formally, the FOI can be defined using formula (1):

$$FOI_{t_2} = \begin{cases} 1 & \text{if } (BA_{t_1} = 0) \wedge (BA_{t_2} = 1) \\ 0 & \text{else} \end{cases} \tag{1}$$

[0020] Training can be performed using a stochastic optimization method. Samples can be balanced, for training purposes, so as to avoid the CNN engine **114** or the LSTM engine **116** trying to achieve low error rates by focusing on a majority class of non-wildfire areas. A ratio of wildfires to non-wildfires can be unbalanced for fitting and prediction purposes, since wildfires generally represent exceptional events. For instance, for an example data set, for each five samples which are labeled as wildfires more than 1300 samples may be labeled otherwise (for a ratio of wildfires to non-wildfires of 0.0037). An unbalanced ratio can be handled by applying under sampling (e.g., removing samples), such that the samples are balanced with respect to their classes.

[0021] The CNN, during training and during prediction, can take as input biophysical data **120**, which may be received from the biophysical data provider **105** as biophysical data **122**. The biophysical data **120** can include one or more of a vegetation index, a dry matter index, a leaf area index, and a fraction of absorbed photosynthetically active radiation index, as described in more detail below. The biophysical data provider **105** can provide a series of biophysical indicators on the status and evolution of land surface at global scale at mid and low spatial resolution. The biophysical data provider **105** can derive the biophysical data **122** by applying algorithms on satellite images, such as those produced by a space agency. The biophysical data **120** can be associated with geographical data **121** to map the biophysical data **120** to particular geographic locations.

[0022] A CNN can be configured by the setting of CNN parameters **124**, such as a patch size, activation function selection, output neuron count selection for each layer, pool shape and pool strides for max pooling, and dropout probability thresholds. CNN parameters are described in more detail below. A single CNN can be used to generate predictions **112**. A single CNN can include an input layer, a set of hidden layers (which can include convolution layers and fully connected layers), and an output layer. CNNs are described in more detail below with respect to FIG. **2**.

[0023] As another example, multiple CNNs can be used in a LSTM network by the LSTM engine **116** to generate predictions **112**. A LSTM network can be configured by the setting of LSTM parameters **126**, such as a number of LSTM units, a time period length (e.g., fifteen days), a dropout keep probability, activation function selection, input vector length passed between CNN units, and other parameters. LSTM parameters and operation are described in more detail below with respect to FIGS. **3** and **4**.

[0024] Performance of the predictions **112** can be quantified using qualitative factors **128**, which can include a Receiver Operating Characteristic (ROC) and an “Area under the Curve” (AUC) score. As described in more detail below, the predictions can be evaluated with respect to the qualitative factors **128** by comparing prediction maps with the ground truth data **118**. Categorical cross-entropy can be used as an objective function for evaluating the performance of the CNN engine **114** and the LSTM engine **116**.

[0025] As used in the present disclosure, the term “computer” is intended to encompass any suitable processing device. For example, although FIG. **1** illustrates a single server **102** and a single client device **104**, the system **100** can be implemented using a single, stand-alone computing device, two or more servers **102**, or two or more client devices **104**. Indeed, the server **102**, the external biophysical data provider **105**, and the client device **104** may be any computer or processing device such as, for example, a blade server, general-purpose personal computer (PC), Mac®, workstation, UNIX-based workstation, or any other suitable device. In other words, the present disclosure contemplates computers other than general purpose computers, as well as computers without conventional operating systems. Further, the server **102** and the client device **104** may be adapted to execute any operating system, including Linux, UNIX, Windows, Mac OS®, Java™, Android™, iOS or any other suitable operating system. According to one implementation, the server **102** may also include or be communicably coupled with an e-mail server, a Web server, a caching server, a streaming data server, and/or other suitable server.

[0026] Interfaces **140**, **142**, and **144** can be used by the client device **104**, the server **102**, and the external biophysical data provider **105**, respectively, for communicating with other systems in a distributed environment—including within the system **100**—connected to the network **106**. Generally, the interfaces **140**, **142**, and **144** each comprise logic encoded in software and/or hardware in a suitable combination and operable to communicate with the network **106**. More specifically, the interfaces **140**, **142**, and **144** may each comprise software supporting one or more communication protocols associated with communications such that the network **106** or interface’s hardware is operable to communicate physical signals within and outside of the illustrated system **100**.

[0027] The server **102** includes one or more processors **146**. Each processor **146** may be a central processing unit (CPU), a blade, an application specific integrated circuit (ASIC), a field-programmable gate array (FPGA), or another suitable component. Generally, each processor **146** executes instructions and manipulates data to perform the operations of the server **102**. For example, each processor **146** executes the functionality required to receive and respond to requests from the client device **104**, for example.

[0028] Regardless of the particular implementation, "software" may include computer-readable instructions, firmware, wired and/or programmed hardware, or any combination thereof on a tangible medium (transitory or non-transitory, as appropriate) operable when executed to perform at least the processes and operations described herein. Indeed, each software component may be fully or partially written or described in any appropriate computer language including C, C++, Java™, JavaScript®, Visual Basic, assembler, Peri®, any suitable version of 4GL, as well as others. While portions of the software illustrated in FIG. **1** are shown as individual modules that implement the various features and functionality through various objects, methods, or other processes, the software may instead include a number of sub-modules, third-party services, components, libraries, and such, as appropriate. Conversely, the features and functionality of various components can be combined into single components as appropriate.

[0029] The server **102** includes the memory **148**. In some implementations, the server **102** includes multiple memories. The memory **148** may include any type of memory or database module and may take the form of volatile and/or non-volatile memory including, without limitation, magnetic media, optical media, random access memory (RAM), read-only memory (ROM), removable media, or any other suitable local or remote memory component. The memory **148** may store various objects or data, including caches, classes, frameworks, applications, backup data, business objects, jobs, web pages, web page templates, database tables, database queries, repositories storing business and/or dynamic information, and any other appropriate information including any parameters, variables, algorithms, instructions, rules, constraints, or references thereto associated with the purposes of the server **102**.

[0030] The client device **104** may generally be any computing device operable to connect to or communicate with the platform server **102** via the network **106** using a wireline or wireless connection. In general, the client device **104** comprises an electronic computer device operable to receive, transmit, process, and store any appropriate data associated with the system **100** of FIG. **1**. The client device **104** can include one or more client applications, including the analytics application **108**. A client application is any type of application that allows the client device **104** to request and view content on the client device **104**. In some implementations, a client application can use parameters, metadata, and other information received at launch to access a particular set of data from the server **102**. In some instances, a client application may be an agent or client-side version of the one or more enterprise applications running on an enterprise server (not shown).

[0031] The client device **104** further includes one or more processors **150**. Each processor **150** included in the client device **104** may be a central processing unit (CPU), an application specific integrated circuit (ASIC), a field-programmable gate array (FPGA), or another suitable component. Generally, each processor **150** included in the client device **104** executes instructions and manipulates data to perform the operations of the client device **104**. Specifically, each processor **150** included in the client device **104** executes the functionality required to send requests to the server **102** and to receive and process responses from the platform server **102**.

[0032] The client device **104** is generally intended to encompass any client computing device such as a laptop/notebook computer, wireless data port, smart phone, personal data assistant (PDA), tablet computing device, one or more processors within these devices, or any other suitable processing device. For example, the client device **104** may comprise a computer that includes an input device, such as a keypad, touch screen, or other device that can accept user information, and an output device that conveys information associated with the operation of the server **102**, or the client device **104** itself, including digital data, visual information, or a GUI **154**.

[0033] The GUI **154** of the client device **104** interfaces with at least a portion of the system **100** for any suitable purpose, including generating a visual representation of the analytics application **122**. In particular, the GUI **154** may be used to view a FCM, various Web pages, or other user interfaces. Generally, the GUI **154** provides the user with an efficient and user-friendly presentation of business data provided by or communicated within the system. The GUI **154** may comprise a plurality of customizable frames or views having interactive fields, pull-down lists, and buttons operated by the user. The GUI **154** contemplates any suitable graphical user interface, such as a combination of a generic web browser, intelligent engine, and command line interface (CLI) that processes information and efficiently presents the results to the user visually.

[0034] Memory **156** included in the client device **104** may include any memory or database module and may take the form of volatile or non-volatile memory including, without limitation, magnetic media, optical media, random access memory (RAM), read-only memory (ROM), removable media, or any other suitable local or remote memory component. The memory **156** may store various objects or data, including user selections, caches, classes, frameworks, applications, backup data, business objects, jobs, web pages, web page templates, database tables, repositories storing business and/or dynamic information, and any other appropriate information including any parameters, variables, algorithms, instructions, rules, constraints, or references thereto associated with the purposes of the client device **104**.

[0035] There may be any number of client devices **104** associated with, or external to, the system **100**. For example, while the illustrated system **100** includes one client device **104**, alternative implementations of the system **100** may include multiple client devices **104** communicably coupled to the server **102** and/or the network **106**, or any other number suitable to the purposes of the system **100**. Additionally, there may also be one or more additional client devices **104** external to the illustrated portion of system **100** that are capable of interacting with the system **100** via the network **106**. Further, the term "client", "client device" and "user" may be used interchangeably as appropriate without departing from the scope of this disclosure. Moreover, while the client device **104** is described in terms of being used by a single user, this disclosure contemplates that many users may use one computer, or that one user may use multiple computers.

[0036] FIG. **2** illustrates layers of an architecture **200** of a CNN. The architecture **200** includes several layers. For each layer, initial weights can be randomly selected from a normal distribution. An input layer **202** can provide input to the CNN. The input layer **202** can provide data of a size of N×P×P×F, where N is a number of samples, P is a patch height and width, and F is a number of features. The input layer **202** can require a partial preservation of the local structures of an image. Therefore, concatenated world maps can be split into equally sized parts, which can be defined as patches and represent the samples. For example, an image of size 256×256 can be split into 10 patches (samples), with the size of each patch equal to 16×16.

[0037] Regarding features, data for four features **203** for a given geographical area can be provided by the input layer **202** to a first hidden layer **204**. The four features **203** can each be biophysical indicators, for example, and can be received from an external service. Raw data of each world map for a given date can be loaded into one or more arrays. The raw data for a geographic area can be divided into granules (e.g., tiles) and arrays can be stitched together to form stitched maps. A mask that includes references to invalid pixels (e.g., clouds, water surfaces) can be generated. The stitched maps can be transformed to patches for the CNN.

[0038] Biophysical indicators can be associated with values that indicate the vegetation for particular areas. A reduction in biophysical activity (e.g., vegetation) in an area can be associated, for example, with either a lack of resources such as water or an excess of solar activity, and either can increase the chance of wildfire in the area. Biophysical indicators can include Normalized Difference Vegetation Index (NDVI), Dry Matter Productivity (DMP), Leaf Area Index (LAI), and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR).

[0039] The NDVI is a graphical indicator for quantifying the vegetation in an area. The NDVI can be based on the amount of visible and near-infrared light reflected by vegetation. Visible light (VIS) is absorbed mostly by healthy vegetation, but reflected by unhealthy vegetation, whereas for near-infrared (NIR) light, this relationship is generally inverted (NIR light is generally reflected by healthy vegetation but absorbed by unhealthy vegetation). The properties of VIS light and NIR light can be used when calculating the NDVI using formula (2) below:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \tag{2}$$

[0040] The DMP indicator can measure the overall growth rate or dry biomass increase of vegetation in an area, and can be expressed as kilograms of dry matter per hectare per day (kgDM/ha/day). The calculation of DMP can include biophysical variables such as canopy water content, surface temperature and leaf phenology. Since DMP estimates the increase of dry biomass, high DMP values can indicate vegetation areas, for example. As another example, low DMP values can be indicative of plants losing high quantities of dry biomass due to a drought.

[0041] The LAI quantifies the thickness of the vegetation cover in an area. The LAI can be derived from satellite images and can correspond to a total green area of all the canopy layers in an area, including the under-story, which may represent a very significant contribution to the LAI, especially for forests. The LAI can be defined as half the developed area of photosynthetically active elements of the vegetation per unit horizontal ground area.

[0042] The FAPAR indicator can refer to amounts of green and alive elements of the canopy and can depend on canopy structure, vegetation element optical properties, and angular configuration. Although related to the canopy like LAI, a FAPAR value can quantify a fraction of the solar radiation absorbed by live leaves for photosynthesis activity.

[0043] Other indicators can be used, such as raw image data (with images of a same width, height and time interval, for example), FCOVER (Fraction of Vegetation Cover), VCI (Vegetation Condition Index), or other indicators. FCOVER measures a fraction of ground covered by green vegetation, quantifies a spatial extent of vegetation, is independent from the illumination direction and is sensitive to a vegetation amount. The VCI compares a current NDVI to a range of values observed in a same period in previous years. The VCI can be expressed as a percentage and provides an indication where an observed value is situated between extreme values (minimum and maximum) in previous years. Lower and higher VCI values indicate bad and good vegetation state conditions, respectively.

[0044] Each of the features **203** can share some or all of several characteristics. Each data set can be for a particular number of days (e.g., 10 days), a particular spatial resolution (e.g., one square kilometer), use a particular value range (e.g., 0-255 as an unsigned 8 bit integer), use a particular data format (e.g., Hierarchical Data Format 5 (HDF5), use a particular type of geographic projection (e.g., regular latitude-longitude), use a particular geodatical datum (e.g., WGS84 (World Geodetic System 84), and use a particular pixel size and accuracy (e.g., 1/336° and minimum 10 digits accuracy). Each data set may include invalid values, which can be caused, for example, by clouds, snow, sea, or other factors.

[0045] Each data set in a feature **203** can be identified using an identifier that includes a horizontal and vertical component. For instance, an example identifier is: g2_BIOPAR_NDVI_2016080 10000_H21V4_PROBAV_V2.1, where NDVI is a product type generated with PROBAV satellite data with an algorithmic approach of version 2.1 on the date 1 Aug. 2016 with a position or location identifier of H21V4 relative to the whole map of data associated with the product. For example, H21V4 can mean position 21 out of 35 in the horizontal direction and 4 out of 15 in the vertical direction. A feature **203** may include, for example, 35×15=525 granules. However, some granules can represent a water surface, so less granules, e.g., **330**, may be included in an actual data set. Each such granule can include a quicklook image, metadata, and actual data, which can be stored as an HDF5 file and used for model fitting and prediction.

[0046] A parser can be used to generate an overview about the input data and to evaluate subsequent predictions later on by comparing actual wildfires to predicted wildfires. The parser can extract data for a specific time range and initialize selected products and their granules for a specific date. The values of the granules values can be stored in an HDF5 file as an array of a particular size (e.g., size 1121×1121), and can be concatenated according to location identifier, which can result in a map. As mentioned previously, products can include invalid pixels (e.g., sea surface or clouds). The invalid values can be stored in a HDF5 file together with valid values and can represent the last values of an interval scale (e.g., values of 254 and 255). To avoid reducing the generalization of classifiers (e.g., categorical variables in interval scales), a mask can be used to skip the invalid values while training and predicting.

[0047] Referring again to FIG. **2**, and as illustrated by an operation **205**, the first hidden layer **204** is a rectified convolutional layer that uses data from the input layer **202** to generate output neurons (e.g., thirty two output neurons) for use by a second hidden layer **206**. As illustrated by an operation **207**, the second hidden layer **206** is a rectified convolutional layer that uses data from the first hidden layer **204** to generate output neurons (e.g., a larger number of output neurons than generated by the first hidden layer **204**, such as sixty four) for use by a third hidden layer **208**. As illustrated by an operation **209**, the third hidden layer **208** is a rectified convolutional layer that uses data from the third hidden layer **208** to generate output neurons (e.g., a larger number of output neurons than generated by the second hidden layer **206**, such as one hundred twenty eight), for use by a fourth hidden layer **210**. Each of the hidden layers **204**, **206**, and **208** can use a L2-regularizer, with the outputs of each layer processed by local response normalization and by max-pooling using, for example, a pool shape of 2×2 and a pool stride of 1×1.

[0048] In general, for the convolutional layers, a number of maps, kernel sizes and skipping factors can characterize a given convolutional layer. On each convolutional layer, a kernel of size (K_x, K_y) can be shifted over a valid region of an input image (e.g., the kernel can be completely inside of the input image for each convolutional layer). Strides S_x and S_y, which can control how the kernel convolves around the input image, can define an amount of pixels skipped by the kernel in x- and y-directions between subsequent convolutions. A shifting process can result in an output map for a layer with a size equal to the previous layer, if padding (adding additional values to the border of the image) is utilized.

[0049] The fourth hidden layer **210** is a fully connected layer that uses an activation function (e.g., a tan h function) and data from the third hidden layer **208** to generate output neurons **211** (e.g., a larger number of output neurons than generated by the third hidden layer **208**, such as five hundred twelve) for use by a fifth hidden layer **212**. The fifth hidden layer **212** is a fully connected layer that uses an activation function (e.g., a tan h function) and data from the fourth hidden layer **210** to generate output neurons **213** (e.g., a larger number of output neurons than generated by the fourth hidden layer **210**, such as one thousand twenty four) for use by an output layer **214**. For the fourth hidden layer **210** and the fifth hidden layer **212**, neurons can be kept if a computed probability is more than a threshold (e.g., 0.5).

[0050] The output layer **214** is a fully connected layer that uses an activation function (e.g., a softmax function) and data from the fifth hidden layer **212** to generate two output neurons including a first output neuron **216** and a second output neuron **218** (e.g., one output neuron per class label). The first output neuron **216** represents a calculated likelihood of a wildfire for the geographical area for an upcoming time period (e.g., a next fifteen days). The second output neuron **218** represents a calculated likelihood of there not being a wildfire for the geographical area in the upcoming time period. Values for the first output neuron **216** and the second output neuron **218** can add up to one hundred percent.

[0051] When determining the first output neuron **216** and the second output neuron **218**, to summarize the information about each patch, one of two approaches can be used. In a first approach, a patch can be labeled positive if the patch includes more than one pixel indicating a positive value and otherwise labeled negative. In a second approach, all positive occurrences in a patch can be counted and the patch can be labeled positive if the sum of the positive occurrences in the patch is above a predetermined threshold. The first approach can result in maps that include an unacceptable amount of more fire risk areas than the actual ground truth. Therefore the second approach may be preferable. For the second approach, the threshold can be optimized (e.g., to a ratio of eight pixels) so that the summarized ground truth includes substantially the same amount of wildfire endangered pixels as the original ground truth. With a threshold of eight, if a patch includes more than eight pixels indicating wildfire areas, then the whole patch can be labeled as wildfire endangered.

[0052] In further detail of the hidden layers, the resulting outputs of a topmost convolutional layer (e.g., the third hidden layer **208**) can be combined by a fully connected layer (e.g., the fourth hidden layer **210**) into a one-dimensional feature vector (e.g., the output neurons **211**). In some implementations, to process information of a convolutional layer, kernel sizes of convolutional filters and max-pooling rectangles are used with a specific size and stride, such that the output maps of a last convolutional layer are down-sampled to one pixel per map.

[0053] Max-pooling can be used as an efficient, non-linear method of down-sampling. Max-pooling can include partitioning an input image along each direction by a factor of K and K_y into a set of non-overlapping rectangles of size (K_x, K_y). The output of a max-pooling layer can be calculated by taking a maximum activation of each rectangle. Max-pooling can eliminate non-maximal values, and such elimination can: 1) reduce computation for upper layers; and 2) provide position invariance over larger local regions, which can lead to faster convergence, selection of superior invariant features, and improved generalization.

[0054] Basic definitions of a neuron's output f as a function of its input x can be represented either by $f(x)=(1+e^{-x})^{-1}$ or $f(x)=\tan h(x)$. These functions are saturating non-linear activation functions which can be slower than a ReLU (Rectified Linear Unit) function $f(x)=\max(0, x)$. The ReLU function may be neither saturating nor linear. A ReLU function can be used for faster training as compared to the saturating non-linear activation functions.

[0055] A ReLU function may not require input normalization to prevent saturation. Higher generalization can be achieved using a ReLU function by applying local response normalization, which is a procedure that is inspired by real neurons that stimulates the competition for big activities amongst neuron outputs computed using different kernels. The local response normalization can be applied after the ReLU nonlinearity in certain layers. Applying local response normalization can result in a lower test error rate.

[0056] A dropout method can be used to reduce the complexity of a neural network while training. In a dropout method, the output of each neuron can be retained with a probability p and set to 0 otherwise. Neurons which are dropped out do not participate in the feed-forwarding and back-propagation. Using dropout, neurons may not be able to rely on the presence of particular neurons, which can result in neurons learning more robust features that are useful in conjunction with many different random subsets of the other neurons, which can improve training.

[0057] FIG. **3** illustrates a LSTM network **300**. The LSTM network **300** includes a LSTM layer **302** that includes a series of LSTM units including LSTM units **304**, **306**, and **308**. As described in more detail below, each LSTM unit **304**, **306**, and **308** is respectively associated with a CNN **310**, **312**, or **314**. Each LSTM unit **304**, **306**, or **308** uses a respective CNN **310**, **312**, or **314** to generate output data for use by a successive unit in the LSTM **300**. A fully connected layer **316** can, using input from the last LSTM unit **308**, generate predictions **318** that indicate a wildfire risk for a given geographical area.

[0058] In general, recurrent neural networks (RNN) such as the LSTM network **300** can be used to process sequential inputs such as time series. The architecture of RNNs is based on the neuron structures primarily found in the neocortex in the brain. RNNs can process every element of an input sequence successively and memorize crucial information in each step. The memorized information can be available in a next processing step. Each element can be processed using the same weights. RNNs can map an input sequence $x_t \in R^T$ to a sequence of hidden states $h_t \in R^N$ and an output sequence z_t as shown in formulas (3) and (4) below

$$h_t=g(W_{xh}x_t+W_{hh}h_{t-1}+b_h) \quad (3)$$

$$z_t=g(W_{hz}+b_z) \quad (4)$$

where W_{xh}, W_{hh}, W_{hz} are weights, b_h, b_z are biases, g is an activation function of the RNN layer, T is the length of the sequence and N is the number of hidden units. The computation of the hidden state h_t can require a previous hidden state h_{t-1}. Accordingly, the RNN can iterate recursively over the input sequence x_t. The hidden state passed to the first RNN cell can be chosen as $h_0=0$.

[0059] The use of a memory unit which can be called cell state Ct can overcome training difficulties caused by vanishing or exploding gradients. The memory unit can enable the network to learn when to forget previous information and when to update a cell state with the current hidden state. A LSTM cell can accept a previous cell state C_{t-1}, the hidden state of the previous cell h_{t-1}, and the input of the according time step x_t as input. The resulting output can be the updated cell state C_t and the hidden state h_t. A decision about which information to keep or throw away can be made in gate layers. Each gate layer can use a sigmoid function σ (or some other type of function), which can be referred to as an inner activation function of the LSTM layer. The output of the inner activation function can range between 0 and 1 (for each hidden unit) and can determine the extent to which information is memorized (e.g., when the σ function output is substantially equal to 1) or forgotten (e.g., when the σ function output is substantially equal to 0). A LSTM cell can include three gates that each take the hidden state of the previous cell h_{t-1} and x_t as input, including a forget gate layer, an input gate layer, and an output gate layer. The forget gate layer can be used to determine to which extent each value of the cell state is kept, using formula (5):

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f) \quad (5)$$

[0060] The input gate layer can be used to determine to which extent the cell state is updated with the cell input of h_{t-1} and x_t, using formula (6):

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i) \quad (6)$$

[0061] The output gate layer can be used to determine to which extent output hidden state h_t is kept, using formula (7):

$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_o) \quad (7)$$

[0062] Using the three gate layers, an output of a LSTM cell can be computed using formulas (8), (9), and (10) below:

$$\hat{C}_t=g(W_C\cdot[h_{t-1},x_t]+b_C) \quad (8)$$

$$C_t=f_t*C_{t-1}+i_t*\hat{C} \quad (9)$$

$$h_t=o_t*g(C_t) \quad (10)$$

where g is the activation function for the LSTM layer.

[0063] FIG. **4** illustrates a LSTM network **400**. Similar to the LSTM network **300**, the LSTM network **400** includes the LSTM layer **302** that includes a series of LSTM units including LSTM units **304**, **306**, and **308**, with each LSTM unit **304**, **306**, and **308** respectively associated with the CNN **310**, **312**, or **314**.

[0064] As described above with respect to FIG. **2**, inputs to a respective CNN can include biophysical indicators. For example, FAPAR indicators **402**, NDVI indicators **404**, DMP indicators **406**, and LAI indicators **408** can be inputted to the CNN **310** associated with the LSTM unit **302**. The CNN **310** accepts input data from a time period of forty five days ago **410**. Other CNNs can accept input data from more recent time periods. For example, the CNN **312** can accept data from thirty days ago **412**, another (not shown) CNN can accept data from fifteen days ago, and the CNN **314** can accept current data **414**. Although time windows of fifteen days are illustrated, other time window lengths can be used, including varying length time windows. Each of the CNNs can use common weights. A last two-neuron layer of a respective CNN can be omitted such that a previous CNN in the chain feeds an input vector with a length of 1024 into a successive corresponding LSTM cell. For example, the CNN **310** can generate a vector of length **1024** which can be accepted as input by the LSTM unit **306** for use by the CNN **312**.

[0065] Several steps can be performed for LSTM layer setup. For example, for the training of the LSTM layer **302**, a dropout keep probability can be determined. For example, a dropout keep probability of 0.7 can be used. An activation function, such as a hyperbolic tangent, can be selected. A number of hidden units can be selected, such as 512 hidden units. A number of time steps can be selected, such as four.

[0066] During prediction, the output of the CNNs can be passed to the LSTM layer **302**. A hidden state of a last LSTM unit **308** can be passed to the fully connected layer **316** with two neurons for each pixel that represents a geographic area, with the two neurons representing probability of a wildfire and probability of not a wildfire (e.g., classes wildfire and non-wildfire), for a given geographic area, for an upcoming time period (e.g., the next fifteen days). A softmax activation function can be used for classification. Predictions **318** can be presented in a map **416**, with different colors or other indications indicating different wildfire risks for different geographic areas presented on the map **416**.

[0067] FIG. **5**A illustrates an example LSTM unit **500**. As illustrated by a flow **502**, various operations can be performed by the LSTM unit to transform a set of inputs into a set of outputs. For example, various functions **504** (e.g., sigmoid, tan h) and various pixel operations **506** (e.g., addition, multiplication) can be used.

[0068] FIG. 5B illustrates example curves **550** and **552** that can be used for performance evaluation. The curves **550** and **552** are receiver operating characteristic (ROC) curves. A ROC can be used for conclusions about distributions of wildfire endangered areas given a few distinct areas where a fire actually breaks out. The ROC curve can be based on two parameters: a true positive rate TPR and a false positive rate FPR, which can be formally defined as shown below:

$$TPR = \frac{T_p}{T_p + F_n} \tag{11}$$

$$FPR = \frac{F_p}{F_p + T_n} \tag{12}$$

where T_p is true positives (e.g., number of samples correctly classified as positives (e.g., wildfire areas correctly classified as wildfire areas)), T_n is true negatives (e.g., number of samples correctly classified as negatives (e.g., non-wildfire areas correctly classified as non-wildfire areas)), F_p is false positives (e.g., number of negative samples incorrectly classified as positives (e.g., non-wildfire areas incorrectly classified as wildfire areas)), and F_n is false negatives (e.g., number of positive samples incorrectly classified as negatives (wildfire areas incorrectly classified as non-wildfire areas)).

[0069] F_p and T_n can be typically within the same order of magnitude, so classifying too many areas as fire-endangered can be penalized while pertaining manageable values (in contrast to the precision). By adjusting a threshold on the prediction score, the TPR and/or the FPR can be improved. The ROC curves **550** and **552** can be constructed by plotting the FPR as a function of the TPR. A high-performing classifier maintains a high value of TPR even for a low value of FPR. Therefore an area under the curve (AUC) score can be utilized as a metric for measuring the performance of a classifier. For the example curves **550** and **552**, the area under the curve **550** is 0.85 and the area under the curve **552** is 0.91, which can indicate that a LSTM network performed better than a CNN, for prediction.

[0070] FIG. **6** illustrates an example user interface **600**. The user interface **600** presents a color coded map **602** with various colors indicating various levels of wildfire risk for a given area. For example, as illustrated by a legend **604**, wildfire risk levels can include very low, low, medium, high, and very high levels of risk. For instance, areas **606**, **608**, **610**, **612**, and **614** have risk levels of very low, low, medium, high, and very high, respectively, as indicated by respective colors used for the respective areas.

[0071] FIG. **7** illustrates an example user interface **700**. The user interface **700** includes a map **702**. The user interface **700** may be displayed, for example, in response to a zoom-in operation received by the user interface **600** described above with respect to FIG. **6**. The user interface **700** includes colored selectable items, such as an item **704**. The color of a selectable item indicates a wildfire risk for a geographic area around the location the item represents, according to a legend **706**. As described below, a user can select a selectable item to view more detailed information about a wildfire prediction.

[0072] FIG. **8** illustrates an example user interface **800**. An interface **802** can be displayed over the user interface **800** in response to selection of a selectable item **804**. The interface **802** displays a prediction score **806** that indicates a wildfire probability for an upcoming time period for a geographic area represented by the selectable item **804**. A date **808** indicates when the prediction score **806** was calculated. The prediction score **806** can be based on values for NDVI **810**, LAI **812**, FAPAR **814**, and DMP **816** indicators. The interface **802** displays values for the NDVI **810**, LAI **812**, FAPAR **814**, and DMP **816** indicators for first **818**, second **820**, third **822**, and fourth **824** time periods, with each successive time period being a previous time period further into the past than the date **808**. The prediction score **806** can be a score determined using a LSTM that uses the first **818**, second **820**, third **822**, and fourth **824** time periods as a time sequence, for example. A user can select a chart tab **826** to view information about the prediction score **806** in a chart form.

[0073] FIG. **9** illustrates an example user interface **900**. The user interface **900** includes an interface **902** that displays line charts for data related to a wildfire prediction for an area represented by a selected item **904**. The interface **902** includes lines **906**, **908**, **910**, and **912** that show data for NDVI **914**, FAPAR **916**, DMP **918**, and LAI **920** indicators for each of first **922**, second **924**, third **926**, and fourth **928** time points, respectively. The first **922**, second **924**, third **926**, and fourth **928** time points can be included in a time series in a LSTM network used to calculate the wildfire prediction.

[0074] FIG. **10** illustrates an example user interface **1000**. Similar to the user interface **600**, the user interface **1000** presents a map **1002**. The map **1002** is a world map that is color coded using colors, according to a legend **1004**, that indicate different levels of wildfire risk for different areas, including an area **1006** having very high risk and an area **1008** having very low risk. Wildfire risk calculation methods can be trained using ground truth data. Wildfire risk predictions can also be compared to ground truth data, for performance evaluation. The user interface **1000** indicates areas that have ground truth data, such as an area **1010**.

[0075] FIG. **11** is a flowchart of an example method **1100** for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties using a CNN. It will be understood that method **1100** and related methods may be performed, for example, by any suitable system, environment, software, and hardware, or a combination of systems, environments, software, and hardware, as appropriate. For example, one or more of a client, a server, or other computing device can be used to execute method **1100** and related methods and obtain any data from the memory of the client, the server, or the other computing device. In some implementations, the method **1100** and related methods are executed by one or more components of the system **100** described above with respect to FIG. **1**. For example, the method **1100** and related methods can be executed by the CNN engine **214** of FIG. **1**.

[0076] At **1102**, a request for a wildfire prediction for at least one geographical area is received. The request can be received, for example, from a user interface. As another example, the request can be received from a system or program.

[0077] At **1104**, at least one biophysical indicator is identified, each biophysical indicator providing biophysical data for the at least one geographical area. The at least one biophysical indicator can include at least one of a vegetation index, a dry matter index, a leaf area index, and a fraction of absorbed photosynthetically active radiation index.

[0078] At **1106**, the at least one biophysical indicator is provided to a CNN. The CNN can be trained using ground truth data that includes historical information about wildfires for at least one ground truth geographical area. One or more of the geographical areas for which a prediction is requested can be different from ground truth areas. The CNN can include an input layer, at least one rectified convolutional layer, at least one fully connected layer, and an output layer.

[0079] At **1108**, the CNN to generate at least one prediction for wildfire risk for the at least one geographical area. The generated prediction can include, for each geographic area, a first output neuron and a second output neuron, the first output neuron and the second output neuron indicating a probability of a wildfire and a probability of no wildfire for the geographic area for an upcoming time period, respectively.

[0080] At **1110**, the at least one prediction is provided responsive to the request. Prediction information can be presented on a map that displays the at least one geographic area. The prediction can be evaluated by comparing ground truth data for the at least one geographic area to the generated prediction.

[0081] FIG. **12** is a flowchart of an example method **1200** for predicting wildfires on the basis of biophysical indicators and spatiotemporal properties using a LSTM network. It will be understood that method **1200** and related methods may be performed, for example, by any suitable system, environment, software, and hardware, or a combination of systems, environments, software, and hardware, as appropriate. For example, one or more of a client, a server, or other computing device can be used to execute method **1200** and related methods and obtain any data from the memory of the client, the server, or the other computing device. In some implementations, the method **1200** and related methods are executed by one or more components of the system **100** described above with respect to FIG. **1**. For example, the method **1200** and related methods can be executed by the CNN engine **214** of FIG. **1**.

[0082] At **1202**, a request for a wildfire prediction for at least one geographical area is received. The request can be received, for example, from a user interface. As another example, the request can be received from a system or program.

[0083] At **1204**, at least one biophysical indicator is identified, each biophysical indicator providing biophysical data for the at least one geographical area. The at least one biophysical indicator can include at least one of a vegetation index, a dry matter index, a leaf area index, and a fraction of absorbed photosynthetically active radiation index.

[0084] At **1206**, the at least one biophysical indicator is provided to a LSTM network, the LSTM network including a CNN for each of multiple LSTM units, each LSTM unit and each CNN associated with a historical time period in a time series.

[0085] At **1208**, the LSTM is used to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period. The outputs of each CNN except a last CNN associated with a last historical time period can be respectively provided to a CNN associated with a more recent time period in the time series. The provided outputs of each CNN can be outputs generated by a hidden layer of a respective CNN. The outputs of the last CNN can be provided to a fully connected layer of the LSTM. The fully connected layer can be used to generate the at least one prediction. The at least one prediction can include, for each geographic area, a first output neuron and a second output neuron, the first output neuron and the second output neuron indicating a probability of a wildfire and a probability of no wildfire for the geographic area for an upcoming time period, respectively.

[0086] At **1210**, the at least one prediction is provided responsive to the request. Prediction information can be presented on a map that displays the at least one geographic area. The prediction can be evaluated by comparing ground truth data for the at least one geographic area to the generated prediction.

[0087] The preceding figures and accompanying description illustrate example processes and computer-implementable techniques. But system **100** (or its software or other components) contemplates using, implementing, or executing any suitable technique for performing these and other tasks. It will be understood that these processes are for illustration purposes only and that the described or similar techniques may be performed at any appropriate time, including concurrently, individually, or in combination. In addition, many of the operations in these processes may take place simultaneously, concurrently, and/or in different orders than as shown. Moreover, system **100** may use processes with additional operations, fewer operations, and/or different operations, so long as the methods remain appropriate.

[0088] In other words, although this disclosure has been described in terms of certain embodiments and generally associated methods, alterations and permutations of these embodiments and methods will be apparent to those skilled in the art. Accordingly, the above description of example embodiments does not define or constrain this disclosure. Other changes, substitutions, and alterations are also possible without departing from the spirit and scope of this disclosure.

What is claimed is:

1. A computer-implemented method, the method comprising:

receiving a request for a wildfire prediction for at least one geographical area;

identifying at least one biophysical indicator, each biophysical indicator providing biophysical data for the at least one geographical area;

providing the at least one biophysical indicator to a long short term memory (LSTM) network, the LSTM network including a convolutional neural network (CNN) for each of multiple LSTM units, each LSTM unit and each CNN associated with a historical time period in a time series;

using the LSTM to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period; and

providing the at least one prediction responsive to the request.

2. The method of claim **1**, wherein the outputs of each CNN except a last CNN associated with a last historical time period are respectively provided to a CNN associated with a more recent time period in the time series.

3. The method of claim **2**, wherein the provided outputs of each CNN are outputs generated by a hidden layer of a respective CNN.

4. The method of claim **2**, wherein the outputs of the last CNN are provided to a fully connected layer of the LSTM.

5. The method of claim **3**, wherein the fully connected layer is used to generate the at least one prediction.

6. The method of claim **4**, wherein the at least one prediction comprises a first output neuron and a second output neuron, the first output neuron and the second output neuron indicating a probability of a wildfire and a probability of no wildfire for the geographic area for an upcoming time period, respectively.

7. The method of claim **1**, wherein providing the at least one prediction comprises presenting prediction information on a map that displays the at least one geographic area.

8. The method of claim **1**, further comprising evaluating the prediction using ground truth data for the at least one geographical area.

9. A system, comprising:

at least one processor; and

a memory communicatively coupled to the at least one processor, the memory storing instructions which, when executed by the at least one processor, cause the at least one processor to perform operations comprising:

receiving a request for a wildfire prediction for at least one geographical area;

identifying at least one biophysical indicator, each biophysical indicator providing biophysical data for the at least one geographical area;

providing the at least one biophysical indicator to a long short term memory (LSTM) network, the LSTM network including a convolutional neural network (CNN) for each of multiple LSTM units, each LSTM unit and each CNN associated with a historical time period in a time series;

using the LSTM to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period; and

providing the at least one prediction responsive to the request.

10. The system of claim **9**, wherein the outputs of each CNN except a last CNN associated with a last historical time period are respectively provided to a CNN associated with a more recent time period in the time series.

11. The system of claim **10**, wherein the provided outputs of each CNN are outputs generated by a hidden layer of a respective CNN.

12. The system of claim **10**, wherein the outputs of the last CNN are provided to a fully connected layer of the LSTM.

13. The system of claim **12**, wherein the fully connected layer is used to generate the at least one prediction.

14. The system of claim **13**, wherein the at least one prediction comprises a first output neuron and a second output neuron, the first output neuron and the second output neuron indicating a probability of a wildfire and a probability of no wildfire for the geographic area for an upcoming time period, respectively.

15. One or more computer-readable media storing instructions which, when executed by at least one processor, cause the at least one processor to perform operations comprising:

receiving a request for a wildfire prediction for at least one geographical area;

identifying at least one biophysical indicator, each biophysical indicator providing biophysical data for the at least one geographical area;

providing the at least one biophysical indicator to a long short term memory (LSTM) network, the LSTM network including a convolutional neural network (CNN) for each of multiple LSTM units, each LSTM unit and each CNN associated with a historical time period in a time series;

using the LSTM to generate at least one prediction for wildfire risk for the at least one geographical area for an upcoming time period; and

providing the at least one prediction responsive to the request.

16. The computer-readable media of claim **15**, wherein the outputs of each CNN except a last CNN associated with a last historical time period are respectively provided to a CNN associated with a more recent time period in the time series.

17. The computer-readable media of claim **16**, wherein the provided outputs of each CNN are outputs generated by a hidden layer of a respective CNN.

18. The computer-readable media of claim **16**, wherein the outputs of the last CNN are provided to a fully connected layer of the LSTM.

19. The computer-readable media of claim **18**, wherein the fully connected layer is used to generate the at least one prediction.

20. The computer-readable media of claim **19**, wherein the at least one prediction comprises a first output neuron and a second output neuron, the first output neuron and the second output neuron indicating a probability of a wildfire and a probability of no wildfire for the geographic area for an upcoming time period, respectively.

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