Norwegian University of Life Sciences
Faculty of Environmental Sciences
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Philosophiae Doctor (PhD)
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Sensitivity analyses of the Weather Research and Forecasting model for wind resource assessment in coastal Ghana

Følsomhetsanalyser med modell for vær og vindressursprognoser for kystområder i Ghana

Denis Edem Kwame Dzebre

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To my Parents

Fo Atta (of Blessed Memory) and

Uncle Kosi (of Blessed Memory)

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Summary

With the rise of modern wind turbines, wind energy has grown to become a major source of generated electricity, alongside other renewable and conventional energy sources. The geographical and time dependent nature of wind warrants detailed assessments to judge the feasibility of power projects. Pre-feasibility studies play crucial roles in this assessment process and include the performing of large area screening of feasible wind power project sites, designing of effective mast measurement campaigns and feasibility assessments of projects. A source of data for such assessments that has increasingly become popular over the years, is downscaled meteorological datasets which are sometimes produced with Numerical Weather Prediction (NWP) models. Due to uncertainties (from several sources) associated with the outputs of NWP models, their validation is an important step towards their optimization and application for desired purposes. Wind varies geographically. Therefore, the validation of NWP models is an important step towards their application for wind data downscaling for a geographic location.

Though studies have suggested that wind projects are feasible in Ghana, development of the resource still suffers from several challenges, including inadequate resource assessments. This thesis focuses on the application-oriented use of the Mesoscale Weather Research and Forecasting (WRF) model for wind prediction applications in the coast of Ghana and neighboring countries in the West African sub-region.

A local sensitivity assessment of selected numerical options (simulation length or run time and methods of applying the WRF model's Four-Dimensional Data Assimilation (FDDA) nudging technique), as well as selected terrestrial and meteorological datasets on downscaled wind data for coastal Ghana were conducted. Validation of the simulations was done with statistical error metrics from prediction-observation comparisons. The error metrics were compared with performance benchmarks for wind prediction by NWP models that have been reported in scientific literature. In addition, Weibull distribution parameters, as well as probability and cumulative density functions of measured and predicted data were also compared.

Results of this thesis were communicated in four Papers. Paper I sought to deepen the understanding of the impacts of combining varying simulation run time and selected options in the method of applying the WRF model's FDDA nudging technique for wind simulations. It was found that the method of applying nudging above levels automatically determined by the WRF model has a more consistent impact on model predictions. Paper II and Paper III assessed the impacts of Planetary Boundary Layer (PBL) and Surface Layer (SL) parameterization schemes on predictions from the model. It was concluded that the Turbulent Kinetic Energy (TKE) Mellor–Yamada Nakanishi Niino Level 3 (MYNN3) PBL scheme often had relatively better impact on downscaled data, when paired with the Eta SL scheme for simulations. On the terrestrial datasets, it was found that the two global Land Use and Land Cover (LULC) datasets available in the WRF

Geographical Data did not differ significantly in their impact on downscaled data. In addition, among the Gridded Binary (GRIB) meteorological datasets available in the National Center for Atmospheric Research Data Archives, it was realized that the data assimilation systems used in producing these datasets is probably a good criterion for their selection for downscaling for the study area. The findings of this study were reported in Paper IV.

Results of a simulation covering a year with a model configuration based on the findings of the four papers showed that the model is capable of downscaling wind data with error metrics that can meet most of the performance benchmarks that have been reported in literature. The results from this final evaluation also suggest that the configuration established from the studies is probably suitable for offshore assessments in the area but will require further verification.

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Paper II **Dzebre, D.E.K.** and M.S. Adaramola, A preliminary sensitivity study of Planetary Boundary Layer Parameterisation schemes in the weather research and forecasting model to surface winds in coastal Ghana. *Renewable Energy*, 2020. 146: p. 66-86.

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Dzebre D.E.K., Acheampong A.A., Ampofo J, Adaramola M.S. An Overview of utility-scale wind power development in Ghana. Submitted to *International Journal of Ambient Energy*, June 2018.

Abbreviations

ARW	Advanced Research WRF
CC	Correlation Coefficient
FDDA	Four-Dimensional Data Assimilation
GRIB	Gridded Binary
GW	Gigawatt
LSM	Land Surface Model
LULC	Land Use Land Cover
MASS	Mesoscale Atmospheric Simulation System
ME	Mean Error
MODIS	Moderate Resolution Imaging Spectroradiometer
MYJ	Mellor-Yamada-Janjic
MYNN3	Mellor–Yamada Nakanishi Niino Level 3
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environment Prediction
NWP	Numerical Weather Prediction
PBL	Planetary Boundary Layer
PV	Photovoltaic
STDE	Standard Deviation of Error
SL	Surface Layer
TKE	Turbulent Kinetic Energy
RDA	Research Data Archive
RMSE	Root Mean Squared Error
USGS	United States Geographical Survey
UW-TKE	University of Washington-Turbulent Kinetic Energy
WPS	WRF Preprocessing System
WRA	Wind Resource Assessment
WRF	Weather Research and Forecasting
WSI	WRF Software Infrastructure
YSU	Yonsei University

SYNOPSIS

INTRODUCTION

This chapter introduces wind and how wind characteristics affect power production from the resource. The need for wind resource assessment and the role that Numerical Weather Prediction models play in this process is briefly explained. This is followed by the motivation, aim and objectives of the thesis. Thereafter the structure of the rest of the thesis is presented.

1.1 Background

Global energy consumption has been on the rise over the years. This has been in response to factors such as increasing population and industrialization, and better living standards. The increase in energy consumption, coupled with concerns about the greenhouse gases emissions from the utilization of fossil fuels for energy generation, in addition to other reasons, has also increased the global demand for renewable energy over the years. Wind, or the kinetic energy of air flow, has been used in transport, industry and agriculture for thousands of years, and has become one of the three major renewable energy resources that is exploited on a large scale for global power generation [1]. The other two are hydro power, which uses potential energy of flowing river or stored water to generate electricity and solar Photovoltaic (PV) that converts solar radiation directly to electricity. The rise of modern wind turbines, which harness this energy and turn it into electricity has placed the resource as a major power source alongside other renewables and conventional energy sources. As of 2018, global installations of wind power stood at 591 GW, having quadrupled in the past decade [2].

Extractable wind energy depends on wind characteristics such as its speed, density, and prevailing directions. These characteristics play important roles in several aspects of wind energy exploitation (such as the prediction of the economic viability of projects). Wind speed, in particular, is of key interest, as wind power depends on the cube of this characteristic. However, like most renewable energy resources, wind characteristics that can support economical wind energy exploitation exhibit spatial and temporal dependencies. Therefore, understanding the characteristics of the resource in an area is an important step towards the exploitation of the resource. This requires good quality data on wind characteristics, which are best acquired through actual ground-based measurement campaigns. However, owing to the costly nature of these measurement campaigns, data from other sources have increasingly been used in resource assessments activities such as site selection, prefeasibility studies of projects and designing of measurement campaigns.

This thesis focuses on the application-oriented use of the meteorological Mesoscale Numerical Weather Prediction (NWP) Weather Research and Forecasting (WRF) model, as a tool for generating such alternative data by the dynamical downscaling of meteorological datasets.

1.2 Nature of Wind

Wind is the movement of large volumes of air masses. It is generated by pressure differences arising from unequal heating of the earth's surface and are driven by several forces (such as pressure gradient, Coriolis, and turbulent drag among others) which are also sources of variabilities in the wind [3]. As a result of these variations, like other atmospheric phenomena, wind occurs on a wide range of atmospheric scales, as illustrated in Figure 1. Global winds are primarily due to pressure gradients from unequal heating of the earth's surface and the influence of the Coriolis force and exhibit relatively less variation. However, within lowest 1 to 2 km of the earth's atmosphere, referred to as the atmospheric or planetary boundary layer (PBL), factors such as friction at the ground, the orography and the vertical distribution of temperature and pressure give rise to local winds and other wind phenomena (such as turbulence), which vary more significantly, on smaller scales (see Figure 1). Pressure and temperature differences interact with variations in local topography and surface conditions to create circulation systems such as land-sea, cross-valley and along-valley circulations. These result in local winds, common examples of which are land, sea and mountain valley breezes [4, 5]. In addition, synoptically windy conditions can result in winds being modified by mountains producing gap winds, mountain waves, among others [4]. These phenomena are well explained in several textbooks [3-6].

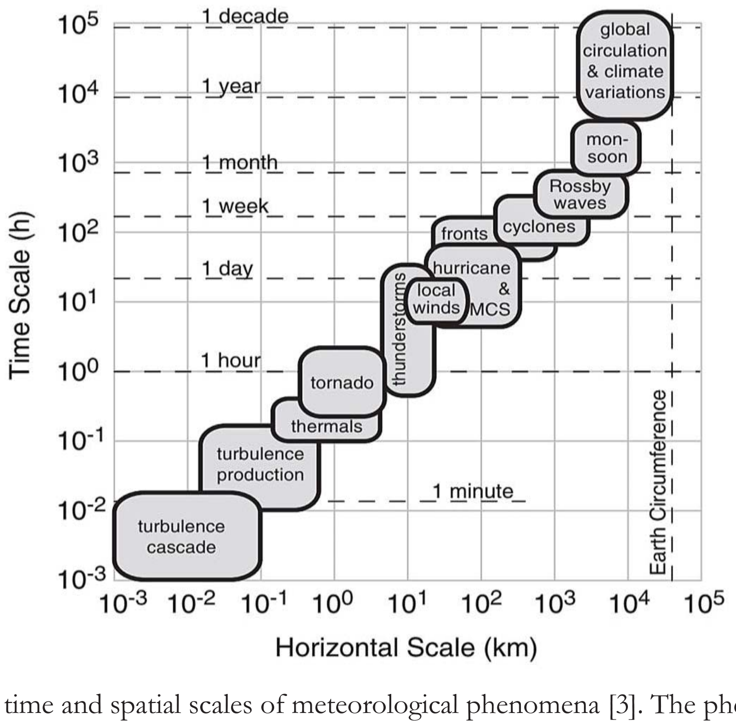

Figure 1: Typical time and spatial scales of meteorological phenomena [3]. The phenomena can be classified according to horizontal scale as; Macroscale (700 – 40000 km), Mesoscale (3 – 700 km), microscale (3 mm- 3 km) [3].

Vertically, wind also varies in the PBL. Wind turbines operate at heights within the PBL, which makes the understanding of vertical variation of wind characteristics within the layer important. A key determinant of the vertical wind speed profile (in addition to terrain, surface roughness, and topography) is the stability of the atmospheric boundary layer. Atmospheric stability can be defined as the tendency to remain in hydrostatic equilibrium with respect to vertical displacements [7]. It is usually explained by the air parcel concept [7] and expressed in terms of the rates at which the temperature of the environment and a parcel of air decrease with increasing height (the environmental and adiabatic lapse rates respectively). In terms of the environmental lapse rate, the atmosphere can be unstable, stable, or neutral. These are well explained in textbooks such as [3, 4, 6, 8, 9]. The vertical wind profile under the three stability conditions is shown in Figure 2.

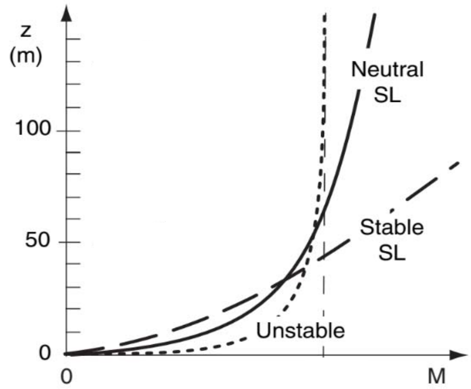

Figure 2: Typical wind speed profiles in the Surface Layer (bottom 5% of the ABL) [3]

1.3 The Role of Numerical Weather Prediction in Wind Resource Assessments

The speed characteristic of wind is of key interest in Wind Resource Assessments (WRA) as the amount of wind energy that can be generated depends on the cube of this characteristic. Due to this relationship, variabilities, uncertainties and errors in wind speeds tend to be amplified, with implications for wind power generation. Therefore, the optimal design of wind projects depends on an accurate and detailed understanding of the distribution of the wind speeds and other characteristics in the project area. This helps in a robust estimation of the energy production over the lifetime of a wind project. WRA involves the use of both existing measurements and modeling approaches to identify potential wind farm sites and determine the optimum siting of wind turbines (micro-siting) in wind farms to estimate the long-term energy production of a project. Though this can be done with relatively easy to acquire data from sources such as nearby meteorological stations, the best source of data for these purposes is measurements of the wind characteristics. However, owing to the expensive and time-consuming nature of wind mast measurement campaigns, it has increasingly become popular over the years to perform preliminary resource assessments with wind data that is downscaled from meteorological datasets.

Mesoscale Numerical Weather Prediction (NWP) models are popular dynamical downscaling tools in this regard. They belong to a category of meteorological models that are used for process studies and weather predictions [10]. They have increasingly been adapted for wind flow prediction over limited areas over the years. They make predictions of the wind speed for locations (that correspond to the model grid) in an area by numerically downscaling meteorological datasets and can be coupled to microscale models for these purposes. They have traditionally been applied in the generation of wind maps for large area screening of feasible wind power project sites. However, in recent times, downscaled data are also being used in the design of mast measurement campaigns and to conduct pre-feasibility assessments of wind power projects.

Model validation (or reliability assessments) assesses uncertainties in the predictions of NWP models. The process plays a key role in the optimization of these models for desired purposes. Uncertainties (, as explained by [10]) are primarily due to;

(a) an imperfect understanding of atmospheric processes, especially at the sub-grid scale,

(b) insufficient simulation of these processes because of the models' grid resolutions, and

(c) errors associated with the numerical assumptions.

The validation process of NWP models involves several techniques (as described by [10]), which may be applied separately to address specific needs. Sensitivity analyses are one such validation techniques. The Sensitivity analyses of NWP models involves verifications of model predictions made with different model options or inputs to establish the extent to which an option performs better than another, and the possible explanations for the difference in performance [10]. Wind sensitivity studies that have been reported in scientific literature have been found to adopt the local approach, which, as explained by [10], examines the impact of a limited range of inputs and options on the estimation of specific events or output parameters by NWP models. A challenge with sensitivity analyses for wind prediction applications is that, due to the influence of local factors (such as terrain features and atmospheric conditions which vary geographically) on the performance of some of the options (such as parameterization schemes) in NWP models [1, 2], it is often difficult to generalize the results of such studies for different geographic areas.

1.4 Motivation

With an Energy use per capita that is equivalent to one-third that of the world, the problem of low and unreliable access to electricity is one of Sub-Saharan Africa's greatest obstacles to social and economic development [11]. Power crises stemming from low and unreliable access to electricity is an issue all over the region.

Ghana has experienced not less than four of such crises since the turn of the century, costing the nation about US$680 million in 2014 alone [12]. Electricity supply challenges in Ghana have stemmed from several factors over the years. These include over-dependence on electricity from thermal and hydro sources (which together constitute over 99% of the country's electricity mix). Demand for electricity in Ghana increased by over 50 percent between 2006 and 2016 [12] and currently, electricity from thermal plants that run on fossil fuels alone constitutes over 60% of the total generation capacity of the country. Solving the country's electricity challenges requires measures that include diversifying the electricity generation mix through the development of other energy sources, including renewable sources such as wind and solar energy [12]. Several studies have reported the feasibility of the large-scale generation of electricity from wind in Ghana [13-19]. And though some efforts (such as a wind mapping activity in 2004, and ground-based mast measurements in selected areas along the coast) have been made towards the exploitation of the resource, development of the sector is still facing several challenges. These include limited or non-availability of reliable data for pre-feasibility or feasibility studies of projects [20].

Numerical Weather Prediction (NWP) models have increasingly been adapted for limited area mesoscale (and even microscale) downscaling of wind data from meteorological datasets for the purpose of mapping wind resources and providing data for pre-feasibility studies. Indeed, the wind mapping (at 50 m) for Ghana was conducted with one such Mesoscale-Microscale coupled models; the MESOMAP system from AWS Truepower (which comprises the Mesoscale Atmospheric Simulation System (MASS) and WindMap Microscale models). However, in addition to being a propriety model, limited verifications and adjustments were done during that exercise, due to a lack of adequate mast measurements at the time [21]. In addition, with the increasing hub heights of modern wind turbines, assessments at higher heights (other than the 50 m of the 2004 mapping), and the availability of time-series to enable the effective designing of mast measurements and pre-feasibility studies on power projects, are increasingly warranted. Furthermore, due to climate change and change in land use in Ghana over the past years, there is the need to update wind maps for Ghana using reliable and easily accessible tools.

The NWP Weather Research and Forecasting (WRF) model [22] is a widely used operational and research mesoscale model. Owing to diverse physics and dynamics options, several model-validation studies towards the application of the model for different purposes have been reported in the literature. However, no known studies have been reported on the validation of the model towards wind resource assessments in Ghana and the West African sub-region. Furthermore, sensitivity tests (of the WRF model for wind energy applications) in the international literature, have often been limited to high wind speed periods. In addition, they have often not considered all PBL schemes (which have been found to significantly affect model wind outputs) with all compatible surface layer physics options, and have often used decision making criteria that in our opinion, leaves room for potentially misleading conclusions to be drawn from these studies.

1.5 Aim and Objectives

Against this background, this thesis sought to verify the capability of the WRF model to dynamically downscale wind data from large-scale global meteorological datasets for resource assessments in Coastal Ghana. The aim was to identify and suggest possible ways of optimization of the WRF model (in terms of selected options) for applications such as wind mapping and generation of time series data for pre-feasibility wind assessments primarily along the coast of Ghana.

The thesis involved a local sensitivity study (as explained earlier) of selected numerical and input data options of the model, to wind predictions at three heights. The options, (which are explained in Chapter two of this thesis) are;

i. Simulation length and options in the WRF's Analysis Nudging technique (Paper I),
ii. Planetary Boundary and surface layer Parameterization options (Paper II and Paper III), and
iii. Input Land Use and Land Cover (LULC) and meteorological Gridded Binary (GRIB) datasets (Paper IV).

In achieving the aim of this thesis, insights, other than what had been reported in the literature, were offered into optimum combinations of the simulation run time and nudging options for wind simulations (Paper I). An alternative experimental approach in sensitivity studies of PBL schemes that deviates from a common practice in past studies in that, it considers high and low wind periods (as against the common practice of considering only high wind periods), is explored in Paper II. In addition, another limitation in the scope of several sensitivity studies in the tropics (in not exploring all SL schemes that can be used with a PBL scheme) is explored in Paper III. Factors that should be considered in selecting meteorological datasets from the NCAR's RDA archive for dynamical downloading to generate time series data for coastal Ghana were explored (Paper IV). The consistency in performance of the options, irrespective of evaluation criteria is used as a decision-making criterion to reduce the potential of drawing incidental test conclusions.

1.6 Thesis outline

Following this chapter, Chapter 2 of this thesis presents the verification data and criteria. The chapter begins with a brief description of the key features and options of the WRF model, with emphasis on the model options that were tested in this thesis. Details of the data that are used for the validation of model outputs are also presented in this chapter. The evaluation criteria on which the tested model options were inter-compared are also introduced.

The main findings from the tests are summarized and briefly discussed in Chapter 3. The main conclusions of each test and their possible implications for model performance in predicting wind speeds for resource assessment purposes are also discussed. The overall conclusion drawn from the thesis is presented in chapter 4, with recommendations for future researches.

An Appendix of Supplementary test results, as well as the 4 papers that were produced from the thesis follow the four chapters of this thesis.

DATA AND METHODOLOGY

This chapter presents brief overview of the WRF model. The overview covers descriptions of key model components, and the options that were the focus of this study. This is followed by the general framework of the thesis, and brief descriptions of verification criteria and the verification (or reference) data. The postprocessing method for model output is also presented

2.1 A Brief Overview of the Weather Research and Forecasting Model (WRF)

The WRF model is the product of a multi-organizational effort to build a mesoscale forecast and assimilation system that would be accurate, efficient, scalable to small atmospheric scales – primarily 1 to 10 km – and capable of operating on workstation-computer platforms [10]. As was the case in this thesis, all the simulations for this thesis were run on a workstation laptop with a quad-core (Xeon E3-1505M v6) processor. The model comprises the following principal programs, illustrated in Figure 3;

a. The WRF Preprocessing System (WPS) which creates inputs for the ARW pre-processor (real) program for real-data simulations by using meteorological and terrestrial data
b. the WRF software infrastructure (WSI) which accommodates key program components that includes the WRF the dynamics solvers; the Non-hydrostatic Mesoscale Model (NMM) core, and Advanced Research WRF (ARW) core, physics schemes and interface to interact with the dynamics, among other key programs.
c. Postprocessors for analysis and verification of predictions.

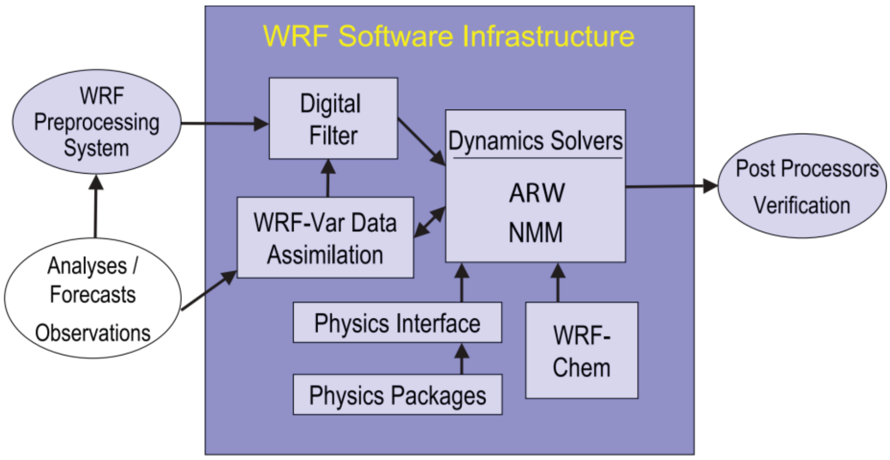

Figure 3: A Schematic of the main components of the WRF model [22]

2.1.1 The WRF Software Infrastructure

2.1.1.1 The ARW Dynamics and Numerics

The Governing Equations

The ARW core of the WRF model was used in this thesis. It incorporates fully compressible, non-hydrostatic Euler equations (with a run-time hydrostatic option available).

Descriptions of how the Euler equations are derived and other details are provide by [22]. Simplified versions of these governing equations (neglecting the Coriolis effect) as presented by [10] in cartesian coordinates comprise;

The equation of steady state given as;

$$p = \rho R_d T \tag{1}$$

The conservation law of mass;

$$\frac{\partial \rho}{\partial t} + \frac{\partial U}{\partial x} + \frac{\partial V}{\partial y} + \frac{\partial W}{\partial z} = 0 \tag{2}$$

Conservation law of momentum;

$$\frac{\partial U}{\partial t} + c_p \Theta \frac{\partial \pi}{\partial x} = -\frac{\partial Uu}{\partial x} - \frac{\partial Vu}{\partial y} - \frac{\partial Wu}{\partial z} + F_x \tag{3.1}$$

$$\frac{\partial V}{\partial t} + c_p \Theta \frac{\partial \pi}{\partial y} = -\frac{\partial Uv}{\partial x} - \frac{\partial Vv}{\partial y} - \frac{\partial Wv}{\partial z} + F_y \tag{3.2}$$

$$\frac{\partial W}{\partial t} + c_p \Theta \frac{\partial \pi}{\partial z} + g\rho = -\frac{\partial Uw}{\partial x} - \frac{\partial Vw}{\partial y} - \frac{\partial Ww}{\partial z} + F_z \tag{3.3}$$

Conservation law of energy;

$$\frac{\partial \theta}{\partial t} = -\frac{\partial U\theta}{\partial x} - \frac{\partial V\theta}{\partial y} - \frac{\partial W\theta}{\partial z} = 0 \tag{4}$$

In the above equations, $U = \rho u,\ V = \rho v,\ W = \rho w,\ \Theta = \rho\theta.$ T is the absolute temperature, $c_p = 1004.5 JK^{-1}kg^{-1}$ and $R_d = (2/7)c_p$ is the heat capacity and the gas constant for dry air respectively, F_y, F_x and F_z are friction terms. π denotes the Exner function which is given as $\left(p/p_o\right)^\wedge\left(R_d/c_p\right)$, where p_o is the reference pressure.

In formulating these equations, the Earth's atmosphere over a geographic region is represented in the model by a three-dimensional (x, y, z) grid. The x and y dimensions are in equally spaced Cartesian coordinates, while the z dimension is over vertical levels in a terrain-following sigma or mass vertical coordinate system. For the flat (x, y) projection of the earth's spherical surface, map projections are used. Several map projection schemes are supported by the solver. However, specific projections are recommended to keep the map-scale factor (a measure of distance distortions from the transformation) close to 1 for numerical stability [23]. The map scale factor is defined as the ratio of the distance in computational space (Δx, Δy) to the corresponding distance on the earth's surface [22].

Denoted by η, the vertical coordinate varies in spacing and ranges in value from one at the surface of the earth to a value of zero at the top of the atmosphere in the model (defined as constant pressure surface). The η coordinate at each level is calculates as;

$$\eta = (p - p_t)/(p_s - p_t) \tag{5}$$

where p is the pressure at a particular level in the atmosphere, p_s is the surface pressure, and p_t is the pressure at the top of the atmosphere.

Model discretization and other issues for Numerical stability

Numerical solutions to the governing equations are solved using finite-difference approximations which requires the simulation domains to be discretized and the equations reduced to their finite difference equivalents [3]. For temporal discretization, the ARW solver uses the third order Runge-Kutta (RK3) time-split integration scheme [24]. An explanation of the scheme and how the ARW solver uses the scheme to advance a solution for prognostic equations at model time steps is provided by [10]. The model time step is limited by the advective Courant number, with implications for numerical stability, as explained by [10]. To ensure numerical stability in the WRF model, it is recommended that its value (in seconds) is maximum six times the horizontal grid distance in kilometers [22, 25].

The spatial discretization is performed on the staggered Arakawa C-grid, which allows for resolving gravity waves more accurately [7]. On the staggered C-grid the westerly (*U*) wind component is evaluated at the centres of the left and right grid faces and the southerly (*V*) and vertically (*W*) wind components at the centres of the upper and lower grid faces as illustrated in Figure 4. Further details of the grid system are provided by [7, 10].

Other numerical issues as well representation of sub-grid scale processes such as turbulence mixing, that cannot be solved on the simulation grid are addressed by filter and damping options as well as other formulations in the ARW solver [7]. Detailed descriptions of these are provided by [10, 22]. Vertical mixing filtering is disabled when a PBL parameterization is applied in simulations, as it is parametrized within the PBL physics [10]. Selection of filter and damping options in this thesis followed recommendations from [25].

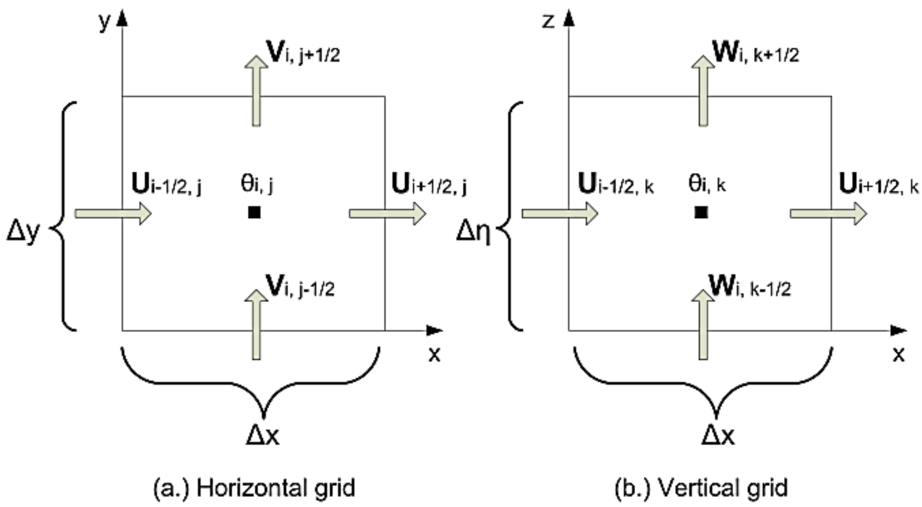

Figure 4: (a) Horizontal and (b) vertical grids of the ARW solver [7].

2.1.1.2 The ARW Physics Parameterization Options

Unresolved physical processes are approximated by physics parameterization schemes in the ARW solver. The physics parameterization schemes in WRF are divided into the following categories; Long-wave and Short-wave Radiation, Microphysics, Cumulus, Planetary Boundary Layer (PBL), and Surface (which comprises the Surface Layer (SL) as well as Land Surface Model (LSM) schemes) categories. A schematic of the interactions of the parameterization scheme categories is illustrated in Figure 5. Atmospheric temperature tendencies and surface radiative (downward longwave and shortwave) fluxes for the surface heat budget are provided by the radiation schemes [7]. Cumulus schemes parameterize vertical convective motions at sub-grid scales and provide atmospheric heat and moisture vertical profiles and sometimes cloud and rainfall tendency profiles in the atmospheric column [7]. The PBL and Surface (LSM and SL) schemes interact directly to parameterize the vertical sub-grid scale transport processes in the atmosphere.

Turbulence (which produces vertical mixing) plays a key role in these processes and acts as a feedback mechanism in wind circulation [5, 29, 30]. In addition, several studies have reported significant impacts of the choice of PBL schemes in wind energy applications of the WRF model. Therefore Papers 1 and 2 examined the impacts of these options on the wind prediction capability of the WRF model. The choice of all the other parameterization options were based on practices from past studies (mostly in the tropics) [26-30] and recommendations from [25]. A more detailed overview of PBL and SL parameterization in WRF is provided in Paper III. Details and descriptions of the PBL, SL and LSM schemes available in the WRF model are available in several papers and textbooks [7, 8, 10, 31-33].

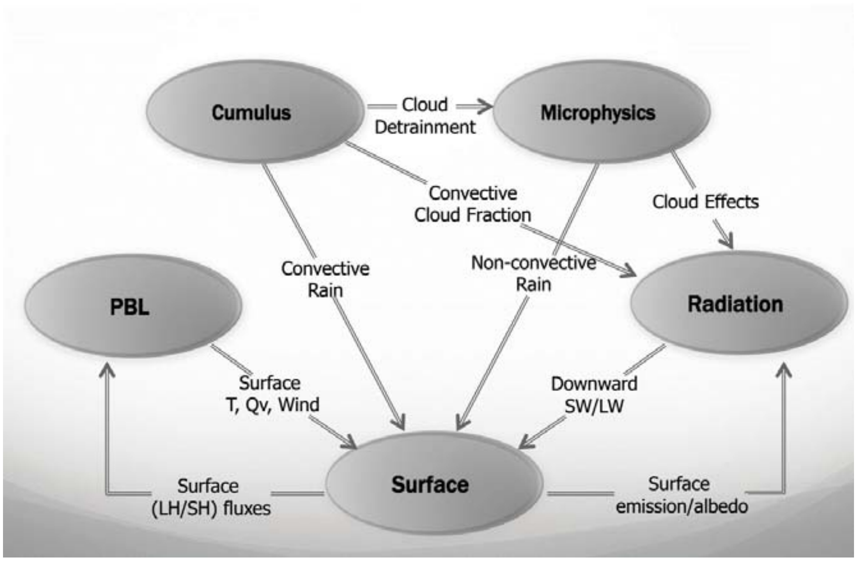

Figure 5: Interaction of parameterization schemes in WRF [34]

2.1.1.3 WRF Nudging

Nudging is a technique in the Four-Dimensional Assimilation (FDDA) [35-39] system of the WRF model, that helps keep the simulations close to the analyses or/and observations over a simulation period (Skamarock et al., 2008). The available nudging techniques in the WRF model can be used for dynamical initialization, to create four-dimensional meteorological datasets and to improve the boundary conditions for the solver. However, the analysis or grid nudging technique attempts to bridge the gap between predictions of physical variables and time-interpolated large-scale meteorological conditions from the input data [7] by adding an additional tendency term to the nudged variable's equation, as explained by [40]. The technique has been used in several studies [20, 51, 52] on wind downscaling. Options in using the technique include; a choice of variables to nudge, the nudging strength or co-efficient, and the choice of whether to nudge variables in the PBL or not. Disabling nudging in the PBL is a common practice in simulations, followed with the aim of allowing mesoscale processes to freely develop (within the PBL) [29, 41, 42]. To achieve this in WRF, one can choose to apply nudging to variables above a fixed vertical level, or apply it to levels above a model-determined level (that corresponds to PBL height predictions) during the simulations [43, 44]. It has been reported that the two methods have different impacts on wind simulations [44]. Paper I investigated the impacts of combining these methods (in addition to a third method) of applying nudging with varying simulation lengths (run times) on model predictions of wind.

2.1.2 Input Data and the WRF Preprocessing System (WPS)

Input data for WRF model comprises terrestrial or static data (land-use, terrain, soil types) and time-varying meteorological fields (from forecast, analysis/re-analysis and climate model data) of different origins and different horizontal resolutions and projections. The program real in the ARW prepares the initial and lateral boundary conditions for the WRF solver with these datasets after they have been interpolated onto the projected simulation domains by the WRF Preprocessing System (WPS). The program components and data flow in and out of the WPS is shown in Figure 6. The model comes with several LULC datasets and two terrain datasets the USGS GTOPO30 [45], and the GMTED2010 [46]. It is possible to run the model with datasets apart from these.

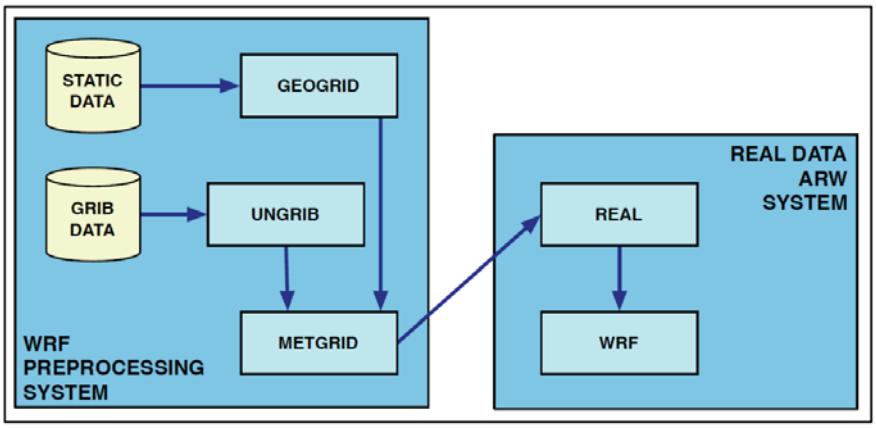

Figure 6: Schematic of the program components and data flow in and out of the WPS [22]

The impacts of selected input datasets on data downscaled with the WRF model were examined in Paper IV. The input datasets comprised the two global LULC datasets that are available on the WRF version 3 Geographical Static Data Downloads Page [47], as well as selected Gridded Binary (GRIB) datasets from the National Centre of Atmospheric Research (NCAR) Research Data Archive (RDA) [48]. Descriptions and characteristics of the datasets are summarized in Paper IV. Terrain datasets were not tested as we found little difference between the two global datasets that cover coastal Ghana in the results of a comparison presented by [49].

2.2 Methodology

2.2.1 Study Framework

The general framework for the thesis (illustrated in Figure 7) is based on a proposed framework by [50] for exploring optimal model configurations of NWP models for different purposes. The reference data, evaluation criteria, and model options that were selected for testing are elaborated on in the sections that follow.

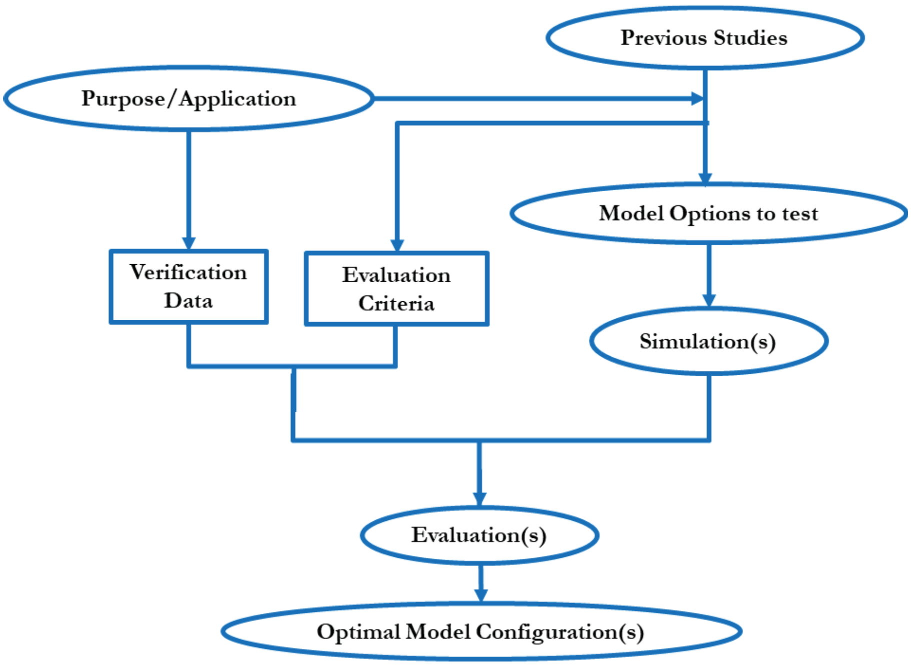

Figure 7: Study Framework.

2.2.2 Evaluation Criteria and Observational Data

Several verification criteria can be used in sensitivity studies [10]. In this thesis, statistical verifications of the model predictions were done by prediction-observation comparisons, in which the following statistical error metrics (which were selected based on their use in similar wind sensitivity studies [30, 41, 51-53]) were calculated;

i. Mean Error or Mean Bias (ME) which was used as a measure of the tendency of the options to underpredict or overpredict wind speeds,
ii. Root Mean Squared Error, which was used as a measure of accuracy,

iii. Standard Deviation of the Error (STDE) which was used as a measure of error dispersion and consistency [41, 52], and

iv. Correlation Coefficient (CC).

The error metrics were calculated according to formulations (which are provided in the appendix) taken from past WRF wind sensitivity studies such as [30, 41, 51-53]. They were combined into a Skill Score which was calculated with the formulation from [54]. The skill score was used to rank the options. In addition, error metric benchmarks (RMSE < 2 m/s, ME < $\pm$0.5 m/s, CC $\geq$ 0.7) as used by [28, 55]) were also used to evaluate the impacts of the options on model performance.

The Weibull distribution is widely used in many fields of the wind energy industry for modelling wind speed data [56]. Therefore, the model predictions were also verified in comparisons of the Weibull probability and cumulative density plots generated from predicted and observational data. Quantitative comparisons of the Weibull cumulative densities errors as well as mean wind power densities estimated from predictions and observations were also compared. Formulations of the Weibull parameter estimations and the functions of the distributions were as has been used in several past studies [14, 40].

The observational data for evaluations were derived from mast measurements of wind data that were conducted by the Energy Commission of Ghana, in the year 2013. Selected details of the data and instrumentation are summarized in Table 1. In addition to these data, monthly average wind speeds of measurements at 60 m from [57] were also used for verification.

Table 1: Selected Details of Observational data and instrumentation.

Period	12 months (January - December 2013)
Data time step	10 minutes
Mast location	5.7861 °N and 0.9188 °E
Mast type	NRG 60m XHD
Measurement heights	40 m, 50 m, 60 m
Anemometer type	NRG #40C

2.2.3 Postprocessing of Model Outputs

As the WRF model predicts wind speed components on vertical levels, (not heights in meters at which observational data were measured), and given the staggered nature of the wind components, postprocessing of model outputs were necessary to determine actual wind speeds at the heights (in m) at which observational data were measured and at the mast location for direct comparison. In this thesis, all such postprocessing calculations were done with a script written in the R programming software. The script generally followed the steps outlined in the flowchart shown in Figure 8.

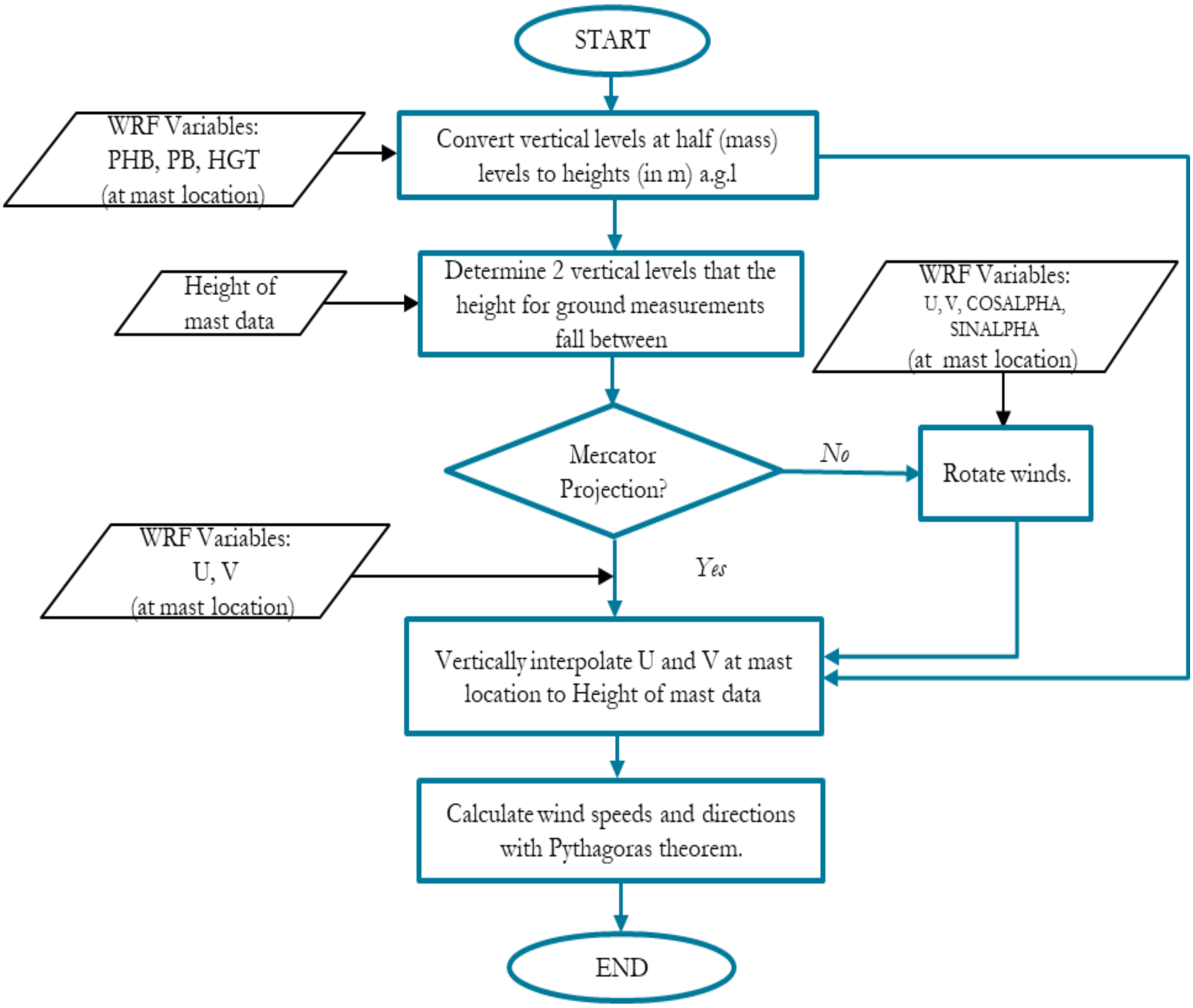

Figure 8: Flowchart for postprocessing of model outputs. Conversion of the vertical levels to heights in meters used formulations from [58, 59], and rotation of winds was according to [60].

SUMMARY OF MAIN FINDINGS

Results and findings were communicated in four papers, which are summarized and discussed here. In addition, supplementary results from an evaluation run of the model with a configuration based on the finding of the four papers is also discussed.

3.1 Overview

In achieving the aim of this thesis, the relative impacts on wind predictions of the choices of model simulation run times, vertical levels above which predictions should be nudged, planetary boundary and surface layer parameterization schemes, as well as input (terrestrial and GRIB meteorological) datasets were investigated.

NWP models diverge and accumulate approximation errors with increasing simulation run times [30, 52]. Carvalho et al. [52] reported that, relatively short run times of 2 days, combined with grid nudging reduces this error. Ohsawa et al. [1] reported that, applying nudging above PBL heights predicted by the Mellor-Yamada-Janjic (MYJ) PBL scheme produces better results as compared to disabling it below a fixed height. Paper I was aimed at deepening the understanding of the impact of several combinations of these two options on wind simulations. It combined five run times that had commonly been used in other studies [29, 30, 32, 33, 41, 52, 61-63], with three methods of applying nudging. On the choice of PBL schemes to use in simulations, it was also realized from studies in the literature that most sensitivity studies on wind predictions do not test PBL schemes with all their compatible SL schemes. These issues (comparative performance of different PBL schemes, and they affected when paired with different SL schemes) were investigated in Paper II and Paper III. A potentially more effective (and more novice friendly) approach to sensitivity studies of PBL options (and possibly other options) was used in Paper II. Paper IV explored impacts of selected terrestrial datasets from [47], and available Gridded Binary (GriB) datasets available from [48] on model performance. The main findings from the four papers are summarized in the sections that follow.

3.2 Impact of Simulation Run times and vertical levels for nudging.

Graphical comparisons of the error metrics of the options tested in Paper I are presented in Figure 9. As can be seen, a combination of simulations of shorter runs with the grid nudging technique did improve most of the speed prediction error metrics from the WRF model as reported by [52]. However, it was found that the margin varied with choice of method of applying (disabling) nudging. In short simulations (lasting 1 or 2 days at a time), nudging above the default 10 vertical levels (N-10-L) resulted in predictions with relatively better bias (lower ME) and accuracy (lower RMSE), but relatively worse consistency (higher STDE) and prediction-observation correlation (CC). However, with increasing run times, all error metrics deteriorated at a relatively faster rate, as compared to an alternative approach of nudging (above a model determined level (N-PBLH). In addition, the latter approach exhibited relatively better consistency (lower STDE) and acceptable prediction-observation correlation (CC $\geq$ 0.7), irrespective of the run times it was tested with. Results of the third method and the first (N-10-L) were very similar, so they are not presented here.

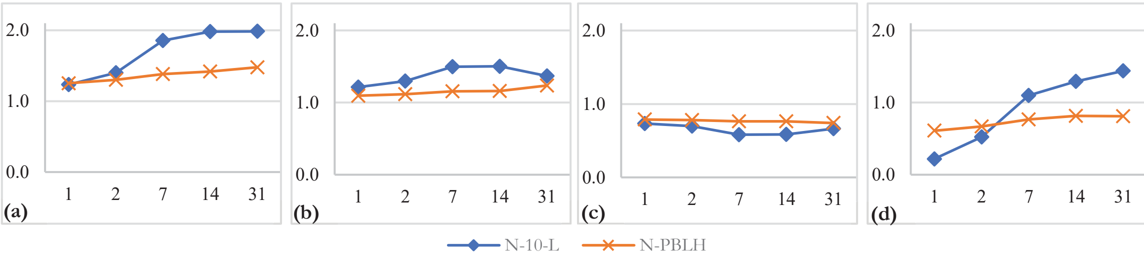

Figure 9: Comparative performance (at 60 m) of two methods of applying nudging in terms of; (a) RMSE (b) STDE (c) CC (d) Absolute ME

Based on results on speed prediction from Paper I, it was concluded that, consistent with the findings of [52], running simulations of relatively shorter run times does reduce prediction error metrics in wind data that that is downscaled with the WRF model. The analysis nudging option of disabling nudging variables above a model determined vertical level offers more consistent and better observation-correlated predictions. Furthermore, consistent with the reports of [44], with relatively longer run times it was also more accurate, as compared to its alternative option (of nudging above the default 10 levels). Based on these, it was concluded that it is probably the more reliable method for applying nudging during downscaling of wind data with the WRF model.

3.3 Impact of PBL and SL parameterization schemes on predictions.

Given the importance of PBL-SL pairs in modelling wind flow in the PBL, their impact was also examined in Paper II and Paper III. A limitation that was realized in several of the past studies in the tropics [26-30] that were consulted during this study was that, they often did not test PBL schemes with multiple compatible SL schemes. In addition, it was realized it is common practice in studies for studies to be conducted in periods with high wind speed conditions only. Furthermore, few studies have examined the relative performance of all the available PBL schemes in WRF over a period comprising a wide range of wind conditions. In Paper II, a preliminary assessment of almost all the PBL schemes with their most commonly paired SL schemes (in the literature) was conducted. This preliminary assessment aimed at reducing the number of PBL schemes to be examined with all their compatible SL schemes. A second aim was to see how the results of a novel approach for conducting these sensitivity tests (illustrated in Figure 10) would compare with findings that have been reported in the literature. The approach differs from what has been used in previous published studies in that, it relies on the criterion of consistency in performance (in terms of several error metrics) of assessing the relative performance of the PBL schemes being tested. In addition, it considers a wider range of wind conditions (high and low wind speed conditions as against the common practice of only high wind conditions for tests as observed in the literature) and uses fewer simulations to draw a conclusion on the relative performance of the schemes. Based on the results of this preliminary assessment (which was found to be largely consistent with what had been reported in other studies in the tropics), five PBL schemes were selected for further testing with all their compatible SL schemes. Findings of this second test are reported in Paper III.

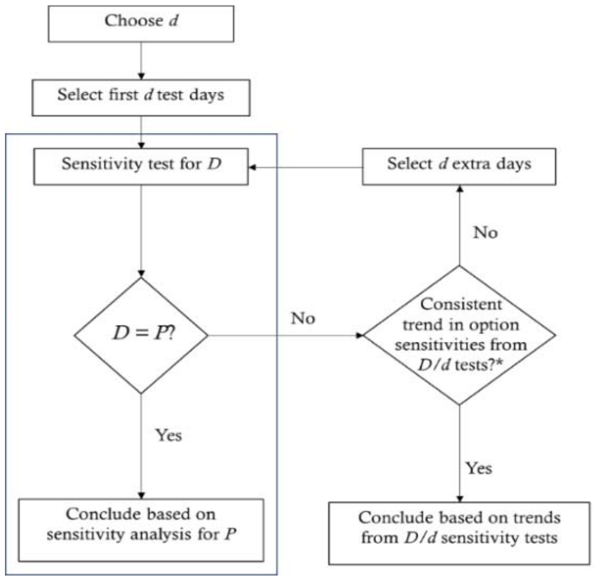

Figure 10: Flowchart of test approach used in Paper II.
(*d* = number of test days for each sensitivity test (2 was used in Paper II); *D* = Total number of test days; *P* = total number of days in entire test period; *Larger *D*/*d* means more points to assess trend.)

Based on results of the two tests, it was concluded that the second order Mellor–Yamada Nakanishi Niino Level 3 (MYNN3) Turbulent Kinetic Energy (TKE) PBL scheme is probably best for wind predictions at this site and perhaps coastal Ghana. The MYNN3 often predicted wind speeds with the best, (or one of the best) combination of error metrics when it was paired with the Eta SL scheme. In addition, Wind Power Densities (WPD) and cumulative probability estimates of the scheme often compared relatively better to estimates from the mast data. Furthermore, predictions of the MYNN3-Eta PBL-SL pair for 4 other locations in the regions were mostly found to be within the benchmarks for error metrics. Based on these, it was concluded that the MYNN3-Eta PBL-SL pair is probably good for wind speed downscaling with the WRF model for coastal Ghana and perhaps other coastal areas in the West-African sub-region.

3.4 Possible impact of different Input Datasets.

The possible impact of five Gridded Binary (GriB) datasets available from [48] and the two LULC datasets available for version of the WRF model from [47] were investigated in Paper IV. Available static terrain datasets (, also from [47]) were not included in this study as, based on results of a comparison from [49], it was concluded that concluded there is little difference between them for coastal Ghana. Results suggested that the Moderate Resolution Imaging Spectroradiometer (MODIS) LULC generally produced downscaled data with better error metrics and more accurate Mean Wind Power Densities (WPD), probably because it is relatively newer than the United States Geological Survey (USGS) LULC. However, the difference between the error metrics and Mean WPD of the two were not so large. On the Gridded Binary (GRIB) meteorological datasets that were tested, it was realized that data assimilation techniques that were used during the analysis/reanalysis process of preparing these datasets often correlated well with how well they performed in terms of verification. It was therefore concluded that this characteristic of the datasets could probably be a good criterion for selection of datasets for downscaling wind data. The Japan Meteorological Agency Reanalysis (JRA-55) and the National Centre for Environmental Prediction Final Operational Global Analysis (NCEP GFS-FNL) performed relatively better than the 3 other datasets that were tested in this study.

3.5 Performance assessment of based on the sensitivity tests.

Following the findings reported above, a configuration based on the findings of the four papers was tested in an evaluation run spanning the entire year of 2013. This configuration is presented in Table A1 in the Appendix. Results for the site at which we had full data, (presented in Table A2 in the Appendix) indicate that the proposed configuration could predict annual wind speeds for coastal Ghana, with most error metrics within the benchmarks. However, the predictions for the two locations further inland (i.e., SEG, and DEN) exhibited larger bias compared to the two locations nearer to the coast (See Table A3 in the Appendix). This suggests that predictions of the configuration tend deteriorate further inland, when the annual mean prevailing wind direction in the area (shown in Figure A1 in the appendix) is considered in addition to this trend. They also suggest that the configuration is probably good for downscaling data for offshore areas near Ghana.

CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

4.1 Conclusions

The focus of this thesis was on the sensitivity analyses of the Weather Research and Forecasting (WRF) model towards its application for the dynamical downscaling of wind data for wind resource assessment in Coastal Ghana. Wind data that were downscaled with selected numerical options and input data options were compared with observations to assess the relative capabilities and limitations of the options, so that informed decisions can be made on how to apply them for wind resource assessment purposes in coastal Ghana. It is concluded from the results of the study that;

- The method of disabling analysis nudging below a model-determined level is probably more reliable for wind predictions, especially in simulations with relatively longer run times (more than 2 days in our tests). And the choosing of simulation run times should for wind data downscaling should probably be done taking nudging options into consideration.
- A test approach that considers the consistency in performance of candidate model options when assessed with several criteria, is worth considering as a decision-making criterion in sensitivity tests, especially by novices and people without the requisite background in Meteorology who want to apply the WRF model. In addition, future sensitivity tests (for wind energy applications) should be over a wider range of wind conditions and should consider PBL schemes with all their compatible SL schemes.
- The Higher order TKE closure Mellor–Yamada Nakanishi Niino Level 3 (MYNN3) Planetary Boundary Layer (PBL) scheme is probably better for wind simulations at this site (and probably Coastal Ghana and perhaps west Africa, given the similarity in climate), when combined with the Eta Surface Layer scheme. The prevailing annual mean wind directions and the mast locations suggest that, these schemes are probably also good for predicting offshore wind in Ghana. However, verification is needed on this. Other PBL schemes that show promise include the University of Washington-TKE (UW-TKE), and the Yonsei University (YSU) schemes.
- The two global Land Use Land Cover datasets from WRF Geographical Static Data probably do not differ significantly, in their impacts on wind data that is downscaled for Coastal Ghana with the WRF model. The impacts of different Gridded Binary (GRIB) meteorological datasets vary more significantly. And the data assimilations techniques that are used in the reanalysis/analysis process of preparing these datasets is worth considering as a criterion for their selection for downscaling with the WRF model.
- When correctly configured, the WRF model is capable of downscaling time series wind data that can meet the benchmarks used in this study for this site (and probably other areas in coastal Ghana, and the West African sub-region).

4.2 Recommendations for Future Work

The following are recommended for consideration in future works;

- Given the limited amount of mast measurement data that was used in this study, future studies should focus on the verification of the promising configurations with data from other locations and preferably at greater heights and over longer study periods. Verifications of the offshore wind prediction capability of the model along the Ghanaian and West-African Coast should also investigated.
- Future tests of the input meteorological datasets at better temporal resolutions. In addition, given the nature of the local wind, the test of different Sea Surface Temperature (SST) data is also recommended.
- Ensemble prediction systems incorporating multiple relatively good options to reduce uncertainty should also be investigated.

APPENDIX

Configuration and results of evaluation run.

Table A1: Configuration for one-year evaluation test

Initial and boundary conditions	NCEP Final Analysis (GFS-FNL): 1^{O} x 1^{O} and 6 hrs resolution.		
Land Use data	MODIS (with lakes) + WRF defaults **(Paper IV)**		
Topographical data	30-arc-second USGS GMTED2010		
Map Projection	Mercator		
Vertical Resolution	45 terrain following eta levels (automatically set)		
Horizontal resolution (km)	25	5	1
Domain size (grid points)	121 x 120	141 x 186	181 x 121
Model timestep (seconds)	120		
Simulation length and Nudging options	Monthly runs with Nudging above model determined levels **(Paper I)**		
Parameterization Schemes:			
Cloud Microphysics (MP)	Eta microphysics (ETA) [64]		
Long-wave Radiation (LW-Rad)	Rapid Radiative Transfer Model (RRTMG) [65]		
Short-wave Radiation (SW-Rad)	Dudhia [66]		
Surface Layer (SL)	Eta Similarity (Eta) [67-69] **(Paper III**)		
Land Surface Model (LSM)	Unified Noah [70]		
Planetary Boundary Layer (PBL)	MYNN3 **(Paper II and Paper III)**		
Cumulus	Kain-Fritsch [71] (for domain 3 only [22, 52])		

Table A2: Wind speed comparisons at 60 m for mast and WRF downscaled data at site ANL

	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Annual**
Mast Mean	5.14	6.33	6.57	5.42	4.68	6.79	6.95	7.10	7.43	6.35	5.98	5.92	6.21
WRF Mean	5.28	6.67	7.41	6.11	5.51	7.87	7.18	7.26	7.04	6.23	6.06	5.54	6.51
Mean Error	0.14	0.33	0.84	0.70	0.84	1.08	0.24	0.17	-0.39	-0.12	0.08	-0.37	0.29
RMSE	1.67	1.42	1.71	1.96	2.25	2.78	1.55	1.53	1.20	1.22	1.21	1.38	1.72
STDE	1.66	1.38	1.48	1.83	2.08	2.57	1.53	1.52	1.14	1.21	1.21	1.33	1.69
CC	0.63	0.76	0.55	0.56	0.42	0.27	0.50	0.42	0.73	0.73	0.69	0.74	0.61

Table A3: Comparisons of error metrics (from monthly averages of data) for three other sites.

	ME	**RMSE**	**STDE**	**CC**
SEG (5.872° N, 0.345° E)	-0.80	1.00	0.60	0.73
DEN (6.112° N, 1.141° E)	-1.19	1.31	0.56	0.66
DZI (5.774° N, 0.714° E)	-0.20	0.53	0.50	0.84

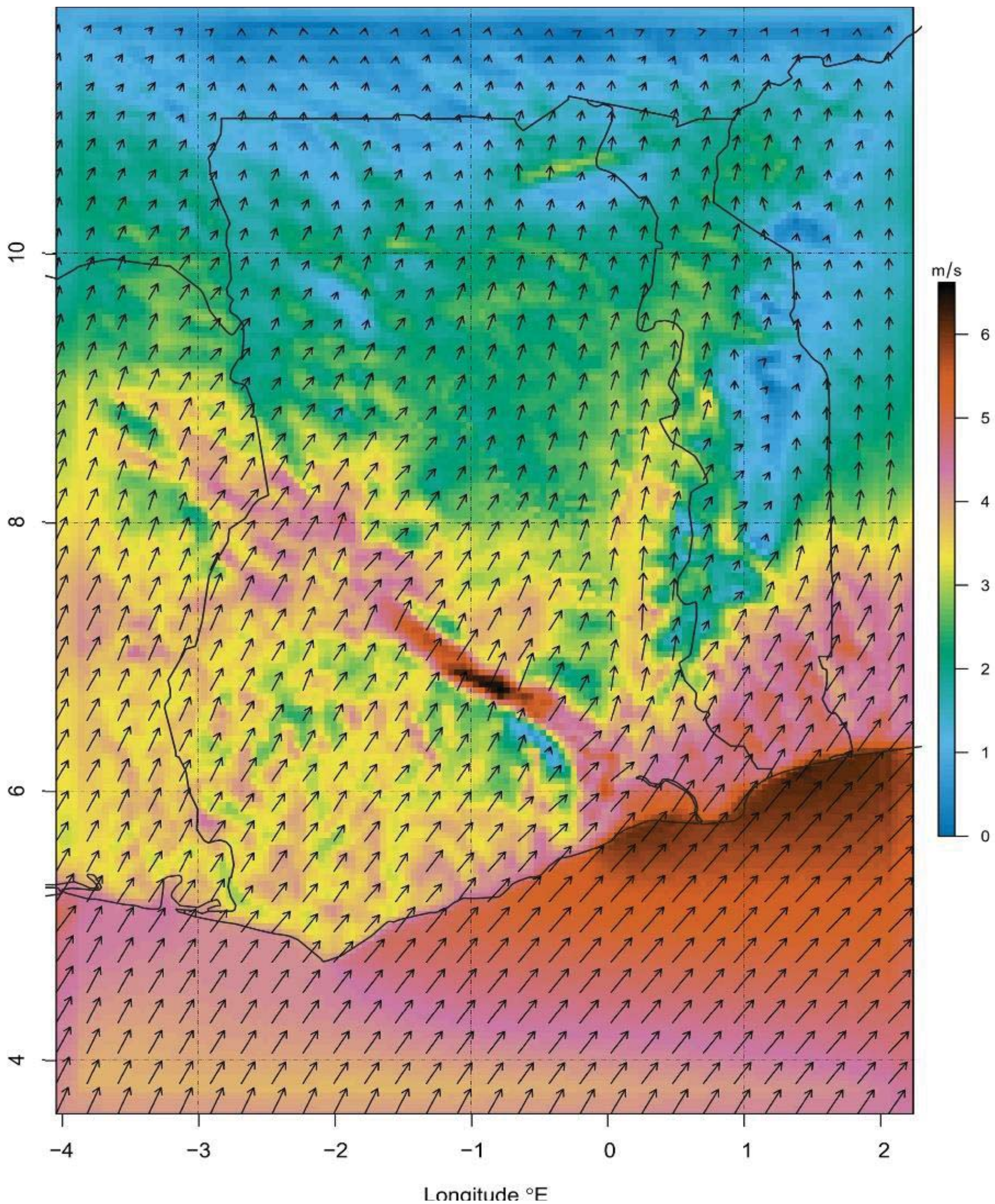

Figure A1: Annual mean wind fields for Ghana and neighboring countries

(at **60 m a.s.l** on 5 km x 5 km grid)

Selected Formulas that were applied in the evaluation of options

- Root Mean Squared Error

$$RMSE = \left(\frac{1}{N} \sum_{i}^{N} \left(v_{sim} - v_{obs} \right)^2 \right)^{0.5}$$

N – number of data points, v_{sim} – downscaled wind speed, v_{obs} – observed wind speed

- Mean Error (Mean Bias)

$$ME = \frac{1}{N} \sum_{i}^{N} \left(v_{sim} - v_{obs} \right)$$

- Standard Deviation of the Error

$$STDE = \left(RMSE^2 - ME^2 \right)^{0.5}$$

- Correlation Coefficient

$$CC = \frac{\sum \left(X - \overline{X} \right)\left(Y - \overline{Y} \right)}{\sqrt{\sum \left(X - \overline{X} \right)^2 \sum \left(Y - \overline{Y} \right)^2}}$$

where X and Y are the simulated and observed wind speeds respectively

- Combined Error Metrics (Skill Score)

$$\text{Skill Score} = \left(1 - RMSE_{NORMALIZED} \right) + \left(1 - \left| ME \right|_{NORMALIZED} \right) + \left(1 - STDE_{NORMALIZED} \right) + CC_{NORMALIZED}$$

- Empirical method of calculating dimensionless Weibull parameters

$$k = \left(\frac{\sigma}{\overline{v}} \right)^{-1.086}$$

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k} \right)}$$

k – shape parameter, c – scale parameter, v – average wind speed, Γ – gamma.function

- Weibull Cumulative Distribution Function

$$\mathrm{F(v)} = 1 - \exp\left[-\left(\frac{v}{c} \right)^k \right]$$

- Maximum absolute Cumulative Density Function Error

$$\text{Max CDF Error} = \max \left| F(v_i)_{\text{obs}} - F(v_i)_{sim} \right|$$

- Mean Wind Power Density

$$\text{Mean WPD} = \left[\frac{1}{2}\rho c^3 \Gamma\left(1 + \frac{3}{k}\right)\right]$$

ϱ - density.

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Paper I
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Paper II
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