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Forecasting Climate Change Pattern for Bolero Agriculture Extension Planning Area in Malawi

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Abstract

Bolero community in Malawi, like most rural communities in Sub-Saharan Africa, is very vulnerable to climate variability and change because of its reliance on local biological diversity, ecosystem services, cultural and religious landscapes as source of sustenance and well-being. For this reason, a study was conducted to forecast climate change pattern for Bolero Agriculture Extension Planning Area based on temperature data from 1982 to 2013 in order to inform the policy makers and community on the future prospects of climate change and its effects. The data was collected by Malawi Government Department of Meteorology and Climate Change at Bolero weather station using fixed temperature recording thermometer. The study used Univariate Autoregressive Integrated Moving Average to model and forecast temperature variability. Based on ARIMA and its components autocorrelation and partial autocorrelation functions, Normalized Bayesian Information Criterion, Box-Ljung Q statistics and residuals estimated, ARIMA (1,1,3) was selected for the maximum temperature data which helped in explaining the temperature time series and forecasting the future values. From the forecast available from the fitted ARIMA model, it is concluded that forecasted maximum temperature will increase by 1.6°C from 27.7°C in 1982 to 29.3°C in 2030. The temperature increase suggests that climate change could continue to negatively impact on agricultural livelihood options in Bolero community and this call for increased adaptive capacity for the community.

Keywords: Forecasting; Climate change; Adaptation; stochastic

Introduction

There is a widely-held agreement now amongst scientists and even policy makers across the entire globe that climate change is real and will continue to impact on future adaptation strategies [1-6]. For most people in developing areas like Bolero, climate change has just added an extra layer of burden on top of the already existing socio-economic challenges such as high levels of poverty and inequality, poor agriculture production leading to chronic and acute food shortages and undeveloped markets. For instance, by merely altering the productivity of natural resources, climate change exerts far reaching implications on the people in Bolero who usually depend on the climate sensitive natural resources for their livelihoods [3]. No wonder that the majority of people in the area, and developing nations in general look severely exposed to the impacts of climate variability and change [7-9]. By forecasting future temperature values for Bolero, the research in effect enriched the body of knowledge about climate variability. Greater understanding about the recent past to present (1982 to 2013) and future (forecasted) temperature variability was important to both practitioners and policy makers in establishing the extent of vulnerability of the Bolero Community to climate change and setting strategies for adaptation.

The main impact of climate change is predicted to be an increase in global temperature beyond acceptable levels over the most land surfaces. The temperature records for a period of over the recent 100 years denote a warming of surface temperature, with the most obvious increases observed between 1983 to 2012 period [10]. As far as temperature is concerned, it is expected that the temperature will continue to rise. However, choices that people make now and in the years to come will determine by how much the earth's average temperature will rise. Higher temperatures have effects on droughts, changing rainfall patterns and availability of surface water whose consequences range from less food supply to general fewer water supplies. Research has shown that although the average global trend shows an increase in temperature, there are localized places that have not become warmer yet. Research has further proven that changes in temperature are easier to project because temperature in contrast to precipitation is a large-scale variable [10,11].

Bolero community, like most rural communities in Sub-Saharan Africa, is very vulnerable to climate variability and change because of its reliance on local biological diversity, ecosystem services, cultural and religious landscapes as source of sustenance and well-being. The degree of vulnerability to climate change in the area is in actual fact dependent on the magnitude of climate variability and the socio-economic characteristics of households. Although, general knowledge about climate change exists in Bolero, Malawi, the extent of temperature variability remains a gap of knowledge in the area. There is also little knowledge about how the Bolero communities modify their livelihoods, traditional practices and religious values in order to adapt to climate change [12] suggested that the understanding of how communities modify their livelihoods, traditional practices, religious values, and production and consumption practices in amidst climate change is prerequisite in designing and implementation of any adaptation strategies particularly at a local level. Therefore, the study was conducted to forecast climate change pattern for Bolero Agriculture Extension Planning Area based on temperature data from 1982 to 2013 in order to inform the policy makers and community on the future prospects of climate change and its effects. The study hypothesis is that maximum and minimum temperatures of Bolero have not increased

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over time to influence climate change and variability. The results of the study will inform policy makers, stakeholders and community to design appropriate adaptation measures to the effects of climate change.

Materials and Methods

The research was conducted in Bolero Extension Planning Area (EPA) in Rumphi district located in the northern region of Malawi. The EPA has 12 functional sections with 58,550 people living in 112 villages. The area has 11,710 farm families holding a mean land size of 2.7 hectares per household of 5 persons. The area presented itself suitable for this nature of study mainly because of its vulnerability to climate variability and change besides being deeply rich in both culture and modern religion. The area is characterized by droughts and erratic rains resulting in crop failure and perpetual food shortages. Average annual rainfall range from 300mm in bad seasons to far less than 800mm in good seasons. With the majority of the inhabitants being rain fed agrarians, the area is more vulnerable to climate variability and change.

Secondary data on maximum temperature were obtained from the meteorological section of the Planning and Crops Departments at the Rumphi District Agriculture Development Office. The temperature data covered a period of 31 years from 1982 to 2013. The data was collected by the Department of Meteorology and Climate Change at Bolero weather station using fixed temperature recording thermometer. The data were used to fit the ARIMA model to forecast the future temperature patterns.

As the aim of the study was to model and forecast climate change pattern for Bolero Agriculture Extension Planning Area, various forecasting techniques were considered for use. ARIMA model introduced by [13] was frequently used for modeling and forecasting the pattern of climate change in Bolero. Among the methods based on univariate techniques, the ARIMA models by [13] stand out because of their wide range of application Singini et al.used univariate ARIMA model to model and forecast small *Haplochromine* fish species production in Malaŵi. Singini W [14] also used univariate ARIMA to model and forecast *Oreochromis* fish species production in Malawi. Tsitsika [15] used univariate and multivariate ARIMA models to model and forecast the monthly pelagic production of fish species in the Mediterranean Sea during 1990-2005. Jai Sankar et al. [16] used ARIMA model to model and forecast milk production in Tamilnadu during 1978-2008. Kannan et al. [17] also used stochastic modeling for cattle production and forecast the yearly production of cattle in the Tamilnadu state during 1970-2010. Jai Sankar et al. [18] used a stochastic model approach to model and forecast fish product export in Tamilnadu during 1969-2008.

ARIMA modelling and forecasting involved four steps: Identification, estimation, diagnostic checking and forecasting. To check for stationarity of the catch data, graphical analysis method was used. Model identification involved examining plots of the sample autocorrelograms and partial autocorrelograms and inferring from patterns observed in these functions the correct form of ARMA model to select. Gujarati [19] pointed out that when the PACF has a cutoff at p while the ACF tails off it gives an autoregressive of order p (AR (p)). If the ACF has a cutoff at q while the PACF tapers off, it gives a moving-average of order q (MA (q)). However, when both ACF and PACF tail off, it suggests the use of the autoregressive moving-average of order p and q (ARMA (p, q)).

Autoregressive process (AR) of order p

$$Y_t=\varphi_1 Y_{t-1}+\varphi_2 Y_{t-2}+\ldots,\varphi_t Y_{t-p}$$

Moving Average process (MA) of order q

$$Y_t=\phi_1 \in_{t-1} +\phi_2 \in_{t-2} +\ldots,\phi_t \in_{t-p}$$

Autoregressive Moving Average (ARMA) of order (p, q)

$$Y_t=\varphi_1 Y_{t-1}+\varphi_2 Y_{t-2}+\ldots,\varphi_t Y_{t-p}$$
$$+\phi_1 \in_{t-1} +\phi_2 \in_{t-2} +\ldots,\phi_t \in_{t-p}$$

The general form of ARIMA Model of order (p, d, q)

$$Y_t+\sum_{i=1}^{p}\varphi_i Y_{i-1}+\sum_{j-i}^{q}\phi_j Y_{j-i}+\in_t$$

Where Y_t is the observation at φ and ∅ are coefficients and ε is an error term.

Model fitting consisted of finding the best possible estimates for the parameters of the tentatively identified models. In this stage, maximum likelihood estimation (MLE) method was considered to estimate the parameters. (MLE) method for estimation of ARIMA was applied in SPSS version 16.0. MLE runs an algorithm several times, using as the starting point the solution obtained in the previous iteration/run. Basically SPSS maximizes the value of a function by choosing the set of coefficient estimates that would maximize the function. Each time, it uses the estimates obtained in the previous iteration/run. In model diagnostics, various diagnostics such as the method of autocorrelation of the residuals and the Ljung-Box-Pierce statistic were used to check the adequacy of the identified models. If the model was found to be inappropriate, the process was returned back to model identification and cycle through the steps until, ideally, an acceptable model was found.

Plots of autocorrelation and partial autocorrelation of the residuals were used to identify misspecification. For evaluating the adequacy of ARMA and ARIMA processes, various statistics like Correlogram of the residuals; Normalized Bayesian Information Criterion (BIC), R-square, Stationary R-square, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Maximum Absolute Percentage Error (MaxAPE), Mean Absolute Error (MAE) and Maximum Absolute Error (MaxAE) were used.

Results and Discussion

Data stationarity testing

Data stationarity was tested by means of sequence charts. Figure 1 shows that the time series for temperature data were not stationary. The non-stationarity was explained by the unstable means which increased and decreased (sharp ups and downs) at certain points throughout the 1982 to 2013 period. According to Pierce et al. [20] and Georgakarakos et al. [21] the use of ARIMA models requires that the time series is stationary. Therefore, the non-stationarity in mean was corrected through first differencing of temperature data and the newly constructed Y_t for the data set was then reexamined for stationarity (Figure 1).

Model identification

Since, Y_t was stationary in mean after first differencing (d = 1), the autocorrelations (ACF and PACF) of various orders of Y_t were computed and are presented in Figures 2 and 3 in order to identify the values of p and q. Guti´errez-Estrada et al. [22]. Indicated that a good autoregressive model of order p (AR (p)) has to be stationary, and a

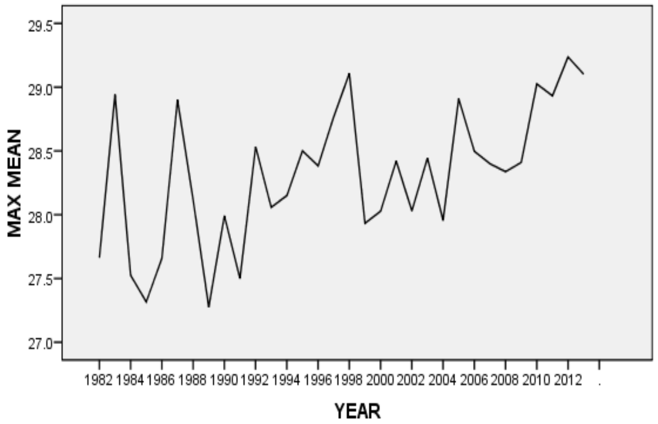

Figure 1: Time series plot of the maximum temperature data.

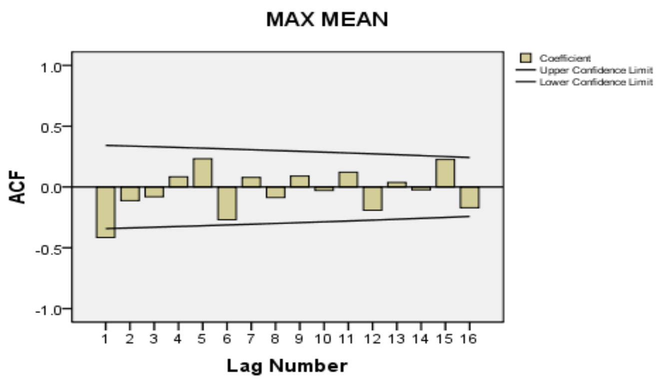

Figure 2: ACF of the first differenced maximum temperature data.

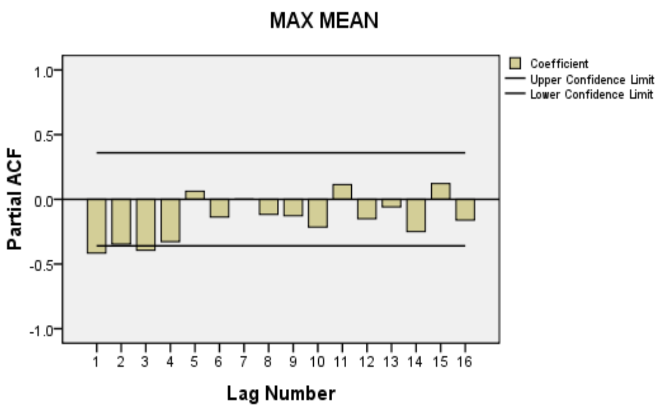

Figure 3: PACF of the first differenced maximum temperature data.

good moving average model of order q (MA (q)) has to be invertible. Invertibility and stationarity will give a constant mean, variance, and covariance (Figures 2 and 3).

The tentative ARIMA models are discussed with values differenced once (d=1) and the model which had the minimum Normalized BIC was selected. The various ARIMA models and the corresponding Normalized BIC values are given in Table 1. The value of the Normalized BIC of the selected ARIMA model was -0.544 (Table 1).

Model estimation

Model parameters estimated are presented in Table 2. Having obtained some suggested models the best possible estimates for the parameters were found by considering the final estimates of parameters and the model selection criteria. Estrada et al.[22] indicated that quality of the coefficients has to meet the following requirement; it must be statistically significant for each coefficient of the estimated model. Czerwinski et al. [23] Indicated that the Normalized BIC test reveals that the model with the least Normalized BIC is better in terms of forecasting performance than the one with a large Normalized BIC. The most suitable model for temperature forecasting is ARIMA (1, 1, 3), as this model had statistically significant coefficient, the lowest Normalized BIC, good R^2 and model fit statistics (MaxAPE and MAPE) (Table 2).

Diagnostic checking

In trying to verify the model, the residuals of the model were checked if they contained any systematic pattern for possible removal to improve the selected ARIMA model. This was done by examination of the autocorrelations and partial autocorrelations of the residuals of various orders. Abrahart et al. [24] Argued that for the model to be acceptable, the residuals should be independent from each other and constant in mean and variance over time. For this cause, various autocorrelations up to 9 lags were computed. The plots of the ACF and PACF residuals as indicated in Figure 4 shows that the sample autocorrelation coefficients of the residuals were low and lay within the limit of (-0.5 and +0.5) implying that none of the autocorrelations is significantly different from zero and any reasonable level. This proves that the chosen ARIMA model (1, 1, 3) is appropriate model for forecasting the temperature data for Bolero Area (Figure 4).

Hence the fitted ARIMA model for minimum temperature data is:

$$Y_t = -1.723 - 0.782Y_{t-1} + 0.105Y_{t-2}$$
$$+0.997Y_{t-3} - 0.107Y_{t-4} + 5.346 \in_t$$

Forecasting

Table 3 and Figure 5 show the actual and forecasted value of maximum temperature with 95% confidence limit. In order to ascertain

Model	SR-squared	R-squared	RMSE	MaxAPE	MAE	MaxAE	MAPE	NBIC
1,1,1	0.390	0.125	0.537	4.351	0.393	1.259	1.389	-0.800
1,1,2	0.388	0.123	0.548	4.352	0.398	1.260	1.405	-0.649
1,1,3	0.421	0.170	0.544	4.350	0.393	1.259	1.386	-0.544

Table 1: Model selection criterion for the maximum temperature data for Bolero.

Model	Model type	Coefficient	SE-Coefficient	T-value	P-value
1,1,1	Constant	-1.726	5.258	-0.328	0.745
	AR1	0.008	0.223	0.038	0.970
	MA1	0.994	2.87	0.346	0.732
1,1,2	Constant	-1.726	5.259	-0.328	0.745
	AR1	0.125	6.874	0.018	0.986
	MA1	1.155	5.614	0.206	0.839
	MA2	-0.159	6.535	-0.024	0.981
1,1,3	Constant	-1.723	5.346	-0.322	0.750
	AR1	-0.782	0.343	-2.281	0.031
	MA1	0.105	37.390	0.003	0.998
	MA2	0.997	40.677	0.025	0.981
	MA3	-0.107	3.853	-0.028	0.978

Table 2: Final estimates of the maximum temperature ARIMA models.

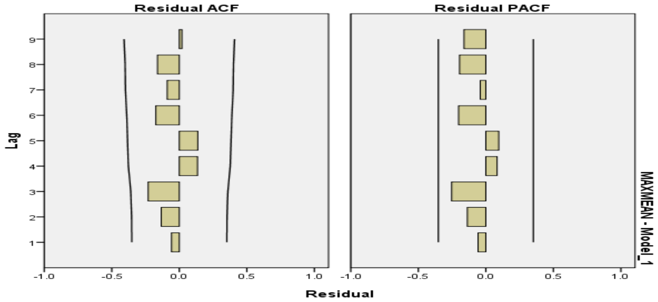

Figure 4: Residuals of ACF and PACF for the maximum temperature data.

Year	Forecasted maximum temperature	95% LCL	95% UCL
2015	27.7	26.3	29.1
2016	28.4	27.1	29.7
2017	27.9	26.8	29.1
2018	28.1	26.9	29.2
2019	27.8	26.7	28.9
2020	28.2	27.1	29.3
2021	27.9	26.8	28.9
2022	28.2	27.1	29.2
2023	28.0	26.9	29.0
2024	28.1	27.0	29.1
2025	28.1	27.1	29.2
2026	28.0	27.0	29.1
2027	28.2	27.2	29.3
2028	28.2	27.1	29.2
2029	28.3	27.3	29.3
2030	28.3	27.3	29.3

Table 3: Forecast of maximum temperature for Bolero EPA.

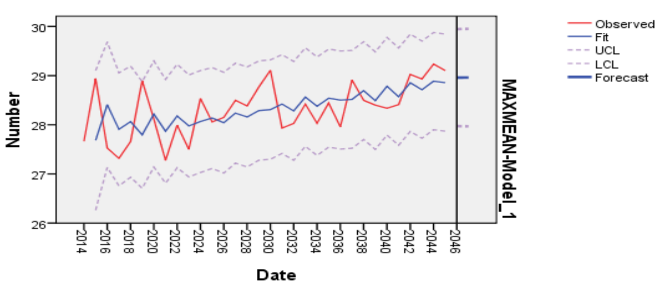

Figure 5: Forecasted value of maximum temperature data.

the forecasting ability of the fitted ARIMA model, the measures of the sample period forecasts' accuracy were computed. The results of the computation show that this measure had low forecasting inaccuracy. Czerwinski et al. [23] stated that a good model should show low forecasting error. This study found that the magnitude of the difference between the forecasted and actual values were low for the selected model. The noise residuals were combinations of both positive and negative errors which shows that, the model is not forecasting too low on the average or too high on the average. Having this positive, the model has outperformed as far as the forecasting power of the model is concerned. The temperature increase suggests that climate change could continue to negatively impact on agricultural livelihood options in Bolero community and this call for increased adaptive capacity for the community. With the magnitude of future climate change as forecasted in this study the less privileged and marginalized social groups would continue to remain vulnerable and unless deliberate efforts are put in place to help the community to adapt to climate change effects. Higher temperatures have effects on droughts, changing rainfall patterns and availability of surface water whose consequences range from less food supply to general fewer water supplies in Bolero (Table 3 and Figure 5).

Conclusion

The most appropriate ARIMA model for temperature forecasting was found to be ARIMA (1,1,3). The fitted ARIMA model shows that temperature will increase by 1.6 C from 27.7°C in 1982 to 29.3°C in 2030. The results of the modelling show that the measure had low forecasting inaccuracy. This study found that the magnitude of the difference between the forecasted and actual values were low for the selected model. The noise residuals were combinations of both positive and negative errors which shows that, the model is not forecasting too low on the average or too high on the average. Having this positive, the model has outperformed as far as the forecasting power of the model is concerned. The temperature increase suggests that climate change could continue to negatively impact on agricultural livelihood options in Bolero community and this call for increased adaptive capacity for the community. With the magnitude of future climate change as forecasted in this study the less privileged and marginalized social groups would continue to remain vulnerable and unless deliberate efforts are put in place to help the community to adapt to climate change effects. Higher temperatures have effects on droughts, changing rainfall patterns and availability of surface water whose consequences range from less food supply to general fewer water supplies in Bolero.

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