Indigenous Knowledge Mobile Based Application that Quantifies Farmers' Season Predictions with the Help of Scientific Knowledge

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Abstract. This paper presents the development of the indigenous knowledge (IK) mobile based application that quantifies farmers' season predictions with the help of weather data, satellite imagery data and the Single Exponential Smoothing (SES) model. The system facilitates the indigenous knowledge indicators' collection and processing to compute farmers' certainty level of an oncoming rainy season behaviour which is mainly categorized into abundant, droughts and floods. Despite the value of IK indicators, they can only tell the behaviour of the season without stressing on valuable scientific information such as rains onset, distribution, magnitude and cessation. To solve this problem, the researcher integrates the use of IK indicators with farmers' historic data of periods when they have experienced abundant(normal) rains, less rains (below normal) and excessive rains (above normal). For each period, weather data (rains and average temperature) and satellite imagery data were collected, processed and stored in the database for use by the application. For each satellite image, the following land cover features: vegetation, soil moisture and waterbodies area cover were computed. The indigenous knowledge indicators were also systematically structured to enable certainty level computation of an oncoming season. Based on farmers' predictions of the oncoming season behaviour, the system extracts historic data with respect to the predicted season and send the data to the SES model. The SES model will predict the next season's weather data, vegetation, soil moisture and waterbodies cover data to help the farmer to have robust knowledge on the possible season outcome. The data is also downscaled to provide meaning to the farmers.

Keywords: indigenous knowledge · alpha · single exponential smoothing · vegetation · waterbodies · soil moisture

1 Introduction

Climate change continuous to demoralize the livelihood of many people particularly in Sub-Saharan Africa where rain-fed agricultures underpin food production for many Africans. The IK is a primary shield many local farmers use to adopt and or mitigate the

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impacts of climate change. Farmers use IK indicators which are classified mainly into environmental (e.g. trees, birds, insects etc.), meteorological (e.g. wind, temp, rains pattern etc.) and astronomical (e.g. shape of moon, pattern of stars etc.) to predict oncoming season behaviour which is mainly classified into abundant rains, droughts and floods. From their predictions, farmers, can be able to execute their cropping plans accordingly such as cultivation of drought tolerant crops when there is expectation of less rains during the season. The farmers' certainty level is built through an observation of multiple indicators. These indicators are also associated with weights based on their precision towards season prediction. Some are more reliable or trusted than others. Even though IK indicators are well trusted to predict the season behaviour, they are failing to signify exact rains onset, distribution, magnitude and cessation to enhance farmers cropping decisions. To address this problem, the researcher integrates the IK indicators and farmers' historic data of the seasons when they have experienced abundant rains, less rains and excessive rains to be able to quantify the farmers' predictions. For each period, weather data (weekly rains and average temperature) collected from the weather station close to the farmers' location and weekly satellite imagery data collected within the farmers' location are extracted. For each satellite image, the researcher computes the vegetation cover pixel values using Normalized Difference Vegetation Index (NDVI), soil moisture cover pixel values using Normalized Difference Moisture Index (NDMI) and waterbodies cover pixel values using Mc Feeter's Normalised Difference Water Index (NDWI). The data is stored in the database for use by the mobile application. The IK indicators are also systematically structured to enable computation of certainty level of an oncoming season. Based on farmers' predictions of the season, the system extracts the historic data with respect to the predicted season and send the data to SES model which will predict the next season's weather data and satellite imagery data to enable farmers to foresee possible movement of precipitation and temperature to enhance their cropping decisions. The motivation behind the use of satellite images, is to complement mainly the rains data which is not scaled down to the region of interest. These predictions are also scaled down to the range of 1 to 4 for simplicity purposes, where 1 represents no change, 2 below normal change, 3 represents normal change, and 4 represents above normal change.

2 Literature Review

Climate change is a predator that feeds in agricultural sector leaving billions of people under nutrition especially in Sub-Saharan Africa (SSA) that is characterized by inadequate technological, economical and financial resources to tackle the climate change impacts particularly in rain-fed agricultures that underpin the livelihood of many people [9]. The aggressiveness of climate change impacts is exacerbated by increase in human population, pollution, land degradations, industrialization, deforestation and many more putting sustainability of land, water and food in an imbalanced situation.

The indigenous knowledge is the primary shield many local farmers relying on to tackle harsh realities brought by the change in climate [3, 6, 8]. It is known as a body of knowledge existing within or acquired by local people over a period of time through accumulation of experiences, society nature relationships, community participations and handed down through generations [8]. The IK indicators are fundamental phenomena that make up the IK system and are mainly used to predict the weather patterns to enable farmers to implement key cropping decisions to improve and sustain crop yield [3]. The IK indicators are mainly categorized into environmental, meteorological and astronomical. Despite the value of the IK indicators, they cannot emphasize valuable information about precipitation such as rains onset, distribution, magnitude and cessation. The seasonal climate forecasts provided by the meteorologists, can only tabulate total rainfall for the oncoming season. This also creates problems given that farmers are interested in more than just total rainfall and they need the forecasts to stress duration and distribution of rains over time and space to be most valuable [2, 6]. Further, the seasonal climate forecasts are not well supported by many local farmers since they do not incorporate the knowledge of the farmers, they have credibility, legitimacy, scale, cognitive capacity and institutional barriers [2, 3].

With respect to the fact that farmers are the main custodians of historic weather events occurred in their environment, the use of remote sensing techniques collaborated with statistical methods can assist farmers at the local level with season predictions. The remote sensing is a technology of acquiring knowledge about the earth surface without coming into contact with it. The satellite imagery is a remote sensing technique that is equipped with powerful sensors and cameras used to collect images of the world surface [5]. This technology is extensively applied in agricultural sector to track and monitor vegetation cover, soil moisture cover and surface water bodies cover to assist the decision makers to effectively and timely device mainly drought planning and mitigation strategies to lessen the effect and reduce the economic loss [7]. Given that these land cover features (soil moisture, vegetation cover, waterbodies cover) are sensitive to precipitation and are good proxy of it, they can be utilized to downscale the precipitation data to allow increase in spatial resolution [4].

The time series models are statistical models that are used to learn from the past observations and predict the future. They are used to forecast change of the variable over time by first analyzing its historical movement and extracting hidden patterns such as seasonality effects and the mean of the variable. The Long Short-Term Memory (LSTM) deep learning networks and Autoregressive Integrated Moving Average (ARIMA) family models are among powerful and sophisticated time series models that are used mainly to predict weather parameters and with remarkable effects.

To specifically address the communities in their localities, IK can be integrated with the scientific knowledge for as long as the IK is systematically modelled accordingly. According to [1] measuring of IK indicators' weights based on the impact they have towards season behaviour predictions is among good approaches in quantifying their processing. This is motivated by the fact that some indicators continue to lose value while others gain it towards season predictions.

3 Methodology

The action based-research methodology was adopted with an intention to get the depth ground information on farmers' historic data of the past weather events, information on how IK indicators are collected and processed to build farmers' certainty level and then come up with mobile-based application that will facilitate the IK collection and processing with the help of weather data, remote sensing and machine learning techniques to enhance farmers' cropping decisions. The qualitative research paradigm was adopted where focus group interview was selected to get the depth and variety of knowledge from the phenomena. The purposive sampling technique was used to sample 20 respondents on the basis that they reside in a study area (Hennenman, Whites Village Free State, South Africa) for over 10 years, known to be the primary custodians of the IK, doing crop farming, and rely heavily on rains to sustain the development of their crops. The sample consist of 13 male and 7 female farmers aged between 50 and 70. During the focus group interview, farmers were requested to measure the IK indicators based on their accuracy towards the predicted rainy season behaviour. Farmers also emphasized that the indicators are no longer precise and therefore, their weight must be complemented with the frequency of their observations. Farmers further elaborated on rules associated with the IK indicators' collection and processing. These rules will be discussed later. Lastly, farmers were requested to tabulate historic data of periods they could remember where they have experienced abundant rains, less rains and excessive rains during the rainy periods categorized in to warm rainy season (starts from September to February) and cold rainy season (starts from March to May). All these data were documented for further processing.

The Sentinel 2 weekly satellite images with spatial resolution of 10 m were extracted from United States Geological Survey (USGS) Earth Explorer database for the periods tabulated by the farmers. An approximate of 300 images ranging between 2013 to 2022 were extracted. Cloud masking and image mosaic were performed with the help of Semi-Automatic Classification Plugin (SCP) tools from Geographic Information System (GIS) software to smooth noisy images by mapping and replacing cloudy pixels of one image with non-cloud pixels from another images. Given coarse spatial resolution and high synoptic view of the satellite images, the BaseMap and SCP tools were utilized to locate and extract pixels that covers the region of interest. The atmospheric effects were removed by converting images from calibrated digital numbers (DN) to reflectance pixel values to enable quantitative analysis. The raster calculator was used to compute the vegetation cover using NDVI, soil moisture cover using NDMI and surface waterbodies using Mc Feeters' NDWI.

3.1 NDVI

It is a vegetation index utilized to analyze the changes in vegetation cover. It is computed by manipulating the Red and near infrared(NIR) spectral bands of the satellite image as shown below.

$$NDVI = \frac{\mathrm{Re}d - NIR}{\mathrm{Re}d + NIR} \tag{1}$$

Its normalized values ranges between –1 to 1, where values close to 1 reflect high vegetation greenness and values close to –1 indicates stressed or non-vegetated areas.

3.2 NDWI

Introduced by Mc Feeters, is one of the most commonly used water index to detect open surface waterbodies or waterlogged areas and is computed by manipulating green and NIR spectral bands as shown below.

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{2}$$

Its normalized values ranges between –1 and 1, where 1 represents high surface water reflectance and values close to –1 represents non-waterbodies area.

3.3 NDMI

This type of an index quantifies water content in vegetation leaf canopies and soil moisture using NIR and Short-Wave Infrared (SWIR) spectral bands computed as:

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \tag{3}$$

Its normalized values ranges between –1 to 1, where values close to 1 represents high moist or saturated soil or high water content in leaves and the values close to –1, represent dry soil or water stressed vegetation.

For each satellite image, the vegetation (NDVI) spectral values greater than 0.3, soil moisture (NDMI) spectral values greater than 0 and waterbodies (NDWI) spectral values greater than 0 were classified and pixel intensity values representing their coverage in m^2 were recorded.

3.4 Mobile Application Development

The Entity Relationship Diagram (ERD) presented in Fig. 1 shows the relationship between an indicator, observer and observation entities.

From the diagram above, an observer can observe one or many indicators. An indicator can be observed once or many times by either one or many observers. Below is set of rules stipulated by the farmers regarding the validity assessment of the indigenous knowledge indicators:

- All indicators should be observed and registered strictly in the farmers' location.
- An indicator should only be environmental, meteorological and astronomical in nature. Hence, indicators of spiritual type are not considered.
- For an indicator observation to be valid, it must be observed more than once and by different observers.
- For an observation of environmental indicator, the location, time stamp and image of the indicator need to be recorded.
- For an observation of either meteorological or astronomical indicator, only the time stamp will be recorded. There are limited restrictions regarding the two (meteorological or astronomical indicator) because they can be witnessed by everyone in the area.

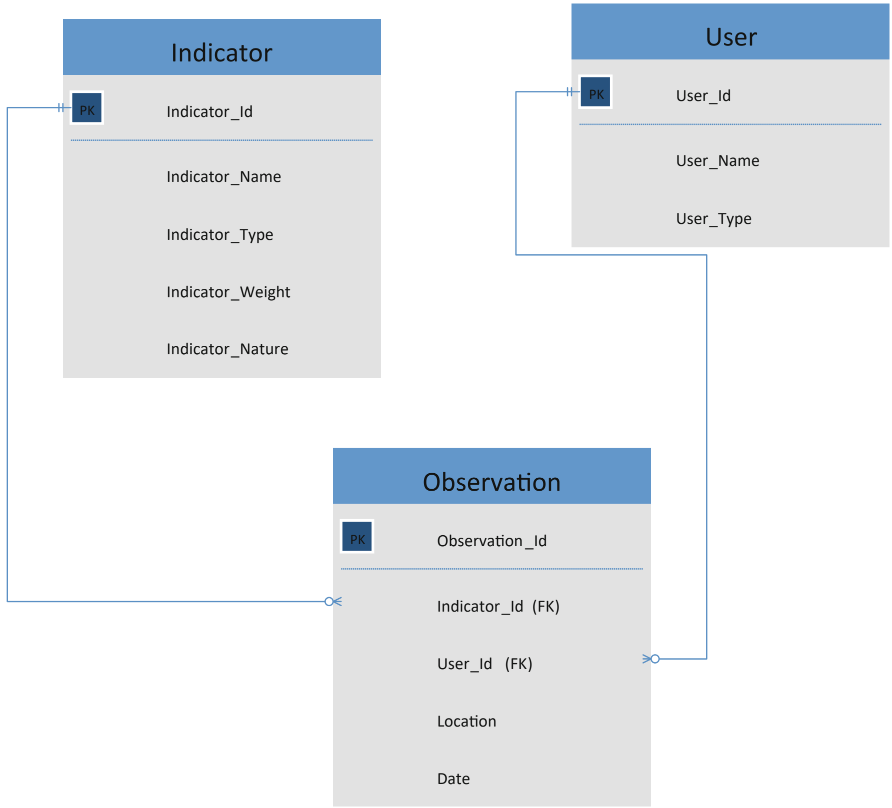

Fig. 1. Relationship between Indicator, User and Observation entities

- No duplicate entries should be allowed. For instance, one environmental indicator can be observed many times in a day by one or many observers for as long as they are observed at different locations (at least 1 km apart).
- An environmental indicator can be observed once or many times in one location for as long as they are observed at different time stamps (days)
- This also goes to meteorological and astronomical indicators that can be observed in different days.

The above-mentioned rules were utilized in the development of a mobile application that will facilitate registration and authentication of the IK indicators' observations.

Initially, the user will be requested to register before making use of the application.

A registered user will be displayed with the following screen to select the IK type (drought, floods or abundant) that they have observed. Based on the user's selection, list of indicators will be displayed as shown in the Fig. 2 below.

A user will select an indicator that they have observed, and based on the nature of the indicator, the following operations will be performed when the Register button is clicked. If the nature of the indicator is environmental, the observer information (username and Id), Global Positioning System (GPS) coordinates and date of observation

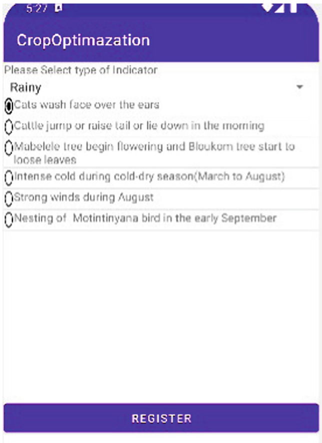

Fig. 2. List of indicators that represents Rainy Season

will be collected to create an indicator observation object. Otherwise, only the observer information and date of observation will be collected to create indicator observation object. The object created will be validated by the following algorithm presented in Fig. 3.

```
 boolean ValidateAndInsertObservation(Observation observation)
      Declarations
        num timeStampDistance
        num locationDistance
        boolean flag = false
        Collection observations = conn.readObservationsForIndicator(observation.getIndicator())
      if observation.getLocation().toLowerCase().contains( "hennenman")
AND observation.getLocation().toLowerCase().contains( "whites ")  then
            flag=true
          if observations.size() = 0 then
            flag = conn.createObservation(observation)
         else
            if  (NOT)observation.getIndicator().getNature().equals("environmental") then
               for num count = 0, count < observations.size(), count++
                  timeStampDistance= getTimeStampDistance(observations.get(count).getCreated(), observation.getCreated())
                  if timeStampDistance = 0 then
                     flag = false
                  endif
               endfor
            else
               for num count = 0, count < observations.size(),count++
                  timeStampDistance= getTimeStampDistance(observations.get(count).getCreated(), observation.getCreated())
                  locationDistance = getLocDistance(observations.get(count).getLatitude(),
                                          observations.get(count).getLongitude(),
                                          observation.getLatitude(), observation.getLongitude())
                  if timeStampDistance = 0 AND locationDistance < 1000 then
                     flag = false
                  endif
               endfor
            endif
         endif
      endif
   return flag
```

Fig. 3. Validation of an IK observation

The algorithm in Fig. 3 receives the tested observation object passed as a parameter. It will first check if the observation was made in the region of interest. If so, it will extract all observations of the same indicator object from the cloud storage. If there are no observations made for that indicator, the tested observation will be declared valid and it will be registered. Otherwise, the algorithm will first check the nature type of an observed indicator. If it environmental, it will compute the timestamp distance and location distance of a tested observation against all extracted observations of the same indicator with the aim to avoid duplicate entries. For meteorological or astronomical indicator observation, only the timestamp distance will be computed. The observation will be registered only when its location or timestamp parameters meet the stipulated criteria tabulated by farmers.

The Harvesine equation presented below is utilized to compute the shortest location distance between two points on an earth surface using their latitudes and longitudes.

$$d = 2r\sin^{-1}\left(\sqrt{\sin^2\left(\frac{x_2 - x_1}{2}\right) + \cos(x_1)\cos(x_2)\sin^2\left(\frac{y_2 - y_1}{2}\right)}\right) \quad (4)$$

Where:

r represents the radius.

x_1 represents latitude of point A.

x_2 represents latitude of point B.

y_1 represents longitude of point A.

y_2 represents longitude of point B.

The time distance is computed as a days' difference between two dates.

The observation images collected for the environmental indicators will be assessed by an administrator. An image is declared valid if it corresponds with the observation made, otherwise the image together with its observation object will be removed.

3.5 Season Prediction

Before computation of season predictions, the system will first compute the farmers' certainty level of the predicted season behaviour using the weights of all the observed indicators. If the certainty level is greater than the threshold set by the farmers, then it means farmers are certain of the oncoming season behaviour.

3.6 Certainty Level Computation

To compute the certainty level, the indicators observed will be extracted from the observations table inside the database. Distinct indicators will be identified, their frequency (how many times they were observed) and the number of observers. This is illustrated on a Table 1 below.

Table 1. List of indicators, their frequency and frequency of observers

Indicator Id	Count of Indicators	Count of observers	Valid ?
1	5	3	☑
2	3	1	☒
3	1	5	☒
7	3	2	☑

The certainty level will be computed for only the indicators that qualifies based on the following farmers' rule:

- An indicator observation is declared valid if it was made 3 times or more by 2 or more observers at different locations and or time stamps depending on the indicators' nature.

The qualifying indicators will be grouped based on their type (rains, drought and floods). The system will compute which group has a maximum total of certainty weights. This is motivated by the fact that any indicator of any type can be observed by the farmers. The group considered as a winner will be selected and will be utilized to compute the certainty level (CL) which is a total weight of observed indicators divided by the sum of weights of all indicators of the same type as shown below.

$$CL = \left(\frac{1}{\sum_{i=1}^{n} F_i} * \sum_{b=1}^{k} L_b \right) * 100 \tag{5}$$

Where L_b represents sum of observed indicators and F_i represents sum of all indicators.

3.7 Next Season Prediction

If the certainty level is greater than the threshold set by the farmers, the system will extract the farmers' historic data based on the indicators' type that was declared as a winner and also the season type (warm rainy season and cold rainy season) that will be selected by the user. These data will be sent to the SES model which will predict every record of the historic data as shown in the Table 2 below where $t + 1$ is the forecast that will be generated from the historic data (past observations indicated as *t, t-1, t-2, t-3……t-n*).

The weekly predictions will be made from September to January for warm rainy season and March to May for cold rainy season.

Table 2. Example of historic, current and future data points

	t-5	t-4	t-3	t-2	t-1	t	t+1
Week 1	0	24	13	12	10	5	?
Week 2	12	0	0	34	44	0	?
.	.	.	.	.	.	.	?
.	.	.	.	.	.	.	?
Week 20	21	34	0	23	50	121	?

3.8 SES Model

The SES model is among powerful and simple to use time series smoothing and prediction model that works well with time-series data that does not have a trend or seasonality effects. It is an extension of moving(rolling) average model where more recent observations get higher weight. It utilizes the learning rate mechanism known as alpha(α) which is a constant value ranging between 0 and 1. The formula is generalized as.

$$f_{t+1} = \alpha F_t + \sum_{i=1}^{n} a(1-a)^i F_{t-i} \tag{6}$$

Where f_{t+1} represents the next forecast,

F_t represents the today's forecast,

α represents the learning rate parameter that takes value of 0 to 1

n represents number of observations

The weighting scheme of this model assigns high weight to recent data and it exponentially decays as observations gets older. The accuracy level of SES depends on the selection of the learning rate based on a cost function that needs to be optimized. In simplest form, the optimum alpha value is the one that has less error rate. The extreme values of alpha (0 and 1) are ignored to avoid under-smoothing and over-smoothing where the model doesn't learn.

The function in Fig. 4 runs through the learning rate candidate values and the farmers' historic data arranged into rows and columns with the motive to find the optimum learning rate parameter.

The function presented above in Fig. 4 invokes the SES model's fit() function presented below in Fig. 5. This fit() function receives every farmers' historic data record and the candidate alpha value. It will perform the learning process and return the error rate for the candidate alpha value. This function will be repeatedly called to evaluate every candidate value on farmers' historic data records. The fit() function is sectioned into three iterations. In the first iteration, predictions are performed starting from the old observations towards the recent observations. The model predicts the next forecast as a today's forecast plus an error term of today adjusted by the learning rate. The second iteration computes the error by comparing the model's predictions and the actual values.

```
Collection fitting(num[][] weeklyRecords)
    Declarations
        num error = 0, alpha, col, row
        Collection errors=new Collection(), colElements = new Collection(), errors =new Collection()
        ExponentialSmoothing model = new ExponentialSmoothing()
    for alpha = 0.1, alpha < 1, alpha += 0.1
      for col = 0, col < weeklyRecords[0].length, col++
        for row = 0, row < weeklyRecords.length, row++
          colElements.add(weeklyRecords[row][col])
        endfor
        error += model.fit(colElements, alpha)
        colElements = new Collection()
      endfor
      errors.add(error)
    endfor
return errors
```

Fig. 4. Evaluation of different model parameters

The error rate is computed as an absolute difference between the predicted value and the actual value. The third iteration sum all errors for a given record and the learning rate. Finally, the model will return the average of absolute errors.

```
num fit(Collection dataPoints, num alpha) {
    Declarations
        num error, actual,count,prediction
        Collection predictions=new Collection(), errorList=new Collection()
    for num count = 1, count < dataPoints.size(),count ++
      if count = 1 then
        prediction = dataPoints.get(0)
      else
        prediction = prediction + alpha * (dataPoints.get (count - 1) –
prediction)
      endif
      predictions.add(prediction)
    endfor
    for num count = 0, count < predictions.size(), count++
      actual = dataPoints.get(count + 1)
      prediction = predictions.get(count)
      error = Math.abs(actual - prediction)
      errorList.add(error)
    endfor
    for num count = 0, count < errorList.size(), count++
      sum += errorList.get(count)
    endfor
return sum / errorList.size()
```

Fig. 5. Model's fit function

The model's predict() function is shown in Fig. 6. This function receives an optimum alpha computed during the training phase and every historic data record to perform next prediction.

```
num predict(Collection dataPoints, num alpha)
    Declarations
        num count,prediction
    for count = 1, count <= dataPoints.size(), count ++
        if count = 1 then
            prediction = dataPoints.get(0)
        else
            prediction = prediction + alpha * (dataPoints.get(count - 1) –
prediction)
        endif
    endfor
return prediction
```

Fig. 6. Next season predictions using best alpha

3.9 Downscaling of Predictions

At this stage the predictions are still in pixel cover values for remote sensing data, in millimetres(mm) for rain data and in degree Celsius for temperature data. Hence, they are not presentable to the farmers. To scale down the predictions, the system extracts the historic data and perform mathematical computations to scale the predictions to the range of 1 to 4, where 1 represents no change, 2 represents below normal change, 3 represent normal change and 4 represents above normal change. For instance, to scale down the satellite imagery data, the system will first compute the average pixel values of periods when floods were received, when abundant rains were received, and when drought were received. The researcher's expectation is that during excessive rains periods, average pixel values will be high than during abundant and drought seasons, however, that is what the system will figure out using its algorithms. From this data, the system will create the following values *min*, *middle* and *max* pixel values. The median will be computed as the average between the corresponding small and large values. As shown in the Fig. 7 below.

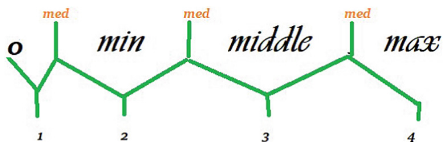

Fig. 7. Scaling down of predictions

The unknown pixel value will be categorized based on the range to which it falls. For instance, it will be assigned 1, if it is between 0 and median, it will be assigned 3, if it is greater than median between min and middle and less than the median between middle and max and so forth. The rains data will be computed in the same manner. To scale the temperature values, the system will compute the average of temperature during warm rainy seasons and cold rainy seasons. The middle value will be computed as the average between the computed values.

Finally, the data will be presented in a form of a graph as shown in Fig. 8 below. From this data, farmers will be able to identify possible rains pattern by analyzing weather data predictions and remote sensing data predictions.

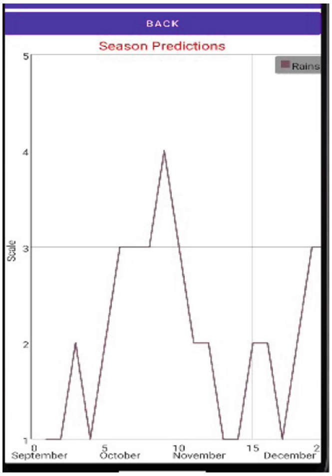

Fig. 8. Rains predictions using rains data

4 SES Model Evaluation

The farmers' historic data were split into two subsets (training and testing sets). The data from 2013 to 2019 was used for training set while the remaining portion (2020 to 2022 data) was used for testing set. The training was performed on both cold and warm rainy seasons' collected data where farmers have experienced abundant rains, scarce rains and excessive rains. The model was trained with training set and was validated with testing set. The Mean Absolute Percentage Error (MAPE) was computed and the overall accuracy of the model was approximately 60%.

The main reason for the poor model's performance was due to scarcity of historic data. However, this can be improved as years progress for as long as farmers document every season behaviour.

5 Conclusion

This paper presented the development of the IK mobile based application that quantifies farmers' season predictions with the help of scientific data to enhance farmers' cropping decisions. The development of this application was motivated by the under-resourced and overlooked IK system that many local farmers rely on to tackle the impacts of climate change. This paper emphasized that the IK indicators can be systematically collected and processed to compute the farmers' certainty level of the oncoming season. The results are also integrated with farmers' historic knowledge of different weather events with the aim to quantify the season predictions.

Given the fact that the application is decoupled from the cloud database holding the IK indicators and farmers' historic data, this implies that the same system can be adopted by other farmers from different regions where they will inject their own IK indicators and their own historic data. However, the challenge will only be when the rules governing the collection and processing of the indicators varies from region to region.

The system is equipped with SES model that is automatically evaluated with different learning rate parameters to come up with the optimal learning rate parameter to optimize the predictions. However, the model cannot accurately predict the data that has trend and seasonality effects. This can be addressed by adopting more sophisticated algorithms such as Double Exponential Smoothing (DES) model that can handle data with trend, and Holt-Winter's Model that can handle data with both trend and seasonality effects.

Although, farmers' predictions can be quantified, they still need to be integrated with scientific forecasts to come up with robust predictions that can address the harsh realities of climate change.

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