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ARTICLE

Forage Monitoring and Prediction Model for Early Warning Application over the East of Africa Region

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ABSTRACT

Rangelands dominate arid and semi-arid lands of the Greater Horn of Africa (GHA) region, whereby pastoralism being the primary source of livelihood. The pastoral livelihood is affected by the seasonal variability of pasture and water resources. This research sought to design a grid-based forage monitoring and prediction model for the cross-border areas of the GHA region. A technique known as Geographically Weighted Regression was used in developing the model with monthly rainfall, temperature, soil moisture, and the Normalized Difference Vegetation Index (NDVI). Rainfall and soil moisture had a high correlation with NDVI, and thus formed the model development parameters. The model performed well in predicting the available forage biomass at each grid-cell with March-May and October-December seasons depicting a similar pattern but with a different magnitude in ton/ha. The output is critical for actionable early warning over the GHA region's rangeland areas. It is expected that this mode can be used operationally for forage monitoring and prediction over the eastern Africa region and further guide the regional, national, sub-national actors and policymakers on issuing advisories before the season.

1. Introduction

The Greater Horn of Africa (GHA) region is one of the regions in the world that are most vulnerable to climate change and extreme climate events. This is particularly so in the arid and semi-arid lands (ASALs). The ASALs are dominated by rangelands home to pastoralist and agro-pastoralist communities who are dependent on livestock for their livelihoods. It receives a bimodal rainfall pattern, that is, March to May (MAM), known as the long rain season [1], and October to December (OND) as the short rain season. These rainfall seasons are mostly modulated by the Inter-Tropical Convergence Zone (ITCZ) [1-3].

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The rainfall variability over the GHA region has also been linked to the variability of the sea surface temperatures over Tropical Pacific and Western Indian Ocean basins [4-7]. The two rainy seasons are followed by a dry season, characterized by a shortage of natural forage/pasture and water resources, especially if a season's rainfall (amount and distribution) is below the long-term average. Consequently, reducing animal feeds availability within the rangelands in the region affects the livestock sector's operation and sustainability [8]. This further impact severely the pastoral livelihood, thus the need for natural pasture forage prediction for an effective Early Warning System (EWS).

The GHA region remains the largest producer of traditional livestock globally [9], with major export of animals to the Middle East countries and Gulf States [10]. Livestock in this region is the primary source of livelihood [11,12] and is currently experiencing several challenges due to scarcity of water and feed. Governments have reduced the grazing areas within the rangelands through the creation of conservation schemes, game reserves, and national parks [11]. This restricts seasonal mobility and prevents pastoralists from accessing these areas, which leads to conflict with the security personnel during the period of scarcity. Non-Governmental Organizations (NGOs) operating in ASALs also introduced crop cultivation in the pastoral range areas, which deprived pastoralists of valuable pasture [11]. In addition to these challenges is drought, which is the significant devastating hazard over the GHA region that depletes pasture and widespread death of livestock and humans in extreme cases [10,12]. Hence, it is critical to manage and monitor the remaining grazing areas for pastoral communities in the region.

Seasonal livestock mobility is central in the pastoralist way of life [10], and such mobility largely disregards national and international boundaries. Their seasonal movement is mainly dictated by climate conditions which affect pasture and water availability, and sociocultural conditions [10,11]. The seasonal movement is critical in terms of ecosystem preservation and sustainable use of pastoral resources over the ASALs. For example, transhumant pastoralists within Kenya and Ethiopia's cross-border area are influenced by the rainfall pattern, causing them to live half of the year in Kenya and the other half in Ethiopia [11]. Pastoralist mobility sometimes induces conflict related to resource use, and the conflicts intensify during the periods of drought and famine [10-12]. Thus, areas with permanent pasture need to be identified and managed to act as a safety net for pastoralists during the periods of drought in the ASALs. Managed dry season grazing combined with forage prediction will help in early action before a major catastrophe in the ASALs of the region. This is critical as a shrink in natural pasture can worsen conflicts in the region.

Opio [8] gives the current practice in the livestock sector within the East Africa region. The paper formulated a feed resource sharing plan across communities and countries where the pastoralist faces similar challenges. This plan is critical in resilience building for the livestock sector in the Horn of Africa [8], which can improve significantly with the incorporation of fodder/forage prediction for early warning. The work of range fodder early warning in some of the Inter-Governmental Authority on Development (IGAD) Member States so far depends on instant rangeland feed assessment, without projection into the future, which has a limitation in providing advance early warning for preparedness and response. The Kenyan National Drought Management Authority (NDMA) monitors drought in the ASALs of the country through the Standardized Precipitation Index (SPI) [13,14] and Vegetation Condition Index (VCI) [14,15]. This only gives the state of situations, reporting time, in the counties without anticipating the future using climatic conditions. Thus, in most cases reactive measures are taken instead of proactive measures.

Matere [14] attempted to develop a Predictive Livestock Early Warning System (PLEWS) for Kenya in terms of forage status. This is an upgrade of the Livestock Early Warning System known as LEWS [16]. The PLEWS use PHYGROW (Phytomass Growth Model) model and the Auto-Regressive Integrated Moving Averages (ARIMA) model with a moving average to forecast forage condition. This is still at a pilot stage, and it is worth noting that the PHYGROW model used is not freely available. This system's output is based on administrative boundaries [14], which is a limitation since vegetation/forage condition knows no political boundary. Climate as a driver of vegetation condition should be considered in forage prediction [17,18] which is not the case in the used ARIMA model.

Rainfall over time has been documented as a variable for predicting forage in rangelands [17,19] due to the strong correlation between rainfall and the Normalized Difference Vegetation Index (NDVI) [17] with NDVI being the dependent variable. While confirming the strong relationship, Georganos [18] indicated that the relationship is somewhat complex and non-linear. Thus, for modeling, there is a need to develop a regression model that allows the relationship between rainfall, temperature, soil moisture, and NDVI to vary in space other than traditional Ordinary Least Squares (OLS) regression [18]. The development of the forage prediction model in this study is based on the Gray System theory [20], which solves a time-varying non-linear system [21-23]. It provides an approach to investigate the input-output process's relationships with unclear inner relationships, uncertain mechanisms, and insufficient information [22,23]. This technique will be used in achieving the research objective which is to design and customize a grid-based prototype rangeland feed monitoring and prediction system for the cross-border areas of the GHA region.

2. Material and Methods

2.1 Study Area

The study covers transboundary areas along Ethiopia, Kenya, Somalia, South Sudan, and Uganda borders. These areas are known as Karamoja Cluster (along Uganda, South-Sudan, Kenya, Ethiopia border), also known as IGAD Cluster 1; IGAD's Cluster 2 and 3 (cross-border area shared by Kenya, Ethiopia, and Somalia). The clusters specifically cover the districts in the Karamoja region of Uganda; West Pokot, Turkana, Marsabit, Wajir, and Mandera counties in Kenya; South Omo, Borana, and Liben Zones in Ethiopia; and Gedo region in Somalia (Figure 1). Much of the study area is covered by shrubs and grassland, which defines the area as a pastoral zone (Figure 1). The study area receives a similar rainfall pattern in two seasons: March to May and October to December. This rainfall pattern and amount directly link to vegetation distribution over the study area.

2.2 Data Source

The datasets used in the study were: land cover (LC), NDVI, rainfall, temperature, soil moisture, and livestock mobility. The administrative boundary data used in the study were taken from the Global Administrative boundary (GADM) database (www.gadm.org), version 3.4. The LC data adopted here are the "S2 prototype LC map at 20 m of Africa 2016" released by the European Space Agency (ESA) on the 2nd of October 2017 (https://www.esa-landcover-cci.org/). Climatic and environmental datasets, i.e. rainfall and NDVI, were obtained from the IGAD Climate Prediction and Applications Centre (ICPAC). ICPAC is a specialized institution of IGAD located in Nairobi-Kenya with the mandate of providing climate related services to eleven-member countries.

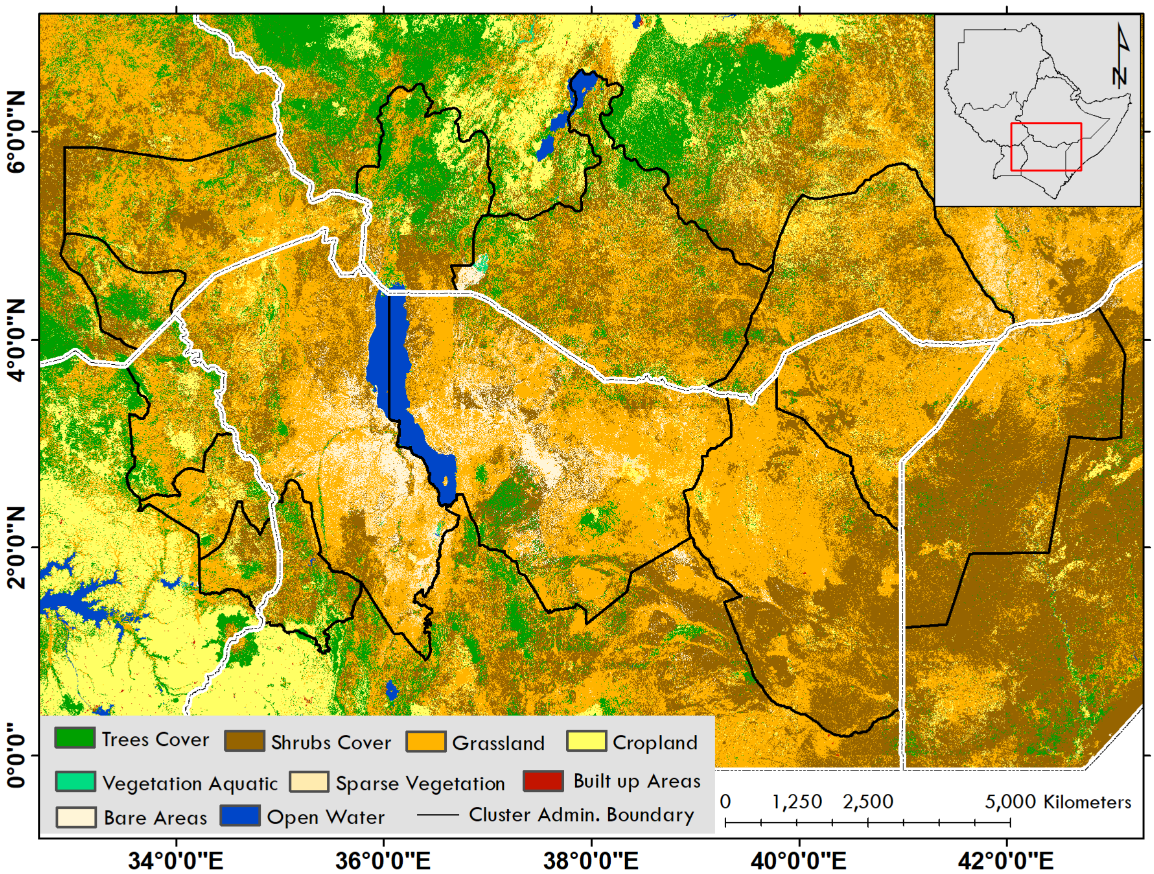

Figure 1. Land cover types over the study area, which covers the IGAD Cluster 1 (cross border area shared by Uganda, South-Sudan, Kenya and Ethiopia), IGAD Clusters 2 and 3 (cross-border area shared by Kenya, Ethiopia, and Somalia)

The NDVI data was available from 1999 to the near-present (http://gmes.icpac.net/data-center) at a spatial resolution of 0.01° and monthly temporal resolution. This is preferred over MODIS data since they are cloud-free [17] and used as an indicator for biomass production. Rainfall data known as Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) monthly dataset [24] was obtained from the ICPAC database at a spatial resolution of 0.05°. The dataset is available from 1981 to the near present, originally from the Climate Hazard Group (CHG). This dataset has been used over the region in past studies and shown to perform well [24-27]. Temperature is a variable that does not significantly vary in space and was obtained from the National Oceanic and Atmospheric Administration (NOAA) database, with a spatial resolution of 0.05° at a monthly temporal resolution from 1948 to near present. Soil Moisture data adopted here is the Soil Moisture Active Passive (SMAP) data from the National Aeronautics and Space Administration (NASA) database launched in January 2015 [28]. The SMAP covers have a global extent and can be obtained at 3 km spatial resolution [28].

2.3 Methods

As a prerequisite for modeling, all the datasets were grouped into three sets, that is, fifteen years for model development (1999-2013), four years to bias correct the model (2014-2017), and the remaining two years for model validation (2018-2019) at a seasonal time scale. This is because livestock mobility is based on seasonal rainfall. These seasons are March-May (MAM), which has the highest amount of rainfall over the study area, thus more forage production, and October-December (OND), known as the short rain season. These datasets were subjected to a multicollinearity test which is a critical step before developing a model with more than one independent variable. The collinearity test helps improve model performance and has been used and discussed in several studies [29-32].

An experimental technique known as Geographically Weighted Regression (GWR) was used in developing a prototype rangeland feed prediction model. The GWR technique is preferred over the Ordinary Linear Regression (OLR) method due to its capability of examining the existence of spatial non-stationarity in the relationship between a dependent variable and a set of independent variables [18,33-35]. This technique is fully described by Fotheringham [33]. This method allows estimation of the local parameter by considering the location of observation as shown by the equation below;

$$\boldsymbol{y_i = a(u_i, v_i) + b(u_i, v_i)x_i + \varepsilon_i, \qquad i = 1:n}$$

In the model above, the coordinates of location $\boldsymbol{i}$ are represented by $\boldsymbol{ui, vi}$ while $\boldsymbol{a}$ and $\boldsymbol{b}$ are local parameters to be estimated, particularly at location $\boldsymbol{i}$ [18]. In brief, the technique uses a moving window over the data, estimating one set of coefficient values at every chosen "fit" point [36]. The fit points are often the grid points at which observations were made, and if the local coefficients vary in space, it is taken as an indication of non-stationarity [37]. The prediction model's output was converted to total forage biomass using the technique described by Hobbs [38] and its output in Kg/ha. The unit was then converted to tonnes per hectare (ton/ha) i.e. 1 ton/ha = 1000 kg/ha. Available forage biomass was computed from the total forage biomass using a factor presented by Toxopeus [39] as in the equation below.

$$\text{Available Forage} = \text{Total.Forage.Biomass} * 45\%$$

2.3.1 Model Skill Assessment and Validation

The "eyeball" method is still the most commonly used method in spatial verification [40] and was adopted in this study to compare the results side by side and uses human judgment to discern forecast errors. However, this method is not quantitative [40]. In addition to this, quantitative methods were also used in model skill assessment, i.e., the Mean Error (ME) also known as bias and Relative Mean Absolute Error (RMAE). Both of these methods estimate the average prediction error [35], and give a perfect score when the value is zero [41]. Reliability diagram [42] also known as attribute diagram was used to determine the model's skill. A model's reliability is indicated by the proximity of the plotted curve to the diagonal line [42-44]. The deviation of this curve from the diagonal line gives a conditional bias. If the curve lies below the diagonal line, this indicates over-prediction; but above the line means under-prediction.

3. Results and discussion

3.1 Result from the Multicollinearity Test

A multicollinearity test on the dataset was done at each grid point for the two seasons (MAM and OND) using the diagnostic test. The result of the diagnostic test was then subjected to the variance inflation factor (VIF) with a cut point of 2.5 to determine collinearity and the Klein rule to give the location of collinearity. The results (Table 1) show no multicollinearity in the dataset, hence no need for data filtering.

In addition to this, seasonal rainfall and soil moisture were well correlated spatially with maximum NDVI over the study area for the two seasons. Few places had a negative correlation, especially with rainfall. This was attributed to the growth of the vegetation's with a continuous increase of rain in rainless areas [45]. On the other hand, the temperature gave poor correlation with maximum NDVI, temperature was thus dropped from the prediction model development. Hence, seasonal rainfall and soil moisture were considered as predictands of NDVI.

Table 1. Seasonal multicollinearity diagnostic to determine the location of collinearity for rainfall, temperature and soil moisture, for March to May and October to December seasons

	MAM		OND	
	VIF	Klein	VIF	Klein
Rainfall	1.4355	0	1.1556	0
Temperature	1.7686	0	1.4565	0
Soil Moisture	2.2734	0	1.6415	0

3.2 Results of the Model Output

The model constants differ for each season and this is attributed to different rainfall drivers for the two seasons [1,3,46]. Hence, each season had its independent model, which was used to predict seasonal forage biomass. The prediction for MAM 2018 showed that forage biomass greater than 2 ton/ha was observed over much of the study area with high values over the western, northern, and eastern parts of the study area and much in the northern part in 2019 (Figure 2). A closer pattern to this was observed for the OND season (Figure 3) with different magnitudes in ton/ha since the two are important seasons over the study area in terms of rainfall amount. The observed pattern in the model output is attributed to rainfall and soil moisture patterns over the region. These outputs were then compared with observed forage biomass for verification purposes using the "eyeball" verification method [40], which examines the prediction and observation side by side. The model generally performs well in all the seasons (Figures 2 and 3) with few pocket areas of under-prediction in the eastern part and over-prediction in the western part, which was also evident in spatial analysis of ME and RMAE. The over-prediction areas were noted to be high altitude areas, and the converse is true for areas with under-prediction.

In order to manage livestock resources effectively, the model can be run with a one moth lead time for each season using predicted seasonal rainfall and soil moisture data from ICPAC. The prediction of rainfall and soil moisture is done using the Weather and Research Forecasting (WRF) model run operationally by ICPAC at seasonal time scale with a one-month lead time.

3.3 Reliability Diagram

The diagram was used to determine how well the predicted events correspond to their observed frequency and is said to be reliable if the curve falls on the diagonal line and skillful if it falls on the gray area of the plot [42-44]. The prediction models for MAM and OND were found to be reliable, with small parts of the curve fall outside the gray area; thus, the model has good skill in predicting forage biomass. An example for OND season is shown in Figure 4. This result gives confidence in using the model for seasonal prediction.

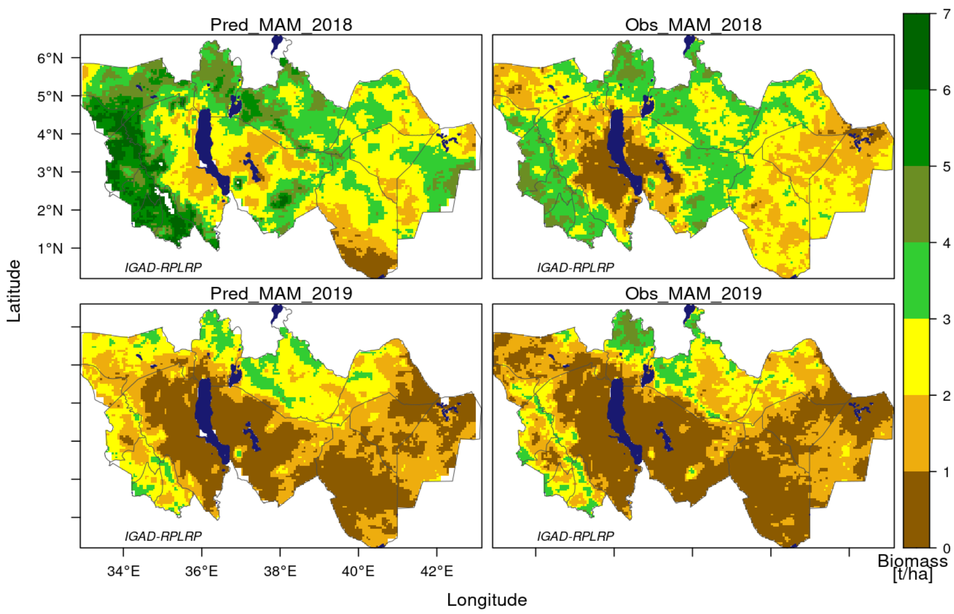

Figure 2. Bias corrected predicted forage biomass compared with observed forage biomass for the March to May seasons from 2018 to 2019

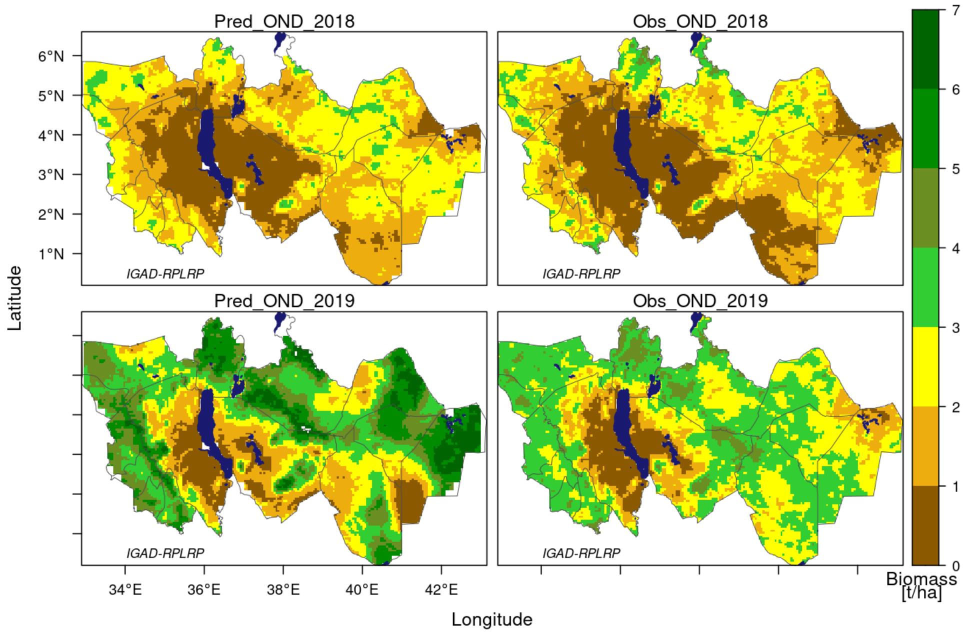

Figure 3. Bias corrected predicted forage biomass compared with observed forage biomass for the October to December seasons from 2018 to 2019

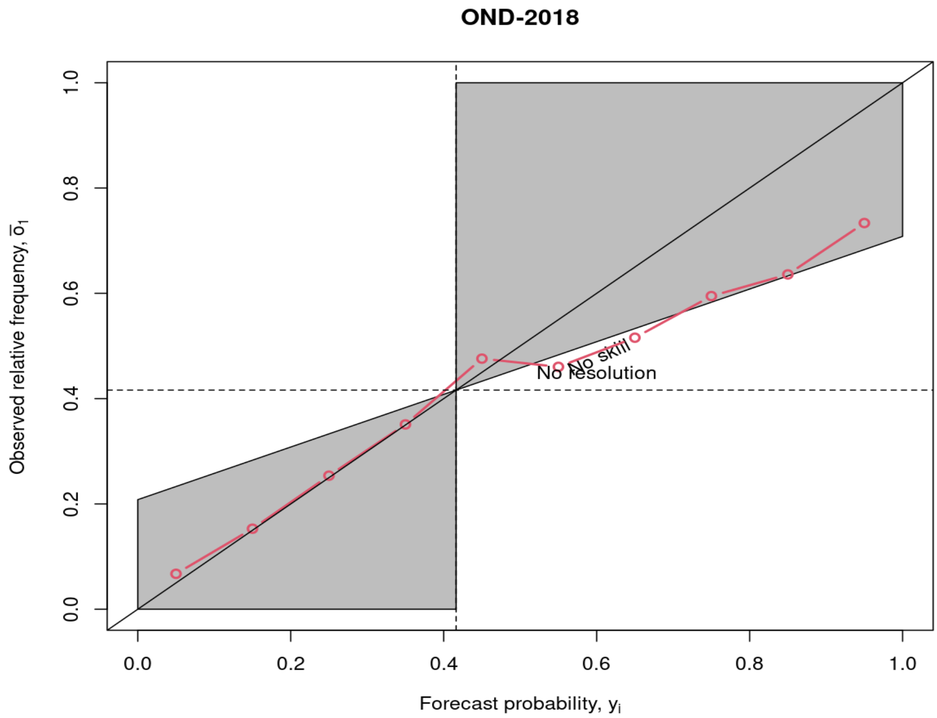

Figure 4. Reliability diagram for observed relative frequency against predicted probability for October-December 2018 season. It is reliable if the curve falls on the diagonal line and skillful if it falls on the gray area of the plot

4. Conclusions

Pastoralists in the Horn of Africa adapted to the temporal and spatial variability of critical resources (water and rangeland forage) in their landscape by practicing seasonal mobility with livestock (transhumance) to optimally utilize scarce resources. Such transhumance primarily crosses political boundaries. It is essential to develop early warning tools covering international borders; hence, a grid-based prediction is critical as it gives information across borders. This prototype prediction model is grid-based and performs well in forage biomass prediction over the study area, with rainfall and soil moisture being the significant drivers. It is currently running operationally at IGAD and at a seasonal time scale. This model's output informs the livestock sector group discussion at the Greater Horn of Africa Climate Outlook Forum (GHACOF), a regional early warning platform organized by ICPAC three times a year. This model contributes to timely and actionable early warning information for the rangeland, critical to pastoralists, sub-national key actors (government and NGOs), and other relevant policymakers within the region.

Author Contributions

Jully Ouma: Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing - Original Draft. **Dereje Wakjira**: Conceptualization, Validation, Resources, Writing - Review & Editing, Project administration. **Ahmed Amdihun**: Conceptualization, Methodology, Formal analysis, Writing - Review & Editing. **Eva Nyaga**: Methodology, Validation, Resources, Data Curation. **Eugene Kayijamahe** and **Viola Otieno**: Data Curation, Validation, Resources. **Franklin Opija**: Conceptualization, Methodology,Validation,Writing - Review & Editing. **John Muthama**: Validation, Writing - Review & Editing. **Solomon Munywa**: Resources, Supervision. **Guleid Artan**: Resources, Supervision.

Competing Interest

All authors consent with one accord that there is no conflict of interest for this publication.

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