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Verification of numerical weather predictions for the western Sahel by the United Kingdom Met Office Limited Area Model over Africa

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Verification of numerical weather predictions for the western Sahel by the United Kingdom Met Office Limited Area Model over Africa

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Summary

Numerical Weather Predictions (NWPs) are subject to systematic errors and biases. Hence, the continuous verification of NWP model outputs in order to contribute to model improvement became very important over recent years. Verification results provide numerical measures of how well NWP models perform, in an objective way. It also allows for monitoring of how NWPs improve over time. In the day-to-day operation of weather forecasting one might find biases in either forecasts generated by the NWP model, or biases that result from the weather forecaster's interpretation of NWP output, or both. The use of verification statistics might help to identify the source of these biases, which might lead to research targeted to improve the scientific understanding of the underlying processes required to improve NWP forecasts. This study investigates the potential of the 20km x 20km resolution Limited Area Model over Africa (Africa LAM) developed by the United Kingdom Meteorological Office (UK Met Office) to be used as supplementary tool to improve weather forecast output to end-users over the Western Sahel (WS) and Nigeria.

In the study, Africa LAM T+24h forecasts dataset was verified against daily observed rainfall, maximum and minimum temperature data, of 36 selected meteorological point stations over the WS from January 2005 to December 2006. 12 meteorological point stations were selected across each of the three identified climate zones of the WS, namely (1) Wet Equatorial (WE) climate zone (from the southern coastline up to a latitude of 8.00ºN), (2) Wet and Dry Tropics (WDT) climate zone (between latitude 8.00ºN and 12.00ºN) and (3) Semi-Arid (SA) climate zone (between latitude 12.00ºN and 15.00ºN). The dataset was also stratified into four seasons, namely (1) January-February-March (JFM), (2) April-May-June (AMJ), (3) July-August-September (JAS) and (4) October-November-December (OND). The verification algorithms and measures used in this study are in accordance with the WMO NWP verification standards.

The verification results indicate that the Africa LAM model temperature forecasts show skill, more so during the raining seasons (AMJ and JAS) than during the dry seasons (JFM and OND) over the WS. The model rainfall forecasts, however, show more skill during the dry seasons (JFM and OND) than during the raining seasons (AMJ and JAS). The results further indicate that, on a regional basis, the model temperature forecasts show more spatial skill over the WE climate zone than over the WDT and SA climate zones of the WS, while rainfall forecasts show more skill over the SA climate zone than over the WDT and WE climate zones of the WS. Additional results from simple bias corrections and Model Output Statistics (MOS) which are some of the suggested post-processing techniques in this study are presented. These results give a better understanding of the model forecast errors, and also provide the feedback necessary for a possible improvement of Africa LAM forecasts by scientists at the UK Met Office.

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LIST OF SYMBOLS

A_e	:	Mean model bias
A	:	MOS regression intercepts
ß	:	Average anomalies from the mean of original model forecasts
C	:	Correction values
d_i	:	Difference between each rank of corresponding values of forecasts and observations
F	:	Model forecast
$\overline{F}$	:	Mean model forecast
F_{ADJ}	:	Regression-based correction
f_{MOS}	:	MOS regression coefficient
F_x	:	Empirical cumulative distribution function of observations
n	:	The number of pairs of values
MSE'	:	Mean Squared Error between corrected model forecasts and observations
N	:	Number of events
O	:	Point station observation
$\overline{O}$	:	Mean point station observation
O_{stn}	:	Archived point station observations
O_t	:	MOS forecast
r_{OF}	:	Product-moment correlation between the forecasts and observations.
r_p	:	Pearson's product moment correlation coefficient
r_s	:	Spearman's rank order correlation coefficient
S_O	:	Standard deviation of point station observations
S_F	:	Standard deviation of Africa LAM raw forecasts
T+24h	:	Forecasts of 24 hours from time T
x	:	Independent variable
X_{nwp}	:	Archived raw model forecasts
x_t	:	Africa LAM Forecast pertaining to the future time t
y	:	Dependent variable

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LIST OF ABBREVIATIONS

ACMAD	African Center of Meteorological Applications and Development
ADS	Administration and Supply
Africa LAM	UK Met Office Limited Area Model over Africa
ALADIN	Aire Limitée Adaptation dynamique Développement InterNational
AMJ	April May June
AMS	Applied Meteorological Services
AMSL	Above Mean Sea Level
ARPEGE	Action de Recherché Petite Echelle Grande
AS	Administration and Supply
AWS	Automatic Weather Stations
BESK	Binary Electronic Sequence Calculator
BMSL	Below Mean Sea Level
CAPE	Convective Available Potential Energy
CFO	Central Forecast Office
DG	Director General
ECMWF	European Center for Medium-Range Weather Forecasts
ENIAC	Electronic Numerical Integrator and Computer
EPS	Ensemble Prediction System
ESMF	Earth System Modelling Framework
ETS	Engineering and Technical Services
FA	Finance and Accounts
FEWS	Famine Early Warning System
GCM	Global Circulation Model
GLOBE	Global Land One-km Base Elevation
GMT	Greenwich Mean Time
Grib	Gridded Binary
GTS	Global Telecommunication System
HadAM4	Hadley Centre Atmospheric Model version 4
IAS	Institute for Advanced Study
IRI	International Research Institute, USA.
ITCZ	Inter-tropical Convergence Zone
JAS	July August September
JFM	January February March

LAM	Limited Area Model
LBCs	Lateral Boundary Conditions
LCA	Legal and Corporate Affairs
LEPS	Linear Error in Probability Space
MAE	Mean absolute error
MATLAB	Matrix Laboratory
MDD	Meteorological Data Distribution
MOS	Model Output Statistics
MOSES	UK Met Office Surface Exchange Scheme
MPP	Massively Parallel Processor
MSE	Mean Squared Error
MSG	Meteosat Second Generation
MSLP	Mean Sea Level Pressure
NCDC	National Climatic Data Centre
NCEP	National Centers for Environmental Prediction
NCEP/GFS	NCEP Global Forecast System
NIMET	Nigerian Meteorological Agency
NMHS	National Meteorological and Hydrological Services
NWP	Numerical Weather Prediction
OND	October November December
PC	Proportion Correct
PDF	Probability Density Function
PDUS	Primary Data User System
R&T	Research and Training
RH	Relative Humidity
RMSE	Root Mean Squared Error
RMSE’	Root Mean Squared Errors of raw model forecasts
$RMSE_{mos}$	Root Mean Squared Errors of MOS forecasts
SA	Semi-Arid climate zone
TKE	Turbulent Kinetic Energy
UK Met Office	United Kingdom Meteorological Office
UM	UK Met Office Unified Model
UNDP	United Nations Development Programme
USA	United States of America

WAM	West African Monsoon
WDT	Wet and Dry Tropics climate zone
WE	Wet Equatorial climate zone
WFS	Weather Forecasting Services
WMO	World Meteorological Organization
WS	Western Sahel
3DVAR	3-dimensional variation data assimilation
4DVAR	4-dimensional variation data assimilation
%IM	Percentage Improvement

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Processes in the atmosphere are not perfectly predictable in a deterministic sense because the atmosphere is regarded as a non-linear dynamic or "chaotic" system. This implies that the dynamic flow of the atmosphere is inherently non-predictable. In addition many physical parameterization schemes have been introduced in efforts to resolve physical processes in the atmosphere, such as cloud processes, rainfall and radiation fluxes, which all also have an influence on the atmospheric flow dynamics (Lorenz, 2006). Our ability to predict atmospheric flow and processes is also restricted by limitations in spatial as well as temporal observations of the weather. Numerical Weather Prediction (NWP) models incorporates most of these aspects by numerically integrating (estimating) the equations of atmospheric flow dynamics, and by estimating physical processes, mostly by means of parameterization (Straus, 2007). Many NWP models are currently operational to forecast weather all over the world on various spatial scales. These models are still far from perfect, although much progress has been made over recent years to improve on NWP (Mesinger, 2005). NWPs results might be improved by the use of statistics. The reason for this is because there are fundamental surface and atmospheric forcing that influences weather events, and that allow for weather events to be repeated to a certain degree. As a result, stochastic or statistical methods have recently become a very useful application as a post-processing tool, which is employed to improve on weather forecasting at meteorological centers. As emphasized by Kalnay *et. al.* (1990), Wilks (1995) and Kalnay (2003) statistics has many roles to play in the atmospheric sciences.

It is known that surface conditions are simplified and homogenized in NWP models, and that the atmosphere is regarded as a medium that consists of square grid boxes to facilitate the mathematical treatment of the atmosphere. In most models, land use characteristics are represented as an array of horizontal grid squares, while associated grid boxes extend throughout horizontal layers in the vertical atmosphere. Within surface grid squares, one finds smoothed values of important small-scale boundary conditions such as topography, vegetation and soil types, or even small-scale bodies of water, which are spatially variable in reality and important to local weather conditions. Atmospheric turbulence, which plays an important role in atmospheric convection, is another small-scale process that is difficult to resolve analytically. Inaccuracies caused by these estimations of reality in NWP models are a result of limitations in resolving complex processes that occur in the atmosphere. Some NWP models need strong computers to simulate estimated atmospheric flow and processes in order to generate operational weather forecasts, an asset or luxury that many meteorological centers simply cannot afford (Grell, 1993; Lorenz, 2006).

Because of the above-mentioned limitations, NWPs are subjected to systematic errors and biases. Hence, the continuous verification of NWP model outputs in order to contribute to model improvement became very important over recent years. Verification results provide numerical measures of how well NWP models perform, in an objective way. It also allows for monitoring of how NWPs improve over time. In the day-to-day operation of weather forecasting one might find biases in either forecasts generated by the NWP model, or biases that result from the weather forecaster's interpretation of NWP output, or both. The use of verification statistics might help to identify the source of these biases, which might lead to research targeted to improve the scientific understanding of the underlying processes required to improve NWP model forecasts (Jolliffe and Stephenson, 2003). For application, NWP model forecasts or even verification results need to be prepared and presented in such a way that it addresses the need of weather forecasters, and eventually the requirements of end-users, which include a diversity of sectors in the economy, decision making of social society, agricultural and even disaster management activities.

As mentioned before, stochastic methods might be useful to improve NWPs. For example, statistical relationships might be developed between the simulated information generated by NWP models and the desired forecast quantities to reduce the problem of homogenization – known as downscaling (Glahn and Lowry, 1972; Wilks 1995). Since current NWP models have limitations which emanate from both a lack of detailed initial conditions and boundary input, as well as the inherent problem of non-linearity in flow dynamics and the estimation of physical processes, a combination of statistics trained over a long enough record of model output compared to observation might help to quantify and express forecast uncertainties. Statistical re-interpretation or "post-processing' of NWP products might improve weather forecasts from NWP models, and is increasingly regarded as an important addition to assist operational weather forecasters in their duties. Statistical "post-processing" provides a first guess of expected local conditions. Although uncertainties in weather forecasts generated by NWP models or prepared by weather forecasters are difficult to avoid (Wilks, 1995), statistical tools might always be of value to improve weather forecasts. Statistical guidance could add value to NWP model output by providing objective model interpretation in order to reduce systematic biases, to quantify uncertainties, to predict parameters that the model does not predict, and to produce site-specific weather forecasts (Kalnay, 2003).

Despite of the increased importance of the application of NWP as a sophisticated weather forecasting tool, most meteorological centers in Africa have little knowledge of NWP model development, or do not even have the required computer resources to generate in-house NWPs. These centers mostly rely on NWP results from overseas, which are normally made available via the Internet. Currently, the majority of operational National Meteorological and Hydrological Services (NMHS) in Africa only interpret NWP model outputs subjectively when preparing and issuing daily weather forecasts, and not in all cases are these model products a reflection of actual weather conditions. As a result, weather forecasts over Africa are often of poor quality.

However, many other institutions, such as the United Kingdom Meteorological Office (UK Met Office), are running finer resolutions models over Africa, and had even became involved in NWP development for Africa. One such model from the UK Met Office is known as the Limited Area Model (LAM) over Africa (hereafter called Africa LAM). In this study, NWPs generated by the Africa LAM over the Western Sahel (WS) are verified against point observations using internationally recognized verification algorithms. In addition, statistical "post-processing" methods that could be of value in improving model forecasts are proposed. Although, most of the classical statistical post-processing method derives separate regression coefficients for each location and forecast lead time using a number of forecast parameters, the post-processing method advanced in this study is based on a simple bias correction and regression of the model forecast parameter corresponding to the station observations. Results from this study might contribute to a better understanding of NWP over the WS, and maybe, to improved weather forecasting over the region of investigation.

1.2 MODEL ERRORS AND STATISTICAL POST-PROCESSING

Most NWP models generate forecasts with systematic errors or biases. Systematic NWP model forecast errors or biases, for example, include progressive atmospheric cooling or warming biases with increasing forecast projections, the tendency for modeled synoptic features to move too slow or too fast during the process of model simulation, and the unavoidable decrease in forecast accuracy with an increase in lead time (Kalnay *et. al.*, 1990). A number of statistical post-processing techniques developed over recent years might allow for the compensation of these model systematic errors or biases. Kalnay (2003; p276) stated that "*In order to optimize the use of numerical weather forecasts as guidance for human forecasters, it has been customary to use statistical methods to "post-process" the model forecasts and adapt them to produce local forecasts*". Glahn and Lowry (1972), Carter *et. al.* (1989) and Wilks (1995) also suggested that statistical guidance is necessary to add value to NWP.

1.3 MOTIVATION FOR THE RESEARCH

The growing demand at NMHS in Africa to issue more accurate weather forecasts, and to improve their capacity to produce these forecasts, inspired the interest in NWP research as documented in this dissertation. Because of the UK Met Office's interest in NWP development for Africa, and because of the important influence of tropical weather systems on global weather events (which includes the UK), the UK Met Office had decided to develop and implement the Africa LAM to generate NWPs at a 20km horizontal resolution over Africa. An important motivation for the operational implementation of the Africa LAM was obviously to provide a NWP asset to the NMHS in Africa who mostly find it difficult to run NWP models in-house. The Africa LAM project is co-funded by the British Government and the World Meteorological Organization (WMO).

As mentioned before, a need for knowledge of the development, implementation, interpretation and verification of NWP models over Africa inspired interest for the research documented in this dissertation. In particular, the verification of NWP results and the possibility to introduce stochastic techniques to improve NWP results are important focus points in the research. The improvement and interpretation of NWPs are important fields of study at some national meteorological centers in Europe (for example the Netherlands, Britain, Italy and Spain) and some other countries such as China, Canada and the United States of America (USA) (Lemcke and Kruizinga, 1988; Carter *et. al.*, 1989). The verification results and statistical post-processing suggestions in this study will contribute to a better understanding of the performance and value of NWP models in not only the WS region of Africa, but also for the rest of Africa.

1.4 THE AIM AND OBJECTIVES OF THE RESEARCH

The overall aim of this study is to verify NWPs generated by the Africa LAM of the UK Met Office over the WS of Africa in order to investigate the potential of the model to be used as a weather forecasting tool to assist operational weather forecasters in their duties. In addition the study will suggest post-processing statistical tools that might be of value to improve NWPs and eventually weather forecasts.

The overall aim will be achieved by the following objectives:

OBJECTIVE 1

The first objective of this study is to examine the performance of the Africa LAM developed by the UK Met Office against point observations and against regional averages of meteorological variables over the WS of Africa by using internationally recognized verification algorithms.

The essence of the verification is to ascertain and evaluate the performance of the Africa LAM to predict rainfall, as well as maximum and minimum temperatures over the study domain, which is the WS of Africa. During this process systematic forecast errors and biases are to be identified.

a) *Daily T+24h (forecasts of 24 hours from time T) Africa LAM forecasts data for rainfall as well as for maximum and minimum temperatures (screen temperatures) will be used as predictors (Antolik, 2003). Africa LAM output that is in Grib format will be interpolated to observational point stations by using MATLAB software (a mathematical analysis software package).*
b) *Daily observed data over the WS of Africa obtained from the National Climatic Data Centre (NCDC) of the USA, and station observations (where available) will be used as predictands.*
c) *As recommended by Wilks (1995), Kalnay (2003) and Antolik (2003), the data sets will be stratified into seasons (dry and wet seasons) and pooled according to climatic zones over the WS.*
d) *The datasets will be seasonally stratified into two dry seasons (January-February-March (JFM) and October-November-December (OND)) and two wet seasons (April-May-June (AMJ) and July-August-September (JAS)). This, according to Wilks (1995), allows for the incorporation of different relationships between predictors and predictands at different periods of the year*
e) *The data will also be pooled into regions in accordance with the climate zones of the WS, namely the Wet Equatorial (WE) (0.00 ºN to 8.00 ºN), Wet and Dry Tropics (WDT) (8.00 ºN to 12.00 ºN) and Semi-Arid (SA) (12.00 ºN to 15.00 ºN) climate zones. This allows for the developmental data used to incorporate groups of nearby climatologically similar stations (Wilks, 1995).*

OBJECTIVE 2

The second objective of this study is to investigate if the Africa LAM has the potential to be employed as NWP model to assist operational weather forecasters in their duty to issue more accurate forecasts.

In order to investigate if the Africa LAM has potential to serve as a weather forecasting tool over the WS of Africa, the study will specifically investigate and outline weather forecasting operations as they happen on a daily basis at the Nigerian Meteorological Agency (NIMET). The study will make suggestions of how NWPs might be incorporated to support operational weather forecasters in their duties.

OBJECTIVE 3

The third objective is to suggest possible statistical post-processing tools that might be of value for improving basic NWPs over the WS of Africa.

Statistical post-processing results derived from using historical observations, and raw NWP output data generated by the Africa LAM, will be discussed. The variables considered will be maximum and minimum temperatures over five (5) selected Nigerian meteorological observation stations.

1.5 ORGANIZATION OF THE REPORT

The study mainly examines the performance of the Africa LAM NWPs generated over the WS against point observations, by using internationally prescribed verification statistics. Also included in the study is the suggestion of post-processing techniques that could improve weather forecasts over the region. The content and results presented in the dissertation is expected to guide scientists especially in the WS, who are interested to issue improved weather forecasts.

In CHAPTER 2, a general overview of the characteristics and natural resources of the study domain is introduced. The chapter is sub-divided into two sections. The first section gives a summary of the overall West African climate, and how it relates to the climate of the WS, while the characteristic of the climate of Nigeria, which forms an integral part of the WS (and the West African) climate, is discussed in the second section.

CHAPTER 3 first gives an historical overview of the development of NWP at various international research centers. Because the study focuses on NWPs generated by the

Africa LAM from the UK Met Office, the historical overview is followed by a technical description of the Africa LAM, and also to some extent, the Unified Model (UM) of the UK Met Office, which forms the basis of the Africa LAM.

CHAPTER 4 explains the statistical formulation and algorithms used to verify NWPs by the Africa LAM against observations over the WS and Nigeria. These algorithms are in accordance to NWP verification standards as required by the WMO.

In CHAPTER 5 the Africa LAM is verified against observations. The verification results highlight the strengths and weaknesses of the model to predicting rainfall, maximum and minimum temperatures over the study domain. The chapter gives an evaluation of the magnitude of the model systematic forecast errors and biases, which might be improved by the statistical post-processing techniques suggested in the study.

CHAPTER 6 provides a general overview on conventional forecasting, and current forecasting that incorporate NWPs in Nigeria. The shortcomings and needs of NIMET, which are also applicable to other NMHS in the WS, to issue improved weather forecasts are examined. A typical weather forecasting process at NIMET is also discussed as part of this chapter, with the view to provide an example for other NMHS in the WS (and beyond) that might consider the incorporation of NWP model results in future.

In CHAPTER 7 statistical post-processing techniques such as simple bias corrections, MOS and Ensemble Forecasting Systems are suggested and discussed. These post-processing methods are useful, and sometimes necessary, to improve systematic errors and biases in NWPs. Some post-processing technique results are also discussed in this chapter through application at five selected Nigerian meteorological stations and during the JFM, AMJ, JAS, and OND seasons.

Concluding remarks are outlined in CHAPTER 8, which is followed by APPENDICES where analyses tools adopted, including the MATLAB scripts applied in this study, are attached.

CHAPTER 2

THE STUDY DOMAIN

2.1 INTRODUCTION

This chapter provides a general overview of the characteristics of the study domain, which is the WS of Africa, as indicated in Fig 2.1. The WS exhibits typical characteristics of the general West African climate, and the country Nigeria covers an extended part of the WS. As such, the climate of Nigeria represents most of the dominant climatic characteristics of the broader WS. The chapter is sub-divided into two sections. The first section gives a summary of the overall West African climate, and how it relates to the climate of the WS, while the characteristic of the climate of Nigeria, which forms an integral part of the WS (and the West African) climate, is discussed in the second section.

2.2 THE WESTERN SAHEL (WS)

2.2.1 Geographical location

The area that extends from longitude 20.00°West (W) to 30.00°East (E), and latitude 0.00 (Equator) to 20.00°North (N) is defined as the WS (Fig 2.1). The WS of Africa is bordered in the north by the Sahara desert, and in the south and west by the Atlantic Ocean. It includes the following countries: Benin Republic, Burkina Faso, Cape Verde, Cote d'Ivoire, Cameroon, Chad, The Gambia, Ghana, Guinea, Guinea Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo and Sudan (Fig. 2.1). It is estimated that more than 290million people live in the WS, which covers a total area of approximately eight million km^2 (ECOWAS-SWAC/OECD, 2006)

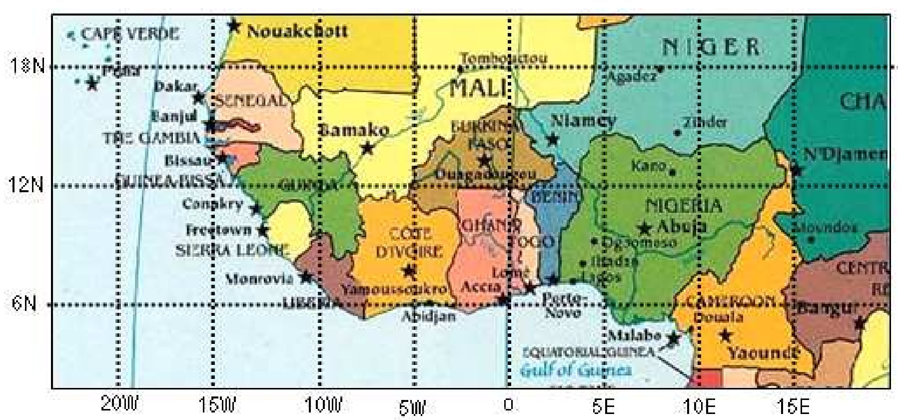


FIG. 2.1: A political map of the Western Sahel (WS), which in this study is defined as the study domain. Note that Nigeria covers a large part of the WS.

2.2.2 Topography and drainage

The highest geographical point in the WS is the Fako Mountain in Cameroon (also known as the Cameroon mountain), which is about 4 095m Above Mean Sea Level (AMSL), and the lowest point is at the Djourab depression in the Chad Republic, which is 160m Below Mean Sea Level (BMSL). Apart from these two extreme elevation points, there are several other high grounds in the study domain, which includes mount Emi Koussi in Chad (3 415m AMSL), mount Kinyeti in Sudan (3 187m AMSL), and mount Chappal Waddi in Nigeria (2 419m AMSL). In general, the WS topography (Fig. 2.2) ranges from low coastal plains to flat, hills, plateaus, mountains and desert plains.

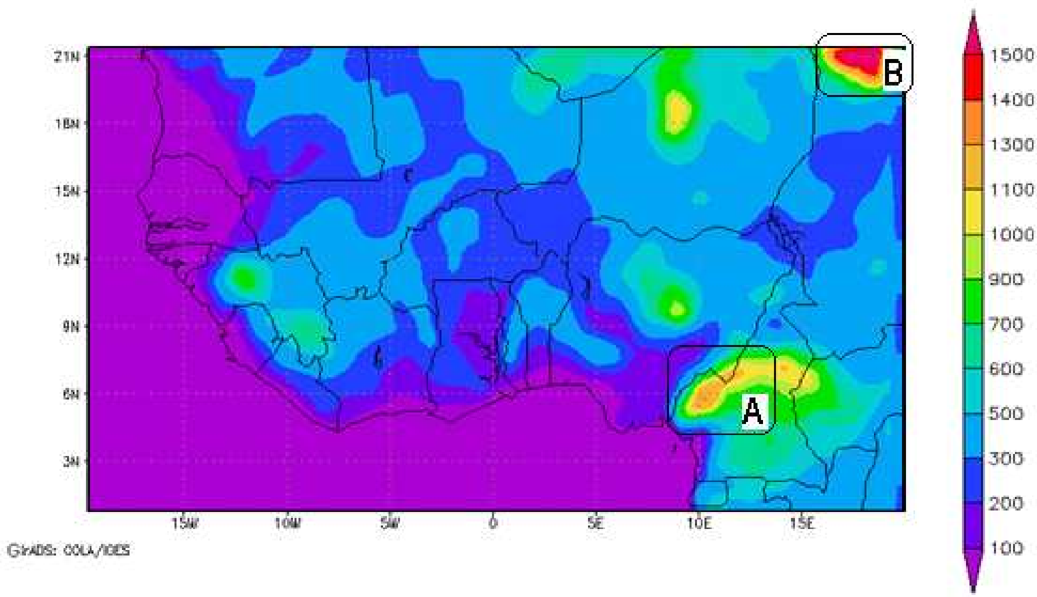


FIG. 2.2: Topography of the Western Sahel (WS) (after Giorgi and Mearns, 1999). Shaded contour values are given in meters as measured from Above Mean Sea Level (AMSL) or Below Mean Sea Level (BMSL). Points A and B on the map represents the Fako and Emi Koussi Mountains, respectively.

Runoff over the WS takes place through a large number of fast moving rivers flowing from higher altitude locations in the WS region towards the Atlantic Ocean. Some of the most important rivers in the WS are the Senegal River, Gambia River, Niger River, Benue River and Volta River. The Niger, Senegal and Gambia rivers originate from the Futa Djallon Highland. There are 28 transboundary river basins in the WS extending over almost 71% of the region's total surface area (Fig. 2.3). Of these trans-boundary river basins, the Niger River Basin, Senegal River Basin, Volta River Basin, Lake Chad Basin and the Comoe River Basin are the most prominent (Anyadike, 1992). In the WS, each country shares at least one watercourse with the other. A watercourse is part of the inland territory where all surface water flows towards the same outlet. There are eight watercourses in Cote d'Ivoire, seven in Cameroon and Liberia, and five in Nigeria and Sierra Leone.

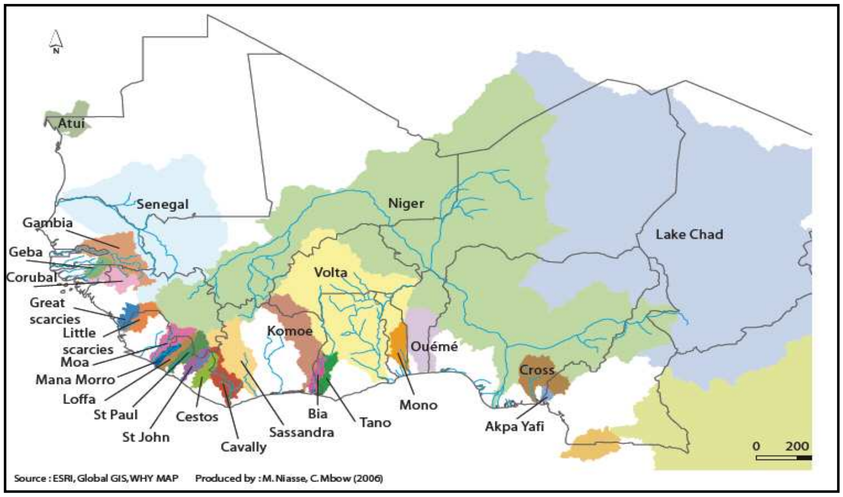


FIG. 2.3: River Basins and trans-boundary watercourses in the Western Sahel (WS) of Africa (Source: ECOWAS-SWAC/OECD, 2006).

2.2.3 Climate

The WS of Africa has diverse climate characteristics, ranging from wet equatorial climates (from the southern coastline up to a latitude of 8.00ºN), to wet and dry tropics climates (between latitude 8.00ºN and 12.00ºN) in the central region, and semi arid climates (between latitude 12.00ºN and 15.00ºN) in the northern region (see Fig. 2.4).

2.2.3.1 The Wet Equatorial (WE) climate zone

The Wet Equatorial (WE) climate zone (located in the southern part of the WS) receives a significant amount of rainfall each year, with not more than three months recording a total monthly rainfall of less than 50mm. As part of the study domain, the WE climate zone extends across the coasts of Liberia, Sierra Leone, Ivory Coast and Nigeria, southern Cameroon and Equatorial Guinea. The most important economic and agricultural activities found in the WE climate zone include palm kernels and oil, peanuts, rubber and cotton, timber (mahogany), coffee and the most prominent natural resources are copper, manganese, gold, zinc, diamond, tin, petroleum, bauxite and water for hydro-power.

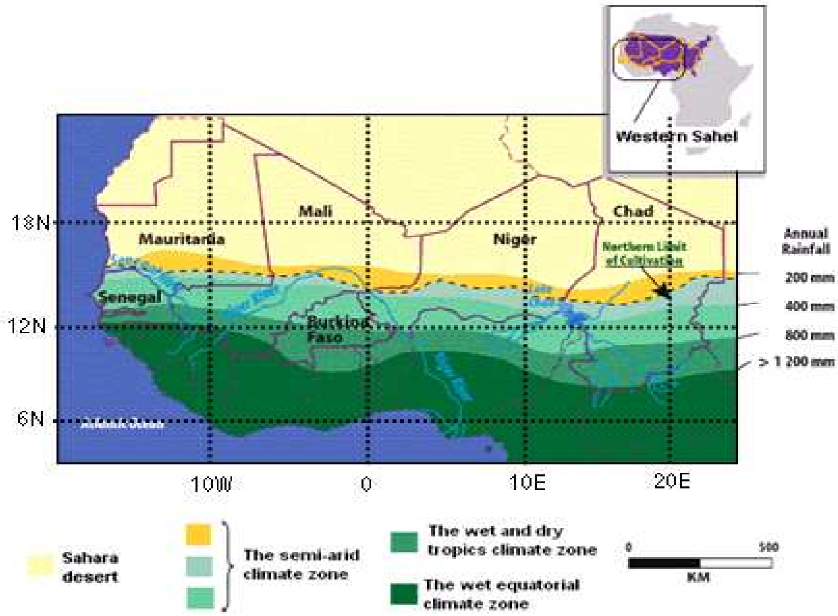


FIG. 2.4: Annual rainfall totals over the Western Sahel (WS). Climate zones of the WS range from tropical to arid. (adapted from FEWS, June 1997).

The WE climate zone is close to the equator, meaning that total outgoing long wave radiation at ground level is relatively high throughout the year. This does not only results in fairly uniform annual temperatures, but also allow for little variability between day and night (or maximum and minimum) temperatures. The WE climate zone falls in the equatorial belt of relatively lower surface pressures, also known as the Inter-tropical Convergence Zone (ITCZ). The ITCZ follows a distinct seasonal meridional propagation across the region. The ITCZ is often associated with rainfall, because of extensive convection and cloud development that occur at the location of the ITCZ. The ITCZ is therefore an important driver of seasonal rainfall over Africa. A larger portion of the available atmospheric energy over the WE climate zone occurs as latent heat of evaporation from soil or water. The high evapo-transpiration rate from the thick vegetation cover, and higher outgoing long wave radiation, are diffused by turbulence in the lower layers of the atmosphere resulting into important vertical fluxes of water vapor and sensible heat (Ojo, 1977). The most dominant wind flow pattern, for most of the year, over the WE climate zone is warm, moist westerly to southerly winds, mostly associated with the West African Monsoon (WAM), which are responsible for high rainfall being recorded over the region. However, drier northeasterly winds prevail over the WE climate zone for a short period of the year (November and December), resulting in a season of lower rainfall totals (as low as 50mm per month). Mean annual rainfall totals over the WE climate zone are high, ranging from 5 000mm over the coast of Liberia to about 1 200mm near the latitude of 10°N. The WE climate zone receives its lowest annual rainfall from mid-December until late March (Griffiths, 1966), from where rainfall again increases to a maximum in June, and a second maximum in September, which is generally lower than the peak in June. This indicates two rainy seasons, which are linked to the south-north propagation of the ITCZ. In the WE climate zone one also finds a so called "little dry season" from late July to August. Daily rainfall in excess of 200mm may be experienced anytime from May to October, and rain may also fall for about 25days during each month from June to October. Rainfall over the WE climate zone is convective of nature and therefore mostly falls during late afternoon hours and during night, with little chance of rain in the morning (Swan, 1958).

Mean annual temperatures over the WE climate zone ranges from 15°C to 37°C, the highest being recorded in March and October and the lowest in December and August. Relative Humidity (RH) over the WE climate zone is generally high, especially along the coast. The lowest RH readings, usually recorded during January in the afternoon, are in the order of 70%, which may increase to about 95% during the early hours of the day. However, RH values significantly decreases during the harmattan period (November to February) when dry continental northeasterly winds prevail. The WE climate zone is exposed to sunshine, especially during the early afternoon hours, and most of the coastal and inland cities experience early morning fog from October to February, with a peak in fog event frequencies in January. The ITCZ influences the prevailing wind direction by means of the WAM. However, local effect of the land and sea breezes are also noticeable during the early morning hours and late at night. Over the coastal cities of the WS (situated within the wet equatorial climate zone), west to southerly WAM winds starts during July and, together with local topographic characteristics, can give rise to a maximum monthly rainfall experienced when the ITCZ is located in its most northern position (Nieuwolt, 1977)

2.2.3.2 The Wet and Dry Topics (WDT) climate zone

The Wet and Dry Tropics (WDT) climate zone (located in the central part of the WS) is a transfer region between semi-arid conditions in the north and wet equatorial conditions in the south. The area approximately extends across latitude 8.00°N to 12.00°N. The WDT climate zone has about seven to nine months of rainfall in excess of 50mm per month. The countries that fall in this climate zone of the WS are the Ivory Coast, Ghana, Togo, southern Sudan, central Cameroon and a large part of Sierra Leone and Nigeria. Average annual rainfall amounts over the WDT climate zone ranges from 1 000mm to 4 000mm. This high rainfall allows for better agricultural production than in the semi-arid areas to the north.

The most prominent agricultural activities over the WDT climate zone are rice, yams, mahogany, corn, cotton, groundnuts, cattle rearing, bananas, palms, citrus fruits, pineapples and coffee. Natural resources include limestone, salt, gypsum, granite and phosphate. Over this climate zone, a warm and humid tropical maritime air mass from the Atlantic Ocean dominates during most of the year, giving rise to adequate rainfall for successful farming. However, for a short period each year (January-February and November-December), continental airflow dominates, which results in low humidity and lower rainfall (Trewartha, 1961). The WDT climate zone experiences both single and double annual peaks of maximum rainfall, and therefore has both one and two rainfall seasons per year. These seasons are related to the meridional shift of the ITCZ. The single annual peak of maximum rainfall over the WDT climate zone is recorded around latitude 10.00°N to 12.00°N, and July (or sometimes August) is the month of highest rainfall. In the double peaked maximum rainfall season (latitude 8.00°N to 10.00°N), June is generally the wettest month with some areas that experience maximum rain in September. February to April is a period with a high number of disturbance lines, which are well-defined belts of intense thunderstorms moving at an average speed of $25kmh^{-1}$ from east to west, with intense rain over relative short time intervals (Ojo, 1977). These disturbance lines usually occur 300 to 600km south of the ITCZ, where humid and hot air are deeper to allow for the development of unstable conditions with the associate heavy rainfall (Adejokun, 1966). Humid WAM air that flows from the ocean, disturbance lines, the ITCZ and topography are the major atmospheric influences that contribute to rainfall development over the WDT climate zone.

The mean annual temperature over the WDT climate zone ranges from 30°C to 36°C, with a small variation of about ± 2°C to 4°C during the year. The mean annual minimum temperature is generally from 19°C to 21°C, but can sometimes increase to 23°C to 24°C. Temperature reaches its highest peaks in February, or March, and its lowest dips in December or January. The lowest maximum temperature occurs in July or August, while the highest minimum temperature occurs in April or May. Over the WDT climate zone, RH is extremely high throughout the year, reaching percentages of about 85% to 95% in most months, especially during the early hours of the day. Afternoon mean annual RH ranges from 50% to 75%, which are still relatively high. However, during December and January, some stations occasionally record an afternoon RH low of about 25% to 30% (Jackson, 1977).

2.2.3.3 The Semi-Arid (SA) climate zone

The Semi-Arid (SA) climate zone (located in the north of the WS) is close to the southern fringes of the Sahara desert (Fig. 2.4). Mean annual rainfall totals over the SA climate zone are normally less than 400mm. The beginning and end of the rain seasons are usually abrupt due to the rapid northward advancement and southward retreat of the ITCZ (Adejokun, 1966). The dominant wind is associated with the advection of a dry and dusty continental air mass, mostly northeasterly in direction. The SA climate zone mostly experiences extensive diurnal variation in temperature, and is also very prone to natural hazards such as drought, sand storms and dust storms. The countries that fall within the SA climate zone are Senegal, Gambia, Mali, Burkina Faso, and Niger, the northern fringes of Nigeria, Chad and Sudan. Agricultural products and activities in the SA climate zone include groundnuts, cattle rearing, livestock, corns, rice, cotton and millets, and are usually aided by flood plain cultivation and irrigation. Some of the natural resources available in the SA climate zone are sand, kaolin, uranium, limestone and granite (Tuller, 1968).

The highest monthly radiation total over the SA climate zone is usually recorded during April, and the lowest is recorded during July or August. The climate zone also has, on average, 7.5h.day^{-1} to 9.3h.day^{-1} sunshine. The mean annual maximum temperature over the SA climate zone ranges from 40℃ to 47℃, which are extremely high, and the mean annual minimum temperature ranges from 7℃ to 9℃. Squall lines are most frequent in April, May, June and October, especially during the late afternoon hours. These squall lines often produce maximum winds gusts of around 80knots, which are usually very destructive (Okulaja, 1970).

2.3 NIGERIA AS PART OF THE STUDY DOMAIN

2.3.1 Geographical location

Nigeria is a West African country, and falls within the WS – as a matter of fact Nigeria covers a substantial part of the WS region. The country extends from latitude 3.30°N to 13.20°N and longitude 3.20°E to 13.20°E (Fig. 2.5), bordered in the north by the Niger Republic, in the south by the Atlantic Ocean, in the east by the Republic of Cameroon and in the west by the Benin Republic. Nigeria covers a total area of 923 770km^2 and a total land area of 910 770km^2. The land boundary is 4 047km long, and the country's coastline is about 853km long. The available irrigated land is estimated at 9 570km^2, land use 35% arable, permanent crops 5%, and permanent pastures 54% and 18% of forests and woodland. The 2006 census figures in the country reveals that Abuja has an estimated population of 1.5million, Lagos 9million, Ibadan 5.6million, Kano 9.4million and Enugu 3.3million (Thisday online, 2007).

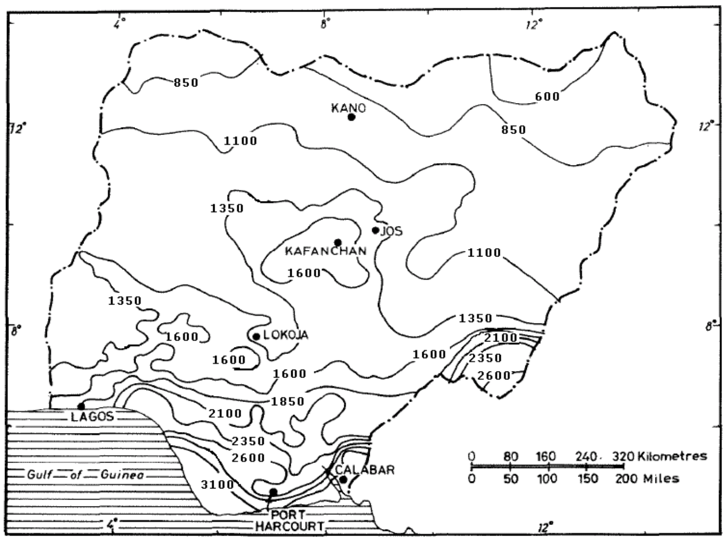


FIG. 2.5: A map of Nigeria with the spatial distribution of mean annual rainfall (mm). The highest rainfall occurs over coastal regions, while it becomes drier towards the Sahara.

2.3.2 Topography

Topographical features of Nigeria range from coastal swamps in the south towards a propagation that ranges from tropical forests, open woodlands, grasslands, and eventually semi deserts in the north. The lowest elevation contour in the country obviously runs along the Atlantic Ocean coastline, and the highest point can be found at Chappal Waddi in Plateau State (about 2 419m AMSL). Some of the major rivers are Rivers Niger, Benue, Anambra, Cross, Gongola, Hadejia, Kaduna, Katsina-Ala, Kamadugu, Ogun, Osun, Owena, Osse, Sokoto, Yedseram, Yobe, and Zamfara.

2.3.3 Population

It is estimated that about 140million people live in Nigeria (Thisday Online, 2007). The country has about 250 ethnic groups, from which the most prominent are the Hausa-Fulani, Igbo and the Yoruba. The Hausa-Fulani dominate over the northern parts of the

country, while the Igbo dominate over the eastern parts and the Yoruba over the southern parts of Nigeria. There are also other ethnic groups, such as the Nupe, Tiv, Kanuri, Efik, Ibibio and Ijaw, who also live in the country. The most commonly practiced religions amongst the population are Islam, Christianity and the indigenous African believe. Although the official language in Nigeria is English, most people have a good knowledge of two or more indigenous languages. Hausa, Yoruba, and Igbo are the most widely spoken indigenous languages. About 32% of all male and 27% of all female citizens of the country are educated. Less than 25% of the population is urban dwellers, and at least 24 cities each have a population of more than one million people.
(Reference: http://www.CountryReports.org).

2.3.4 Climate

As Nigeria falls in the WS, its climate zones are similarly distributed than those of the WS discussed earlier in this dissertation. The climate of Nigeria is generally classified according to dry and wet seasons. There is a clear contrast between the dry and wet seasons, which are, as in the WS climate, closely correlated with the south-northward propagation of the ITCZ over the country (Adejokun, 1966). Over Nigeria, the ITCZ retreats to its most southern position (close to the Equator) in January, and advances to its most northern position (around latitude 20.00°N) in July. The south-north meridional propagation of the ITCZ is also associated with the dominant wind flow over the country, which includes the WAM. During July, the prevailing wind are moist southwesterly winds from the Atlantic Ocean (which is a component of the WAM), and during January the dominant winds are dry northeasterly winds blowing across the Sahara towards the country.

Mean annual rainfall totals over Nigeria ranges from approximately 3 800mm along the coastline to less than 500mm over the far northern parts (Fig. 2.5). In most events rainfall over Nigeria are characterized by local convective thunderstorms and disturbance lines (discussed in section 2.2). The local impact of thunderstorms is usually sporadic, and these storms occur widely over the interior of the country, especially during the peak of the rain season (JAS). The coastal part of the country extends over about 30km in width, and exhibits a very strong oceanic influence on coastal weather. In Nigeria, rainfall patterns run roughly parallel to latitude lines, with exceptions over some of the high elevation areas (Ojo, 1977; Ayoade, 1975). From the coastline to about latitude 10.00°N, one finds two peaks per year in monthly rainfall totals (two seasons) and from latitude 10.00°N and further north, one finds a single season – most probably because the ITCZ does not often propagate that far to the north. The two peaks are usually recorded in June and September, respectively, and the single peak in the north is recorded in August. Average monthly temperatures in Nigeria range from 28℃ to 34℃ (from the coastline to latitude 10.00°N) and 12℃ to 43℃ (from latitude 1 0.00°N to 14.00°N) (Odekunle, 2004).

2.3.5 The relationships between weather and the ITCZ over Nigeria

As noted earlier, the ITCZ and the associated WAM, play an important role in climate characteristics of the WS and Nigeria. The ITCZ retreats to its most southern position in January, and advances to its most northern position in July, when easterly trade winds crosses the geographical equator, and under the influence of the Coriolis force, turns westwards to form the WAM. As a result, moist onshore maritime air from the Atlantic Ocean enters Nigeria in July, while dry and dusty offshore continental winds blows across the Sahara desert towards Nigeria during January. According to the location of the ITCZ five weather zones (A to E) have been defined (see Fig. 2.6) (Adejokun, 1966; Garnier, 1967; Ojo, 1977).

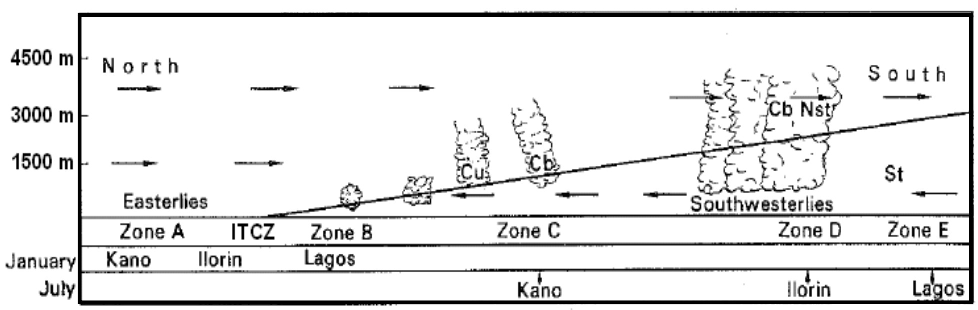


FIG. 2.6: The location of the ITCZ with the five weather zones (A to E) defined at different meridional locations over Nigeria (after Ojo, 1977). The southwesterlies that brings moisture from the Atlantic Ocean form part of the West African Monsoon (WAM).

The weather zone located immediately north of the surface location of the ITCZ has been classified as weather zone A. Weather zone A is a predominantly dry region with dusty continental easterly to northeasterly winds from the Sahara desert. High cloud types do mostly occur with the occasional occurrences of medium cloud types. The zone is usually cool with clear skies during night hours.

Weather zone B covers areas over Nigeria that is located directly south of the surface location of the ITCZ. This weather zone extends over a distance of about 200 to 300km south of the ITCZ. The zone experiences a mixture of the dry easterly to northeasterly winds (at higher altitudes) and moist southwesterly winds (closer to the surface) (Fig. 2.6).

The weather of zone B is characterized with relatively high night temperatures and high humidity values. Early morning fog in the form of stratus (low) clouds is often experienced.

A zone located at a distance of approximately 700km to 1 000km to the south of the surface location of the ITCZ is known as weather zone C. In this zone moist southwesterly winds are found at an altitude of about 6 000m above the land surface. Weather zone C mostly experiences unstable atmospheric conditions, which are characterized by disturbance lines and local thunderstorm activities, resulting in variable and sporadic rainfall (Garnier, 1967). Weather zone C is generally characterized by high RH values, with little diurnal variability in temperatures.

Weather zone D is found at a distance of 1 000km to 1 300km south of the surface location of the ITCZ. It is also a zone with high RH values, and relatively low and mostly constant temperatures (Fig. 2.6). In this zone, the “little dry season” (as mentioned in the discussion of the WS climate) is experienced when inversion or stable conditions above the stratus (low) clouds inhibits the upward movement of air, which results in very little rain, but often in fog events.

The most southerly weather zone is known as weather zone E. This zone only affects a relatively narrow strip along the coastline of Nigeria during July and August. It is a zone of decreasing stratocumulus and stratus clouds, and increasing altostratus, altocumulus and cirrus clouds. Drizzle and rain are the most frequently found over weather zone E.

Although defined in location, Garnier (1967) argued that the type, frequency and duration of weather zones A to E over Nigeria fluctuate, because of fluctuations in position of the ITCZ due to the meridional propagation of the ITCZ. He therefore went one step further by classifying Nigeria into four weather regions (regions I to IV) using the annual frequency distribution of the five weather zones (see Fig. 2.7).

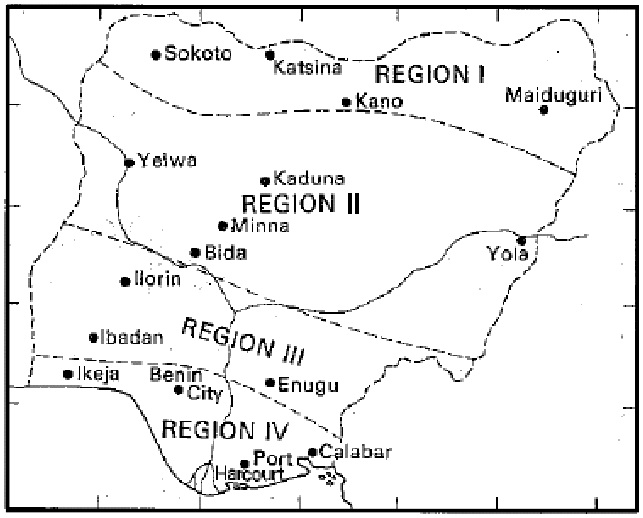


FIG. 2.7: The five most obvious weather zones of Nigeria (after Garnier, 1967). These zones depend on the location of the Inter-tropical Convergence Zone (ITCZ) and especially on their distance from the ground location of the ITCZ.

Accordingly, the area over Nigeria that is mostly affected by weather conditions defined in weather zone A (earlier discussed and illustrated in Fig. 2.6) for at least six months, weather zone B for almost a month and weather zone C for four months during the period of one year is classified as region I. Over region II, the weather conditions of weather zone B are experienced during the greatest part of the year, especially when the ITCZ advances northwards. The area that is predominantly influenced by the weather conditions of all the five weather zones (weather zones A to E) is classified as region III. In region IV weather conditions of weather zone C dominates, with occasional influence from the weather of zone A.

2.4 Summary

The lack of knowledge and resources at many NMHS in Africa to not only run NWP models, but also to interpret and apply NWP model output inspired this research. The researcher is an operational weather forecaster at NIMET who has a passion for weather forecasting and also appears on National Television to present weather forecasts to end-users. Over recent years he became interested in various tools that can help improve weather forecasts, and started to investigate the use, application of NWPs, as well as the improvement of these predictions by means of post-processing techniques.

The objectives of this study are to introduce the Africa LAM from the UK Met Office as a NWP model for Africa, and in particular the WS region, and to investigate the potential of this model to be used as supplementary tool to improve weather forecast output to end-users over the WS and Nigeria. At the end of the study selected post-processing techniques are suggested.

It is advisable for weather forecasters to have a good background of the general weather and climate of the region they forecast for, and to be aware of the economic, agricultural and social activities (amongst others) of these regions that are influenced by the weather. That is why it was decided to include a discussion on the geography, population, agriculture, economy, and most importantly the climate and weather of the WS and Nigeria. These discussions might serve as background information in the rest of the dissertation where the Africa LAM is investigated in more details.

CHAPTER 3

NUMERICAL WEATHER PREDICTION

3.1 INTRODUCTION

Recent advances in the knowledge and understanding of atmospheric dynamics and physics, improved meteorological observations, modern communication facilities and increasing supercomputer power have played an ever expanding role in the performance and development of NWP models. This chapter first gives an historical overview of the development of NWP at various international research centers. Since the study focuses on NWPs generated by the Africa LAM from the UK Met Office, the historical overview is followed by a technical description of the Africa LAM, and also to some extent, the Unified Model (UM) of the UK Met Office, which forms the basis of the Africa LAM.

3.2 HISTORICAL REVIEW OF THE DEVELOPMENT OF NWP MODELS

Scientific understanding of the atmospheric equations of motion, following the work of Leonhard Euler (1707 – 1783), motivated Cleveland Abbe (1838 – 1916) to propose a mathematical approach to weather forecasting through the solution of the hydrodynamic and thermodynamic equations. Abbe (1901) published his ideas in a paper with the title "*The physical basis of long-range weather forecasting*" in 1901. Around 1904 he has met with Vilhelm Bjerknes during a visit by Bjerknes to the United States. Bjerknes first mentioned the idea of NWP as a solution to the problem of predicting the state of the atmosphere through the integration of the fundamental atmospheric equations (Mesinger, 2005; Lynch, 2006). Bjerknes further pursued his NWP idea by building on the concept that if subsequent atmospheric states develop from the preceding ones according to physical laws, as every scientist believes, then the rational solution to weather forecasting problems will be a sufficient accurate knowledge of the initial state of the atmosphere, and the understanding of the governing laws that describe how one state of the atmosphere develops from another. He recognized that the future state of the atmosphere is completely determined by its detailed initial state and known boundary conditions, together with Newton's equations of motion, the Boyle-Charles-Dalton equations of state, the equation of mass continuity and the thermodynamic energy equation (Lynch, 2006).

Although, meteorologists long knew about the difficulties of predicting the weather since they could not find a simple set of causal relationships to relate the state of the atmosphere at one instant of time to its state at another (Kalnay, 2003; Mesinger, 2005). Bjerknes (1904) proposed two steps to be followed in NWP, namely (1) diagnostic and (2) prognostic steps. The diagnostic step requires observational data to define the three-dimensional structure of the atmosphere at a particular time, while the prognostic step requires the assembling of a set of equations which describe the forward propagation of atmospheric processes, one for each dependent variable describing atmospheric propagation. He agreed that for convenience, the prognostic procedure could be separated into two parts, namely (1) a hydrodynamic part and (2) a thermodynamic part. The hydrodynamic part could determine the propagation of an air mass over a defined time interval, whereas the thermodynamic part could then be used to deduce changes in its state. In order to further enrich Bjerknes understanding of the atmospheric systems, he persuaded the Norwegians to support an expanded network of observation stations and also established the Bergen School of Synoptic and Dynamic Meteorology in Norway. Bjerknes provided a clear goal and physical approach towards NWP, and even transferred his ideas towards his students - some of whom were Rossby, Eliassen and Fjortoft (Kalnay, 2003). Bjerknes embarked most systematically on achieving his NWP idea, and he never seemed to have doubts on the feasibility of producing a relatively accurate weather prediction. He emphasized that, once the initial conditions and the governing atmospheric equations are known with sufficient accuracy, the state of the atmosphere could be determined completely by some super-mathematician at any subsequent time with a fundamental scientific study of atmospheric processes based upon the laws of mechanics and physics.

The first tentative attempt to generate a mathematical forecast of synoptic changes by the application of physical principles was made by Felix Exner (1908). Though Bjerknes proposed that the full system of hydrodynamic and thermodynamic equations be used to predict the weather, Exner followed a different approach. Exner’s method assumed the atmospheric flow to be geostrophically balanced, and the thermal forcing to be constant in time. He used observed temperature values to deduce a mean zonal wind, and then derived a prediction equation representing advection of pressure patterns with a constant westerly speed, modified by the effects of adiabatic heating. This method yielded a realistic forecast between the predicted and the observed changes, although the method could not be used as a general utility. Exner understood the limitations of his method as he recognized the difficulty identified by Margules (1904) who suggested that wind measurements are not nearly as accurate as needed to calculate pressure changes.

Later, during World War I, the English scientist Lewis Fry Richardson (1883 - 1953) went ahead and performed the numerical integration of a full set of governing equations. His work was published in 1922. Many of his numerical calculations were performed by hand, and not by a computer. The single 6-hour time step he considered for the prognoses of the atmosphere produced unreasonable results wherein errors increased rapidly with follow up time steps. Richardson (1922) then introduced the use of an *Index of Weather Map*. This index was constructed by classifying old synoptic charts into categories. According to Gold (1960) the index assisted forecasters by finding previous maps that resembled the same pressure patterns as the current one, and therewith deduce the likely development after carefully studying the evolution of the weather during previous events. Richardson's commitment to a sound scientific approach towards NWP made him uncomfortable with the idea of using the *Index of Weather Map*. He compared the Nautical Almanac used by Astronauts, which is not based on the principle that astronomical history repeats itself in the aggregate to weather forecasting, and concluded that there is no reason to believe that weather maps could exactly be represented in a catalogue of past weather events. He therefore introduced a scheme of weather prediction resembling a process which is founded upon the principle of using prognostic differential equations, and not upon partial occurrence of phenomena in their ensemble (Lynch, 2006).

Richardson's forecasting scheme, where he had proposed to integrate the equations of motion numerically, was a precise and detailed implementation of the prognostic component of Bjerknes' method. Richardson assumed that the state of the atmosphere at any point could be specified by seven atmospheric variables, namely pressure, temperature, density, water content and the three orthogonal coordinate velocity components of the wind. He subsequently formulated seven differential equations that described atmospheric phenomena. To solve these equations, a numerical method was developed, where Richardson divided the atmosphere into discrete columns of three degree east-west and 200km north-south, giving 120 x 100 = 12 000 columns that covered the entire globe. In addition, each one of these columns was divided vertically into five cells. By using this, the values of the atmospheric variables were calculated arithmetically (Lynch, 2006). Richardson, however, had agreed that his scheme was as complicated as the atmosphere, but was optimistic that some day in the future it would become possible to advance the computations faster than actual weather system advances. Paucity of observational network, the need for large computational task and gross inadequacies of computational facilities were some of the barriers faced by Richardson in the realization of his dream. His original computing tool was a 10-inch slide ruler and a table of five–place logarithms. Richardson then was not aware of the computational stability criterion of Courant *et. al.* (1928), which put restrictions on numerical time steps according to model grid resolution. He did also not understand the necessity for geostrophic balance between mass and motion in the initial conditions (Shuman, 1989). Despite of this, Richardson's efforts had led to the first NWPs, which escalated significantly in complexity and accuracy over recent decades.

Professor Milutin Milankovic (1909 – 1958) who accepted his professorship in applied mathematics in 1913 at Belgrade had also contributed to the development of NWP. He was looking for a field in which he could use his mathematical talents and came across the science of meteorology. At first, Milankovic was struck by the difficulty of the task of numerically predicting the weather. He explained that at least for the time being, since the atmosphere evolves in such a complicated manner, it seems impossible to subject both diagnostic and prognostic processes in the atmosphere by a simple mathematical analysis. Milankovic was, however, encouraged to solve the NWP problem through his assumption that every region on Earth has its average climate that has not changed much over the centuries. He used this principle as basis for his mathematical analysis. As efforts continued by atmospheric scientists to provide solution to the problem of predicting the atmosphere through numerical models, a stepwise approach was adopted. In the stepwise method, instead of attempting to deal with the atmosphere in all its complexity, assumptions were introduced where initial model simulations were performed by incorporating the most important forces that govern atmospheric flow. Subsequently other influences were gradually introduced. This approach ensured that the pitfalls encountered by earlier scientists were avoided (Ellsaesser, 1968).

By the mid-1940s electronic computers were invented. This was rapidly followed by new efforts by Vladimir Zworykin and John von Neumann to compute atmospheric prognoses, which contributed to the development of NWP. They have both agreed in late 1945 to make use of computers to solve meteorological problems. Zworykin had an interest in weather modification while Neumann's interest was in fluid dynamics, which allow for them to address a wide spectrum of the atmospheric sciences. Interesting to note is that they had a dream of connecting a television and a computer into what is now referred to as a Personal Computer (Kalnay, 2003; Shuman, 1989). The first electronic computer, then called the Electronic Numerical Integrator and Computer (ENIAC), was developed by the Moore School of Electrical Engineering at the University of Pennsylvania in the USA in the 1940s. In 1946, John von Neumann organized the Electronic Computer Project at the Institute for Advanced Studies (IAS) in Princeton, New Jersey, USA. The goal of the project was to design and build an electronic computer that would by far exceed the power of any other electronic computers that were available in 1948. The Meteorology Group that was established by Charney as part of the project aimed to apply physical flow dynamic laws to address the problem of weather forecasting, and to use the electronic computer developed by the project to simulate atmospheric propagation. The concept of NWP was one of the three thrusts of the Electronic Computer Project, with the two other components defined as numerical mathematics and engineering (Goldstine, 1972). The two most important features of the electronic computer was that it was build so that computer programs could be stored in internal memory, and computing could be done in parallel on more than one processor. On 10 June 1952, the IAS announced the successful development of their first new computer (Shuman, 1989).

Eliassen (1949) and Charney *et. al.* (1950) proffered a solution to the atmospheric problem by deriving the "filtered" equation of motion, where gravity and sound waves were filtered out. These equations were based upon pressure fields alone. The approach where wind fields could serve as a basis for dynamic weather forecasting, instead of pressure fields as explained by Rossby (1940), was a great challenge for Charney. He was inspired to develop the equations that later became the basis for NWP modeling. Like Richardson, Charney looked forward to a day when weather forecasts could be generated numerically. Charney (1950) solved the atmospheric equations by first simplifying the equations, and subsequently to start introducing more complex features (Lorenz, 2006).

The Charney's quasi-geostrophic equations were three-dimensional, and would demand extensive computing power from the ENIAC computer that was then available. Charney therefore decided to first test the two-dimensional barotropic vorticity equation, which was effectively what the three-dimensional equation reduces to if one disregards vertical variations of atmospheric flow. It is, however, relevant to mention that the simplified barotropic model of Charney *et. al.* (1950) took 24-hours to complete a 24hour forecast on the ENIAC computer, but required less than 5-minutes to complete the same set of equations on a new computer developed at IAS in 1952 (Shuman, 1989). The Charney *et. al.* (1950) NWPs were considered a great success. The barotropic model, however, does not have the capability to explicitly predict thunderstorm development. Charney concluded that NWPs should make use of the full set of primitive equations, and further came up with a list of the physical processes at scales too small to be resolved. These processes are currently incorporated in NWP models through the parameterization of sub grid-scale physics (Kalnay, 2003). Phillips (1952) further contributed to the development of NWP when he simplified the atmosphere's vertical dimension into two discrete sigma (terrain following) layers. This was the beginning of baroclinic forecasting and soon afterward came the introduction of refined two-layer models as suggested by Eady (1952), Sawyer and Bushby (1953) and Thomson (1953). In a two-layer model, it is a common practice to use the sum and difference of the stream functions as prognostic variables, which are usually identified geostrophically. The development of two-layer models has continued to be one of the most popular tools in basic atmospheric modeling research (Lorenz, 2006).

The Royal Swedish Air Force Weather Service in Stockholm, Sweden, was the first to introduce a successful operational NWP system in December 1954. This NWP model was developed by the Institute of Meteorology at the University of Stockholm, in association with Carl – Gustaf Rossby. Forecasts were made three times a week for the North Atlantic region on the Binary Electronic Sequence Calculator (BESK) using the barotropic model. In 1954, Charney, Fjortoft and von Neumann had established the Joint NWP Unit in Maryland, USA, where routine real-time weather forecasting using NWPs began in May, 1955. Until the 1960's, when NWP models were based upon the Bjerknes/Richardson's primitive equations, NWP models used simplifying assumptions of barotropic and baroclinic methods (Kalnay, 2003).

Recent advances in our understanding of the physics and dynamics of the atmosphere, as well as the ocean, are now being fully exploited in NWP models, and these models continuously provide us with powerful information towards exploring the real behavior of the atmosphere and ocean. NWP modeling has currently reached a high level of sophistication, with an increasing level of accuracy in atmospheric predictability (Shuman, 1989). Modern NWP models manage to predict atmospheric conditions up to a week or more in advance. With sophisticated satellite systems to observe the atmosphere and oceans continuously, we now also have dedicated communication networks to distribute weather data at a high speed.

3.3 RICHARDSON'S FORECAST FACTORY

As part of Richardson's contribution to improved weather forecasting through numerical processes, he proposed a system in 1922 that is referred to as the "*Forecast Factory*". He described his *Forecast Factory* (Fig. 3.1) as follows …"*imagine a large hall like a theatre, except that the circles and galleries go right round through the space usually occupied by the stage. The walls of this chamber are painted to form a map of the globe. The ceiling represents the north Polar Regions; England is in the gallery, the tropics in the upper circle, Australia on the dress circle and the Antarctic in the pit. Myriad computers are at* *work upon the weather of the part of the map where each sits, but each computer attends only to one equation or part of an equation. The work of each region is coordinated by an official of higher rank. Numerous little "night signs" display the instantaneous values so that neighboring computers can read them. Each number is thus displayed in three adjacent zones so as to maintain communication to the North and South on the map. From the floor of the pit a tall pillar rises to half the height of the hall. It carries a large pulpit on its top. In this sits the man in charge of the whole theatre; he is surrounded by several assistants and messengers. One of his duties is to maintain a uniform speed of progress in all parts of the globe. In this respect he is like the conductor of an orchestra in which the instruments are slide-rules and calculating machines. But instead of waving a baton he turns a beam of rosy light upon any region that is running ahead of the rest, and a beam of blue light upon those who are behindhand. Four senior clerks in the central pulpit are collecting the future weather as fast as it is being computed, and dispatching it by pneumatic carrier to a quiet room. There it will be coded and telephoned to the radio transmitting station. Messengers carry piles of used computing forms down to a storehouse in the cellar. In a neighboring building there is a research department, where they invent improvements. But there is much experimenting on a small scale before any change is made in the complex routine of the computing theatre. In a basement an enthusiast is observing eddies in the liquid lining of a huge spinning bowl, but so far the arithmetic proves the better way. In another building are all the usual financial, correspondence and administrative offices. Outside are playing fields, houses, mountains and lakes, for it was thought that those who compute the weather should breathe of it freely…*" (Richardson, 1922, p. 219-220 cited by Lynch, 1993).

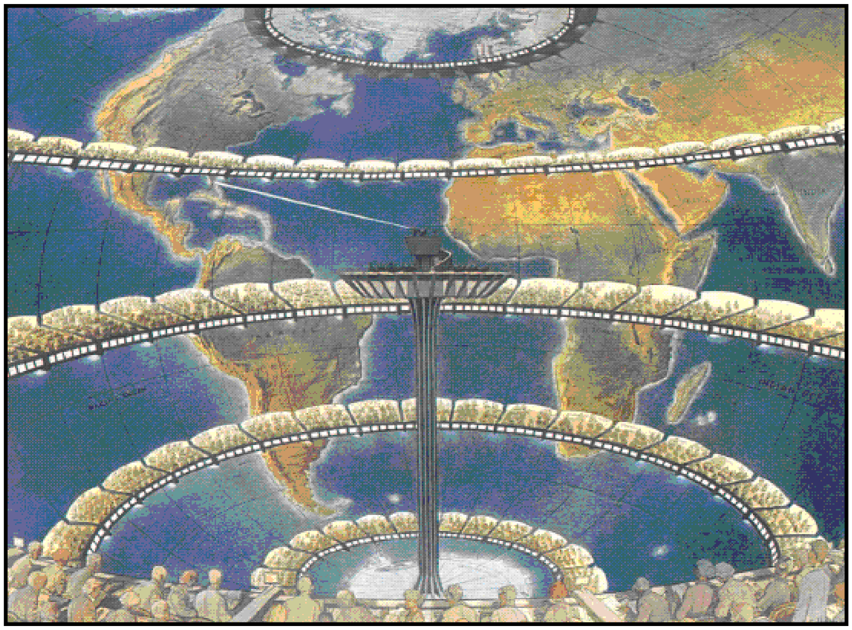


FIG. 3.1: An Artistic impression of Richardson's *Forecast Factory* (after Lynch, 1993).

Richardson's idea of a *Forecast Factory* has since been explored by many scientists. As of June 2005, the fastest computer (IBM BlueGene/L) which is a modern Massively Parallel Processor (MPP), has 65 536 processors. This is very close to the 64 000 processors required by Richardson in his Forecast Factory, though his computers are not the silicon chip machines of today but human-beings using slide-rules and tables to undertake the task of making calculations for a weather forecast. Richardson also subdivided or parallelized the forecasting tasks, a procedure similar to the domain decomposition method being used nowadays by the MPPs. He used the 'night signs' to provide nearest neighbor communication which is analogous to the message-passing techniques in MPP. The man in the pulpit in the *Forecast Factory* with the blue beams is similar to the synchronization and control unit of the MPP. Although, the processing speed of the modern day MPP are by far more than that proposed in the *Forecast Factory*, they both have very similar logical structures (Lynch, 2006).

Knox (1997) wrote in his paper "*The Forecast Factory: A Technique for Teaching Science through Active Learning*" that he has transformed his university lectures on weather forecasting into an experiment in active learning using the example of the *Forecast Factory* in a play. This is done by means of having students role-play the various stages of the forecasting process. He used the active learning format to enhance comprehension and retention amongst students, excite and involve students who find passive lectures interesting, link weather forecasting to its historical roots while emphasizing the scientific nature of modern weather forecasting, highlight the importance of observation in modern science, portray the interconnection in science between observation, theory, and computing and reinforce the importance of negative results or “failures” in advancing science (Knox, 1997).

3.4 THE BAROTROPIC, BAROCLINIC AND PRIMITIVE EQUATION MODELS

Long ago Bjerknes (1904) and Richardson (1922) have identified that the solution to the problem of NWP requires essential knowledge and understanding of the mathematics of fluid dynamics in the atmosphere. However, due to limited skill and inadequate computer facilities at that time, the solution of simplified assumptions that is representative of a barotropic and baroclinic atmosphere was adopted. It is only until the early 1960s, when computers have become increasingly available and when mathematical skills improved, that NWP models based on the Bjerknes/Richardson’s primitive equations were considered for the simulation of future atmospheric conditions (Lorenz, 2006).

3.4.1 Barotropic Models

Barotropic models are developed on the assumption that throughout the motion of the idealized atmosphere, that pressure and temperature surfaces coincides, that vertical motion and vertical wind shear are absent, and that no horizontal velocity divergence and conservation of the vertical component of absolute vorticity exist. A barotropic atmosphere has its density dependent only on pressure, so that pressure surfaces are the same as the surfaces of constant density. The isobaric surfaces in a barotropic atmosphere are also isothermal surfaces where the geostropic wind is independent of height. The simplest form of a barotropic model is based upon the barotropic vorticity advection equation. This equation is derived by assuming that the vertical portion of the atmosphere is barotropic (density is constant on pressure surfaces) and non-divergent. There are no vertical variations or thermal advection processes in a barotropic model, and therefore such a model does not predict the development of thunderstorms (Shuman, 1989).

Typically, the barotropic assumption is not regarded as very realistic, and therefore the single-level, two dimensional barotropic vorticity equation model developed by Charney (1950) was found to be lacking in essential skill, although it was founded on sound theory for research. In principle, there are three shortcomings in barotropic models (Shuman, 1989), from which two are fundamental. The two fundamental issues with early barotropic models were firstly that it was found that the models have generated too many anticyclones over the mid-latitudes, and secondly, had excessive retrogression of the planetary-scale waves. The large model errors in the development of anticyclones were due to the divergence of the geostrophic wind, which was explicitly used in the early barotropic model. This error was resolved by replacing the geostrophic wind with a non-divergent wind defined by a stream function derived from the balance equation (Shuman, 1989). The retrogression of the planetary-scale wave errors was due to a lack of an adjustment mechanism between mass and motion, and was at first resolved by holding wave numbers 1, 2, and 3 fixed during the period of prediction (Wolff, 1958). Later, a more natural solution was applied that was derived from free-surface models (Cressman, 1958). The third deficiency of barotropic models was related to restrictions in stability during integration, although this problem was generally confined to integrations of longer than 24 hours. The ideal solution to these shortcomings in barotropic models would be to allow for variations in the zonal wind with latitude. This was suggested by Kuo (1949), where he had introduced a simplification related to Rossby numbers through the two-dimensional non-divergent basic flow. To add to the problem of numerical stability, Kuo (1949) explained that the presence of neutral and amplifying waves between maximum and minimum wind velocities along the belt of strong westerly jet is because of the existence of critical points where the absolute vorticity is the largest. He concluded that waves moving at a velocity of the flow at a critical point become neutral, while waves with speeds intermediate to the minimum speed and critical point speed become unstable. The problem arising from the two dimensional variation in the amplitudes of the perturbation quantities was bypassed in barotropic stability conditions through the introduction of multilayer models (Wiin-Nielson, 1961).

3.4.2 Baroclinic Models

The first comprehensive study on baroclinic models was performed by Charney (1950) following the initial attempt by Rossby (1939) to establish a relationship between the equations of hydrodynamics and the observed upper-air waves in extra-tropical and mid-latitude regions (Lynch, 2006). In baroclinic models, density depends upon both temperature and pressure, thereby adequately accounting for factors such as atmospheric energy balance. Charney's (1950) baroclinic model includes derived stability criteria where it was assumed that perturbation quantities are independent of latitude. He showed that instability increases with vertical wind shear, lapse rate and latitude but decreases with wavelength. The local effect of the vertical variation of the vertical component of the earth's rotation, coupled with the basic zonal westerly flow, was therefore first recognized as the main determinant of the speed of atmospheric perturbations. The two main shortcomings of the earlier baroclinic models were the retrogression of very long waves and their neural character. Solar radiation is known as the source of energy for atmospheric motion and it is therefore generally accepted that large-scale disturbances are energy conversion agents participating in the transport of momentum and heat (Lynch, 2006).

In an effort to address the problems that models had to predict the development of thunderstorms, a three-level filtered baroclinic equation model was developed by Cressman (1963). In developing the model, Cressman (1963) not only utilized the theory and structure of the Princeton three-level model (Blumberg and Mellor, 1987) along with new corrections and theory essential for filtered baroclinic models. He had also derived an additional term to account for the advection of vorticity by the divergent component of the wind, and used the balance equation to maintain a proper relationship between the mass field and the wind field during integration. In addition, he carefully constructed a finite difference formulation to prevent systematic accumulation of truncation errors. Another important success in addressing atmospheric instability in baroclinic models was the simplification of the eigenvalue problem that governs the vertical velocity (Ellsaesser, 1968). These simplifications were based upon the introduction of small Rossby number. The remarkable success of baroclinic models to predict upper level winds was realized by the skill in which meteorologists were capable to forecast winds for aviation purposes (Shuman, 1989).

3.4.3 Primitive Equations

The primitive equations are mathematical equations that describe the atmospheric flow dynamics according to the laws of Newton, and its associated heat and flux exchanges. The total set of equations comprises of three main coupled individual vector equations, namely (1) the momentum equation, (2) the continuity equation and (3) the thermodynamic energy equation. The terms in the momentum equation originate from the laws of Newton, and therefore involve forces such as gravity, pressure gradient, Coriolis and friction. For synoptic scale circulation, the vertical component of the momentum vector equation is often replaced by the hydrostatic balance assumption. The continuity equation represents conservation of mass in the atmosphere, while the thermodynamic equation addresses the conservation of energy. The latter is related to changes in internal energy of an air parcel due to adiabatic heating, heat fluxes and pseudo adiabatic heating (specific heat capacity of air at constant volume). Adiabatic warming is due to changes in the volume of the air parcel for example, through ascent, and the diffusion components with radiation. The thermodynamic energy equation may also be expressed in terms of potential temperature.

Early developers of NWP models have recognized that a complete solution of the primitive equations is a crucial requirement when resolving atmospheric prognosis, but were hindered to achieve this due to limited skill and inadequate computer facilities. They thereby proposed the use of simplified assumptions - an approach that has led to the development of barotropic and baroclinic models. However, the limitation of NWP models to generate reliable weather forecasts was partially attributed to simplified assumptions, which have contributed, apart from non-linearity significantly to the accumulation of truncation errors (Krishnamurti, 1967). The time-forward difference systems used have been devised to address this problem, which currently allows for NWP models to run well beyond the limits of predictability with little or no significant loss of energy (Shuman, 1989).

3.5 PARAMETERIZATIONS IN NWP MODELS

The physical processes associated with radiative transfer, turbulent mixing, sub grid-scale orographic drag, moist convection, clouds and surface/soil processes have a significant impact on the large scale flow of the atmosphere. However, these mechanisms are often active at scales smaller than the model's horizontal grid size. As a result, most NWP models could not explicitly resolve and predict convection on the space and time scales at which they occur. Physical parameterizations are therefore necessary in NWP models to properly describe the impact of these sub grid-scale mechanisms on the large scale flow of the atmosphere. In other words the ensemble effect of the sub grid-scale processes has to be formulated in NWP models in terms of the resolved grid-scale variables.

The procedures whereby NWP models attempt to effectively predict convection, and also account for the collective influence of small-scale convective processes on large-scale model variables in each grid box, are referred to as cumulus or convective parameterization schemes (see Fig. 3.2). The sub grid-scale parameterization schemes are therefore the most important components of any NWP model performance, since they represent those processes not explicitly governed by the equations in the model dynamics (Kuo *et. al.*, 1996). For example, the forecast weather parameters such as the two-meter temperature, precipitation and cloud cover, are computed by the parameterization part of NWP models.

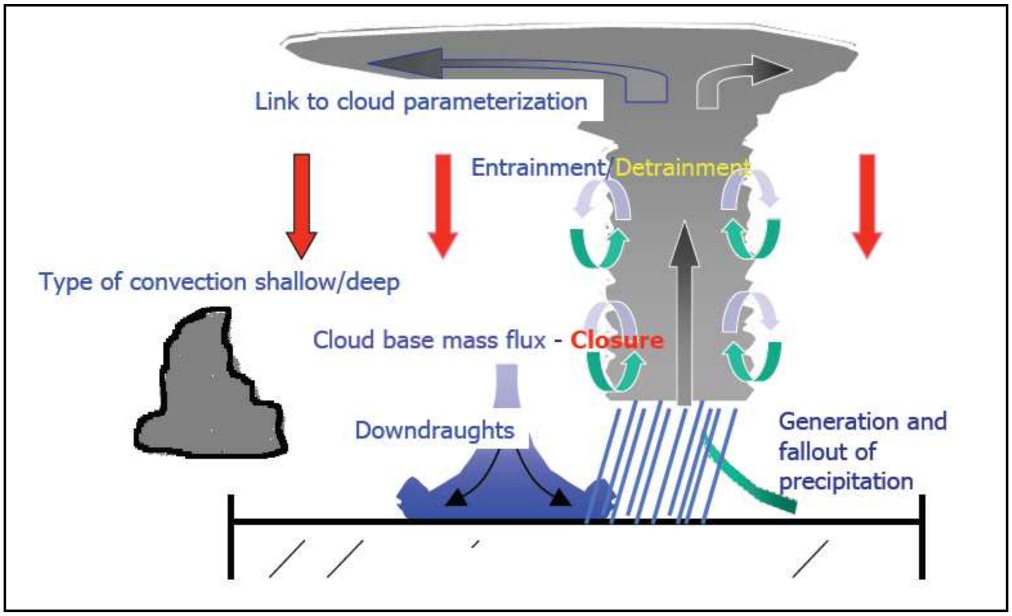


FIG. 3.2: A schematic diagram depicting atmospheric processes that are considered in a typical cloud parameterization scheme (after Straus, 2007).

A major challenge in convective parameterization is to effectively describe the interaction between latent heating, evaporative cooling and outflow boundaries using all available large-scale model variables. Cumulus parameterization, for example, is an attempt to represent the collective effect of cumulus clouds without predicting the individual clouds. This is a closure problem that requires a limited number of equations. The heart of any parameterization scheme lies in the choice of the closure assumptions it uses (Tiedtke, 1989). Although cumulus assumptions vary in formulation, it must address aspects of how the atmosphere in the larger model will rise or sink, and to what extent these processes will feed back into atmospheric circulation of the larger model. The validity of these assumptions is somewhat scale-dependent, which allows for some schemes to be more appropriate for specific grid scales than others. Convective feedback occurs in a model when the vertical temperature and moisture profiles are changed as a result of adiabatic processes, phase changes of water and latent heat exchange. Convective feedback might also affect other processes in the larger model that also may, or may not, be well parameterized (Grell, 1993).

In the real atmosphere, areas of convective activity collectively modify the large-scale temperature and moisture fields through detrainment and storm-induced subsidence in the surrounding environment. Detrainment creates large-scale cooling and moistening, while local subsidence creates large-scale warming and drying. For instance, a thunderstorm might have a significant effect on atmospheric vertical stability by distributing heat, moisture, and momentum throughout layers in the vertical. Likewise, cloud cover associated with convection might noticeably affect both surface heating and other components of the radiation budget. All of this is important since it significantly modifies the static stability and large-scale flow patterns in NWP models over time.

It is therefore essential that a convective parameterization scheme should demonstrate how large-scale weather pattern controls the initiation, location, and intensity of convection, as well as how convection modifies the environment through feedback. In addition, these schemes need to illustrate the most important properties of the parameterized clouds. The methods used in parameterization schemes to evaluate these parameters is often referred to as the dynamic control in the model (Arakawa and Schubert, 1974). However, as horizontal resolutions in NWP models increase, the distinction in scale between the model grid-scale precipitation and convective precipitation might eventually disappear. It is an open question if we will ever have a powerful enough computer to simulate all these processes in great detail, and even if that become possible, will we ever have the detailed observational network to drive or validate these models. One might therefore argue that physical parameterization of small-scale turbulence in NWP models will, at least over the next few decades, remain necessary (Wang and Seaman, 1997).

3.6 THE LIMITED AREA MODEL OVER AFRICA

The implementation of NWP simulations by the Africa LAM over Africa was a special development initiative by the UK Met Office to support a major technical cooperation project for NWP development over Africa. The Africa LAM has the same mathematical and physical configuration as the UM, which is also a LAM commonly used to generate fine resolution NWPs over various regions of the world.

The Africa LAM has a 20km x 20km horizontal resolution that covers the entire African continent and the model consider height (z) as its vertical coordinate. It is a relatively advanced model since it is non-hydrostatic, and finite differences are used as numerical technique during model integrations. The model uses the full set of primitive equations, with virtually no approximations. NWP products generated by the Africa LAM were made available since 2005 to all NMHS in Africa through the UK Met Office's website. Data is also available to other institutions that are interested in using it for research purposes.

3.6.1 The UK Met Office Unified Model (UM)

The UK Met Office UM is an atmosphere-ocean coupled model developed and used to support both global and regional domains. The model configuration consists of a number of numerical sub-models representing different aspects of the earth's environment that influence weather and climate. It allows for "splitting" in a number of different ways, with various sub- model components switched "on" or "off" for a variety of specific modeling applications. The model was developed to be applicable in both climate and NWP studies, which indicates that it can be applied on wide range of temporal and spatial scales. It can also be used as an excellent research tool.

The UK Met Office operationally runs two configurations of the UM, namely the global model and the meso-scale model. The global model normally has a horizontal resolution of 0.5625° longitude (640 columns) by 0.375° latitu de (481 rows) over the globe. The mid-latitude horizontal resolution is therefore approximately 40 km. The global UM has 50 levels (with an extended top domain to 63 km rather than to 40 km). The global model is used to generate boundary conditions to feed the meso-scale model across its lateral boundaries when nested over a confined domain. The UM meso-scale model is a regional model that is currently centered over the UK, although the model can be implemented over other locations of the earth as well. Over the UK domain the model has a horizontal resolution of approximately 11 km with 0.11° longit ude (146 columns) and 0.11° latitude (182 rows), which might be adjusted according to need. To broaden the area of forecast, the UM meso-scale model was extended in 2006 over a domain that covers the North Atlantic and European. The new horizontal resolution is still 0.11°. A finer scale UM model over the UK is now operational with a 0.036° horizo ntal resolution (~4km). All the UM models used an Arakawa C grid in the horizontal, with the u-wind components staggered east and west of temperature grids, and the v-wind components staggered north to south from temperature grids. In the vertical, a Charney-Phillips grid staggering is used, thus potential temperature, moisture variables and tracers and vertical velocity are staggered from pressure, density and horizontal wind (more information is available on: www.metoffice.gov.uk).

A major upgrade referred to as "New Dynamics" was introduced to the UM in 2002. Some details of the "New Dynamics", as provided by the UK Met Office on the web page www.metoffice.gov.uk/research/nwp/numerical, are listed below:

a) The model is a non-hydrostatic model with height as the vertical co-ordinate. The model uses the full set of primitive equations with almost no approximations. This means that the improved UM could be run at a very high resolution.

b) A Charney-Phillips grid-staggering is used in the vertical. The improved UM has potential temperature on the same level as the vertical velocity, including top and bottom boundaries where the vertical velocity is zero. This has led to an improved model thermal wind balance with no computational mode and better coupling with the physics and the data assimilation, with less noise and better stability.

c) An Arakawa C-grid staggering is used in the horizontal. The u-component of the wind is staggered east-west from temperatures, and the v-component of the wind is staggered north-south from temperatures, which resulted into improved geostrophic adjustment, no grid-splitting, better coupling with the physics and data assimilation, and better model stability with less noise.

d) A two time-level, semi-Lagrangian advection and semi-implicit time stepping was introduced. This brought greater accuracy, efficiency, shape preservation and conservation, reduced filtering, and allowed for greater time steps.

e) The Edwards-Slingo radiation scheme with non-spherical ice spectral files was introduced. This scheme models ice crystal as planar polycrystals with sizes related to the temperature as documented by Kristjansson *et. al.* (2000). The model now treated gaseous transmission by using correlated-k methods with six bands in the short wave and nine bands in the long wave, according to Cusack *et. al*., (1999). However Cusack *et. al.,* (1999) suggested eight bands in the long wave, but the ninth band was obtained by splitting one of the bands in the Hadley Centre Atmospheric Model version 4 (HadAM4). The cloud fraction in the UM is therefore treated by distinguishing the convective cloud from the large-scale cloud (Geleyn and Hollingsworth, 1979).

f) Large-scale precipitation includes prognostic ice microphysics. The new model employs a more detailed representation of the micro-physics of cloud formation. Water is contained in vapor, liquid, ice and rain categories, with physically based parameterization of energy and moisture transfer between the categories. Ice content is now a prognostic variable within the model, instead of being diagnosed from the cloud scheme (Wilson and Ballard, 1999).

g) A vertical gradient area large-scale cloud scheme is used. The vertical gradient method calculates the standard Smith large-scale cloud scheme at three heights per grid box (on the grid level and at equal space above and below the grid box), using interpolated input data according to the estimated sub-grid vertical profiles. In the calculation of the volume data of the grid box weighted means are used, while the area cloud fraction is taken to be the maximum sub-grid value. The standard Smith large-scale cloud scheme gives a cloud volume fraction, assumed to occupy the entire vertical depth of the grid box and is therefore taken to be equal to the cloud area fraction, but the modification to the UM using the vertical gradient method allows for the area cloud fraction to exceed the volume fraction and, hence, the radiation scheme, which uses area clouds, can respond to larger cloud area coverage and smaller liquid water paths in cloud.

h) Convection with Convective Available Potential Energy (CAPE) closure, momentum transports and convective anvils are considered. The deep and shallow convection are now included with the adoption of the Lock *et. al.* (2000) boundary layer scheme. Convective cloud base is defined at the local condensation level, thereby preventing overlapping with convection schemes. A new parameterization scheme based on a flux gradient relationship was introduced for convective momentum transports. This is obtained by associating the gradient term with the mean wind shear and the non-gradient term with the transport. The new thermodynamic closure for shallow convection relates the cloud-base mass flux to a convective velocity scale as suggested by Grant (2001), while the thermodynamic closure for deep convection reduces CAPE to zero over a given time scale based on the methods used by Fritsch and Chappell (1980). These new thermodynamic closures assume the large-scale horizontal pressure gradients to be continuous across cloud base, and it replaces the standard buoyancy closure initially in the model. The similarity theory of Grant and Brown (1999) which assumes the entrainment rate is related to the rate of production of Turbulent Kinetic Energy (TKE) is used in the parameterization of the entrainment and detrainment rates of shallow convection.

i) A boundary-layer scheme, which is non-local in unstable regimes, was suggested. The new boundary-layer scheme applies a more direct physical coupling between the turbulent forcing of unstable boundary layers and the transports generated within them. This method is numerically more robust than the Richardson-based scheme, which relates fluxes to local gradients within the boundary-layer.

j) A gravity-wave drag scheme, which includes flow blocking are used. The new parameterization scheme in the UM consists of a bit of gravity-wave drag (due to flow over topography) and a bit of non-gravity wave drag (due to flow around topography). This simplified gravity wave drag scheme includes flow blocking.

k) Topography dataset from the Global Land One-km Base Elevation (GLOBE) Project (approximately 1 km in horizontal resolution) is used to replace the US Navy topography data previously used in the UM. However, before the new GLOBE data was introduced to the model, the data are filtered using a sixth-order low pass implicit tangent filter, so that the filtering is isotropic in real space. This makes the topographic representation in the UM more reliable.

l) The UK Met Office Surface Exchange Scheme (MOSES) surface hydrology and soil moisture scheme is considered. This was developed by Cox *et. al.* (1999) as a parameterization scheme for the UM to represent the surface hydrology and soil moisture.

3.6.2 Technical description of the Africa LAM

As mentioned earlier, the Africa LAM is a 20km x 20km horizontal resolution limited area model, configured from the UM, to provide NWP products for use in operational weather forecasting by NMHS in Africa, as well as by other relevant institutions. Since the Africa LAM is an extension of the UM, most of the improvements implemented in the UM (listed in the previous section) are also available. The Africa LAM has a fixed orthogonal horizontal grid, consisting of 432 rows and 432 columns on an un-rotated latitude – longitude grid which span a latitude range of 37.5ºS to 40.1ºN, and a longitude range of 20.0ºW to 57.6ºE (covering the entire Africa continent). The column and row spacing of the model are both 0.18º (approximately 20km at the equator). In the vertical the model uses the standard 38-level configuration, with the model levels following the terrain at the surface, but smoothed out as heights increases. The lowest model level is at 10 m and the highest level is at 39 km.

During operational NWP simulations, lateral boundary conditions are supplied to the Africa LAM on a three-hourly basis from the UK Met Office global model, and are applied in an eight-grid-point buffer zone around the edge of the nested area. Sea-surface temperatures are kept constant as in the initial state throughout simulations, and lakes are assigned surface temperatures equal to that of their nearest sea-point. The model does not incorporate any diffusion. A time-step of 7.5 minutes is normally used during model simulations.

Before 14 June 2006, the Africa LAM ran once a day from 00:00 Greenwich Mean Time (GMT) up to T+48h, where T is the initial time at 00:00GMT, and T+48h is 48 hours ahead of 00:00GMT. Initial conditions are derived by interpolation from a T+6h output produced by the global model's T=18:00GMT simulation. However, from 14 June 2006 data assimilation was introduced as addition to the NWP process. Most of the UK Met Office limited area models use continuous data assimilation, in which each forecast cycle provides the background fields required for data assimilation in the next cycle. Thus the only role of the global model is to provide boundary conditions and not initial conditions. The Africa LAM uses intermittent data assimilation in which the model is initialized from an interpolated global model state, but is then run like a continuous data assimilation model for a few cycles, before starting again from an interpolated global model state. The reason for doing this is because the global UM uses 4-Dimensional Variational Data Assimilation (4DVAR), while the Africa LAM uses 3-Dimensional Variational Data Assimilation (3DVAR). Although the added benefit of 4DVAR is of such a nature that an interpolated global 4DVAR analysis can be of better quality than the 3DVAR analysis (as directly produced at the Africa LAM resolution) some 3DVAR cycles are still included to reduce spin-up effects that occur when starting directly from an interpolated global model state.

Currently the Africa LAM runs three times per day – 06:00GMT, 12:00GMT and 18:00GMT. The 06:00GMT forecast is a "cold start" from an interpolated global model state, just like the 00:00GMT run described in the previous section. The 12:00GMT and 18:00GMT runs consider 3DVAR data assimilation, using output from the previous cycle as the forecast background fields. The 06:00GMT and 12:00GMT forecasts are relatively short as they simulate forecasts of only nine hours in advance to provide the fields required for the next cycle. The 18:00GMT run is the main run and goes out to T+54h. There is no 00:00GMT run, and the whole process starts again from the 06:00GMT run the following day.

3.7 Summary

In this chapter the history of NWP has been reviewed in order to give the reader a perspective of the major advances that took place over a relatively short period – not only in model development, but also in improved computer technology. Atmospheric or NWP modeling, however, remains a highly complex field of science, as indicated by the many difficulties faced when trying to solve the atmospheric equations and address physical processes through parameterization.

The Africa LAM version of the UM has been selected as the model to investigate in this study. The UK Met Office put in a tremendous effort to contribute to NWP over Africa by making the Africa LAM available. As indicated, the Africa LAM is a highly sophisticated model which includes most of the most advanced dynamics and physics currently available. The application of the Africa LAM in NWP operations over Africa is therefore worth investigating. One of the key focuses of this study is to verify the Africa LAM against observations in order to determine the potential of using the model output as supplementary aid in operational weather forecasting. This is addressed in the following chapters.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 INTRODUCTION

This chapter gives the formulation and explains the algorithms that will be used to verify NWPs by the Africa LAM against observations over the WS and Nigeria. These algorithms are according to NWP verification standards as required by the WMO. The verification of NWPs is not trivial, firstly because model grid points and station points are not always located at the same geographical position. Model grid points also represent the spatial average of boundary and meteorological variables over an entire grid box, while station points are representative of smaller-scale local conditions. For example, in grid boxes with a high variance in actual topography within the specific grid box, the altitude of a model grid point (representative of the average topography) might be completely different than the altitude of a station point (actual altitude value AMSL). This poses problems when trying to verify winds (which are influenced by turbulence) and temperatures (which is a function of height because of adiabatic temperature lapse rates). Temperature data from models (or the observations) are usually adjusted for height differences between the model and the station height using a standard lapse rate. This height adjustment, however, was not been performed in the study. One must therefore be cautious to draw direct conclusions from NWP model verification results, meaning that a broader knowledge of the area of investigation is required when interpreting NWP model verifications.

4.2 DATA COLLECTION

Over the 24-month period January 2005 to December 2006, daily observed meteorological station point data of rainfall, as well as maximum and minimum temperatures were collected from 36 selected weather stations across the study domain, which is the WS region as illustrated in Fig. 2.1. The station data were primarily retrieved from the NCDC in the USA (to be found at: http://www.ncdc.noaa.gov/oa/ncdc.html) with some additional information obtained directly from some local stations. Grid data of total precipitation and maximum and minimum temperatures over the same period (January 2005 to December 2006) were also retrieved from NWP output that was generated by the Africa LAM. In order to compare observations with NWP model results, the model value of the nearest grid point to the selected meteorological station was chosen as the predictor, and the point station data as the predictand (see Appendix B for a list of the grid points and stations selected for this purpose).

4.2.1 Point station observations

As mentioned above, 36 meteorological point stations were selected in this study over the WS: 12 stations across each of the three identified climate zones (SA, WDT and WE climate zones of the WS - see Fig. 2.4). A discussion on characteristics and the spatial coverage of these climate zones can be found in Chapter 2. As suggested by Wilks (1995), the data sets were stratified into seasons (JFM, AMJ, JAS and OND) in order to incorporate different relationships between predictors and predictands at different times of the year. The meteorological variables selected for the verification study are daily rainfall, daily maximum temperatures and daily minimum temperatures. The NCDC point station data for temperatures and rainfall were originally archived in Fahrenheit and Inches, respectively, but were converted to degree Celsius (^{o}C) and Millimeter (mm) for the purpose of model verification. The precision of the station observed temperature and rainfall datasets are to the nearest 0.5 ^{o}C and nearest mm respectively.

4.2.2 Africa LAM datasets

T+24h forecast dataset for total precipitation, as well as maximum and minimum temperature were retrieved from the Africa LAM forecasting data. This study only focuses on T+24h projections as an approach to improve the short-range forecasting ability of the model over the WS. The Africa LAM data were originally coded in Gridded Binary (Grib) format, and span over the latitudes 0.12ºN to 19.92ºN and longitudes 20.0ºW to 29.86ºE. In order to extract the NWP model's precipitation data that would correspond to point station rainfall, 06:00GMT to 06:00GMT forecast accumulation of precipitation from the previous day of the model was obtained. This corresponds to 24h accumulated rainfall observed on the day up to 06:00GMT. The latter was carefully done to properly relate the correct model forecast with station values. Temperature values from both the model grid and point stations were values generated and measured instantaneously.

4.3 DATA PROCESSING AND SOFTWARE

Several methods were used to get the data in an acceptable format for the verification analysis. Africa LAM data sets, which were originally coded in Grib format, were converted to 'NetCDF' using the 'Xconv' software. The 'Xconv version 1.9.1.0' software is a relatively new data converter designed and released by Jeff Cole (contact e-mail: j.cole@reading.ac.uk) of the University of Reading on the 3rd of March 2006. The software, for example, makes it easy to convert Grib fields to NetCDF fields. The model's NetCDF files were subsequently imported into Matrix Laboratory (MATLAB) (discussed in the following section) to extract model grid values that are closest to point observational station locations (see Appendix A for the MATLAB scripts developed for this purpose).

4.3.1 MATLAB

MATLAB is a simple and interactive high-performance programming language that is suitable for use in mathematical or statistical programming and visualization. Data elements in MATLAB are normally required to be in an array or vector format, which does not require dimensioning, and thereby allowing for the quick processing of many technical computing problems. MATLAB features a family of add-on application-specific solutions called toolboxes. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems.

4.3.2 MODEL VALIDATION METHODS

In the following sections verification algorithms, as recommended by WMO, are listed and explained. A focal objective of this study is to determine the skill of the NWP model (Africa LAM) to forecast the three selected meteorological variables (rainfall, maximum temperature and minimum temperature) over the WS. Such a skill evaluation is necessary in order to quantify the magnitude of the model systematic errors and biases that might substantially degrade the quality of the generated weather forecasts that emanate from the NWP output (Wilks, 1995; Erickson *et al*., 2002). The following algorithms represent different measures of the performance of the Africa LAM.

4.3.2.1 Pearson's product moment correlation coefficient (r_p)

Pearson's product moment correlation coefficient (Pearson's correlation) is a measure of the linear association (overall strength) between individual pairs of forecasts and observations. Pearson's correlation does not vary under any shift or re-scaling of the forecast or observed values and is defined as;

$$r_p = \frac{\sum (F-\overline{F})(O-\overline{O})}{\sqrt{\sum (F-\overline{F})^2}\sqrt{\sum (O-\overline{O})^2}} \qquad (4.1)$$

where:

F = Model forecast

O = Station observation.

$\overline{F}$ and $\overline{O}$ represent mean values.

4.3.2.2 Spearman's rank order correlation coefficient (r_s)

The Spearman's rank correlation coefficient (Spearman's correlation) describes the strength of the monotonic association between the model forecasts and observations. It is a statistical correlation method that describes properties that are related to the ranking of forecast data (i.e. related to the position of the values when arranged in increasing order). Spearman's rank correlation coefficient is equivalent to Pearson correlation of the ranks of the data (Wilks, 1995; Jolliffe and Stephenson, 2003). The rank correlation is more resistant (less sensitive) to large extreme values than the product moment correlation coefficient (see section 4.4.2.1). The Spearman's correlation (**r**$_s$) is given by:

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \qquad (4.2)$$

where:

d_i = Difference between the corresponding values from the forecasts and observations - both ranked in increasing order.

n = Number of pairs of values.

4.3.2.3 Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)

The Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are two of the most widely used forecasting skill scores (Wilks, 1995; Jolliffe and Stephenson, 2003), and is given by;

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2 \qquad RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2} \qquad (4.3)$$

As shown in equation 4.3, the MSE represents the mean of the squares of the differences of the forecasts and observations. It is a widely used measure of accuracy that depends on bias, resolution and uncertainty. The square root of MSE is known as the RMSE. Both the MSE and RMSE have the same units as the forecast variable. The RMSE measures the average magnitude of forecast errors. The average errors are weighted according to the square of the error and as such become more sensitive to large forecast errors than smaller errors. A perfect score is zero.

4.3.2.4 Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) defines the average of differences between the forecasts and observations, and is given by;

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | F_i - O_i | \qquad (4.4)$$

4.3.2.5 Bias

Bias defines the difference between the mean of the forecasts and the mean of the observations. The bias is given by;

$$\text{BIAS} = \frac{1}{N}\sum_{i=1}^{N}(F_i - O_i) \qquad (4.5)$$

Where:

F and *O* represent the mean values of the forecasts and observations, respectively.

4.3.2.6 Proportion Correct (PC)

The PC defines the percentage of times the forecast category corresponds with the observed category. It is defined in terms of raw cell counts:

$$\text{PC} = \frac{\text{Correct (number of hits)}}{\text{Total number of events}} \qquad (4.6)$$

The model predicted values cross-checked with exactly the observed values (without any allowance) was considered in counting the number of hits.

However, PC – A and PC – B were used in this study. PC – A defines the PC index of the model predicting the observed values and PC – B defined the PC index of the model predicting the events (Yes, Misses or No), specifically adopted for rainfall.

$$\text{PC} - \text{A} = \frac{\text{Correct (Values)}}{\text{Total number of events}} \qquad (4.7)$$

$$\text{PC} - \text{B} = \frac{\text{Correct (Events)}}{\text{Total number of events}} \qquad (4.8)$$

The PC for rainfall, for example, represents the number of times that the model forecast rain, and rain occurred (as a percentage), plus the number of times that the model forecast no rain, and no rain occurred (as a percentage) - as a fraction of the total number of events considered. The rainfall threshold value was taken as zero (0) to 0.005 mm. Although one might argue that the PC score is not a very robust statistical verification measure, the PC values as provided in this study compliments the other verification results.

4.3.2.7 Linear Error in Probability Space (LEPS)

The Linear Error in Probability Space (LEPS) score is defined as the mean absolute difference between the cumulative frequency of the forecast and the cumulative frequency of the observations (Jolliffe and Stephenson, 2003).

$$LEPS = \frac{1}{N}\sum_{i=1}^{N}|F_x(F_i) - F_x(O_i)| \qquad (4.9)$$

Where:

F_x is the (empirical) cumulative distribution function of the observations.

As explained by Jolliffe and Stephenson (2003), the idea of LEPS is that an error of 1ºC in temperature in the tail of the distribution is less important than the same error nearer the mean where it corresponds to a greater discrepancy in cumulative probability. LEPS is a negatively oriented score with values in the range (0, 1). It is only zero when the forecasts are perfect. The LEPS score is sensitive to model biases and is generally best when the median of the forecasts is close to the median of the observations. Potts *et al.* (1996), however, introduced a positively oriented LEPS score as given below. The improved version of LEPS by Potts *et.al.*(1996) is equitable (it does not give better scores for worse forecasts near the extremes).

$$LEPS = 3\left(1 - |F_x(F_i) - F_x(O_i)| + F_x^2(F_i) - F_x(F_i) + F_x^2(O_i) - F_x(O_i)\right) - 1 \qquad (4.10)$$

The LEPS score (equation 4.10), calculates a score defined by using a scoring table that gives different scores for hits depending on the observed category and on the prior probabilities of the categories.

4.4 Summary

In this chapter, the data used in this study, as well as the software used were introduced. Since NWP model verification is a very important and an essential requirement for improved weather forecasting, the Africa LAM NWP output verification was done as part of this study. Model verification measures used in accordance with WMO standards were introduced and briefly discussed.

CHAPTER 5

AFRICA LAM FORECAST VERIFICATION RESULTS

5.1 INTRODUCTION

The primary goal of this chapter is to verify Africa LAM NWPs against observations over the WS by using the skill measures as defined in chapter 4. Shortcomings that might arise from such verification were also mentioned in chapter 4 – for example the fact that NWP model grid points are not always precisely located at point observation locations. Even when spatial averages are considered, verification results may be misleading because they could miss a large error over non-observed regions and so imply the NWP model forecasts are better than they are. The best one can do is to use the NWP model and observational data that are available, and then to be cautious when drawing conclusions by keeping the shortcomings in mind.

It took a significant effort to acquire the data used for the verification, and to prepare the data for the analyses. Not only was software developed to rewrite output results from the Africa LAM in a more appropriate format, but observational records were also not easy to obtain. Appendix A, for example, contains the MATLAB script used in extracting the Africa LAM temperature and rainfall data

The verification in this chapter is done for the seasons JFM, AMJ, JAS, and OND over the WE, WDT and SA climate zones (see section 2.2.3 and Fig. 2.4) of the WS (Figs. 5.1 to 5.12 and Tables 5.1 to 5.3). The verification period extends from January 2005 to December 2006 (24 months). The Verification results should provide adequate information about the NWP model's skill and might also provide the feedback required for the possible improvement of model forecast.

5.2 AFRICA LAM VERIFICATION RESULTS FOR MAXIMUM TEMPERATURE

Results of the skill measures (defined in chapter 4) used to evaluate the Africa LAM NWP model's performance to forecast maximum temperature over the WE, WDT and SA climate zones of the WS during the JFM, AMJ, JAS and OND seasons, and over the period January 2005 to December 2006, are presented in Table 5.1 and Figs. 5.1 to 5.4. Table 5.1 lists Africa LAM's verification results for T+24h forecast maximum temperatures. Fig 5.1 illustrates Africa LAM T+24h forecasts for maximum temperature compared to observations over the SA climate zone, while Figs. 5.2 and 5.3 illustrates the same for the WDT and WE climate zones, respectively. Fig. 5.4, again, depicts the magnitude of Africa

LAM errors (RMSE and MAE) in predicting maximum temperatures over the regions and periods mentioned above.

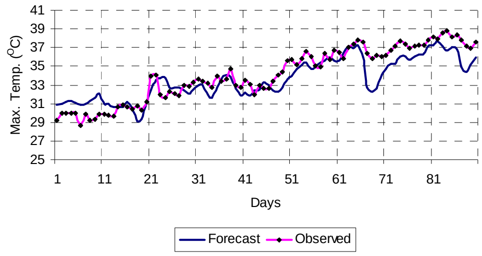
Table 5.1: Africa LAM NWP verification results for T+24h maximum temperatures forecasts during the JFM, AMJ, JAS and OND seasons over the WE, WDT and SA climate zones of the Western Sahel (WS), and over the period January 2005 to December 2006.

	JFM			**AMJ**		
	SA zone	WDT zone	WE zone	SA zone	WDT zone	WE zone
$\mathbf{r}_p$	0.72	0.43	0.27	0.60	0.61	0.62
$\mathbf{r}_s$	0.75	0.44	0.31	0.62	0.63	0.63
MSE	1.96	1.18	9.15	0.97	0.58	7.68
RMSE	1.40	1.09	3.03	0.98	0.76	2.77
MAE	1.21	0.94	3.03	0.79	0.55	2.76
BIAS	-0.51	0.53	-2.98	-0.67	0.37	-2.70
%Above	24.44	60.00	0.00	6.59	41.76	0.00
%Below	58.89	17.67	100.00	64.84	7.69	100.00
PC – A	0.17	0.22	0.00	0.28	0.50	0.00
LEPS (%)	57.08	36.09	21.56	51.64	53.07	49.86
	JAS			**OND**		
	SA zone	WDT zone	WE zone	SA zone	WDT zone	WE zone
$\mathbf{r}_p$	0.33	0.26	0.31	0.58	0.48	0.44
$\mathbf{r}_s$	0.36	0.26	0.30	0.55	0.47	0.47
MSE	3.77	3.88	6.10	4.31	3.55	12.80
RMSE	1.94	1.97	2.47	2.07	1.88	3.58
MAE	1.74	2.01	2.50	1.89	1.64	3.61
BIAS	-1.71	-1.86	-2.40	-1.28	-1.43	-3.54
%Above	0.00	1.09	0.00	16.30	9.78	0.00
%Below	89.13	96.74	100.00	72.83	73.91	100.00
PC – A	0.11	0.02	0.00	0.11	0.16	0.00
LEPS (%)	24.58	16.15	15.24	46.92	35.92	33.28

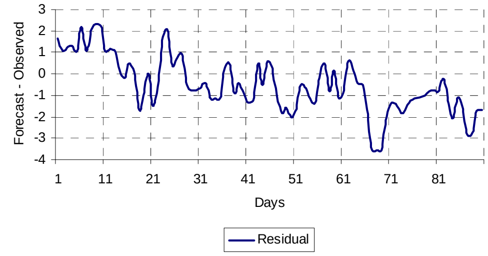
5.2.1 SEMI-ARID CLIMATE ZONE

(A) JFM SEASON

a

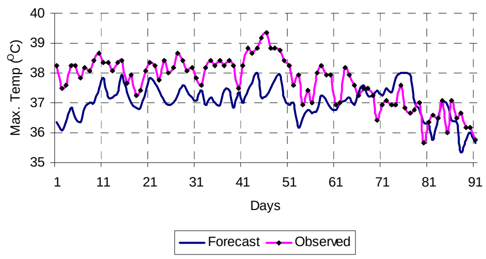


b

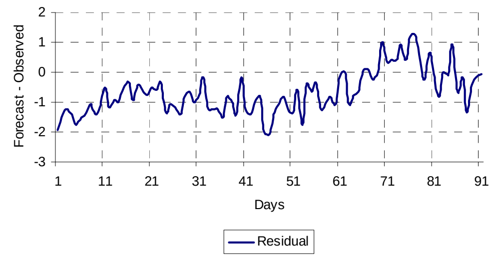


(B) AMJ SEASON

a

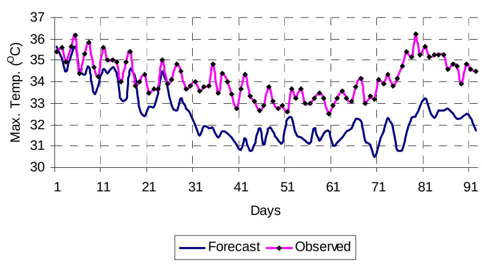


b

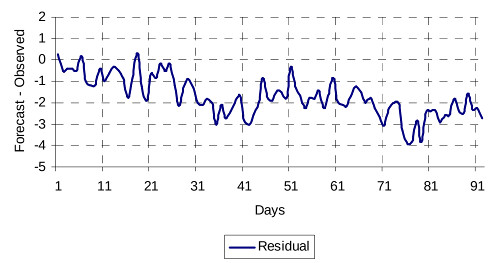


(C) JAS SEASON

a

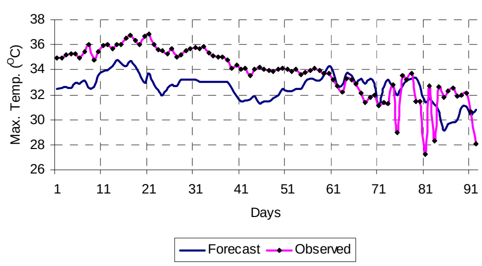


b



(D) OND SEASON

a



b

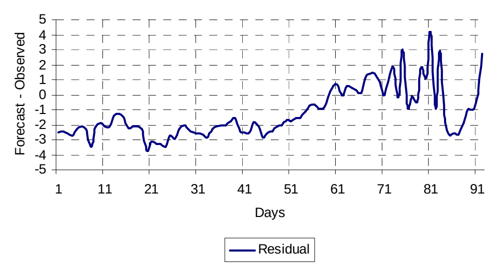
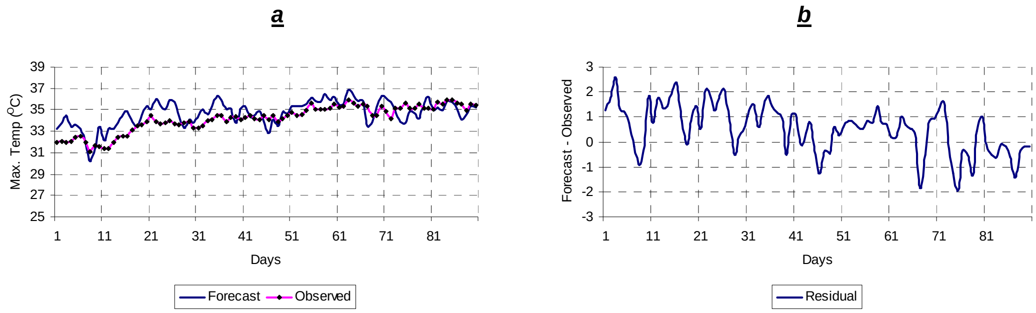


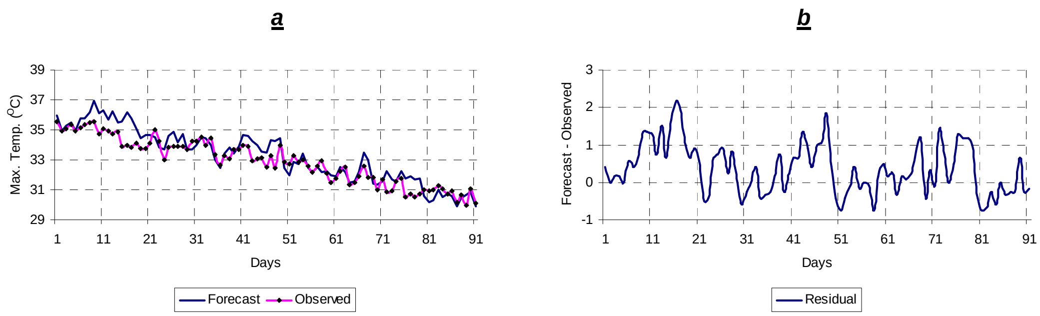
FIG. 5.1: Africa LAM T+24h forecasts for maximum temperature compared with observations over Semi-Arid (SA) climate zone of the Western Sahel (WS) (**a**) Forecast vs. Observed and (**b**) Forecast minus Observed. The time series plotted are the mean values of the observations and model forecasts over the regions.

5.2.2 WET AND DRY TROPICS CLIMATE ZONE

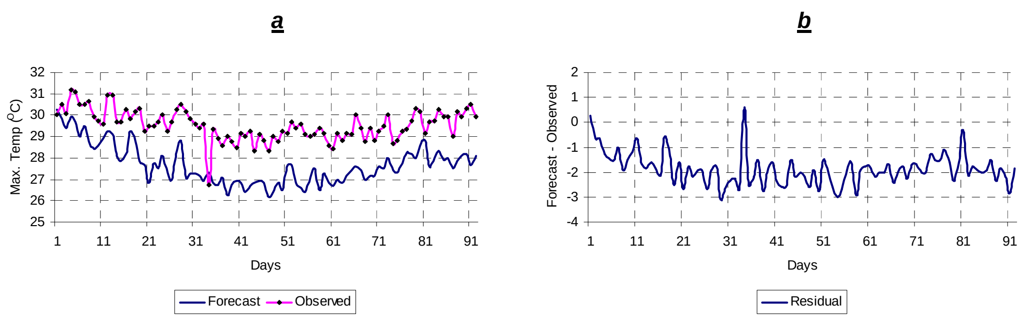
(A) JFM SEASON



(B) AMJ SEASON



(C) JAS SEASON



(D) OND SEASON

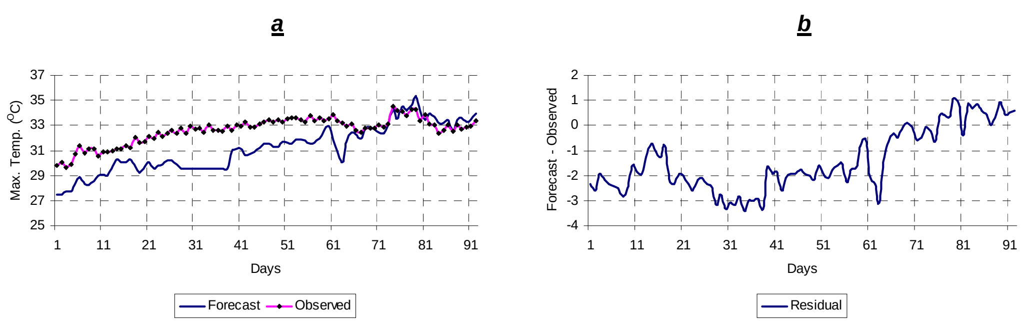
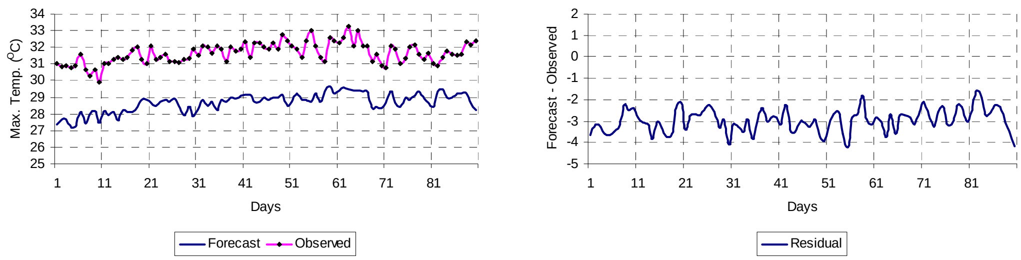


FIG. 5.2: Same as in FIG. 5.1 but for the Wet and Dry Tropics (WDT) climate zone of the Western Sahel (WS).

5.2.3 WET EQUATORIAL CLIMATE ZONE

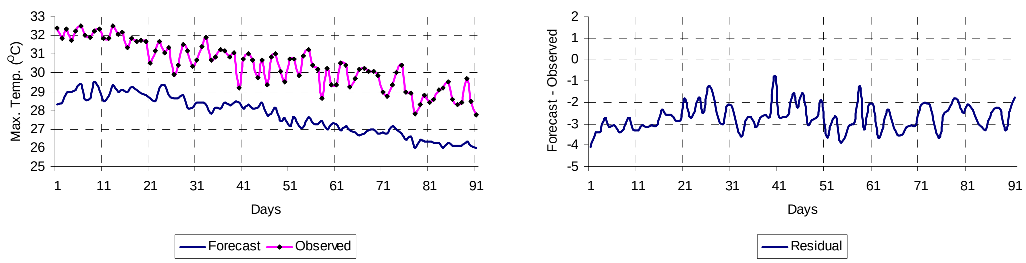
(A) JFM SEASON

a ***b***



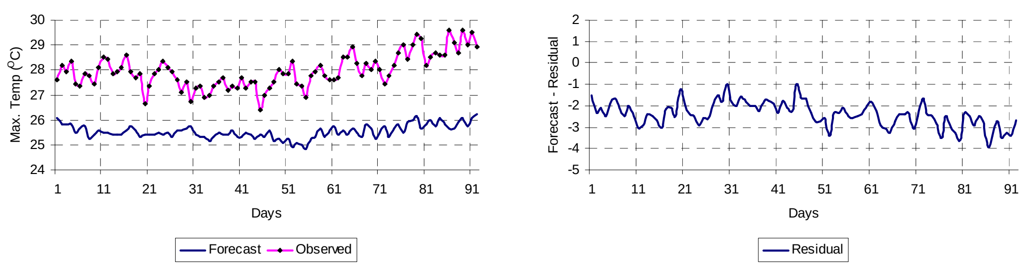
(B) AMJ SEASON

a ***b***



(C) JAS SEASON

a ***b***



(D) OND SEASON

a ***b***

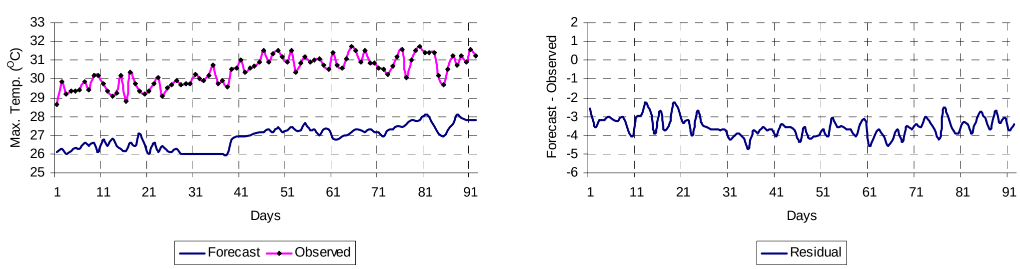


FIG. 5.3: Same as in FIG. 5.2 but for the Wet Equatorial (WE) climate zone of the Western Sahel (WS).

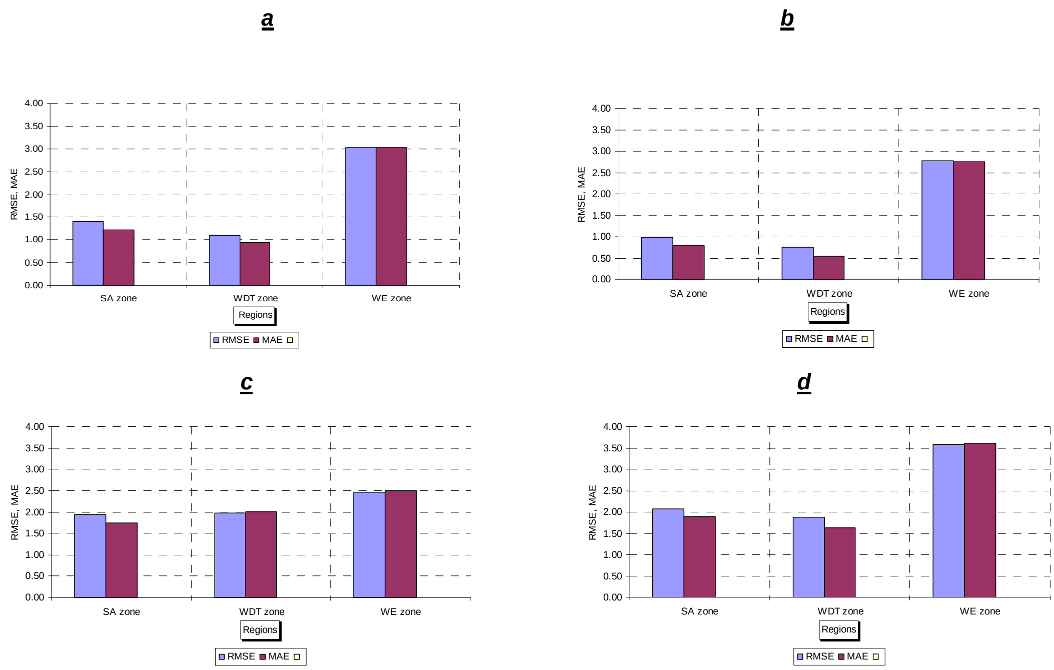


FIG. 5.4: The magnitude of Africa LAM errors (RMSE and MAE) in predicting maximum temperatures T+24h ahead in time over the WE, WDT and SA climate zones of the WS and for the (**a**) JFM, (**b**) AMJ, (**c**) JAS and (**d**) OND seasons, and over the period January 2005 to December 2006.

Over the SA climate zone of the WS (Fig. 5.1), results indicate that Africa LAM generally under-estimated the magnitude of maximum temperature values in T+24h forecasts, with the largest negative bias on an individual day (day 76) being -4.0ºC during the JAS season. The results further show that the model generated the highest PC of 28% during the AMJ season (Table 5.1). Fig. 5.4 illustrates that the maximum temperature forecast error magnitude (RMSE and MAE) over the SA climate zone of the WS is smaller during the AMJ to JAS seasons than during the OND to JFM seasons, meaning that the model had performed better during the rain seasons than during dry seasons, which is a plus point for the model. However, the highest correlation coefficient of about 0.75 was recorded during the JFM season. This could be as a result of the harmattan weather (dry and cold) that prevails over the SA climate zone of the WS during the JFM season, which might have led to lower maximum temperature values which were also less variable in magnitude. This implies that, although the PC was not the highest during the JFM season, the changes between the observed and model forecasts for maximum temperatures over this region during the JFM season were comparable.

Fig. 5.2 illustrates that the model mostly over-estimated maximum temperature values in NWPs over the WDT climate zone of the WS during the JFM and AMJ seasons, but under-estimated values in the equivalent predictions of the JAS and OND seasons. Over the WDT climate zone of the WS, the largest mean negative bias of about -3.2ºC was recorded on an individual day (day 38) during OND, and the largest mean positive bias of 2.5ºC was recorded on an individual day (day 4) during JFM season. The mean bias (Table 5.1) also shows that the model's maximum temperature forecast were not too high, especially over the first few months of the year (JFM). From the time when the rain started (AMJ) over the WDT climate zone, towards the peak of the rainy season (JAS), the model generated lower than observed maximum temperatures, which later returned back to values that are closer to observations when the rain season ended. This could mean that rainfall events are relatively well captured by the model over this region, but that the model's evaporation and downdraught might be incorrect. It could also mean that the interaction with surface properties and hydrology, or even the cloud and radiation, with too much solar flux reflected from over-bright clouds, might have been responsible for the errors. There is scope for improvement of the Africa LAM convective parameterization scheme. The highest PC calculated from model data over the WDT climate zone of the WS was 50%, which was recorded during the AMJ season (Table 5.1). The forecast error magnitude (Fig. 5.4) was also the smallest during this season. The highest correlation coefficient ($\mathbf{r_s}$) of 0.63 was calculated for the AMJ season over the central region of the WS.

Results from Fig. 5.3 indicate that the model under-estimated maximum temperature forecasts over the WE climate zone of the WS, with the largest negative bias of -4.8ºC on an individual day (day 35) recorded during the OND season. The magnitude of the model forecast error over the climate zone was relatively high throughout the year, except for the JAS season when it was slightly lower. This means that the model, in general, could not adequately capture seasonal maximum temperature changes over the WE climate zone of the WS. The model generated the largest under-estimates of the maximum temperature over the WE zone (Fig. 5.3, compared to Figs. 5.1, 5.2). Fig. 5.4 shows that the RMSE and MAE are the largest over WE zone. The model forecasts of maximum temperature were best correlated ($\mathbf{r_s}$ = 0.63) to the observed over the WE climate zone during the AMJ season when the rains normally begins to fall (Table 5.1).

Fig. 5.4 illustrates that the magnitude in model forecast errors was greater during the JFM and OND seasons than during the AMJ and JAS seasons. This suggests that the model has skill to generate better T+24h forecasts of maximum temperature over all three climate zones of the WS during the rain season (AMJ and JAS) than during the dry seasons (JFM and OND). The results (Fig. 5.4) also show that during all the seasons (JFM, AMJ, JAS and OND), the magnitude of the model forecast error was in general the lowest over the WDT and SA climate zones, and higher over the WE climate zone – meaning that the model maximum temperature forecasts were generally better over the north than over the south of the study domain.

5.3 AFRICA LAM VERIFICATION RESULTS FOR MINIMUM TEMPERATURE

Results of the skill measures (defined in chapter 4) used to evaluate the Africa LAM NWP model's performance to forecast minimum temperature over the WE, WDT and SA climate zones of the WS during the JFM, AMJ, JAS and OND seasons, and over the period January 2005 to December 2006, are presented in Table 5.2 and Figs. 5.5 to 5.8.

Table 5.2 lists Africa LAM's verification results for T+24h forecast minimum temperatures. Fig 5.5 illustrates Africa LAM T+24h forecasts for minimum temperature compared to observations over the SA climate zone, while Figs. 5.6 and 5.7 illustrates the same for the WDT and WE climate zones, respectively. Fig. 5.8, again, depicts the magnitude of Africa LAM errors (RMSE and MAE) in predicting minimum temperatures over the regions and periods mentioned above.

Table 5.2: Africa LAM NWP verification results for T+24h minimum temperatures forecasts during the JFM, AMJ, JAS and OND seasons over the WE, WDT and SA climate zones of the Western Sahel (WS), and over the period January 2005 to December 2006.

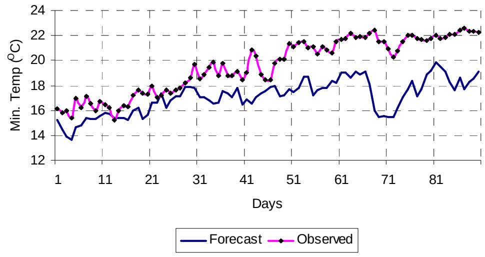
	JFM			**AMJ**		
	SA zone	WDT zone	WE zone	SA zone	WDT zone	WE zone
r_p	0.48	0.44	0.18	0.54	0.48	0.35
r_s	0.51	0.46	0.23	0.54	0.51	0.41
MSE	8.21	2.17	3.60	8.81	0.45	3.45
RMSE	2.87	1.47	1.90	2.97	0.67	1.86
MAE	2.46	1.14	1.76	2.82	0.51	1.77
BIAS	-2.46	-0.56	1.76	-2.77	-0.17	1.77
%Above	0.00	23.33	97.78	0.00	16.48	100.00
%Below	95.56	48.89	0.00	98.90	31.87	0.00
PC - A	0.04	0.28	0.02	0.01	0.52	0.00
LEPS (%)	43.77	32.66	16.80	46.37	40.50	23.47

	JAS			**OND**		
	SA zone	WDT zone	WE zone	SA zone	WDT zone	WE zone
r_p	0.22	-0.02	0.13	0.63	0.31	0.08
r_s	0.26	0.19	0.39	0.62	0.34	0.16
MSE	0.50	0.43	0.62	3.53	1.54	2.46
RMSE	0.71	1.07	0.53	1.88	1.24	1.57
MAE	0.63	0.32	0.66	1.67	0.98	1.49
BIAS	-0.51	-0.20	0.53	-1.58	0.00	1.49
%Above	1.09	4.35	58.70	2.17	27.17	100.00
%Below	59.78	27.17	0.00	86.96	38.04	0.00
PC - A	0.39	0.69	0.41	0.11	0.35	0.00
LEPS (%)	20.75	10.76	17.58	50.08	31.22	14.14

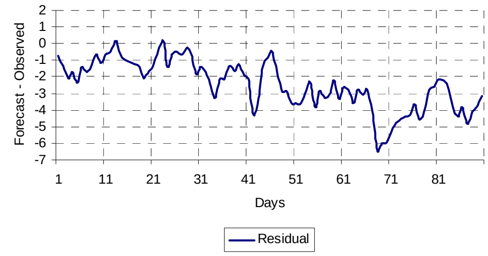
5.3.1 SEMI-ARID CLIMATE ZONE

(A) JFM SEASON

a

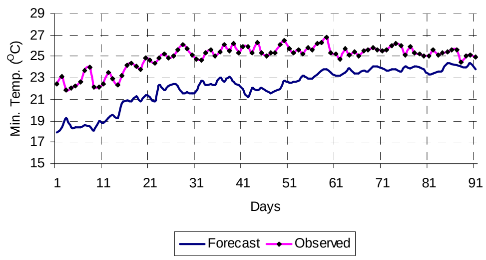


b

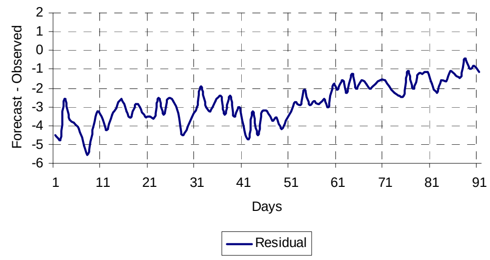


(B) AMJ SEASON

a

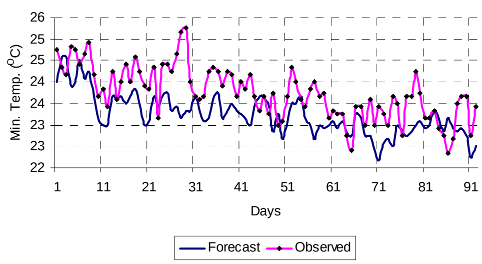


b

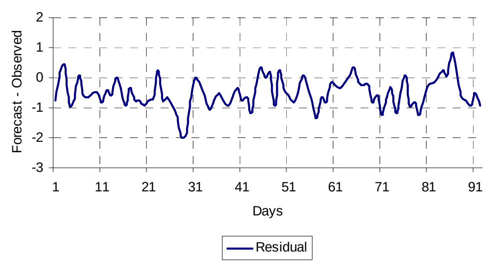


(C) JAS SEASON

a

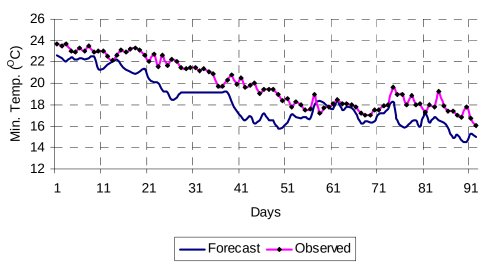


b



(D) OND SEASON

a



b

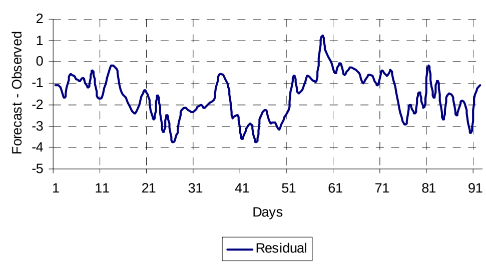
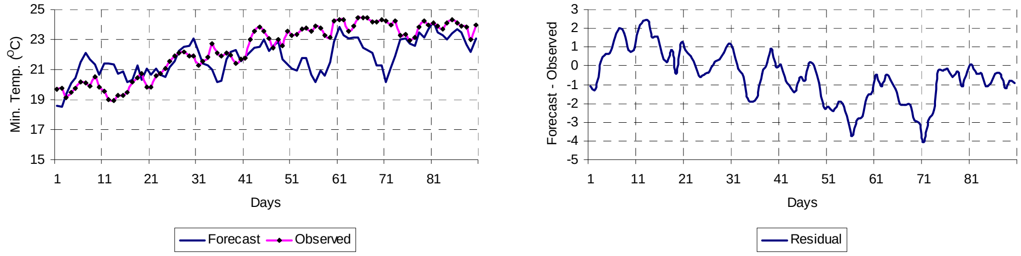


FIG. 5.5: Same as in FIG. 5.3 but for minimum temperature over the Semi-Arid (SA) climate zone of the Western Sahel (WS).

5.3.2 WET AND DRY TROPICS CLIMATE ZONE

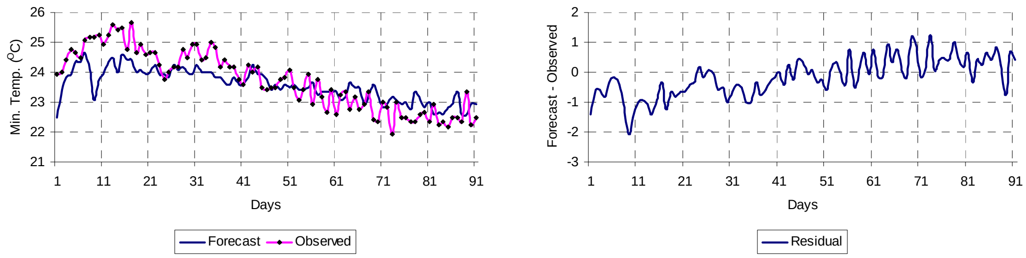
(A) JFM SEASON

a ***b***



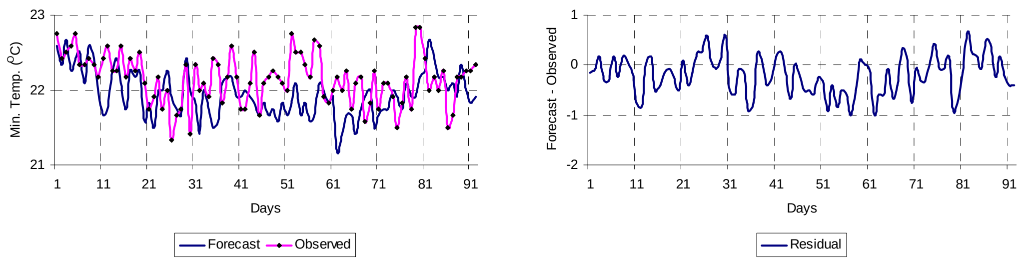
(B) AMJ SEASON

a ***b***



(C) JAS SEASON

a ***b***



(D) OND SEASON

a ***b***

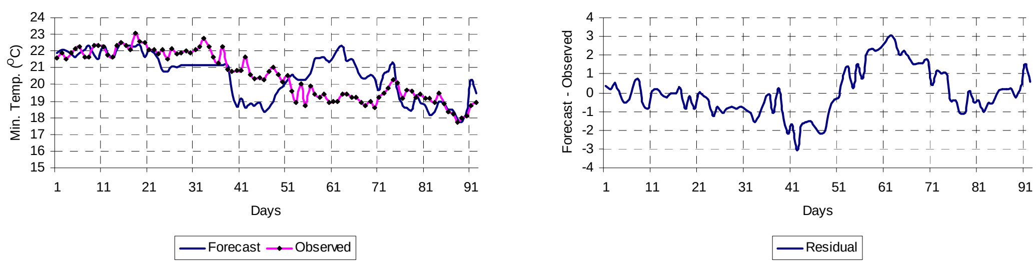
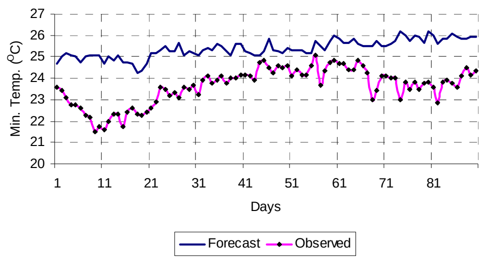


FIG. 5.6: Same as in FIG. 5.5 but over the Wet and Dry Tropics (WDT) climate zone of the Western Sahel (WS).

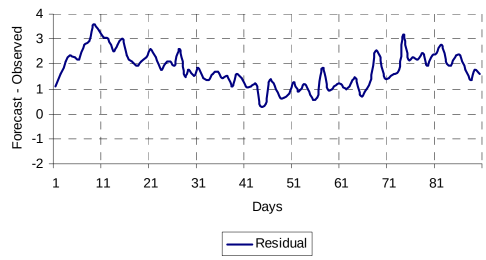
5.3.3 WET EQUATORIAL CLIMATE ZONE

(A) JFM SEASON

a

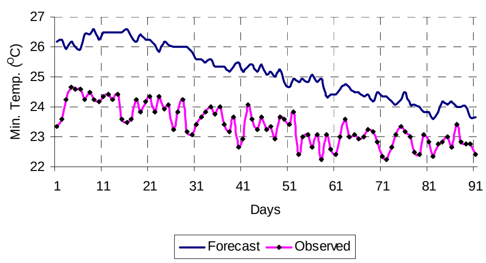


b

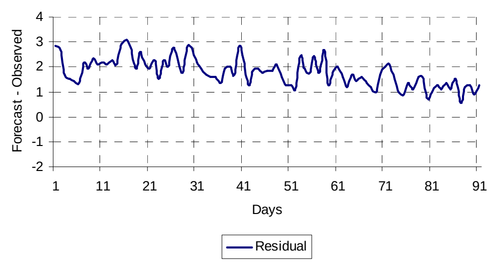


(B) AMJ SEASON

a

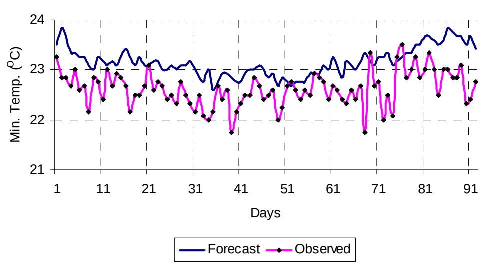


b

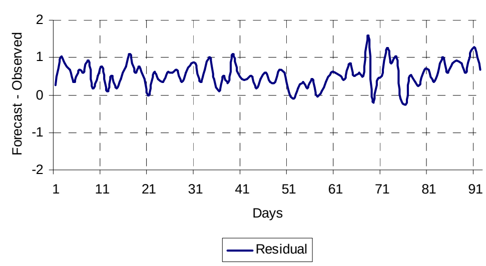


(C) JAS SEASON

a

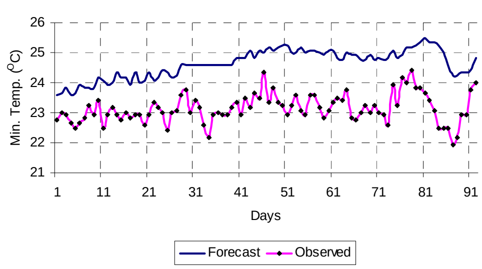


b



(D) OND SEASON

a



b

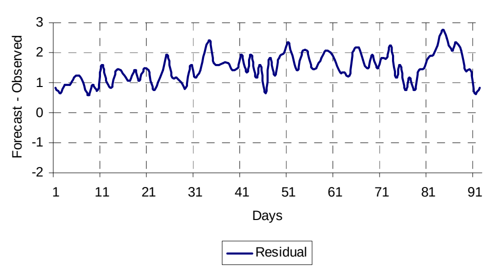


FIG. 5.7: Same as in FIG. 5.6 but over the Wet Equatorial (WE) climate zone of the Western Sahel (WS).

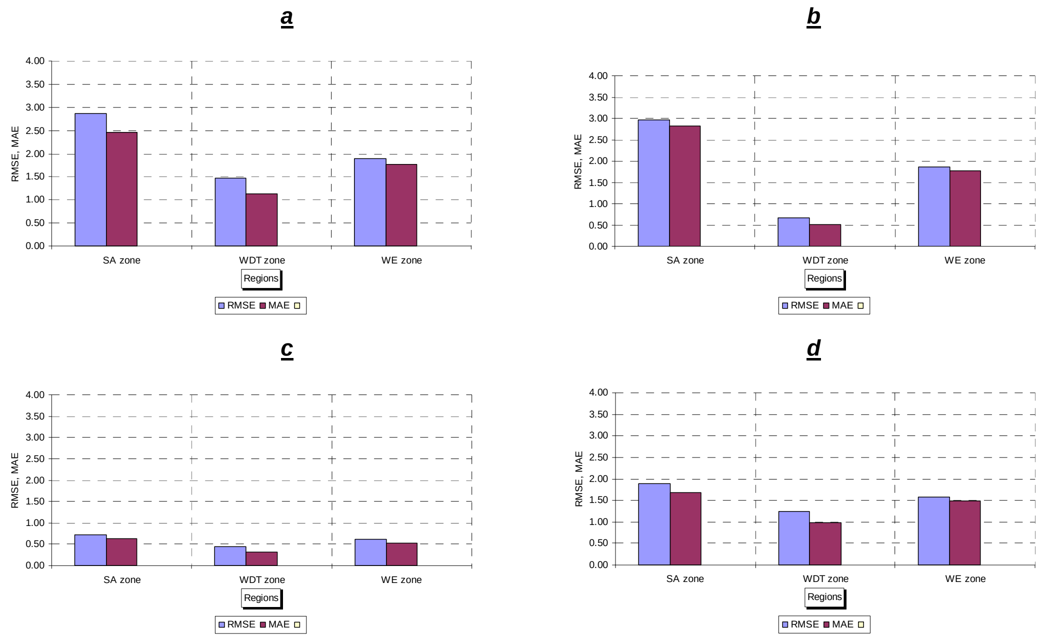


FIG. 5.8: As in FIG. 5.4 but for minimum temperatures.

Results illustrated in Fig. 5.5 and listed in Table 5.2 show that the Africa LAM had generated negative biases in forecasting minimum temperature of T+24h over the SA climate zone of the WS, with the largest mean negative bias of -6.0ºC on an individual day (day 68) during JFM. This implies that the model under-estimated minimum temperature forecasts over the SA climate zone of the WS. The model generated its highest PC of 39% during the JAS season. The magnitude in model forecast error (Fig. 5.8) over the SA climate zone of the WS was greater during the JFM, AMJ and OND seasons than during the JAS season, suggesting that the model performed better in predicting minimum temperatures during most of the rainy season than during the dry seasons (the same results were found for maximum temperature forecasts). The best correlation ($\mathbf{r_s}$) of 0.62 appeared during the OND season over the SA climate zone of the WS.

Fig. 5.6 and Table 5.2 indicate that the model generated a generally negative bias in predicting minimum temperature over the WDT climate zone of the WS. The largest PC of almost 70% was generated during JAS over this climate zone, meaning that the model produced improved predictions in minimum temperature values during JAS. The best correlation ($\mathbf{r_s}$) of 0.51 was recorded during the AMJ season. The greatest errors (Fig. 5.8) appeared during the dry seasons (JFM and OND), implying that the model did well during the rainy seasons over the WDT climate zone of the WS. This suggests that the model adequately captured the minimum temperature characteristics during the onset of rains (AMJ) over the WDT climate zone.

From Fig 5.7, it becomes evident that the Africa LAM generally over-estimates minimum temperature forecasts over the WE climate zone of the WS, with the largest positive bias of about 3.5ºC on an individual day (day 10) during JFM. Results in Fig. 5.8 also indicate that the model performed better in predicting minimum temperature values during the AMJ and JAS seasons than during the JFM and OND seasons. This means that the model did better in predicting minimum temperature values over the south during the rainy seasons (AMJ and JAS) than during the dry seasons (JFM and OND). The largest forecasting error (Table 5.2, Fig. 5.8) was generated in the WE climate zone of the WS during the JFM season. The model also generated a comparatively low PC and low forecasting error (Fig. 5.7, Fig. 5.8) when predicting minimum temperature values over the WE climate zone of the WS. The highest correlation coefficient ($\mathbf{r_s}$) of 0.41 was recorded during the AMJ season.

In general, the results in Figs. 5.5 to 5.7 show that the Africa LAM under-estimates minimum temperature forecasts over the SA and WDT climate zones of the WS, but over-estimates the associated forecasts over the WE climate zone of the WS. Fig. 5.8 illustrates that the model, in general, generated relatively smaller forecasting errors during the rainy season (AMJ and JAS) than during the dry season (JFM and OND), further suggesting that the model predicts minimum temperature values better during rainy seasons than during the harmattan (dry and cold) seasons over the WS study domain.

5.4 AFRICA LAM VERIFICATION RESULTS FOR RAINFALL

Results of the skill measures (defined in chapter 4) used to evaluate the Africa LAM NWP model's performance to forecast rainfall over the WE, WDT and SA climate zones of the WS during the JFM, AMJ, JAS and OND seasons, and over the period January 2005 to December 2006, are presented in Table 5.3 and Figs. 5.9 to 5.12.

Table 5.3 lists Africa LAM's verification results for T+24h rainfall forecasts. Fig 5.9 illustrates Africa LAM T+24h forecasts for rainfall compared to observations over the SA climate zone, while Figs. 5.10 and 5.11 illustrates the same for the WDT and WE climate zones, respectively. Fig. 5.12, again, depicts the magnitude of Africa LAM errors (RMSE and MAE) in predicting rainfall over the regions and periods mentioned above.

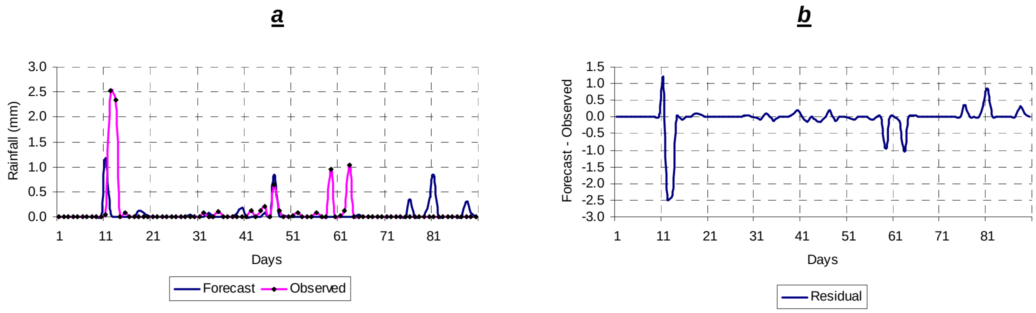
Table 5.3: Africa LAM NWP verification results for T+24h rainfall forecasts during the JFM, AMJ, JAS and OND seasons over the WE, WDT and SA climate zones of the Western Sahel (WS), and over the period January 2005 to December 2006.

	JFM			**AMJ**		
	SA zone	WDT zone	WE zone	SA zone	WDT zone	WE zone
r_p	-0.07	-0.03	0.02	0.07	0.05	0.07
r_s	0.35	0.39	0.25	0.37	0.19	0.21
MSE	0.18	4.32	6.37	1.10	11.21	12.39
RMSE	0.42	2.08	2.52	1.05	3.35	3.52
MAE	0.13	1.70	2.19	0.70	2.55	2.78
BIAS	-0.04	1.69	0.87	-0.05	1.83	1.37
%Above	14.44	98.89	66.67	59.34	72.53	68.13
%Below	15.56	1.11	33.33	30.77	26.37	31.77
PC – A	0.70	0.00	0.00	0.10	0.01	0.00
%YES	4.44	32.22	95.56	67.03	97.80	98.90
%NO	68.89	0.00	0.00	7.69	0.00	0.00
%MISSES	27.00	68.00	4.44	25.27	2.20	1.10
PC – B)	0.73	0.32	0.96	0.75	0.98	0.99
LEPS (%)	75.00	100.00	83.02	96.20	55.35	52.20

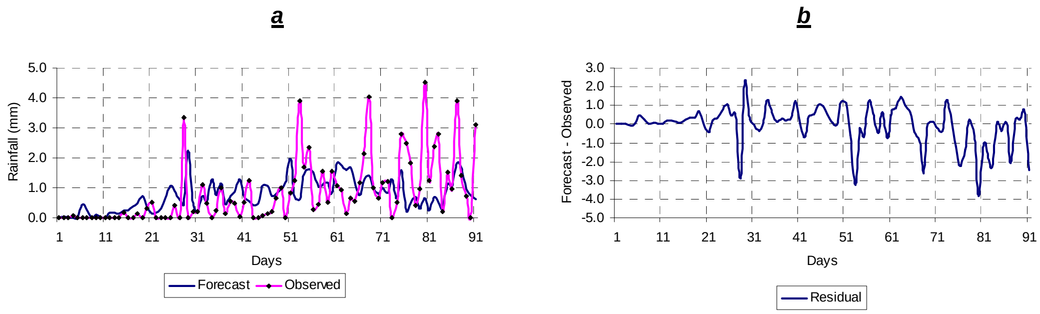
	JAS			**OND**		
	SA zone	WDT zone	WE zone	SA zone	WDT zone	WE zone
r_p	-0.02	-0.06	0.04	0.10	0.20	-0.04
r_s	0.10	0.00	0.19	0.41	0.48	0.13
MSE	11.65	25.09	14.44	0.38	3.04	30.25
RMSE	3.41	5.01	3.80	0.62	1.74	5.50
MAE	2.35	3.85	2.68	0.27	1.17	4.34
BIAS	-0.50	1.24	-1.55	-0.06	0.64	2.94
%Above	43.48	66.30	33.70	27.17	78.26	79.35
%Below	52.17	33.70	66.30	14.13	14.13	19.57
PC – A	0.05	0.00	0.00	0.59	0.08	0.01
%YES	97.83	100.00	98.91	28.26	53.26	92.39
%NO	0.00	0.00	0.00	56.52	6.52	1.09
%MISSES	2.17	0.00	1.10	15.22	40.22	6.52
PC – B	0.98	1.00	0.99	0.85	0.60	0.93
LEPS (%)	52.10	34.01	58.20	91.67	98.45	70.87

5.4.1 SEMI-ARID CLIMATE ZONE

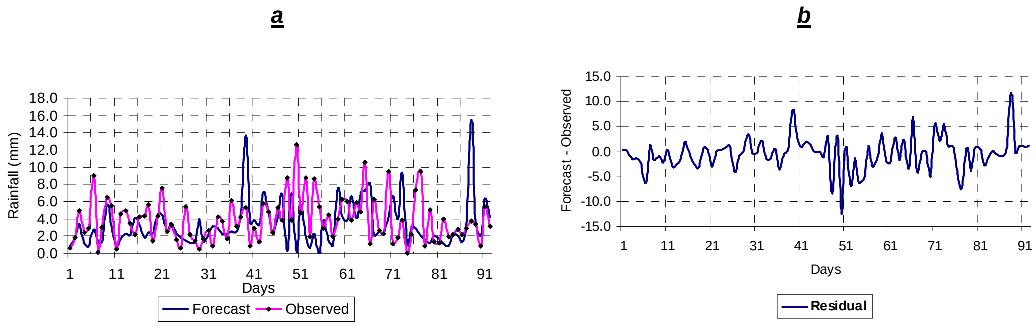
(A) JFM SEASON



(B) AMJ SEASON



(C) JAS SEASON



(D) OND SEASON

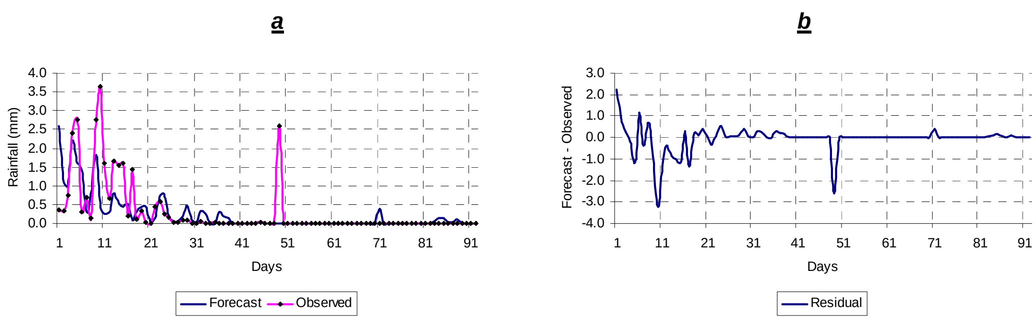
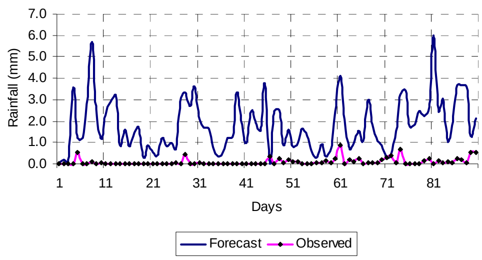


FIG. 5.9: Same as in FIG. 5.7 but for Rainfall over the Semi-Arid (SA) climate zone of the Western Sahel (WS).

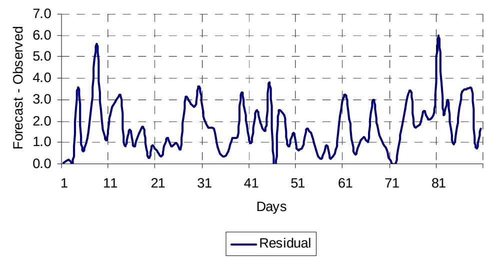
5.4.2 WET AND DRY TROPICS CLIMATE ZONE

(A) JFM SEASON

a

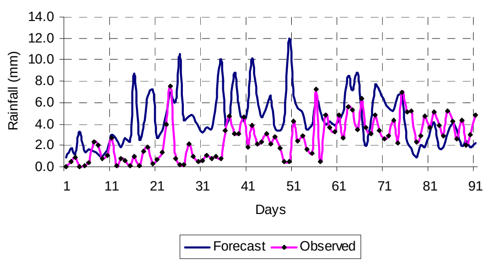


b

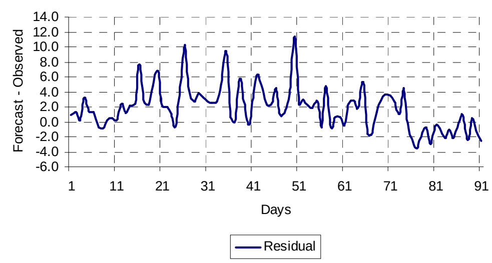


(B) AMJ SEASON

a

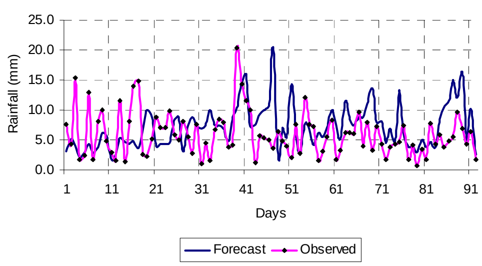


b

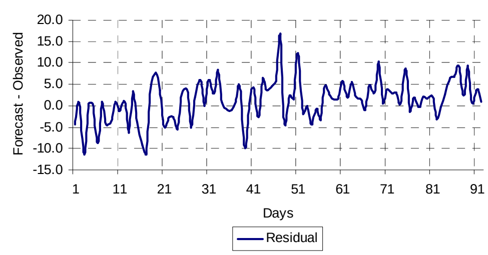


(C) JAS SEASON

a

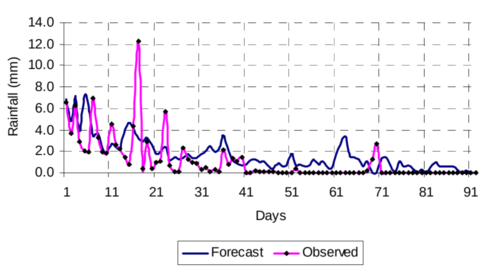


b



(D) OND SEASON

a



b

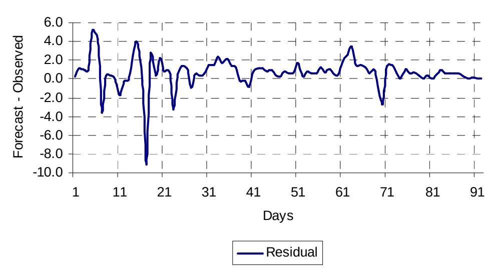
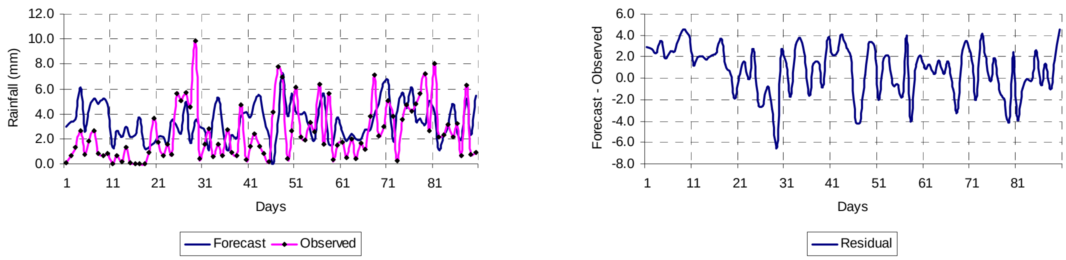


FIG. 5.10: Same as in FIG. 5.9 but over the Wet and Dry Tropics (WDT) climate zone of the Western Sahel (WS).

5.4.3 WET EQUATORIAL CLIMATE ZONE

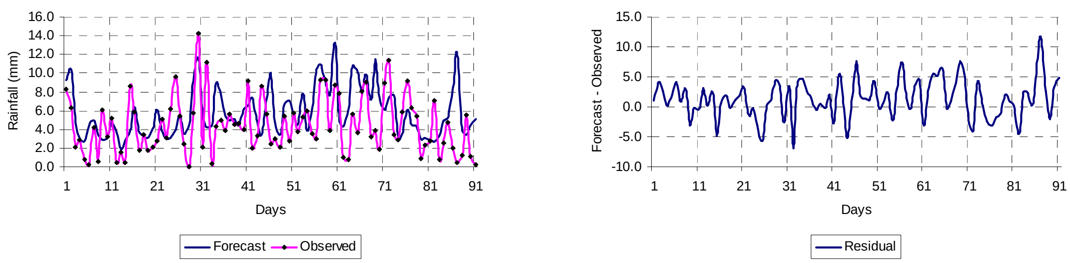
(A) JFM SEASON

a **b**



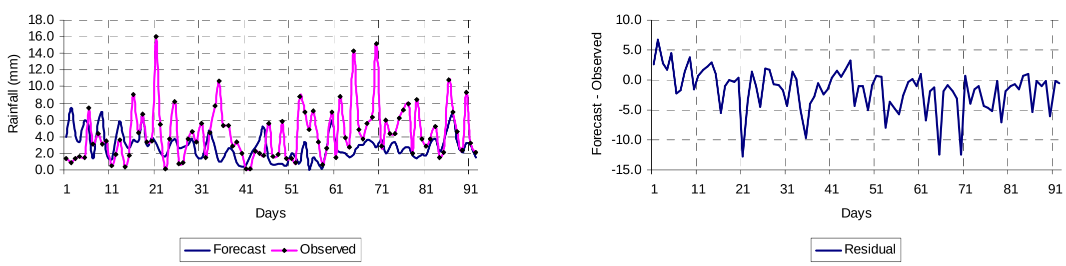
(B) AMJ SEASON

a **b**



(C) JAS SEASON

a **b**



(D) OND SEASON

a **b**

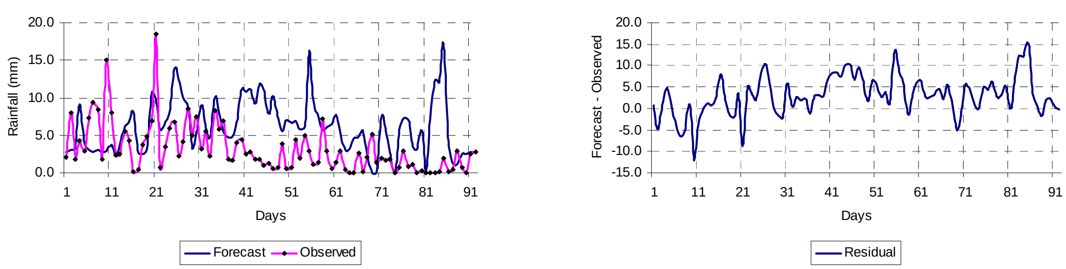


FIG. 5.11: Same as in FIG. 5.10 but over the Wet Equatorial (WE) climate zone of the Western Sahel (WS).

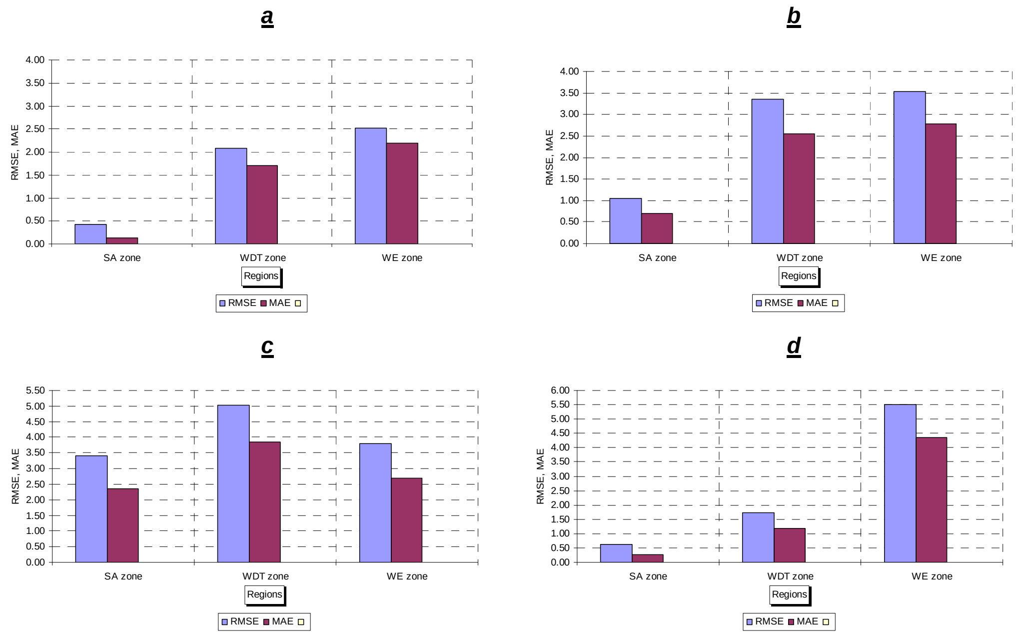


FIG. 5.12: As in FIG. 5.8 but for rainfall.

The Africa LAM's performance in predicting rainfall amounts and rainfall events for a period of T +24h in advance has been listed in Table 5.3. PC – A in Table 5.3 indicates the model's proportional correct index in predicting rainfall amounts, while PC – B indicates the model's proportional correct index in predicting rainfall events.

Fig. 5.9 shows that the model under-estimated rainfall amount forecasts over the SA climate zone of the WS, with the largest negative bias of about -12.0mm on an individual day (day 50) during the peak of the rainy season (JAS). Results (Table 5.3) also denote a relatively high PC – A value of 70% (JFM) and 60% (OND), but a relatively low PC – A value of 10% (AMJ) and 5% (JAS). On the other hand, the results indicate consistently high PC – B for all seasons. This suggests that the model performed very well in predicting rainfall events throughout the year, but has greater success in predicting rainfall amounts during the dry seasons (JFM and OND) than during rainy seasons (AMJ and JAS), especially as indicated by the comparatively low PC – A values calculated during the rain seasons. The magnitudes of forecasting errors (Fig. 5.12) were also correspondingly lower during dry seasons than during rain seasons. The best correlation coefficient (**r_s**) of 0.41 was also recorded during the dry OND season.

Results from Fig. 5.10 point towards a generally positive bias by the model in predicting rainfall amounts over the WDT climate zone of the WS, with the largest positive bias of about 17.0mm on an individual day (day 47) during JAS. This means that the model generally over-estimated rainfall amount forecasts over the WDT climate zone of the WS. From the PC – A and PC – B results in Table 5.3, the model showed a relatively high success in predicting rainfall events, but has a relatively low success in predicting the exact rainfall amounts over the WDT climate zone of the WS. The magnitude of forecasting errors (Table 5.3, Fig. 5.12) was also the greatest during the JAS season. The best correlation coefficient ($\mathbf{r_s}$) of 0.48 was recorded during the dry season of OND, similar to that of the SA climate zone of the WS.

Over the WE climate zone of the WS (Fig. 5.11), results indicates that the Africa LAM over-estimated rainfall amount forecasts, except for JAS, when the model showed under-estimation over the same region. The results (Table 5.3, Fig. 5.11) further show that the model had the largest positive bias of 15mm on an individual day (day 85) during OND season, and the largest negative bias of 13mm on an individual day (day 22) during JAS. The PC – A and PC – B (Table 5.3) indicate that the model has a high proportional correct index in forecasting rainfall events than when forecasting rainfall amounts over the WE climate zone of the WS. This is in agreement with findings over the WDT climate zone of the WS. Fig. 5.12 illustrates that the model has generated its lowest forecast error during the JFM season over the WE climate zone of the WS, meaning that the model successfully captured rainfall events and rainfall amounts during this season, when less rainfall activity are normally expected. Again, the highest correlation coefficient ($\mathbf{r_s}$) of 0.25 was recorded during the JFM season, which also agrees with the conclusion that the model has a better chance to succeed in predicting rainfall amounts and events during the dry seasons than during the rain seasons over the WE climate zone of the WS. It is also shown in Fig. 5.12 that the model has the largest forecast error over the WE climate zone if compared to other regions of the WS. This could be due to the high frequencies of rainfall events and uneven rainfall amounts (monsoon rains) that are more prevalent over the south than over the central and north, which were not well captured in Africa LAM forecasts.

5.5 Summary

The Africa LAM has been verified against station observations over the three different climatic zones and four seasons of the year. In summary, the verification results indicate that the model temperature forecasts show skill, more so during the raining seasons (AMJ and JAS) than during the dry seasons (JFM and OND) over the WS. The model rainfall forecasts, however, show more skill during the dry seasons (JFM and OND) than during the raining seasons (AMJ and JAS). The results further indicate that, on a regional basis, the model temperature forecasts show more spatial skill over the WE climate zone than over the WDT and SA climate zones of the WS, while rainfall forecasts show more skill over the SA climate zone than over the WDT and WE climate zones of the WS. These results give a better understanding of the model forecast errors, and could also provide the feedback necessary for a possible improvement of Africa LAM forecasts by scientists at the UK Met Office.

CHAPTER 6

WEATHER FORECASTING IN NIGERIA

6.1 INTRODUCTION

NWP models have great value when they are employed as an essential tool to assist weather forecasters in their daily duties. One might be able to forecast the weather without NWP models, but over a relatively short period ahead in time. There are two ways to predict the weather without NWP models:

- Assuming persistence, in other words to assume that current synoptic patterns and atmospheric variables will remain in the same state over the period of forecasting. This might work for variables such as temperatures that are fairly constant in diurnal variability over barotropic equatorial regions, but as soon as a variable increases in variance, weather forecasting by assuming persistence becomes less useful and less successful.

- Projecting the propagation of synoptic situation forward in time by using one's knowledge of meteorology and experience of the propagation of similar previous events. This approach has its limitations, especially over regions like the tropics where a zero Coriolis force does not allow for well defined pressure systems. The latter involve the forecast of pressures which might be regarded as a primary variable. As soon as one starts to consider secondary variables, such as rainfall, weather forecasting becomes extremely difficult – even for a day or less in advance.

NWP models have improved significantly over the past decades, and have the ability to forecast most atmospheric variables with a high degree of accuracy over a period of 24 hours, or even two to three days in advance. The incorporation of NWP models in modern forecasting operations therefore becomes unavoidable. Unfortunately NMHSs in Africa currently do not have the infrastructure or human resources to run NWP models in-house, and they therefore have to rely on NWP results from other countries in the international community. These NWP results are in most cases downloaded from the Internet, which is also sometimes not reliable in African countries. Despite of these obstacles, it is worth investigating how NWP could be incorporated in weather forecasting operations in NMHSs of Africa.

This study addresses the use of the Africa LAM over the WS, although the Nigerian Meteorological Agency (NIMET) is regarded as the focus point from where weather forecasts are issued. The following chapter provides a general overview on conventional forecasting, and current forecasting that incorporate NWPs (mostly downloaded from the Internet), in Nigeria. The shortcomings and needs of NIMET, which are also applicable to other NMHSs in the WS, to issue improved weather forecasting are examined. A typical weather forecasting process at NIMET is discussed, with the view to provide an example for other NMHSs in the WS (and beyond) that might consider the incorporation of NWP model results in future. It might also serve as an indication of the overall value that the Africa LAM might have in NWP over the WS.

Some NWP output are shown and compared to observations. It is not the purpose of this part of the study to perform a detailed verification of the NWP models used, but rather to introduce the models used at NIMET, and to briefly consider a few case study examples to indicate how the model output are used in an effort to improve on weather forecasting.

6.2 NWP MODELS AND WEATHER FORECASTING IN NIGERIA

The history of weather forecasting in Nigeria dates back to the time of British colonization when the Nigerian Meteorological Services Department was established in around 1914. A recent need for independence, with the inspiration to develop higher quality meteorological services to end-users in Nigeria, led to the enactment of the NIMET Act in June 2003 by the Federal Government of Nigeria. The Act made NIMET a semi autonomous body which has an obligation to generate part of its income. NIMET is currently managed by a Director-General (DG), under the supervision of the Federal Ministry of Transportation. Apart from the Office of the DG, NIMET operates under seven sub-directorates, namely the directorates of (1) Weather Forecasting Services (WFS), (2) Applied Meteorological Services (AMS), (3) Engineering and Technical Services (ETS), (4) Research and Training (R&T), (5) Finance and Accounts (FA), (6) Administration and Supply (AS) and (7) Legal and Corporate Affairs (LCA).

Weather forecasting activities of the agency are supervised by the WFS directorate. There are five major forecasting offices in Nigeria, namely (1) the Ikeja forecasting office in Lagos State, (2) the Abuja forecasting office in the Federal Capital Territory, (3) the Port Harcourt forecasting office in Rivers State, (4) the Kano forecasting office in Kano State and (5) the Central Forecast Office (CFO) in the operational meteorological Headquarters Oshodi in Lagos State. The CFO co-ordinates all other forecast offices and also issue the daily national public weather forecast. Seasonal weather forecasts and results of any research findings are also disseminated through the CFO. Apart from the forecast offices, NIMET controls a network of about 43 observational weather stations, and many other Automatic Weather Stations (AWS) distributed all around the country. Meteorological observations available from this network of stations are collected on a regular basis - some very close to real time.

Before 1996, when the CFO was established, weather forecasting in Nigeria were issued purely by an analog procedure. As explained by Gutzler and Shukla (1984), the idea of analog forecasting is to search archives of past synoptic maps that closely resembles current observations, and then to assume that the future evolution of the atmosphere will be similar to those that followed from the historical analogs. Wilks (1995) points out that the analog forecasting method is only an estimation of reality because atmospheric synoptics are not often repeated. Fortunately some Nigerian forecasters returned in 1996 from On-Job-Training at the African Center of Meteorological Applications and Development (ACMAD), Niamey, Niger Republic, where they were trained on the use and interpretation of NWP models in weather forecasting. From then, Nigeria started to use NWP model outputs to assist them in the process of routine weather forecasting (Fig. 6.1).

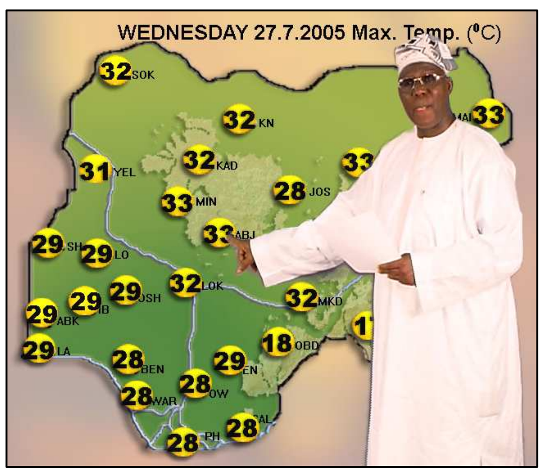


FIG. 6.1: Typical television weather forecasting presentation on national television in Nigeria. Current weather forecast issued incorporated NWP model results.

In Nigeria, as in most other NMHS in Africa, it is difficult to run models in-house, due to a lack of computer resources and limited knowledge of the field of numerical modeling. As a result, available information from international NWP models is currently downloaded from the Internet, in conjunction with the collection of real time observations and satellite imageries, when preparing a weather forecast. The introduction of statistical method to improve forecasts and to provide quantitative information from available NWP products will be a very useful addition in the process of weather forecasting - not only in Nigeria, but also in other NMHS in Africa.

Some of the equipment available for the retrieval and interpretation of NWP model results in Nigeria are the Meteorological Data Distribution (MDD) equipment for T4 chart preparation and the Primary Data User System (PDUS) for satellite image display, which was recently upgraded from funding provided by the PUMA project to the Meteosat Second Generation (MSG) system. From the MSG system, images of the near real time state of the atmosphere are retrieved on a 15 minutes interval. Nigeria also contributes to the global meteorology data network since observed meteorological information is disseminated on a regular basis via the Global Telecommunication System (GTS), although some network problems are experienced from time to time.

Currently a typical weather forecasting process in NIMET, with the inclusion of NWP model results, may be outlined as follows:

a) Available NWP output is carefully studied by the weather forecaster on duty. This is done by comparing model initialization fields with actual observations (such as station reports, satellite imageries, upper-air soundings) in order to identify any possible errors so that adjustments could be made. NWP output from (1) the UK Met Office (Africa LAM), (2) the European Center for Medium-Range Weather Forecasts (ECMWF), (3) the National Centers for Environmental Prediction (NCEP) GFS model and (4) Action de Recherché Petite Echelle Grande (ARPEGE) from Metéo France with the Aire Limitée Adaptation dynamique Développement InterNational (ALADIN) model are considered on a daily basis to incorporate NWP model output in routine weather forecasting in Nigeria.

b) At the same time the weather forecaster needs to use his/her discretion to add extra details to the NWP model forecasts, such as the position of the ITCZ, vortices, troughs and ridges. This is essential since NWP models do not always adequately resolve all micro-scale weather systems. It is here where the experienced weather forecaster can use his/her knowledge of local weather to add value to NWP forecasts

c) A detailed comparison of NWP model results from different global modeling centers are prepared to build the weather forecaster's confidence in the available model results. If all the NWP models are suggesting approximately the same solution, the confidence in the model forecast would be high, but if all the NWP are showing different prognoses, the confidence in the model forecasts reduces.

d) Following a critical debate, discussions and adequate consultation with colleagues, a consensus weather forecast is issued.

From the activities above, it become obvious that NMP model output, even if downloaded from the web, may add significant value to weather forecasting in Africa. However, the ideal would be if a meteorological centre runs their NWP model in-house, since these models have certain limitation (maybe as a result of assumptions) which would not be known to users unless they have hands-on experience in model simulations, or even model development.

6.2.1 A brief overview of some NWP models used in Nigeria

The following sections present an overview of some NWP models used for weather forecasting in Nigeria (as listed in (a) above). A brief assessment of errors and biases in a few cases are illustrated. Please note again that it is not the purpose of this part of the study to perform a detailed verification of the NWP models used, but rather to introduce the models used at NIMET, and to briefly consider a few case study examples to indicate how the model output are used in an effort to improve on weather forecasting.

6.2.1.1 The Africa LAM model

A description and technical details of the Africa LAM is outlined in Chapter 3. However, in this section, a case study (19 October 2006) is considered in a discussion of the possible strengths and weaknesses of the Africa LAM in forecasting significant weather events over Nigeria. There are obviously also other cases that could have been discussed, but due to the availability of information, the case of 19 October 2006 was chosen. On that day, observed synoptic conditions were typical of what is experienced during the rain season. A week before this event, the ITCZ shifted northwards and the moisture laden southwesterly winds picked up in strength. Most of the meteorological stations in the country, especially those in the southern region, recorded unusually high temperatures and their Mean Sea Level Pressure (MSLP) generally maintained a decreasing trend.

A comparison between the Africa LAM wind forecasts at 850hPa level (Fig. 6.2) for 19 October 2006, and the observed satellite image (Fig. 6.3) shows that Africa LAM areas of troughs and vortices (in the wind forecasts) correspond well to the locations where active thunderstorms occurred in satellite image. 850hPa wind forecast is chosen since the 850hPa pressure level is normally considered as the atmospheric reference level when predicting convective weather systems over Nigeria. Troughs and vortices are very useful when tracking the development and propagation of convective weather systems over West Africa, especially over Nigeria. The results therefore suggest that the 850hPa forecast winds from the Africa LAM, especially at 00:00GMT and 06:00GMT, proved to be very useful in forecasting convective weather events over Nigeria and south Cameroon.

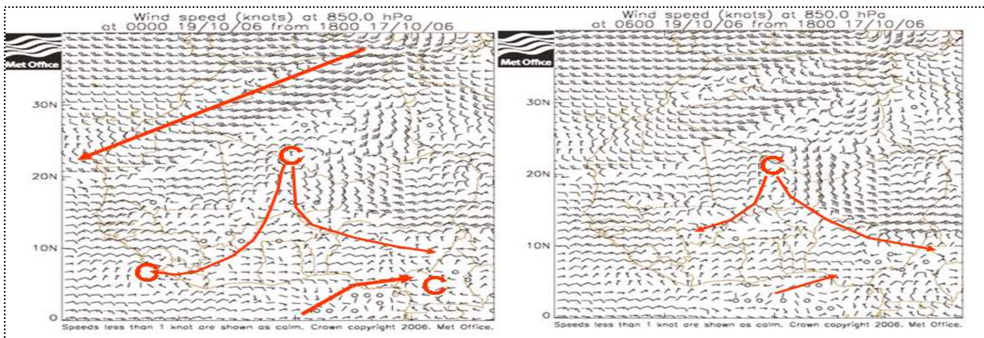


FIG. 6.2: Africa LAM simulated forecasts of 850hPa winds for 00:00GMT (T+6h) (left) and 06:00GMT (T+12h) (right) for 19 October 2006. Marked red lines indicate troughs, while C denotes a vortex.
(Source: http://www.metoffice.gov.uk/weather/africa/lam)

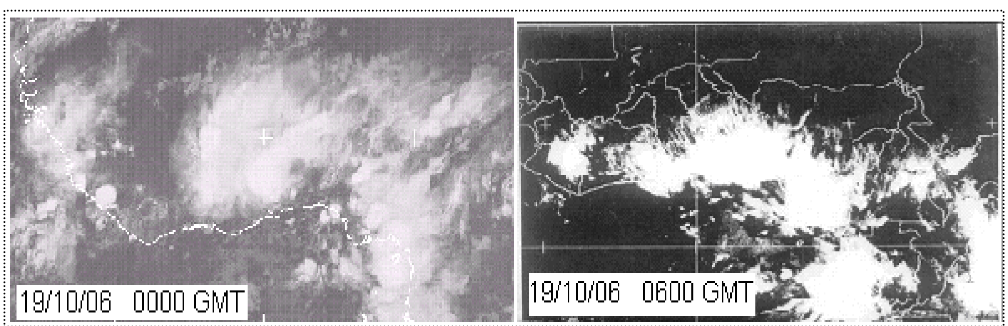


FIG. 6.3: Satellite images for 00:00GMT (left) and 03:00GMT (right) on 19 October 2006. Convective weather over West Africa is clearly indicated (Source: EUMETSAT).

Africa LAM RH forecasts (Fig. 6.4) were also very useful. Vertical wind profile forecasts from the Africa LAM (not shown) indicated that the model in fact did simulate the vertical profile over the West African region very well, with the exception of slight disparities in surface wind directions. Accumulated precipitation forecasts (also depicted in Fig. 6.4) captured observed rainfall patterns that occurred along the coasts of Liberia, Sierra Leone, Guinea, south Cameroon, and especially Nigeria reasonably well. The model forecasts also captured some convective cloud development.

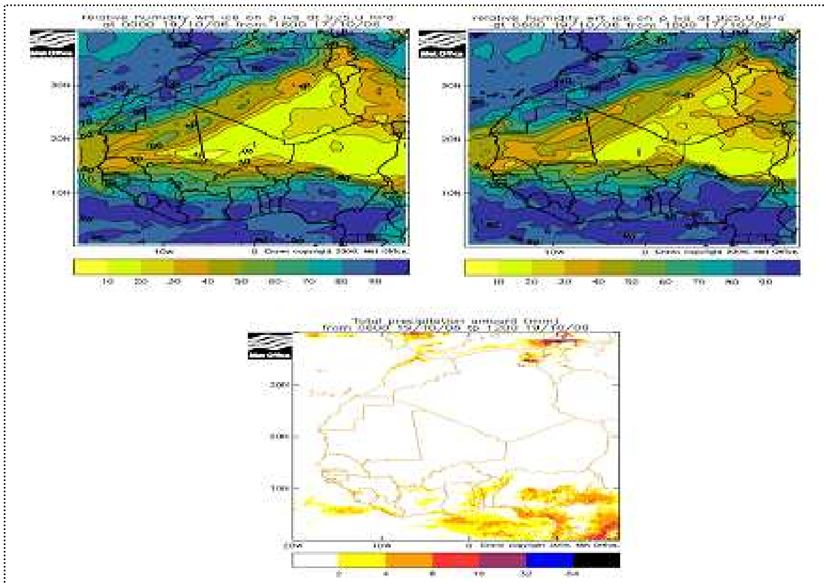


FIG. 6.4: Africa LAM forecasts of Relative Humidity (RH) T+6h forecasts for 00:00GMT (top left) and T+12h forecasts for 06:00GMT (top right) with accumulated precipitation T+6h forecasts (bottom) for 19 October 2006 (Source: http://www.metoffice.gov.uk/weather/africa/lam).

6.2.1.2 ECMWF model

The ECMWF NWP model has recently been upgraded from a spectral triangular truncation of TL319L60 (60km grid to point spacing at mid-latitudes) to TL511L60 (40km grid to point spacing at mid-latitudes). The model consists of dynamical, physical and coupled ocean wave components. The upgraded version of the model has a new cycle which includes a new formulation of convective entrainment and relaxation timescales with reduced free atmospheric vertical diffusion. The model also has a new soil hydrology scheme, new radiosonde temperature and humidity bias corrections. The model uses a 4-dimensional data assimilation scheme to estimate the actual state of the atmosphere. In the model, dynamical quantities, such as pressure and velocity gradients, are evaluated in spectral space, while computations involving processes such as radiation, moisture conversion, turbulence, are calculated in grid point space. This combination preserves the local nature of physical processes, and retains the superior accuracy of the spectra method for dynamical computation. The physical processes associated with radiative transfer, turbulent mixing and moist processes are active at scales smaller than the horizontal grid size. ECMWF model products are widely used for medium range forecasts, but in many African countries, especially in Nigeria, the model products are used for short range forecasts together with other NWP models (Palmer, 1997).

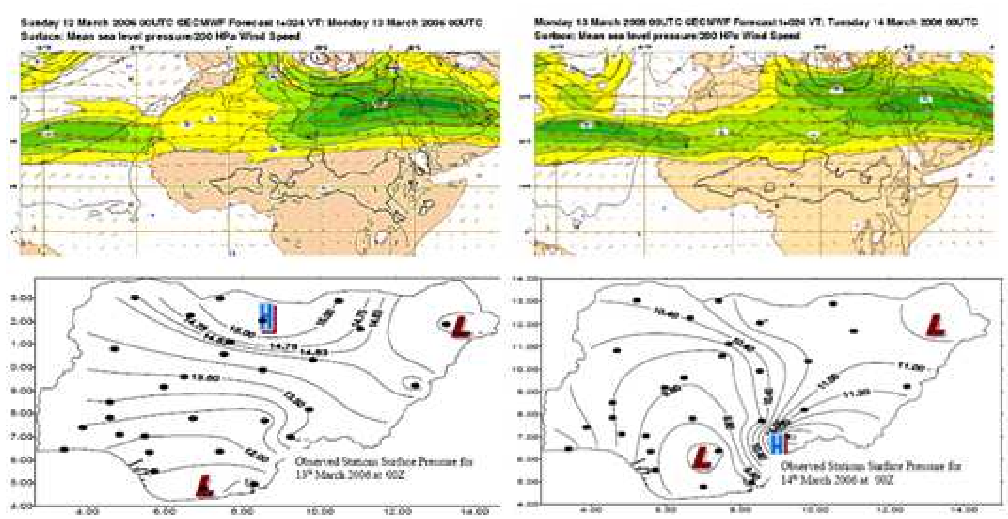


FIG. 6.5: ECMWF Mean Sea Level Pressure (MSLP) T+24h forecasts at 00:00GMT on 13 and 14 March 2006 (top, left and right, respectively) compared to observed MSLP across Nigeria (bottom, left and right) (Source: http://www.ecmwf.int/products/forecasts/d/charts/medium/deterministic/).

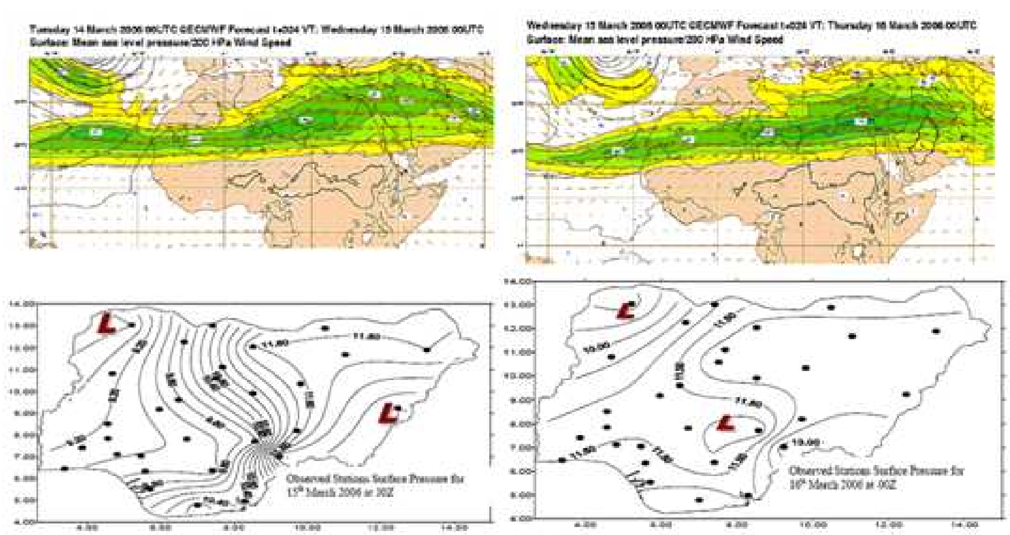


FIG. 6.6: ECMWF Mean Sea Level Pressure (MSLP) T+24h forecasts at 00:00GMT on 15 and 16 March 2006 (top, left and right, respectively) compared to observed MSLP across Nigeria (bottom, left and right). (Source: http://www.ecmwf.int/products/forecasts/d/charts/medium/deterministic/).

Results from an investigation carried out to evaluate the forecasting performance of some ECMWF products over Nigeria are presented in Figs. 6.5 and 6.6. Only verification results for ECMWF MSLP compared to actual MSLP across Nigeria at 00:00GMT on 13, 14, 15 and 16 March 2006 are considered.

Figs. 6.5 and 6.6 indicate that ECMWF MSLP forecasts from 13 to the 16 of March 2006 successfully captured the general spatial and temporal variability of MSLP over Nigeria, especially over the north eastern part of the country. Values are, however, slightly underestimated. These results further show that the model did not perform very well over the southern parts of Nigeria. It is necessary to mention here that ECMWF cloud cover output remains very important as a diagnostic tool for predicting coastal rainfall over Nigeria. More so, the 925hPa level winds and the 10m wind plots are very relevant in diagnosing the interaction between ocean and continental winds. The 850 and 700hPa level winds are also regarded as important for weather forecasts over the country.

6.2.1.3 NCEP/GFS model

The NCEP Global Forecast System (NCEP/GFS) is a NWP forecasting system with global spectral data assimilation. The NCEP/GFS model's horizontal resolution has been increased from May 2005 to approximately 35km (T382) for both the analysis and forecast products. The model has 64 horizontal levels in the vertical with its top at approximately 0.2hPa, and it has a hybrid (sigma / pressure) vertical coordinate. It contains a full suite of parameterized physics with an accompanying sea-ice and land-surface models. The NCEP/GFS model's structure is computationally efficient for use in the Earth System Modelling Framework (ESMF). NCEP/GFS forecast products are available for every six hours at 00:00, 06:00, 12:00 and 18:00GMT. The model's main time integration is leapfrog for nonlinear advection terms, and semi implicit for zonal advection of vorticity and moisture. The time step is 7.5 minutes for computation of dynamics and physics, except that full calculation of long-wave radiation is done once every 3 hours and shortwave radiation every hour (but corrections made at every time step for diurnal variations in the shortwave fluxes and in the surface upward long-wave flux).

As mentioned before, the NCEP/GFS model forecasts (Fig.6.7) are also downloaded from the Internet for use in weather forecasting at NIMET. The NCEP/GFS model's 850hPa temperature combined with MSLP forecast maps, as well as 10m winds combined with the 2m temperature forecast maps, as depicted in Fig. 6.7, are the two most commonly used NCEP/GFS model forecast maps in Nigeria. The 850hPa heights combined with the

MSLP forecast map provides information about the above-continental level (850hPa) temperature and MSLP distribution over the country. Experience reveals that for any location where the MSLP forecast is less than or equal than 1008hPa, and the 850hPa temperature less than or equal than 20℃, there is a strong possibility that convective weather, for example thunderstorms or at least strong winds might be experienced. The 10m winds combined with the 2m temperature maps are also used for forecast information about low level wind characteristics and 2m temperature distribution over the country. When ocean track winds are converging at low levels, forecasters are informed about the extent of the low level moisture influx into the country. These NCEP/GFS model forecast products have proved very useful, and to some extent, reliable in providing forecast guidance over Nigeria and in other part of the WS. However, the experience of the forecasters and the continuous improvements on the model products are still regarded as essential.

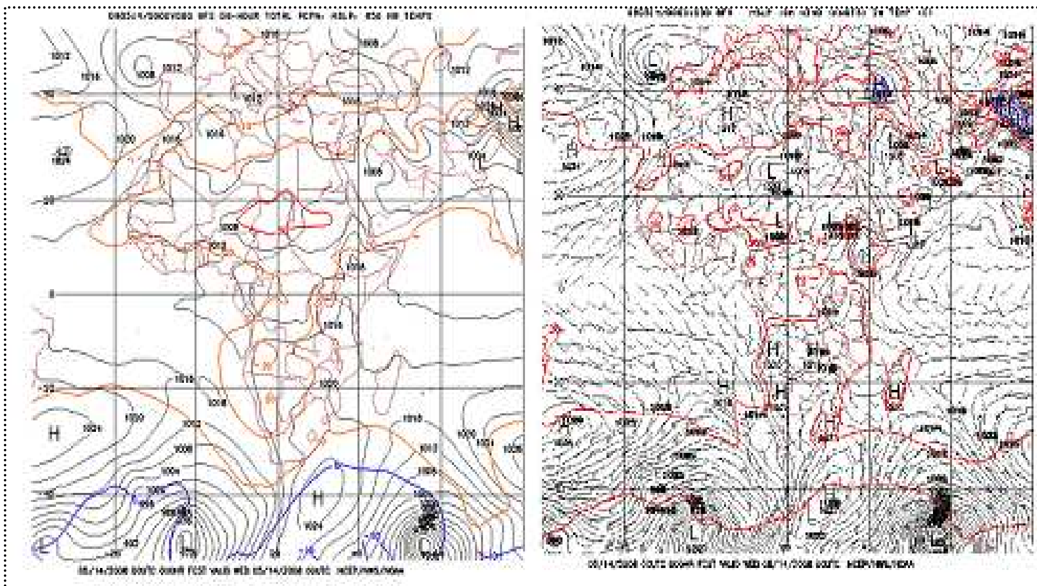


FIG. 6.7: Examples of NCEP/GFS 850hPa heights, combined with Mean Sea Level Pressure (MSLP) T+24h forecasts (left) and the 10m winds combined with 2m temperatures T+24h forecasts (right), as used to assist weather forecasters in their duties at the Nigerian Meteorological Agency (NIMET)
(Source: http://www.nco.ncep.noaa.gov/pmb/nwpara/analysis/index_africa.shtml)

6.2.1.4 ARPEGE and ALADIN model

As outlined in (a) above (under a typical weather forecasting process in NIMET), the ARPEGE and ALADIN models are also available for use in weather forecasting over

Nigeria. The ARPEGE model has a horizontal representation that is based on spectral harmonic functions, which transforms to a Gaussian grid in order to calculate the nonlinear quantities and physics. However, the Gaussian grid in the ARPEGE model is reduced longitudinally near the poles to avoid clustering of grids at Polar Regions – a known problem in global models. The ARPEGE model has code that allows for the spectral basis functions to be mapped con-formally from a geographical sphere to a transformed sphere with the poles and latitude-dependent local derivatives preserved. As such, the model's resolution may vary, and the centre of highest resolution may be located at any geographical point. The model dynamics are expressed in terms of the vorticity, divergence, temperature and specific humidity equations, and natural logarithm of the surface pressure. Land surface characteristics in the model are represented by specifying both the primary and secondary vegetation cover in each grid box.

The ALADIN model, however, is a limited area bi-spectral model with 31 horizontal levels in the vertical. The model uses initial conditions of both 12:00GMT and 00:00GMT from ARPEGE models. The ALADIN model allows for a zoom effect on the ARPEGE global model with a very small computer power requirement. The ALADIN model project was initiated by Metéo France with the aim to prepare and maintain a NWP system for smaller domains, with high spatial resolution, on the assumption that important meteorological events at those finer scales (such as local land and sea breezes) are mainly the result of the so called dynamical adaptation to the characteristics of the earth's surface. In Africa, ALADIN model simulations are performed at the Kingdom of Morocco National Weather Service.

Maps of 850hPa temperatures, RH and winds, as well as a map of precipitable water and CAPE (Fig. 6.8) are the most common ALADIN model forecast products used for weather forecasting at NIMET. Since the ALADIN model runs on a relatively high resolution over a limited area (extending over North and Equatorial Africa), most of the meso-scale weather systems over Nigeria are captured by the model. Local wind patterns, especially over high elevation points in Nigeria, are also clearly defined in most cases by the ALADIN 850hPa wind forecasts. The ALADIN CAPE forecast products are very useful for forecast diagnosis on the effectiveness of any identified trough or vortex at the 850hPa level over the country. For instance, when a vortex is located over a particular area, and the CAPE value over the same area is not significant (less than 1 500J/Kg), the forecaster knows to put less emphasis on the presence of the vortex and also knows that the vortex might not produce any significant storm or active weather over Nigeria.

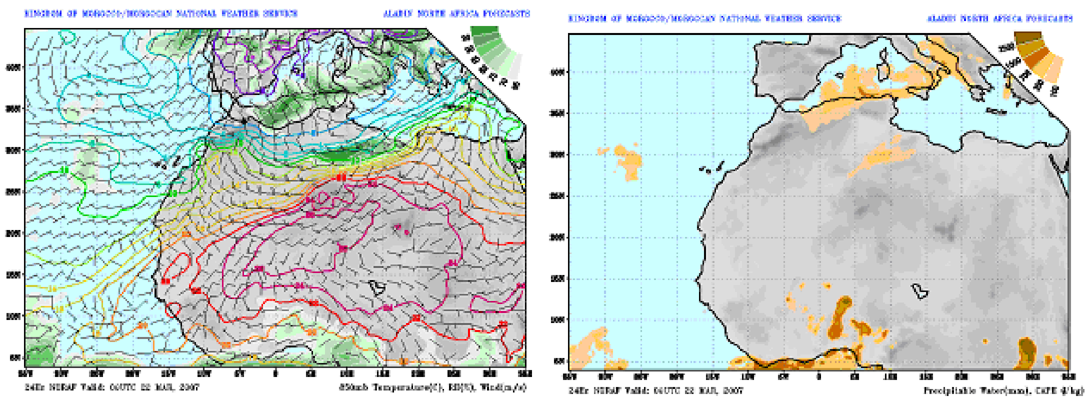


FIG. 6.8: ALADIN 850hPa temperature, Relative Humidity (RH) and winds for the T+24h forecast (left), and precipitable water and Convective Available Potential Energy (CAPE) for the T+24h forecast (right) over North and Equatorial Africa (Source: http://www.marocmeteo.ma/spn).

6.3 Weather forecasting shortcomings and needs in Nigeria

In Nigeria, and at most other NMHS in Africa, NWP model forecasts are not generated in-house, mainly due to a lack of adequate computer resources, and in many cases also because of limited knowledge of the code/theory of numerical modeling or technical aspects of NWP. As a result, available information from NWP model simulations provided by global modeling centers are currently downloaded, in conjunction with real time observations and satellite images, during the process of weather forecasting. Meso-scale convective weather systems are the most common weather events over Nigeria, which are often not well captured in the output of these NWP models. A major challenge to weather forecasters is therefore to decide whether meso-scale weather is correctly simulated by these models, or not. Since the models are not developed or simulated in-house very little can be done to adjust model code in order to improve simulations of Nigerian weather conditions. The long term experience and judgment of forecasters by using previous weather events forms an essential part in the interpretation of NWP model results. The WMO Severe Weather Forecasting Demonstration Project (SWFDP) recently implemented at Southern Hemisphere meteorological centers, is a good example of international efforts to improve weather forecasting skills and capabilities at African meteorological centers, especially for forecasting severe weather events. Hopefully, WMO might extend the training that forms part of the project in future to the West African sub-region. NIMET will benefit tremendously from such an initiative. The SWFDP aims to contribute to capacity-building and to help developing countries to access NWP results, and to make the best possible use of existing NWP products for improving warnings of hazardous weather conditions.

The availability of more accurate and near real time station observations is also very important in ensuring that accurate and timely weather forecasts are issued over Nigeria. Currently, most of the weather observatories in the country do not perform sufficiently. Most of the weather observation equipment needs to be upgraded and recalibrated to meet internationally acceptable standards. Although, very recently there have been conscientious moves by NIMET to improve on meteorological observation over the country. International cooperation might complement this effort. Effective data transmission from observation stations to the major forecasting offices is regarded as essential to complement available information from NWP models in order to issue better weather forecasts. Apart from national networks, the ability to provide locally observed data on time to global modelling centres via the GTS to be included in the analysis or initial conditions of running NWP is also regarded as very important. One can conclude by mentioning that the observation and communication network over Nigeria needs further improvement to allow for the country to optimally benefit from NWPs.

In Nigeria, the distribution of weather forecasts to end-users, such as agriculture, aviation, marine, hydrology, tourism, sports and many more, is an important process. As a matter of fact, it is the national responsibility of NIMET to prepare and make these weather forecasts available. For instance agriculture which is regarded as a key economic sector, need weather forecast information in an applicable and easily understandable format for application. Efforts should therefore be geared towards research and application studies that will further improve NIMET capacities to issue useful and relevant weather forecast information to different end-users. Acknowledged as some efforts by NIMET to meet these demands are the Public Weather Forecasts issued on TV (see Fig. 6.1), Radio and the Print Media; the Agro-meteorological, hydrological and marine bulletins etc. However, more funding and international cooperation should be harnessed by NIMET in order to sustain these efforts, especially since it is very relevant to economic growth in the country.

6.4 Summary

In summary, this chapter provided information on the current status and applications of NWP products for weather forecasting in Nigeria, and on how NWPs are incorporated in the day-to-day duties of weather forecasters. The sequence of events during a typical weather forecasting process at NIMET is discussed, also with the view to document a baseline approach for consideration by some weather centers in the WS. Characteristic features of some of the available NWP models that are used for operational weather forecasting in the country were discussed. Examples of NWP products are shown and discussed in order to introduce the reader to the type of maps and variables used during the weather forecasting process, and some emphasis was put on the evaluation of NWP maps generated by the Africa LAM and the ECMWF models over the country – although it was not an objective in this chapter to provide a detailed verification of the NWP models. Brief highlights on the shortcomings and needs of NIMET to ensure improved weather forecasting were also provided.

CHAPTER 7

SUGGESTED POST-PROCESSING METHODS

7.1 INTRODUCTION

The first and second objectives of this study are to verify Africa LAM NWPs against observations over the WS, and to determine the value of Africa LAM to be used by weather forecasters at NIMET in their daily duties. The third, and last, objective is to suggest possible statistical post-processing tools that might be of value for improving basic NWPs over the WS of Africa. As previously indicated, NWPs are not perfect, and it might be appropriate to employ statistical post-processing techniques, where historical forecast are compared to observations, in order to minimize systematic errors and biases (see discussion in chapter 5).

This chapter presents results from some suggested post-processing techniques as applied at each one of five (5) randomly selected meteorological point stations in Nigeria. The post-processing is applied over the same seasons as used in the Africa LAM NWPs (chapter 5), namely JFM, AMJ, JAS and OND. The variables considered are maximum and minimum temperatures (rainfall is excluded). The purpose of this chapter is to serve as background for researchers and weather forecasters who might be interested to use post-processing techniques in the WS in future.

7.2 SUGGESTED POST-PROCESSING TECHNIQUES

An important feature of statistical post-processing techniques is that historical observations are used, and compared with historical forecasts, in an effort to correct or minimize systematic errors and biases in NWPs (see Fig. 7.1).

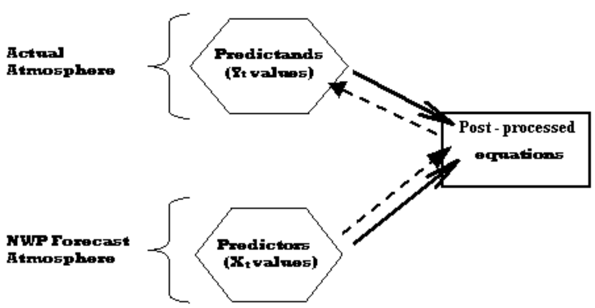


FIG. 7.1: A schematic flow diagram that illustrates a typical statistical post-processing approach. Solid arrows indicate information sources required in the development of the statistical forecasting equations, and dashed arrows indicate the information flow when the corrections are implemented (adapted from Wilks, 1995).

7.2.1 SIMPLE BIAS CORRECTION

In general, a simple bias correction might significantly improve output generated by a NWP model. The decomposition of MSE (equations 7.1 to 7.4), according to Wilks (1995), is used to determine how Africa LAM forecasts might be improved when applying a simple bias correction method:

$$MSE = B^2 + S_O^2 + S_F^2 - 2 S_O S_F r_{OF} \qquad (7.1)$$

where MSE = MSE between the model forecasts and observations

B = Mean bias of the model forecasts

S_O and S_F = standard deviations of the observations and forecasts

r_{OF} = product-moment correlation between forecasts and observations.

Replacing $F' = F_i - C$ to correct the model forecast bias at each of the station, gives

$$MSE' = (B - C)^2 + S_O^2 + S_F^2 - 2 S_O S_F r_{OF} \qquad (7.2)$$

where MSE' *is the MSE* between the corrected model forecasts and observations and C is the correction value. However, since S_O, S_F and r_{OF} are unaffected by a constant shift, minimizing MSE' implies that $C = B$. Equation (7.2) may therefore be written as

$$MSE' = S_O^2 + S_F^2 - 2 S_O S_F r_{OF} \qquad (7.3)$$

As suggested by Davis (2004), the percentage improvement by the bias-corrected forecasts relative to the NWP forecast is measured by:

$$Improvement\ (\%) = ((RMSE - RMSE')\ /RMSE) \times 100 \qquad (7.4)$$

7.2.1.1 Bias correction results

To quantify improvements that might be made to original Africa LAM forecasts of maximum and minimum temperatures over Nigeria, the MSE of the original model forecasts and of the bias-corrected forecasts are calculated (see equations 7.2 and 7.3). The percentage improvements (%IM) are also calculated by using equation 7.4. Results are as presented in Tables 7.1 and 7.2.

The bias correction results for maximum temperatures (Table 7.1) shows a very significant improvement of about 75% to the original Africa LAM forecasts over Lagos, especially during the JFM and OND seasons. When compared to the improvements introduced to the model forecasts at other stations, Lagos recorded a significantly high %IM throughout the year. The results shows very little improvement (%IM = 0) of Africa LAM maximum temperature forecasts at Abuja during the JFM season. Abuja also recorded a relatively low %IM in maximum temperature forecasts throughout the year, except for the JAS season when a 33% improvement was calculated. This suggests that the Africa LAM perform better in predicting maximum temperatures over Abuja, in comparison to other stations.

Furthermore, results in Table 7.1 suggest that for most of the stations in the north of Nigeria (i.e. Kano, Jos and Abuja), %IM to Africa LAM maximum temperature forecasts are lower than for stations over the south, except for Jos where a relatively high %IM were calculated. This could be due to the high elevation of Jos, in comparison to the other stations. Applying simple bias corrections could add more value to the original NWP model forecasts and could consequently lead to improved weather forecasts issued by NIMET.

Table 7.1: Africa LAM T+24h forecast output of maximum temperatures compared to that of the bias corrected forecasts. The RMSE is for the original model forecasts, RMSE' for the bias-corrected forecasts and %IM is the percentage forecast improvement achieved by introducing bias corrections.

	JFM			**AMJ**		
	RMSE	RMSE'	%IM	RMSE	RMSE'	%IM
Kano	2.53	2.01	21	4.01	2.07	49
Jos	6.10	3.19	48	5.98	3.79	37
Abuja	2.24	2.24	0	2.67	2.28	14
Lagos	4.88	1.20	75	3.62	1.40	61
PortHarcourt	4.52	2.20	51	3.58	2.10	41
	JAS			**OND**		
	RMSE	RMSE'	%IM	RMSE	RMSE'	%IM
Kano	2.04	1.88	8	3.12	2.66	15
Jos	3.49	2.03	42	4.26	2.63	38
Abuja	2.31	1.55	33	2.06	1.73	16
Lagos	3.25	1.28	61	4.00	1.18	71
PortHarcourt	2.63	1.73	34	3.76	1.75	53

Bias correction results for minimum temperatures (Table 7.2) generally indicate lower %IM to the original Africa LAM forecasts when bias corrections are applied - compared to the %IM of maximum temperatures (Table 7.1), especially at the southern stations. This suggests that the Africa LAM performs better when predicting minimum temperatures than when predicting maximum temperatures. Of significance is the obvious lower %IM values recorded in Abuja. This could imply that the Africa LAM has higher skill in predicting minimum temperatures in Abuja than at other stations. Results also show that Kano (located in the northern part of Nigeria) records the biggest %IM value of about 66% when compared with the %IM values recorded at other stations, except for the AMJ and JAS seasons. The JFM and OND seasons are seasons when the dry and cold northeasterly trade winds are prevalent over the north, and as such, minimum temperatures values are extremely lower than during the AMJ and JAS seasons. This suggests that Africa LAM minimum temperature forecasts over the northern part of Nigeria are more biased during the dry and cold harmattan season than during the rain seasons.

Table 7.2: Africa LAM T+24h forecast output of minimum temperatures compared to that of the bias corrected forecasts. The RMSE is for the original model forecasts, RMSE' for the bias-corrected forecasts and %IM is the percentage forecast improvement achieved by introducing bias corrections.

	JFM			**AMJ**		
	RMSE	RMSE'	%IM	RMSE	RMSE'	%IM
Kano	8.69	2.99	66	6.22	3.73	40
Jos	4.19	2.64	37	1.86	1.13	40
Abuja	3.12	2.97	5	1.40	1.38	1
Lagos	2.10	1.34	36	2.96	1.45	51
PortHarcourt	1.77	1.63	7	1.60	1.51	5
	JAS			**OND**		
	RMSE	RMSE'	%IM	RMSE	RMSE'	%IM
Kano	2.06	1.56	24	6.26	3.07	51
Jos	1.97	1.01	49	2.71	1.97	27
Abuja	1.02	0.96	6	2.61	2.47	6
Lagos	1.40	1.21	14	2.27	1.50	34
PortHarcourt	0.94	0.85	10	1.64	1.41	14

7.2.2 MODEL OUTPUT STATISTICS / UPDATEABLE MODEL OUTPUT STATISTICS

In order to reduce systematic errors and biases between observed maximum and minimum temperatures, and the corresponding Africa LAM output over the WS, Model Output Statistics (MOS) is also suggested as a valuable post-processing statistical technique. MOS is a statistical method that relates weather elements (predictands) to appropriate variables (predictors). In this study, the predictands are observed atmospheric variables, while the predictors are forecasts as generated by the Africa LAM. Predictors may also be obtained from NWPs, prior surface weather observations and geo-climatic information (Antolik, 2003; Kalnay, 2003; Wilks, 1995). MOS uses large multiple regression equations (Wilks, 1995; Breiman *et. al.,* 1997), but in this study, a simple linear regression approach is adopted where the same model variable was related to the predictand variable. MOS has the advantage of recognizing model predictability, removing some systematic model bias, providing optimal predictor selection, providing reliable probabilities and producing specific element forecasts. The MOS technique is regarded as a good standard for post-processing of NWP output when applied under ideal circumstances. The MOS technique is usually employed to incorporate NWP information into statistical weather forecasts, because of its capacity to directly include the influences of specific characteristics of different NWPs into the MOS regression equations (Glahn and Lowry 1972).

Although several years of archived NWP model data (generated by the same NWP model configuration) is required to develop a stable set of MOS equations, it is often difficult to obtain such long records, since most NWP models are in a state of internal development over time, meaning that the model configuration might change over time. To overcome this problem, other techniques, such as the Updateable MOS (UMOS) where relationships are continually re-derived using Kalman Filter, are proposed (see: Mao *et. al*., 1999). A typical application of the UMOS system is described by Wilson and Vallée (2002). Note that Ross (1986), Wilks (1995), Antolik (2003) and Kalnay (2003) argued that MOS equations could still be developed using data over limited time periods, since long time series of predictors from NWP models are not always available.

7.2.2.1 MOS Regression Analysis

MOS regression analysis has the advantage of recognizing model predictability, and thereby to provide the adjustment coefficients required to remove systematic model biases (Antolik, 2003; Kalnay, 2003). It maximizes inter-relationships between predictors and predictands (in this study Africa LAM NWPs and station observations). In essence, MOS linear regression summarizes the relationship between predictors and predictands as a single straight line which produces the least error in providing future predictands from given predictors. The MOS regression analysis therefore assumes that the relationship between predictands and predictors is a linear function, although this assumption does not often appear in reality. Another limitation of all the regression techniques is that despite of the fact that a regression line expresses the best prediction of the dependent variable (y), given the independent variable (x), nature is rarely perfectly predictable. As such, there is sometimes a noticeable variation between observed points and the fitted regression line. These limitations however do not greatly affect results from MOS regression techniques (Wilks, 1995).

In order to determine the relationship between two variables x and y, where y is the predicted value based on a given x, the linear regression equation is expressed as:

$$y = a + bx + e \qquad (7.5)$$

where

a	= regression intercept
b	= regression coefficient (or the slope)
e	= error or residual.

Here the regression coefficient b is calculated as:

$$b = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (7.6)$$

and the regression intercept is calculated as:

$$a = \bar{y} - b\bar{x} \qquad (7.7)$$

7.2.2.2 MOS Equations

The MOS equations in this study are suggested equations to be used as post-processing tool in order to improve Africa LAM forecasts over the WS. The MOS equation may be written as:

$$O_t = X_t + F_{ADJ} \qquad (7.8)$$

where

O_t	= the MOS forecast
X_t	= Africa LAM forecast pertaining to the future time t
F_{ADJ}	= the MOS adjustment term.

Equation (7.8) is derived by using equations (7.9 to 7.11). As stated by Wilks (1995), Glahn and Lowry (1972), the multivariate linear regression approach to MOS forecasting uses an equation of the form;

$$O_t = A + f_{MOS_1} {}^*X_{t_1} + f_{MOS_2} {}^*X_{t_2} + \ldots\ldots f_{MOS_n} {}^*X_{t_n} \qquad (7.9)$$

where O_t = the MOS forecast
A = the MOS regressions intercept
$f_{MOS's}$ = the MOS regression coefficients
$X_{t's}$ = the predictors (future model forecasts)
n = the number of predictors used in the equation

However, a simple linear regression approach is adopted in this study, since we are looking for MOS equations to adjust Africa LAM forecasts at selected Nigerian point stations and for selected variables (maximum and minimum temperatures) separately.

Hence, equation (7.9) becomes:

$$O_t = A + f_{MOS} * X_t \qquad (7.10)$$

An alternative MOS formulation was suggested by Mao *et. al.* (1999), where the MOS regression is used to forecast corrections rather than forecast the particular value directly. This is referred to as the regression-based correction (F_{ADJ}) to NWP model forecasts (Mao *et. al.*, 1999; Neilley *et. al.*, 2004).

Equation (7.10) is therefore re-written as:

$$O_{stn} - X_{nwp} = A + f_{MOS} * ß \qquad (7.11)$$

where O_{stn} = archived observations
X_{nwp} = archived raw model forecasts
ß = average anomalies from the mean of original model forecasts, or

$$ß = \text{Average}\,(X_{nwp} - \overline{X}_{nwp}) \qquad (7.12)$$

The approach of Mao *et. al.* (1999) adopted in equation (7.11) regresses historical model forecast errors against a set of model parameters. However, in this study only one model parameter is considered, namely the regression of $O_{stn} - X_{nwp} - A_e$ against ß, where A_e is the negative of the mean model bias.

Substituting $F_{ADJ} = O_{stn} - X_{nwp}$ into equation (7.11), where F_{ADJ} is the MOS adjustment, yields

$$F_{ADJ} = A + f_{MOS} * ß \qquad (7.13)$$

The term A in equation (7.13) represents the negative of the mean model bias (A_e), and f_{MOS} is the MOS regression coefficient (calculated from equation 7.7). These two terms are treated and computed separately. Equation (7.13) therefore becomes;

$$F_{ADJ} = A_e + f_{MOS} * ß \qquad (7.14)$$

7.2.2.3 The MOS results

For each of the seasons (JFM, AMJ, JAS and OND), and for each of the five (5) selected Nigerian point stations, the MOS adjustment terms and the corresponding MOS equations suggested above are listed in Tables 7.3 to 7.6. F_{ADJ} could be computed and automatically implemented as part of the operational MOS forecast procedure. However, since most of the NMHSs in Africa have limited computer resources, station dependent correction biases could be obtained from the result tables and manually incorporated into operational weather forecasting.

Table 7.3: MOS correction terms used to formulate the MOS equations required for adjusting Africa LAM T+24h forecasts of maximum temperatures. A_e is negative of the mean model bias, f_{MOS} the MOS regression coefficient and ß the average anomaly from the mean of model forecasts.

	JFM			**AMJ**		
	A_e	f_{MOS}	ß	A_e	f_{MOS}	ß
Kano	-1.53	11.37	-0.0033	-3.44	3.48	-0.0330
Jos	-5.20	28.71	0.0044	-4.63	15.34	0.0000
Abuja	-0.10	33.43	0.0011	-1.39	17.16	0.0022
Lagos	4.73	23.97	0.0111	3.34	-3.26	-0.0022
PortHarcourt	3.94	46.63	-0.0011	2.90	10.85	-0.0044
	JAS			**OND**		
	A_e	f_{MOS}	ß	A_e	f_{MOS}	ß
Kano	-0.79	18.20	0.0048	1.62	20.79	0.0033
Jos	-2.84	7.50	0.0000	-3.35	21.84	-0.0033
Abuja	1.72	23.48	-0.0030	1.11	15.44	0.0038
Lagos	2.99	26.02	0.0074	3.83	-5.55	-0.0016
PortHarcourt	1.99	10.69	0.0044	3.32	2.75	0.0044

Table 7.4: The MOS equations required to adjust Africa LAM T+24h forecasts of maximum temperatures over the five (5) selected Nigerian meteorological stations for the JFM, AMJ, JAS and OND seasons.

	JFM	AMJ	JAS	OND
Kano	$O_t = X_t – 1.57$	$O_t = X_t – 3.55$	$O_t = X_t – 0.71$	$O_t = X_t + 1.68$
Jos	$O_t = X_t – 5.07$	$O_t = X_t – 4.63$	$O_t = X_t – 2.84$	$O_t = X_t – 3.42$
Abuja	$O_t = X_t – 0.06$	$O_t = X_t – 1.35$	$O_t = X_t + 1.65$	$O_t = X_t + 1.17$
Lagos	$O_t = X_t + 5.00$	$O_t = X_t + 3.35$	$O_t = X_t + 3.18$	$O_t = X_t + 3.84$
PortHarcourt	$O_t = X_t + 3.89$	$O_t = X_t + 2.85$	$O_t = X_t + 2.04$	$O_t = X_t + 3.34$

Table 7.5: MOS correction terms used to formulate the MOS equations required for adjusting Africa LAM T+24h forecasts of minimum temperatures. A_e is negative of the mean model bias, f_{MOS} the MOS regression coefficient and ß the average anomaly from the mean of model forecasts.

	JFM			**AMJ**		
	A_e	f_{MOS}	ß	A_e	f_{MOS}	ß
Kano	8.16	15.23	-0.0022	4.98	25.27	-0.0033
Jos	-3.26	3.21	0.0056	-1.48	10.74	0.0022
Abuja	-0.97	1.86	-0.0033	0.24	5.68	0.0055
Lagos	-1.61	0.90	0.0056	-2.58	1.17	0.0011
PortHarcourt	-0.67	-16.94	0.0022	-0.52	9.45	0.0033
	JAS			**OND**		
	A_e	f_{MOS}	ß	A_e	f_{MOS}	ß
Kano	1.35	21.19	-0.0035	5.46	15.00	0.0005
Jos	-1.70	16.89	0.0000	-1.86	6.30	-0.0000
Abuja	0.37	19.61	0.0009	-0.86	7.28	-0.0000
Lagos	-0.72	15.10	0.0035	-1.71	21.26	0.0038
PortHarcourt	-0.39	19.74	0.0009	-0.83	7.16	-0.0011

Table 7.6: The MOS equations required to adjust Africa LAM T+24h forecasts of minimum temperatures over the five (5) selected Nigerian meteorological stations for the JFM, AMJ, JAS and OND seasons.

	JFM	AMJ	JAS	OND
Kano	$O_t = X_t + 8.12$	$O_t = X_t + 4.90$	$O_t = X_t + 1.27$	$O_t = X_t + 5.46$
Jos	$O_t = X_t - 3.24$	$O_t = X_t - 1.46$	$O_t = X_t - 1.70$	$O_t = X_t - 1.86$
Abuja	$O_t = X_t - 0.97$	$O_t = X_t + 0.27$	$O_t = X_t + 0.39$	$O_t = X_t - 0.86$
Lagos	$O_t = X_t - 1.61$	$O_t = X_t - 2.58$	$O_t = X_t - 0.67$	$O_t = X_t - 1.63$
PortHarcourt	$O_t = X_t - 0.70$	$O_t = X_t - 0.50$	$O_t = X_t - 0.37$	$O_t = X_t - 0.83$

The results listed in Tables 7.3 to 7.6 suggest that the MOS equations proposed in this study might be useful in adjusting Africa LAM forecast biases over Nigeria, since most of the F_{ADJ} values used in formulating the MOS equations (Table 7.4 and 7.6) are relatively close to the mean model biases. However, there are some marginal differences between the adjustment values and mean model biases, which also suggest that one also needs to be cautious when considering these MOS equations for application in weather forecasting. Also important to note is that the MOS equations were derived from seasonally stratified datasets, and as such, the correction coefficients may not directly be applicable to daily forecasting operations. Nevertheless, this section gave some valuable background on the formulation of general MOS equations and the advantages of using MOS. A comprehensive study to ensure an understanding of MOS is recommended before the consideration of MOS as a post-processing tool in NWP to improve weather forecasts.

7.2.2.4 Comparison between the bias correction and the MOS results

Graphs of the RMSEs of the original Africa LAM forecasts, the bias corrected forecasts and those of the MOS forecasts are presented in this section. These graphs (Figs. 7.2 and 7.3) are used to compare the benefits that the two statistical post-processing techniques discussed above hold in improving the original Africa LAM forecasts of maximum and minimum temperatures over the five selected meteorological stations in Nigeria.

Fig. 7.2 shows that the RMSE' and the $RMSE_{mos}$ values for maximum temperatures are almost the same throughout the year, especially at the southern stations (Lagos and PortHacourt). Of significance is that both the post-processing techniques resulted in improvements to the original model maximum temperature forecasts, as depicted by the consistently lower RMSE' and $RMSE_{mos}$ values when compared to the RMSE values - with the exception of Kano during the JFM season, where the bias correction techniques had failed to improve the original forecast. At Jos and Abuja (northern part of Nigeria), results indicate that MOS had a higher skill in improving original maximum temperature forecasts than bias corrections, especially during the JFM, AMJ and OND seasons.

Fig. 7.2 suggests that the best maximum temperature forecast improvement by both post-processing techniques was noted throughout the year at Jos and Lagos. This is supported by the large differences recorded between the RMSE of the original Africa LAM forecast, the RMSE' of the bias corrected forecasts and the $RMSE_{mos}$ for the MOS forecasts over Jos and Lagos, especially during the JFM, JAS and OND seasons.

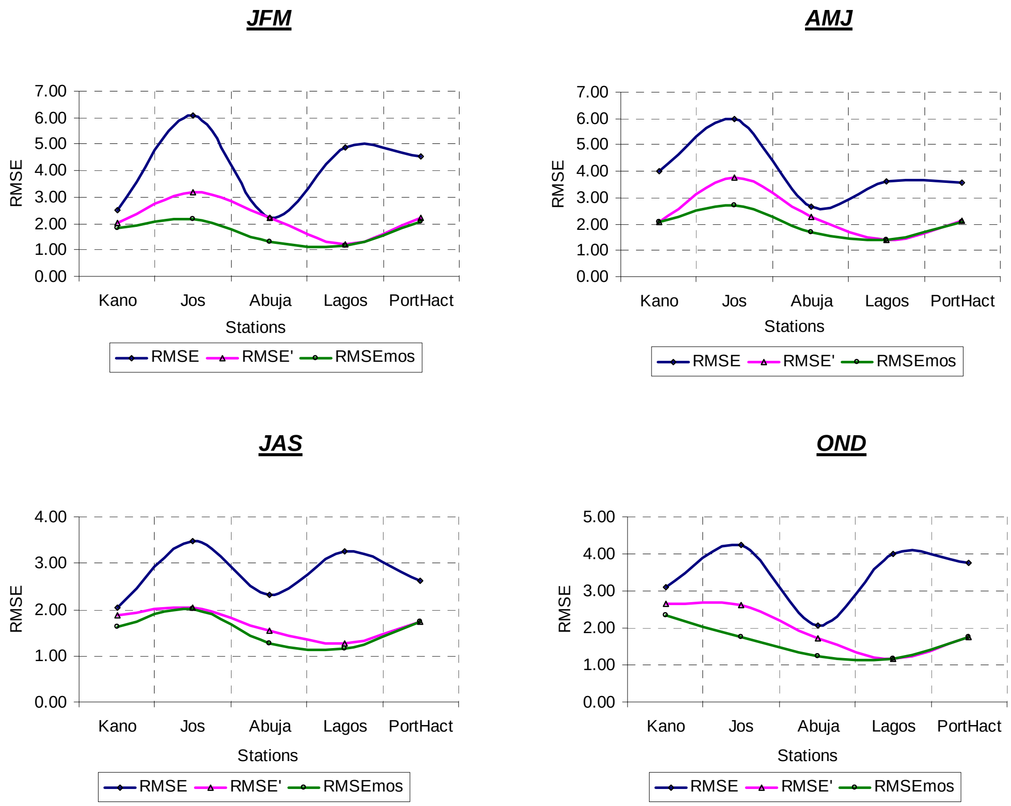


FIG. 7.2: Root Mean Squared Errors (RMSEs) of the Africa LAM T+24h forecast output of maximum temperatures compared to that of the bias corrected and MOS forecasts. RMSE is for original model forecasts, while RMSE' and $RMSE_{mos}$ are for the bias-corrected and MOS forecasts, respectively.

Fig 7.2 also suggests that better maximum temperature forecasts could be generated by post-processing techniques during the peak of the rain season (JAS) towards the end of the rain season (OND) over Jos and Lagos. It is also evident that the best MOS modification to the original NWP of maximum temperature over Kano appears at the onset of the rain season (AMJ), compared to other seasons. Over the southern stations of Nigeria (Lagos and PortHarcourt), the RMSE error difference between Africa LAM forecasts and that of the MOS forecasts in Fig. 7.2 indicates higher values during the JFM and OND seasons. This implies that better MOS modification is expected in the dry seasons of JFM and OND.

For minimum temperature forecasts (Fig. 7.3), results indicate that the MOS forecasts are better than the bias corrected forecasts over Kano, especially during the AMJ and OND seasons. The result also shows that in Abuja, both post-processing methods could not introduce any meaningful improvements to the original Africa LAM forecasts, since RMSE values are almost the same as that of the original Africa LAM forecasts throughout the year. This suggests that the model performs better in predicting minimum temperatures over Abuja, in comparison to the other stations. It is important to mention that with the exception of Kano, where the model RMSE value appears very large, model errors in predicting minimum temperatures were minimal. In comparison to maximum temperature forecasts (Fig. 7.2), the model predicted minimum temperatures much better than maximum temperatures.

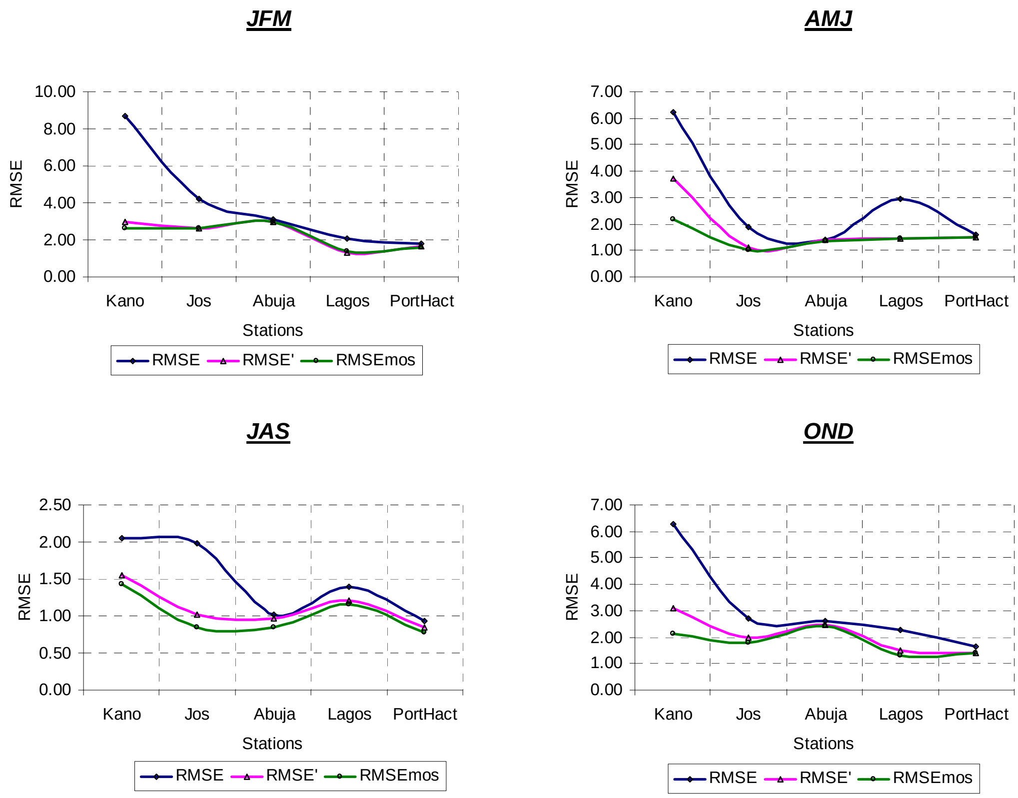


FIG. 7.3: Root Mean Squared Errors (RMSEs) of the Africa LAM T+24h forecast output of minimum temperatures compared to that of the bias corrected and MOS forecasts. RMSE is for original model forecasts, while RMSE' and $RMSE_{mos}$ are for the bias-corrected and MOS forecasts, respectively.

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The RMSE error difference between Africa LAM forecasts, the MOS and the bias corrected forecasts are depicted in Fig. 7.3. It is indicated that the best improvement in minimum temperature forecasts by MOS over Jos (northern station) should be expected during the JAS season, which is during the peak of rainfall over the northern parts of the WS. The MOS method, however, could not contribute much improvement in minimum temperature forecasts over most of the other stations in comparison to the bias correction method. The noticeably low RMSE differences between the model forecasts and the postprocessed forecasts during the JFM, JAS and OND seasons over Abuja, Lagos and PortHarcourt might be due to the fact that the model forecast error in predicting minimum temperatures was the lowest during these seasons.

Both Figs. 7.2 and 7.3 indicate that adjustments introduced to Africa LAM forecasts by using bias correction and MOS post-processing techniques often brought forecasts closer to what have been observed – note the reduced RMSE values. This means that systematic errors and biases in maximum and minimum temperatures forecasts by the Africa LAM could be reduced when using these post-processing techniques.

7.2.3 ENSEMBLE PREDICTION SYSTEM

The introduction of the technique of Ensemble Prediction System (EPS), which involves the use of more than one NWP model or the generation of more than one NWP simulation by the same model but with different initial conditions, has resulted in noticeable improvement in weather forecasting (Tracton and Kalnay, 1993; Toth and Kalnay, 1993; Molteni *et. al.,* 1996; Hamill and Colucci, 1997). EPS techniques have benefits since the atmosphere is sensitive to initial conditions in that small error in the initial conditions might grow exponentially during model integrations (Lorenz, 1993). Since atmospheric observations are limited, it remains impossible to start a mathematical atmospheric model in exactly the same state as the real atmosphere. Deterministic forecasts of future atmospheric behavior will therefore always be uncertain. The EPS tends to predict the probability of future weather conditions (Wilks, 1995). EPS is currently one of the most commonly used methods to generate probability forecasts from NWPs. The EPS is a relatively new operational weather forecasting tool that allows for more rapid and scientifically based comparison of multiple NWP model forecasts.

Each individual forecast within a particular EPS is known as an ensemble member. Ensemble members run from analyses that are slightly adjusted to reflect initial condition uncertainty - called ensemble perturbations. The ensemble forecast that is (usually) made from an interpolated higher resolution analysis, with unperturbed model (no stochastic physics or other parameter variations) is called an ensemble control. There are quite a few assumptions usually made when applying the EPS in forecasting. For example, when an ensemble member's forecast is being examined at a given location, the forecast value is assumed to be representative of an independent sample from the underlying true forecast Probability Density Function (PDF) at that location. Hence, with an infinite set of ensemble forecasts, the relative frequency would converge to the PDF. Again within an EPS, a perfect forecasting model is assumed and the unknown true evolution of the atmospheric state is considered a plausible member of the ensemble. Under these assumptions, each forecast will have independent and identically distributed errors (Hamill and Colucci, 1997).

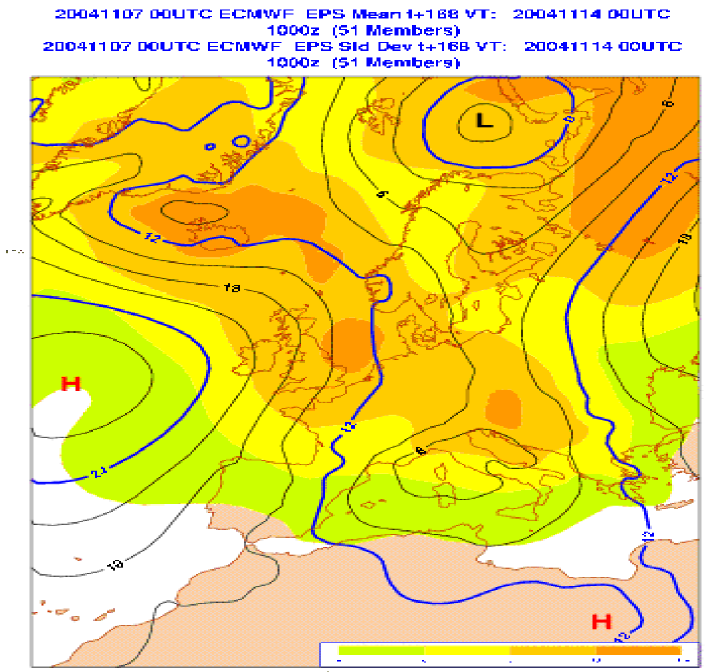

FIG. 7.4: An example of an ECWMF Ensemble Prediction System (EPS) forecast. Solid contours represent the ensemble mean and the shaded contours represent the ensemble spread. Areas with high ensemble spread values indicate areas of high forecast uncertainties.

An EPS is said to be a perfect ensemble (in a perfect reliability sense) when the EPS is statistically consistent with observations, meaning that for a perfectly reliable EPS, the observations (or verifying analysis) should not be statistically distinguishable from the forecasts of each of the ensemble members. Most of the EPS verification tools are specifically developed and designed to evaluate the statistical consistency of the ensemble forecasts, which in most cases, reveals in considerable more detail the nature and causes of statistically inconsistent behavior of the EPS. These ensemble-based measures provide important information necessary for improved probability forecasts (Jolliffe and Stephenson, 2003). In general, reliability and resolution are the two main attributes of any forecasting systems. However, in verifying probability and ensemble forecasts, there are some limitations. One of such limitations is that probability forecasts can only be evaluated on a statistical (and not individual) basis using a sufficiently large sample of past forecasts and matching observations. Additional limiting factors include the presence of observation error, and the use of ensembles of limited size (Jolliffe and Stephenson, 2003).

In order to assist operational weather forecasters in the WS to understand the potential of EPS products, some graphical representation methods and performance measures of EPS are discussed below (note that much of this section is adopted from Jolliffe and Stephenson, 2003; p156 – 161);

7.2.3.1 Ensemble Mean and Spread

Ensemble mean and spread are measures used to assess the most likely outcome and uncertainty in EPS. A small spread indicates low forecast uncertainty and a large spread indicates high forecast uncertainty. The ensemble spread shows how far into the forecast the ensemble mean can provide informative values to forecasters in order to express forecast uncertainties. When the verifying analysis (or observation) is statistically indistinguishable from the ensemble members, its mean distance from the mean of the ensemble members (ensemble mean) must be equal to the mean distance of the individual members from their mean (ensemble standard deviation or spread) – see Buizza (1997). "*For a perfectly reliable EPS, the spread of the ensemble forecasts is equal to the error in the ensemble mean. For such systems the spread can also be considered as a measure of resolution and therefore forecast skill in general. For example, an ensemble with a lower average ensemble spread can more efficiently separate likely and unlikely events from each another, and therefore contains more information. It is worth mentioning that the skill of the ensemble mean forecast is often compared to that of a single control forecast obtained by starting of with the best initial conditions (control analysis). Once non-linearity becomes pronounced, the mean of an ensemble that properly describes the case-dependent forecast uncertainty provides a better estimate of the future state of the system than the control forecast in itself. In good EPS, the ensemble mean error should therefore be equal to, or less than, the error of the control forecast. It follows that in a reliable ensemble, the spread of the ensemble members around the mean will be less than that around the control forecasts.*" (Jolliffe and Stephenson, 2003; p156 – 157)

7.2.3.2 Epsgrams and Spaghetti Diagrams

EPS information at individual grid-point locations are sometimes displayed using the probabilistic meteogram (Epsgram), which indicates the time evolution of a given parameter by all the ensemble members. The spread is indicated by the range of the forecast values. An Epsgram therefore provides discrete probability information sufficient for many applications. The spaghetti diagrams are maps where an isoline for each of the members is plotted. This diagram provides a very efficient way of summarizing EPS information. However, care must be taken when interpreting information from spaghetti diagrams since they are sensitive to gradients of model forecast fields. For instance, over areas with weak contour gradients they easily show large isoline spread, even when the situation is highly predictable. On the other hand, in areas with strong gradients, spaghetti diagrams have the tendency of showing small isoline spread even when there are important forecast variations.

7.2.3.3 Equal Likelihood Frequency Plot

EPSs are designed to generate a finite set of forecast scenarios. *"When ensemble forecasts are used to define forecast probabilities, it is important to know if all ensemble members can be treated in an undistinguishable fashion. This can be tested by generating a frequency plot showing the number of cases (accumulated over space and time) when each member was the forecast closest to the verifying diagnostic. Information from such a frequency plot can be useful as to how the various ensemble members might be used in defining forecast probability values. Equal frequencies indicate that all ensemble members are equally likely and can be considered as independent realizations of the same random process, indicating that the simple procedure for converting ensemble forecasts into probabilistic information is applicable. For short forecast lead-times characterized by too large ensemble spread, flat equal likelihood values at intermediate lead-times are indicative of proper ensemble spread and hence good reliability".* (Jolliffe and Stephenson, 2003; p157)

7.2.3.4 Analysis Rank Histogram

When all ensemble members are equally likely and statistically indistinguishable from nature – meaning that the ensemble members and the verifying observation are mutually independent realizations of the same probability distribution, then according to Jolliffe and Stephenson (2003), each of the m*+1* intervals defined by an ordered series of *m* ensemble members, including the two open ended intervals, is likely to contain the verifying observed value. Anderson (1996) further suggested constructing a histogram by accumulating the number of cases over space and time when the verifying analysis falls in any of the *m+1* interval. *"Such a graph is often referred to as analysis rank histogram. Reliable or statistically consistent ensemble forecasts lead to an analysis rank histogram that is close to flat, indicating that each interval between the ordered series of ensembles forecast values is likely. An asymmetrical distribution is usually an indication of bias in the mean of the ensemble forecasts while a U or inverted U-shape distribution may be an indication of a negative or positive bias in the variance of the ensemble, respectively" (Jolliffe and Stephenson, 2003; p159)*. Whenever any operational EPS exhibits U-shaped analysis rank histograms, it implies that the verifying analysis more often falls outside of the cloud of ensemble forecasts than one can expect by chance, given the finite size of the ensemble. In other words, the ensemble forecasts underestimate the true uncertainty in the forecasts (Adapted from Jolliffe and Stephenson, 2003; p159).

7.2.3.5 Time Consistency Histogram

"The concept of rank histograms can be used not only to test the reliability of ensemble forecasts, but also to evaluate the time consistency between ensembles issued on consecutive days. Given a certain level of skill, an ensemble system that exhibits less change from one issuing time to the next may be of more value to some users. When constructing an analysis rank histogram, in place of the verifying analysis one can use ensemble forecasts generated at the next initial time. The time consistency histogram will then asses whether the more recent ensemble is a randomly chosen subset of the earlier ensemble set. Ideally, one would like to see that with more information, more recently issued ensembles narrow the range of the possible earlier indicated solutions, without shifting the new ensemble into a range that has not been included in the earlier forecast distribution. Such 'jumps' in consecutive probabilistic forecasts would result in a U-shaped time consistency histogram, indicating sub-optimal forecast performance. While control forecasts, representing a single scenario within a large range of possible solutions, can exhibit dramatic jumps from one initial time to the next, ensembles typically show much smoother variations in time" (Jolliffe and Stephenson, 2003; p161).

7.2.4 Multi-model forecasting / poor man's ensemble system

As mentioned earlier, it is currently difficult for most of the meteorological centers in Africa to run NWP models in-house due to a lack of computer resources and limited knowledge in the field of numerical modeling. Majority of these NMHSs therefore only extract and subjectively interpret available information from NWP model outputs when issuing daily weather forecasts. In a way to improvise the usual EPS, forecasters manually compare model results as much as available from different global modeling centers in order to build confidence in the available model results. If all the models suggest approximately the same solution, forecasters confidence in the NWP model output would be high, but if all shows different prognoses, the confidence would rapidly diminish. This improvisation of the usual EPS commonly referred to as the poor man's ensemble or multi-model forecasting is generally acceptable and practiced in Africa, especially over the WS.

7.3 Summary

In this chapter, statistical post-processing techniques such as simple bias corrections, MOS and Ensemble Forecasting Systems are suggested and discussed. These post-processing methods are useful, and sometimes necessary, to improve systematic errors and biases in NWPs. Some post-processing technique results were discussed through application at five selected Nigerian meteorological stations and during the JFM, AMJ, JAS, and OND seasons. Graphs of the RMSEs between the original African LAM forecasts, the bias corrected forecasts and the modified MOS forecasts were used to demonstrate the potential of these post-processing techniques to improve NWPs. From the results it became evident that both of the bias correction and MOS methods generally produced lower RMSE when compared to the RMSE of the Africa LAM (illustrated in Figs. 7.2 and 7.3) and therefore have value in operational forecasting. As earlier mentioned, information given in this chapter is expected to guide scientists and weather forecasters in the WS who are interested to further explore these post-processing techniques in order to improve on weather forecasting in their respective regions.

CHAPTER 8

CONCLUSIONS

This dissertation that addresses weather forecasting and weather forecasting tools over the WS had three principle objectives.

- The first objective was to examine the performance of the Africa LAM developed by the UK Met Office against point observations and against regional averages of meteorological variables over the WS of Africa by using internationally recognized verification algorithms.

- The second objective was to investigate if the Africa LAM has the potential to be employed as NWP model to assist operational weather forecasters in their duty to issue more accurate forecasts.

- The third objective was to suggest possible statistical post-processing tools that might be of value for improving basic NWPs over the WS of Africa.

The study was therefore structured to not only determine the performance of the Africa LAM over the WS, but also to determine the potential of the model to be used as NWP model over the WS, which include the suggestion of post-processing techniques that could improve weather forecasts over the region. This was achieved by firstly verifying rainfall as well as maximum and minimum temperature forecasts generated by the Africa LAM against observations over the study domain of the WS in Africa. Results of the verification statistics were presented and discussed in chapter five. These results provide a baseline for the performance of the model from where improvements by some of the suggested statistical post-processing techniques could be considered, or from where the model could be developed at the UK Met Office in order to generate more accurate NWPs. In order to explore the possibility of employing some statistical post-processing techniques in order to improve on forecasting errors generated by the Africa LAM over the WS, careful attention was given to ensure the incorporation of different relationships between predictors and predictands at different periods of the year. The study had also examined weather forecasting activities at NIMET with the specific aim to determine how NWPs are incorporated in the decision making process before weather forecasts are issued.

In agreement with previous findings (Glahn, 1985; Stanski *et. al*., 1989; Kalnay, 2003; Jolliffe and Stephenson, 2003), results captured in the dissertation had demonstrated that NWP model simulations, such as simulations by the Africa LAM, are subject to systematic errors and biases. An important reason for this is because the non-linear flow dynamics and complex physics of the atmosphere can not yet be resolved in the code of these models. Apart from these constraints, incomplete initial conditions and smoothed boundary forcing further contribute to the propagation of errors in NWP model simulations. Major errors in the development of rainfall systems are difficult to notice and might negatively affect the confidence that a forecaster might have in a NWP model, although, a systematic error in surface temperature due to a mismatch between model and actual altitude at point locations are more readily corrected. Despite of these shortcomings, NWP models remains very useful, and their products still serves as an important aid in all modern weather forecasting bodies. A lot of research and development is currently taking place in efforts to improve output results from NWP models.

One approach that could improve NWP output is to compare NWPs with what have been observed in history, and to use that as an aid to try and, at least, reduce biases in NWPs. Such a process would involve post-process statistics. Hence stochastic methods, such as bias corrections and MOS, have become very useful, and have even become a necessary part of weather forecasting (Wilks, 1995; Kalnay, 2003) at meteorological centers. While the improvement, interpretation and extension of NWP products are a priority at many national meteorological centers in Europe and other developed countries (Lemcke and Kruizinga, 1988; Carter *et al.*, 1989), very little has been done to make NWP results more usable in Africa. In this dissertation selected post-processing techniques have been introduced in an effort to demonstrate how the impact of systematic model errors and biases in the Africa LAM could be reduced. By using both NWP output from the Africa LAM and observations over the period January 2005 to December 2006, MOS equations were derived that might be used to improve NWP results from Africa LAM NWPs. Such improvements might contribute to improved weather forecasting products over Nigeria and the WS, since the principle researcher of this study is a Weather Forecaster at the NIMET, and he might implement similar post-processing techniques for application at NIMET on completion of his MSc studies.

Since the provision of more accurate and reliable weather forecasts to the public, government and other users remains one of the greatest challenges of most NMHSs of Africa, it is required to enhance and strengthen their weather forecasting capacities.

Although, the WMO through its various scientific and technical programmes and network of regional training and specialized centers offer some support in this regard, more active regional collaborative training efforts between NMHSs of Africa should be encouraged. This would involve the development of conceptualized training programmes to address the basic fundamental issues relating to the improvement of weather forecasting capacity across Africa, especially in equatorial Africa and the WS. This regional training collaborative approach, as is being proposed here is expected to contribute significantly to development in the regions indicated.

Weather, climate and water-related disasters have been known to account for more than 90% of disasters worldwide, and the trend is growing, most probably because of an increase of population and infrastructure, and maybe because of greenhouse warming. Despite of this, most of the NMHSs in Africa that are supposed to issue the early warnings are inadequately equipped and poorly funded. Most of these NMHSs operate with little infrastructures and poor training and research facilities. Increased financial support to develop and strengthen these NMHSs, especially by way of promoting and encouraging relevant training and research, should be seen as an investment aimed at reducing the cost of disasters – human mortalities as well as infrastructure damage. Governments and other funding institutions should be encouraged to increase their contributions to the implementation of national, regional and international initiatives aimed at establishing and strengthening mechanisms that would help to improve the weather forecasting capacities of these NMHSs, from which NWP is an important component.

NMHSs in Africa should be strategically well-positioned to make weather related information readily available to policy makers and the general public in an easily understandable manner. Without the appropriate use of available knowledge and information on weather, climate and water, sustainable development efforts of governments would be undermined. Improved weather forecasts information, must therefore be incorporated into the development policies and strategies of all governments because of the influence of weather on society wealth and economic growth – and therefore even on political stability. However, much remains to be done to link advances in weather forecasting to policy and action. Science can improve weather forecasting capacity when integrated into public policy, it can help alleviate poverty and prevent the burden of underdevelopment from growing. Research studies that could further contribute to the provision of improved weather forecasts (such as done in this study) should therefore be encouraged.

APPENDIX A

THE MATLAB SCRIPT USED IN EXTRACTING THE AFRICA LAM TEMPERATURE AND RAINFALL DATA

```
*************************************************************************
This MATLAB script extracts required parameters from the generated NetCDF
files of the Africa LAM
*************************************************************************
% input: netcdf file, latlon.txt, stime
%
clear all;
close all;
N=1:111;
M=1:278;
count=0;
for i=1:12;
    count=count+1;
    dom=num2str(i,'%2i');
    rainA_2005_05.day(count).rain=getnc(['max',dom,'oct2006'],'temp');
    AA=rainA_2005_05.day(count).rain;
     rain_2005_05.day(count).time=timenc(['max',dom,'oct2006'],'t');
     BB=rain_2005_05.day(count).time;
      I=find(BB(:,4)==18);
      MM6.day(count).rain(:,:)=AA(I(1),:,:);
      for j=1:111
         for k=1:278
         MM6.day(count).rain(j,k)= MM6.day(count).rain(j,k)-273.15;
        end
    end
end
M0610=MM6;
clear MM6;
clear AA;
clear count;
clear i;
clear j;
clear k;
clear AA;
```

```
clear BB;
clear rainA_2005_05;
clear rain_2005_05;
clear dom;
clear I;
clear N;
clear M;
save M0610;
*************************************************************************
This section reads the Africa LAM precipitation data.
**********************************************************************
% function M5=cpt_rain_reader (N, M);
% script to read netcdf file
%
% input: netcdf file, latlon.txt, stime
%
clear all;
close all;
N=1:111;
M=1:278;
count=0;
for i=1:12;
    count=count+1;
    dom=num2str(i,'%2i');
rainA_2005_05.day(count).rain=getnc(['rr',dom,'oct2006'],'tot_precip');
    AA=rainA_2005_05.day(count).rain;
     rain_2005_05.day(count).time=timenc(['rr',dom,'oct2006'],'t');
     BB=rain_2005_05.day(count).time;
      I=find(BB(:,4)==6);
      MM6.day(count).rain(:,:)=AA(I(2),:,:);
      for j=1:111
          for k=1:278
             if (MM6.day(count).rain(j,k))<0;
                 MM6.day(count).rain(j,k)=0;
            end
        end
    end
end
% count
```

```
M0610=MM6;
clear MM6;
clear AA;
clear count;
clear i;
clear j;
clear k;
clear AA;
clear BB;
clear rainA_2005_05;
clear rain_2005_05;
clear dom;
clear I;
clear N;
clear M;
save M0610;
% M6=M5;
```

****

This section extracts both the minimum and maximum temperature from the Africa LAM NetCDF files.

****

```
% %
% % pick maximum and mean
stt=mod(stt,24);
ii=find(stt==6);
rain=rain_west(ii,:,:);
%
for r=1:length(ii);
for m=1:length(lat);
          for n=1:length(lon);
          sam.time(r).rain(m,n)=rain_west(r,m,n);
      end
   end
end
clear stt, ii, rain r,m,n
save sam
```

APPENDIX B

THE METEOROLOGICAL STATIONS LIST

North (Lat 12-20ºN) *** Alamlon = The original coding for the Africa LAM longitude

S/N	Station	Name	Country	Station Lat.	Station Lon.	Model Lat.	Model Lon.	Alamlon
1	61017	Bilma	Niger	18.41N	12.55E	18.48	-12.5	137.35
2	61052	Niamey	Niger	13.29N	02.10E	13.26	-2.1	202.28
3	61090	Zinder	Niger	13.47N	08.59E	13.44	-8.6	161.98
4	61223	Tombouctou	Mali	16.43N	3.00W	16.5	3.1	234.75
5	61257	Kayes	Mali	14.26N	11.26W	14.34	11.2	285.14
6	61291	Bamako	Mali	12.32N	07.57W	12.36	7.6	262.74
7	61641	Dakar	Senegal	14.39N	17.30W	14.34	17.3	323.21
8	61695	Ziguinchor	Senegal	12.33N	16.16W	12.36	16.2	316.49
9	61701	Banjul	The Gambia	13.13N	16.12W	13.08	16	315.37
10	65046	Kano	Nigeria	12.03N	08.32E	12	-8.4	163.1
11	64700	Ndjamena	Chad	12.08N	15.02E	12	-15	121.67
12	64753	Faya	Chad	18.00N	19.10E	18.12	-19.1	95.919

Central (Lat 08-12ºN)

S/N	Station	Name	Country	Lat	Lon	Lat	Lon	Alamlon
13	61766	Bissau Aeroport	Guinea Bissau	11.53N	15.39W	11.46	15.3	310.89
14	61831	Conakry	Guinea	09.34N	13.37W	9.3	13.4	298.57
15	61856	Lungi	Sierra Leone	08.37N	13.12W	8.4	13	296.33
16	65125	Abuja	Nigeria	09.15N	07.00E	9.12	-6.9	172.05
17	65134	Jos	Nigeria	09.52N	08.54E	9.48	-8.6	161.98
18	65306	Kandi	Benin	11.08N	02.56E	11.1	-2.6	198.93
19	65418	Tamale	Ghana	09.30N	00.51W	9.3	0.6	219.08
20	65516	Boromo	Burkina Faso	11.45N	02.56W	11.46	2.6	231.4
21	65522	Mangodara	Burkina Faso	09.54N	04.21W	9.48	4.2	241.47
22	65528	Odienne	Cote d'Ivoire	09.30N	07.34W	9.3	7.4	261.63
23	65404	Wa	Ghana	10.03N	02.30W	10.02	2.4	230.28
24	65361	Sokode	Togo	08.59N	01.09E	8.58	-1	209

South (Lat 0-08ºN)

S/N	Station	Name	Country	Lat	Lon	Lat	Lon	Alamlon
25	61931	Sou Tome	S Tome Prin.	00.23N	06.43E	0.3	-6.4	175.41
26	64500	Libreville	Gabon	00.27N	09.25E	0.3	-9.3	157.5
27	64556	Makokou	Gabon	00.34N	12.52E	0.3	-12.5	137.35
28	64650	Bangui	Cent. Af.Rep	04.24N	18.31E	4.26	-18.3	101.52
29	64810	Malabo	Equ. Guinea	03.45N	08.46E	3.54	-8.4	163.1
30	64910	Douala	Cameroon	04.00N	09.44E	4.08	-9.5	156.38
31	64950	Yaounde	Cameroon	03.50N	11.31E	3.54	-11.2	145.18
32	65201	Lagos	Nigeria	06.33N	03.21E	6.42	-3.2	195.57
33	65250	PortHarcourt	Nigeria	04.51N	07.01E	4.44	-6.9	172.05
34	65344	Cotonou	Benin	06.21N	02.23E	6.24	-2.4	200.05
35	65387	Lome	Togo	06.10N	01.15E	6.06	-1.2	207.88
36	65472	Accra	Ghana	05.36N	00.10W	5.34	0.1	215.72

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