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Original Article

Machine Learning-Based Intelligent Weather Monitoring and Predicting System

Semere Gebretinsae[1], Mohd Wazih Ahmad[2], T.Gopi Krishna[3], Nune Sreenivas[4], Biruk Yirga[5]

[1]*Adama Science and Technology University, Adama, Ethiopia*.
[2,3,4,5] *Department of CSE, Adama Science and Technology University, Adama, Ethiopia*.

[1]semedn@gmail.com

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Abstract - *The problem of weather prediction for the agricultural domain is of prime importance for the agriculture experts, farmers and research institutions across Ethiopia. This research proffered time series and machine learning modelling techniques for the design, development and implementation of lightweight, easy deploy models for the meteorology centers and researchers in the field of weather forecasting for Ethiopia. The team proposed Machine learning-based weather prediction models as an alternative way of doing this task. The proposed Machine learning models work on the principle of learning the patterns in the observed data from the recent past. Totally five important weather parameters named Temperature, Precipitation, Sunshine Hours, Relative Humidity and Rainfall were selected for this research in the Adama region. The comparative results and accuracy in the prediction of shortage of resources and simple script based execution of prediction tasks have encouraged meteorology personnel to learn and use techniques proposed in this research. The data was collected from 44 meteorology stations in the region. Past ten years, data for 33 variables were obtained from the Adama Meteorology centre and Addis Ababa meteorology centre.*

Keywords - *Weather prediction, Machine learning, NWP, EMA, ARIMA, AR-ANN.*

1. Introduction

This research is focused on the problem of weather prediction for Adama and nearby areas like Asella, Ethiopia. From the point of view of farmers and agriculture, this area is very important as a variety of crops, vegetables and fruits are produced in this belt. The quantity and the quality of agricultural products are highly dependent on the weather parameters like temperature, rainfall, wind, soil moisture and sunshine across the season. Farmers are always eager to know what kind of weather is expected in the next quarter so that they can select a crop that is better suited for the predicted weather. On a daily basis, farmers are interested to know the variations in the sunshine, wind speed and direction, humidity, rainfall patterns and soil properties so that they can decide on irrigation requirements of the crops, a requirement of insecticides and monitoring of the crop health. Like other countries, this task of agricultural weather prediction is done by meteorology centers in Ethiopia. There are 1200 conventional meteorology centres in Ethiopia, 25 automatic weather stations distributed among 25 directorates and 11 regions, with more than 800 professionals, 400 contractual observations staff and 1200 employees, including one centre in Adama and a central Meteorology station in Addis Ababa [40]. The job of a meteorology centre is to observe, collect and process the data used to predict different weather parameters. This research identifies the time spans of interest, corresponding models for each time span, forecasting scripts that lead to the development of Agro-advisories and the estimation of adverse events.

2. Related Work

Early weather-related research and transmission of important observation data started in 1843, and continued developments between 1870-1903 area are reported in [42]. Initially, weather information was transmitted in the form of weather maps using telegraphy and iconography. This phase involved sharing long term information across various weather monitoring and prediction centres. From 1870 to 1900, the forecasts were based on empirical knowledge. Basic rules of physics started to influence the forecasts starting in 1903 when Vilhelm Bjerknes of Norway put forward the idea of physical models of atmosphere in weather forecasting [41][42]. His research paper introduced seven variables to completely determine the weather of a place, as well as formulated the problem as an initial value problem [41]. The seven basic variables included in his research were air temperature, pressure, air density, moisture content, and the three components of the wind. The seven equations were formulated from the basic physical laws for representing the prediction of the weather conditions, namely, the three hydrodynamic equations of motion, the continuity equation, the equation of state and the equations expressing the first and second laws of thermodynamics. The solution to these equations using the numerical method of finite differences was given by Lewis Fry Richardson in the year 1920 [42]. This method evaluates the equations on every point in the vertical plane as well as in the horizontal plane. Therefore, it requires a huge number of computational steps. The predictions obtained based on only initial values and approximate models were found to be inaccurate for the local predictions; this limitation led to the development of numerical weather prediction (NWP) models with specialized workflow for global atmosphere simulation.

Due to uncertainties, the complexity of computation and other issues like difficulty in integrating with the local information [43], NWP models have a limited area of application in the context of Ethiopia [14] [32]. The full-functioning implementation of these models requires a supercomputer setup, and it is a costly operation [15]. Some of the Ethiopian meteorology centres have recently upgraded to the HPC (high-performance computing) platforms, and special interest groups are planned in various universities for HPC research. However, the need for lightweight, quickly trainable and scalable forecasting models is being felt like a priority. Alternative methods are being explored across the world for the prediction of weather parameters as well as for the post-processing of the results of NWP models. In recent times, Machine learning has evolved as a De-facto alternative for almost all kinds of prediction and forecast related problems [1]. Machine learning is a specialization of artificial intelligence in which predictive models are developed using past experience. In weather prediction cases, ML models employ past data in the form of time series of observations. ML models for the prediction of weather-related events have been used by many recent researchers like [21] [17] [18] [19]. It is found that the limitations of traditional NWP models can be handled using ML and time-series type models at various stages [2]. The superiority of the machine learning models over traditional models is established by the fact that they need very less time to train, they can be trained on ordinary computers, as well as they are easy to update and extend. Therefore many researchers have been attracted to apply ML in weather prediction. In the Ethiopian context, few research reports on using machine learning models for weather forecasting are found [30] [31].

However, it has been a topic of debate whether the new models based on machine learning and deep learning will be able to replace the numerical weather prediction models or not [35], but The team have obtained promising results with short term weather prediction tasks using Auto-Regressive model [17], Moving Average and ARIMA model [18] and Artificial Neural Network-based models like Deep Neural Networks such as Recurrent Neural Networks [19]. The [35] provide an excellent survey over different ANN and Deep learning-based alternatives to the Numerical Weather Prediction models. The main limitations of the NWP models are described, and motivations to employ deep learning solutions to NWP workflow are proposed. The main limitations of DL models are also described with citations to recent publications in the field. In summary, an NWP model requires the exact state of the atmosphere at every grid point in order to be able to optimize the loss function. The initial atmospheric conditions may not be correctly available due to missing data, corrupt sensors, far reach areas and loss of signals from various sensors. In this situation, the NWP model will provide incorrect results. In addition to data issues, the NWP model also needs huge computation power, which is not available in most of the country. The simulation of a physical system involves partial differential equations in terms of multiple variables. This can result in a huge computation.

3. Research Methodology

In this research, the team have used block sampling with a randomized sample selection technique. The block length of the sample is decided as per the requirement of the prediction interval. For a season-long prediction, the team should be able to sample a complete sample, i.e. 3 months of data from training. Missing a season in partial or complete may result in the under-fitting of the models. Similarly, for the short term prediction, the models are trained on 20 days to 1-month block samples up to one year of data in the past. In ensemble settings, the team has used bootstrap block sampling, which involves random sampling by the replacement of individual blocks. The formation of blocks during training ensures that relevant sequences.

3.1 Data Collection

Data for this research was collected from the Adama meteorology centre, Addis Ababa Meteorology centre and some parts of the Asella region. There are a total of 33 variables that are observed across 44 meteorology stations in this region. The team has obtained five-year data starting from the year 2010. The data was organized in separate excel sheets; each year, data was organized into months and days, tagged with the place of observation and the time of observation. The data was encoded and organized in a different way as required by our models. Model specific requirements of the data encoding, format, normalization and feature selection task are given in place while each model is defined. The details of each abbreviation, name of the variable, description and time of observation which are made available for us from the list of meteorology stations, are shown in Table 1.

3.2 Feature Engineering

The statistical and machine learning models learn the parameters from the important features [19]. Therefore, the team has performed the task of feature engineering, such as deletion of duplicate features, elimination of correlated features and selection of appropriate features for each model. Features were normalized as per the requirement of the forecasting model. The feature set was created for three types of models:

Table 1. List of all weather parameters under the observation

Abbreviation	Name	Description	Time of Observations
CLDCOV	Cloud cover	Cloud cover, total cloud cover	06:00,09:00,12:00,18:00
CLDTPH	Cloud type high	Cloud type high	06:00,09:00,12:00,18:00
CLDTPL	Cloud type low	Cloud type low	06:00,09:00,12:00,18:00
CLDTPM	Cloud type medium	Cloud type medium	06:00,09:00,12:00,18:00
DRYBUB	Temp, dry bub	Temperature. Dry Bulb	06:00,09:00,12:00,18:00
EVAPND	Evap, pan dly	Evaporation pan, daily total	9:00
EVAPNH	Evap, pan hly	Evaporation pan, hourly	06:00,09:00,12:00,18:00
GNBELD	Radiation, solar dly	Radiation, Solar daily	06:00,09:00,12:00,18:00
GNBELH	Radiation, solar hly	Radiation, Solar hourly	06:00,09:00,12:00,18:00
GRSMIN	Temp, Grass min	Temperature, Grass minimum	06:00,09:00,12:00,18:00
PERMSL	Pres, sea level	Pressure, Mean Sea Level	06:00,09:00,12:00,18:00
PERSTL	Press, stn level	Pressure, Corrected to Station level	06:00,09:00,12:00,18:00
PITCHE	Pitche, hly	Pitche, evaporation hourly	9:00
PRECIP	Precipitation	Precipitation	9:00
RADDIF	Radiation, diffused	Diffused radiation	06:00,09:00,12:00,18:00
RADDIR	Radiation, direct	Direct radiation	06:00,09:00,12:00,18:00
RADGLO	Radiation, global	Glaobal radiation	06:00,09:00,12:00,18:00
RANINT	Rainfall int	1 hour SUM	06:00,09:00,12:00,18:00
SUNHRS	Sunhrs, dly	Sunshine, Daily total Amount	06:00,09:00,12:00,18:00
SUNINT	Sunshn, intensity	Sunshine, Intensity	06:00,09:00,12:00,18:00
TMPMAX	Temp, dly max	Temperature, Daily Maximum	18:00
TMPMIN	Temp, dly min	Temperature, Daily Minimum	9:00
TSL005	Soil temp, 5cm	Soil temperature at 5cm	06:00,09:00,12:00,18:00
TSL010	Soil temp, 10cm	Soil temperature at 10cm	06:00,09:00,12:00,18:00
TSL020	Soil temp, 20cm	Soil temperature at 20cm	06:00,09:00,12:00,18:00
TSL050	Soil temp, 50cm	Soil temperature at 50cm	06:00,09:00,12:00,18:00
TSL100	Soil temp, 100cm	Soil temperature at 100cm	06:00,09:00,12:00,18:00

3.3 Short Term Prediction Model (STPM)

For the short term, model features were constructed with a time lag of 3:00 hours in observation data. For each member of the selected feature subset, the team has found a daily average of the various physical quantities which directly or indirectly affect the weather on a daily basis. The daily data set is used for learning and forecasting daily events using appropriate models.

3.4 Medium-Term Prediction Models (MTPM)

The Medium-term models try to predict the monthly averages of weather parameters; therefore, a feature set was constructed by taking point averages across the various realizations of the observed data to construct features for the cross-sectional properties of the modelled time series. This type of data is used to learn models for monthly average temperature, humidity, rainfall, and other quantities of interest.

3.5 Long term prediction Model (LTPM)

This type of model is developed for yearly prediction. Therefore the feature set for these models was constructed after selecting important features which cause the weather to behave differently in all the seasons across the whole year.

3.6 Models and Algorithms

The features developed in the form of raw series in the feature construction and feature selection step are subsequently used to develop various time series models like the AR model, Moving Average Model, Moving Average Model, Exponential Smoothing Model, ARIMA Model, VAR Model and Neural Network Model. For each model, the data set is divided into training, validation and test data in its required format. The team has selected target weather parameters based on expert advice and farmers' requirements. The target variables of interest are Temperature, Precipitation, Sunshine Hours, Relative Humidity and Rainfall, but because of similarity in modelling procedure, the team have included only selected models in this report. Ensemble models are developed for the respective time span, and average values of the predicted results are reported. An algorithm to learn the ensemble of the models with block bootstrap sampling is proposed.

3.7 Evolution Criteria

Each class of models are tested under the short term, medium-term and long term settings using a holdout data set. The test data set was created for each model after the main data set was divided in the ratio of 60:20:20. The testing was performed on the different ratios of training and test data. The fivefold cross-validation was applied to select individual models. The training, validation and test errors were reported and analyzed along-with accuracy and mean absolute error and mean square error.

4. Design and Development

The team defined a particular sequence of observations of a weather predictor as a realization. There can be infinite possible realizations, each giving rise to a time series data for that variable. The observed values for the particular variable can be analyzed in two dimensions. The first dimension the team decided to analyze is at a particular instance of the time across different realizations. For example, the team take an average on a monthly basis across various realizations of *TEMP, RH, PRECIP, RANT, SUNHRS, and WINSPD* at a particular instance of time *(i.e. 6:00 AM, 9:00 AM, 12:00 PM, 3:00 PM and 6:00 PM)* across many years to determine the general characteristics of the time series of each individual variable. Therefore, we have decided to model each selected weather predictor as a multivariate time series, which has been generated by a stochastic process under the influence of multiple random variables in the form of a joint probability distribution. The series of observations for each variable can be decomposed into its constituent components, which are defined as the trend component, stationary component (deterministic part), periodic component and a stochastic component. In both cases, the team has used a block of samples to retain complete season information, and the data was sampled using the bootstrap method, which performs sampling from the dataset by replacement. The next section describes the mathematical structure of different models used in this research.

4.1 The Best-Predicted Model

The best prediction model is that which computes conditional expectation of a variable on all the other cause variables observed at various time points. Let the variables be coded as follows:

$Y = \{PRECIP\}$

$X = \{TEMP, RH, WINSPD, SUNHRS\}$

The expected value of Y, given that the X variables are observed at an instant of time, will be computed by following integral

$$E(Y \mid X) = \int yF(y \mid x)dy$$

The limitation of this approach is that the computation of the marginal distribution of Y i.e. $F(Y \mid X)$ requires the knowledge of the joint probability density function $F(Y, X)$, which is not possible to know in advance at every point in time as well as across all the 33 variables in this research. Since the functional form of the weather equation fails to describe the cause-effect relationships among the observed variables in close form, therefore we have decided to approximate models which learn from the past sequence of observations (and at each significant point in time). As an enhancement to the existing models, an ensemble of base models is created in order to predict the value of a particular variable.

4.2 Proposed classes of models

The problem of learning to predict weather parameters as a function of observed predictor variables is an approximation problem. There are many ways to model the prediction of future values of *TEMP, RH, WINSPD, SUNHRS, PRECIP,* taking into account other predictor variables like univariate time series models and multivariate time series models and the models based on Artificial Neural Networks. In this research, the team have proposed two types of ensemble models: Ensemble of univariate time series models, and the second type is pure machine learning-based multivariate ensemble models.

4.3 Auto-Regressive Model

Each variable to be predicted is modeled as a univariate time series under a realization. A realization is a year-long set of observations; the team has multiple temporal resolutions for which models are fitted. The daily, monthly and yearly univariate time series models in each year are considered as an individual realization of the stochastic data generating process for that variable.

In very basic form, an Autoregressive model of each realization is learned in order to estimate the statistical properties and the parameters of the model. The stochastic process which generated the observations for *TEMP, RH, WINSPD, SUNHRS, and PRECIP* in the form of a sequence of observed random variables at different time instances is defined as follows:

$$Fz_{t1}............Fz_{tn}(x_1.......x_n) = P(\omega : z_{t1} < x_1, ...z_{tn} < x_n)$$

Where $Fz_{ti}..............Fz_{tn}$ represent an ***n***-dimensional joint probability distribution of ***n-indexed*** random variables, each given by $F(\omega,t)$ where ω belongs to the sample space. At a particular value of t, $F(\omega,t)$ reduces into a real value called the realization of the random variable, when computed at different time instances, gives rise to a time series for that variable. The model the team developed tries to approximately learn the above distribution function, which has generated this time series data so that the model can be used to predict the future values of the variable.

5. Proposed Learning Algorithm

The algorithm tries to combine individual models with a scaled stochastic sample taken from the original time series after decomposition. First, the team learned an individual time series object, i.e.(TSO), corresponding to each variable of interest for a given forecasting period. The team have used the block sampling method called bootstrap sampling, which is used to take a sample of a certain given number of days in proportion to the time span of the model under development. The block bootstrap sampling is done on the stochastic component of a weather variable, and its scaled version is convoluted before a forecast is generated. Model outputs are aggregated using the averaging method. In fact, bootstrap aggregation is a strong technique to average out the individual errors of the models. Therefore, the above algorithm, when used to train the model across various yearly series of observations, is expected to give better results as compared to individual models.

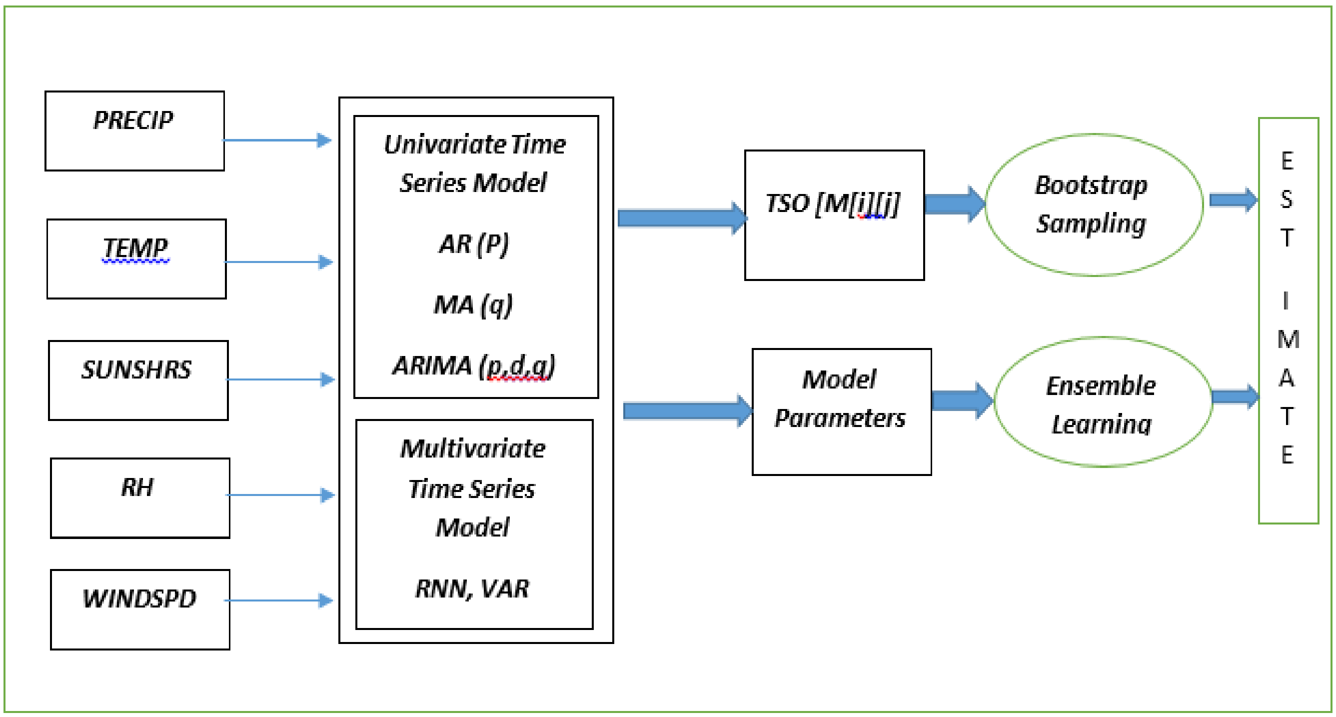

Fig. 1 Architecture of the proposed System

6. Proposed an Ensemble Model

Same as the characteristic equation, each model has a forecast equation, which tells us how much time lags in the future can be forecasted by the certain learned model, with a certain number of parameters of fixed cardinality. Instead of defining each forecasting method, the team have implicitly used previously explained models with the selected hyper-parameters and designed individual fit with the required number of parameters, depending upon the number of variables and time lags taken into consideration. The proposed ensemble model has been developed on a sample of model space. The purpose of the proposed ensemble model is to average out the errors in the prediction of a single model. The architecture of the proposed framework under which models are learned is given in the following Fig. 2.

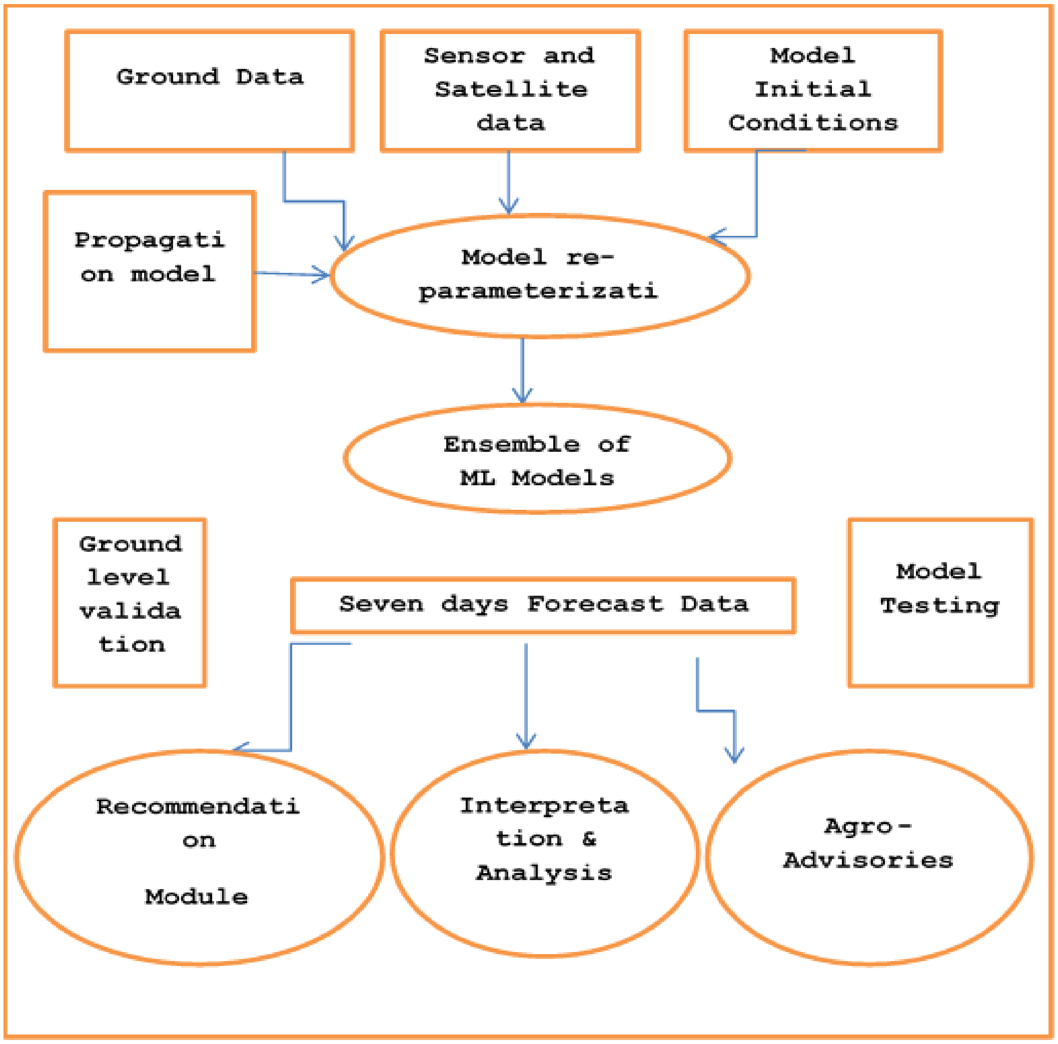

Fig. 2 Modeling and Prediction Framework

The output of each model is combined using averaging to generate the result for a given time interval. The objective of making an ensemble of individually learned models is to control the unnecessary variance in the output and to average out the effect of bad predictions from one model. This kind of ensemble model is more suitable for univariate time series modelling of the weather variables because making ensembles of multivariate neural networks is difficult and computationally not scalable due to the large number of parameters involved. Bootstrap block sampling is a technique used to capture the full season and random components of the weather, such as sudden rain for two or three days in a season of winter. If the training sample size is less than the seasonal block, the important events can be missed and never predicted.

7. Results and Discussions

The following components of the time series are extracted by process of decomposition in our experiments:

7.1 Trend

A *trend* exists when there is a long-term increase or decrease in the data. It need not have to be linear. Sometimes the team will refer to a trend as "changing direction" when it goes from an increasing to decreasing direction and vice versa.

7.2 Seasonal

A *seasonal* pattern occurs when a time series is affected by seasonal factors such as the time of the year or the day of the week. Seasonality is always of a fixed and known frequency.

7.3 Cyclic

A *cycle* occurs when the data exhibit rises and falls that are not of a fixed frequency but repeated.

7.4 Random

This component is used to depict the random or stochastic variations on the same dates across years in a time series data. The team used this component to add stochastic behaviour in the ensemble of the learned models with a certain scale factor while doing ensemble learning.

7.5 Experimental Settings

Each model requires a specific data preparation step in order to learn the parameters from training data. In addition to the general data processing steps as described in the methodology section of this research, the team has included additional data formatting steps along with the model.

7.6 Dataset Preparation

This data has been used to build the time series forecasting models with different lag values. This record was converted to monthly average data. A similar procedure has been followed for all the weather parameters. Regarding the daily forecasting, the team considered 12 months * 31 values totally: 372 data points have been used as a sequence of row data for training univariate time series models. The following tables summarize the monthly average data for relative humidity and max-temp, respectively.

Table 3. Average monthly relative humidity

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	42	54	50.77	48.23	52	52	66	68	61	36.41	40.48	40.29
2011	43.9	36.67	36.25	35	43	50	61.7	79.9	62.9	32.25	51.03	40.8
2012	43.38	35.34	29.67	47	36.9	50.43	71.8	70.51	62	36	38	44.58
2013	48.51	37.42	43	45.66	52.48	51.46	71.25	65.22	55.93	45.8	45.6	39.41
2014	42.93	47.1	47.03	41	45.9	43.53	62	66	62	49	46	40
2015	44	33.89	34.06	30	51.38	52.93	58	61	54	37	47	51

Table 4. Average Monthly Max-Temperature

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	27.3	29.4	29.4	31.7	30.8	30	27.4	26.2	26.7	27.9	26.9	25.8
2012	27.4	29	31	30.3	31.7	30.7	25.8	25.9	27	27.9	28	27.2
2013	27.3	29.41	31	31.19	31.14	30.4	26.08	26.31	27.99	28.08	27.5	26.34
2014	28.11	29.5	29.8	30.7	31.1	31.6	28.3	26.7	27.3	26.9	27.5	26.2
2015	27	30.5	31.3	31.5	30.7	30.5	29.5	27.9	28.9	29.9	28	26.9

The team fitted EMA and ARIMA models on temperature time series objects using R-script written by our team for training and testing with our ensemble learning algorithm. Totally, five-year temperature data is taken for creating the

Block ensemble of each model in a loop structure. The output of individual models was combined using the averaging method. Training time output distribution of maximum temperature for daily and yearly forecasting using the EMA algorithm is plotted in the following figures:

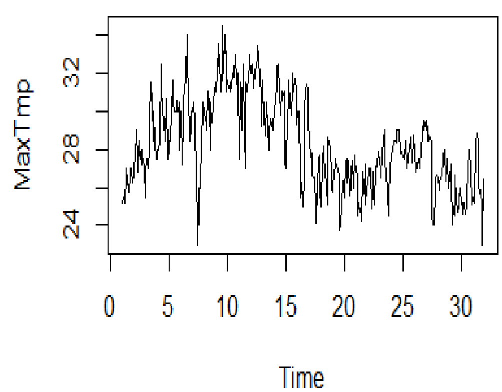

Fig. 3 EMA model on Max Temp for Monthly data

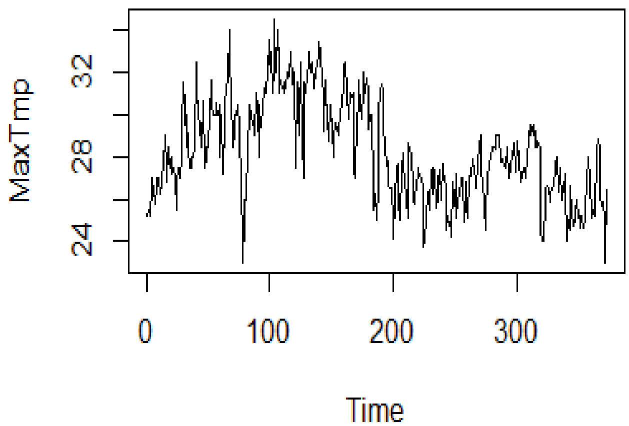

Fig. 4 EMA model on Max Temp for Yearly data

From the above figures 3 and 4, the first figure shows yearly forecasting using the daily records, and the latter figure shows the daily output of the time series. Holt-Winters exponential smoothing estimates the level, slope and seasonal component at the current time point. Smoothing is controlled by three parameters: alpha, beta, and gamma, for the estimates of the level, slope b of the trend component, and the seasonal component, respectively (at the current time point of prediction).

In this study, the team have 372 sequential time-series data points for the daily forecasting purpose. Based on the training data, we have the next 29 days of maximum temperature forecasting using the proposed model. The experimental results of the predicted output are depicted using the following data frame.

Table 5. tempForecast.ts_hw_fcst # using EMA model

Point	Forecast	Lo 80	Hi80	Lo 95	Hi 95
373	25.66613	24.01400	27.31827	23.13941	28.19285
374	25.65401	23.57995	27.72808	22.48201	28.82602
375	25.64190	23.21053	28.07326	21.92345	29.36034
376	25.62978	22.88035	28.37921	21.42488	29.83467
377	25.61766	22.57698	28.65833	20.96734	30.26797
378	25.60554	22.29329	28.91779	20.53989	30.67119
379	25.59342	22.02471	29.16213	20.13555	31.05128
380	25.58130	21.76814	29.39446	19.74958	31.41302
381	25.56918	21.52135	29.61701	19.37856	31.75980
382	25.55706	21.28267	29.83145	19.01995	32.09418
383	25.54494	21.05083	30.03906	18.67179	32.41810
384	25.53283	20.82482	30.24083	18.33255	32.73310
385	25.52071	20.60383	30.43758	18.00100	33.04042
386	25.50859	20.38721	30.62996	17.67612	33.34105
387	25.49647	20.17442	30.81852	17.35710	33.63584
388	25.48435	19.96499	31.00371	17.04321	33.92548
389	25.47223	19.75853	31.18593	16.73389	34.21057
390	25.46011	19.55473	31.36550	16.42861	34.49162
391	25.44799	19.35328	31.54271	16.12693	34.76905
392	25.43587	19.15394	31.71780	15.82849	35.04326

Table 6. temp_model_forecast # using ARIMA model

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
373	26.31909	24.72830	27.90989	23.88618	28.75200
374	26.18163	24.21245	28.15081	23.17004	29.19323
375	26.59271	24.41506	28.77036	23.26228	29.92314
376	26.58004	24.21329	28.94680	22.96040	30.19968
377	26.84465	24.35374	29.33555	23.03513	30.65416
378	26.88573	24.28530	29.48617	22.90871	30.86276
379	27.06523	24.38636	29.74411	22.96825	31.16222
380	27.12537	24.37905	29.87169	22.92523	31.32550
381	27.25315	24.45603	30.05027	22.97533	31.53097

382	27.31602	24.47600	30.15603	22.97259	31.65944
383	27.41072	24.53739	30.28404	23.01635	31.80508
384	27.46919	24.56807	30.37031	23.03231	31.90607
385	27.54159	24.61847	30.46472	23.07106	32.01212
386	27.59306	24.65171	30.53441	23.09466	32.09146
387	27.64967	24.69372	30.60562	23.12894	32.17040
388	27.69365	24.72567	30.66162	23.15451	32.23278
389	27.73860	24.76091	30.71630	23.18462	32.29259
390	27.77554	24.78987	30.76122	23.20935	32.34173
391	27.81162	24.81948	30.80377	23.23553	32.38772
392	27.84234	24.84488	30.83979	23.25812	32.42655

The above prediction results have been plotted in the following figures:

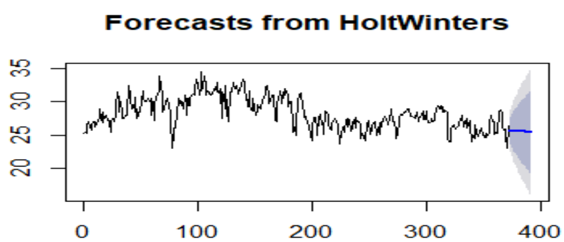

Fig. 5 EMA 20 days forecasting

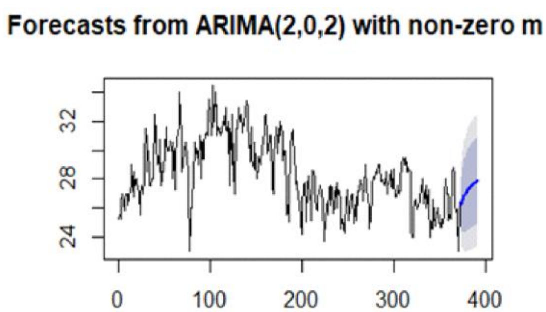

Fig. 6 ARIMA 20 days forecasting output

The same data, when modelled with the ARIMA model, shows a better fit for the training and test data. One of the potentials of the ARIMA model is to automatically obtain the PDQ values to enhance the prediction performance produced by the EMA model in individual and ensemble settings using averaging criteria and a block bootstrap aggregation of the stochastic components between 5 to 20 days block length. Therefore, the ARIMA model was selected for further enhancement and analysis for the temperature variable. The final script was prepared after model tuning, analysis of the residuals and the errors on the test set of 20 days.

After performing the model tuning by the selection of hyperparameters of the EMA model for the short-term prediction task, final results on the test data are obtained. But this kind of manual hyper-parameter selection during fitting indicates a possible overfit for the EMA model. Therefore, the ARIMA model was preferred over EMA under auto-fit configuration. The Autofit ARIMA model has the least MSE (mean square error) for the test data up to 20 days.

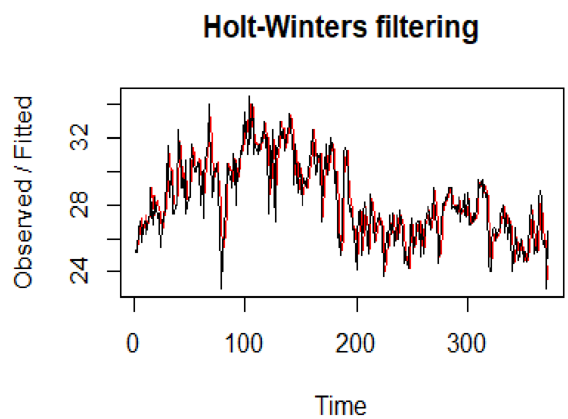

Fig. 7 EMA model with Manual Parameter tuning

The above figure 7 shows the comparison between actual observation values in the test dataset of 20 days and the model predictions for the EMA model after forced model tuning, which is also possible in the case of the ARIMA model with the auto-fit mode of learning the model parameters. In the next section, the team present the comparison of two models based on the evaluation metric like a model. From 20 days ahead daily forecast, the team have realized that the test error produced by the ARIMA model is less than the test error.

Table. 7 Summary of model's performance on temperature forecasting

Temp Dataset	TS model	Accuracy measurement			
		MAE	MASE	ME	ACF1
Max-temperature	EMA	0.97	0.99	0.09348	-0.0199
	ARIMA	0.937	0.958	0.0139	-4.283

Mean square error, mean average square error and mean of the error. The following table summarizes the results of the evaluation and prediction performance of the above two-time series forecasting models using the maximum temperature of the Adama region.

From the above table. 7, the team can see that based on accuracy measurement, the ARIMA model outperforms the prediction result obtained by the EMA model for the given datasets. This can be explained in terms of the capability of the ARIMA model to combine the effects of random components, error components and autoregressive components in one model as compared to the EMA model. Evaluating the statistical distribution of residuals on the training and test data helps us to manage if there are irregularity, skewness, and outliers in our output. From the histogram, it is possible to see that the distribution of residuals is Gaussian in nature, which indicates a proper fit for ARIMA at the training and the test time.

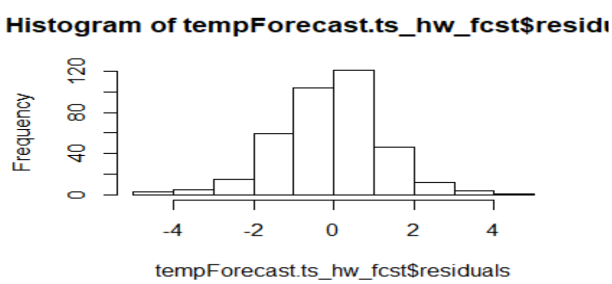

Fig. 8 Distribution of Residual errors

From the experimental results over the proposed models in the short term and medium-term prediction settings, it is clear that the EMA model gives a comparable performance to ARIMA based model for short term prediction. From the results of short term prediction models, it is understood that the univariate ensemble models are capable of learning the past behaviour of the weather conditions individually in the form of a time series, given that they are fitted with proper values of hyperparameters, and the data provided to them follow the stationary of the first and second order. The exponential smoothing model is good for short term forecasting. ARIMA model is found to be superior to the EMA model in the short term as well as in Medium-term settings. This behaviour can be explained in terms of the parameters of the ARIMA model, which have been learned in autofit mode. In R, when this mode is instructed, the parameters P, D, and Q of the model are found using AIC criteria. While the EMA model is fitted with manually selected parameter values, the other hand, ARIMA model is based on the optimal parameters. However, the ARIMA models are also rigid for outlier data points as they lie outside the domain of the learned model.

The models proposed in this research are suitable for the Adama meteorology centre as they are basic models and easy to execute and give comparable results to the traditional models in the short term. In fact, it was the first research up to our knowledge that has used auto-regressive models for the prediction of TEMP, PRECIP, RH etc., in the Adama region.

This research addressed the question of whether the proposed models like EMA, ARIMA, VAR and AR-NN will be able to significantly improve the accuracy of prediction for short, medium and long term prediction tasks. In this case, we have seen that most of the models are able to prove their importance for the short term weather prediction task.

8. Conclusion

This research was conducted to address the problems of the meteorology centers in Ethiopia and to provide alternative models to the currently available traditional NWP models. The work done in this research has been able to identify the main problems of traditional models. The important weather parameters selected for the modelling are TEMP, PRECIP, RHUM, RAINFALL, and SUNHRS. The models and the algorithm developed are found to be efficient in learning the weather prediction task. The scripts of these models have been provided to the EMC centre, and integration of this workflow in their prediction task is expected for the purpose of internal assessment and development of Agro-advisories.

The performance of the models proposed is comparable to the existing WRF model and other prediction tools used by EMC professionals. One of such tools regularly being used to predict days ahead temperature was the leap.

The software is based on the moving average model, but since the team members have found this model weak for short term predictions, we have dropped it from the analysis. We have used better time series models like EMA and ARIMA.

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