

HIGH-RESOLUTION GRIDDED CLIMATE DATASET FOR DATA-SCARCE  
REGION

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## **DEDICATION**

To my wife Esraa, my children Salem and Leen, and family.

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*“.. my success is not but through Allah. Upon Him I have relied, and unto Him I return”.*  
*The Quran, Surah Hud, 88*

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## ABSTRACT

The knowledge of spatiotemporal distribution of climate variables is essential for most of hydro-climatic studies. However, scarcity or sparsity of long-term observations is one of the major obstacles for such studies. The main objective of this study is to develop a methodological framework for the generation of high-resolution gridded historical and future climate projection data for a data-scarce region. Egypt and its densely populated central north region (CNE) were considered as the study area. First, several existing gridded datasets were evaluated in reproducing the historical climate. The performances of five high-resolution satellite-based daily precipitation products were evaluated against gauges records using continuous and categorical metrics and selected intensity categories. In addition, two intelligent algorithms, symmetrical uncertainty (SU) and random forest (RF) are proposed for the evaluation of gridded monthly climate datasets. Second, a new framework is proposed to develop high-resolution daily maximum and minimum temperatures (Tmx and Tmn) datasets by using the robust kernel density distribution mapping method to correct the bias in interpolated observation estimates and WorldClim v.2 temperature climatology to adjust the spatial variability in temperature. Third, a new framework is proposed for the selection of Global Climate Models (GCMs) based on their ability to reproduce the spatial pattern for different climate variables. The Kling-Gupta efficiency (KGE) was used to assess GCMs in simulating the annual spatial patterns of Tmx, Tmn, and rainfall. The mean and standard deviation of KGEs were incorporated in a multi-criteria decision-making approach known as a global performance indicator for the ranking of GCMs. Fourth, several bias-correction methods were evaluated to identify the most suitable method for downscaling of the selected GCM simulations for the projection of high-resolution gridded climate data. The results revealed relatively better performance of GSMaP compared to other satellite-based rainfall products. The SU and RF were found as efficient methods for evaluating gridded monthly climate datasets and avoid the contradictory results often obtained by conventional statistics. Application of SU and RF revealed that GPCC rainfall and UDel temperature datasets as the best products for Egypt. The validation of the  $0.05^{\circ} \times 0.05^{\circ}$  CNE datasets showed remarkable improvement in replicating the spatiotemporal variability in observed temperature. The new approach proposed for the selection of GCMs revealed that MRI-CGCM3 gives the best performance and followed by FGOALS-g2, GFDL-ESM2G, GFDL-CM3 and lastly MPI-ESM-MR over Egypt. The selected GCMs projected an increase in Tmx and Tmn in the range of 2.42 to 4.20°C and 2.34 to 4.43°C respectively for different scenarios by the end of the century. Winter temperature is projected to increase higher than summer temperature. For rainfall, a 62% reduction over the northern coastline is projected where rain is currently most abundant with an increase of rainfall over the dry southern zones. Linear and variance scaling methods were found suitable for developing bias-free high-resolution projections of rainfall and temperatures, respectively. As for the CNE, the high-resolution projections showed a rise in maximum (1.80 to 3.48°C) and minimum (1.88 to 3.49°C) temperature and change in rainfall depth (-96.04 to 36.51%) by the end of the century, which could have severe implications for this highly populated region.

## ABSTRAK

Pengetahuan mengenai agihan ruang-masa bagi pemboleh ubah iklim adalah penting untuk kebanyakan kajian hidro-iklim. Walau bagaimanapun, kekurangan atau jarangnyanya pemerhatian jangka panjang merupakan salah satu halangan utama bagi kajian sedemikian. Objektif utama kajian ini adalah untuk membangunkan rangka kerja metodologi bagi penjanaan data sejarah dan unjuran iklim masa depan yang bergrid pada resolusi tinggi untuk rantau yang kekurangan data. Mesir dan kawasan utara tengah yang padat penduduknya (CNE) dipilih sebagai kawasan kajian. Pada peringkat pertama kajian, beberapa set data bergrid yang sedia ada dinilai dalam penghasilan semula sejarah iklim di kawasan kajian. Prestasi lima produk curahan harian bersumberkan dari satelit dinilai terhadap data curahan yang direkodkan dengan menggunakan metrik berterusan dan berkategori dan kategori keamatan pilihan. Sebagai tambahan, dua algoritma pintar, *Symmetrical Uncertainty* (SU) dan *Random Forest* (RF) dicadangkan untuk penilaian set data iklim bulanan bergrid. Kedua, satu kerangka kerja baru telah dicadangkan untuk membangunkan data suhu harian maksimum dan minimum (Tmx dan Tmn) beresolusi tinggi dengan menggunakan kaedah pemetaan agihan ketumpatan kernel yang utuh. Ini bagi membetulkan kecerungan dalam anggaran interpolasi menggunakan pemerhatian dan menyesuaikan kebolehubahan ruang dalam suhu menggunakan suhu iklim WorldClim v.2. Ketiga, rangka kerja baru dicadangkan untuk pemilihan *Global Climate Models* (GCMs) berdasarkan keupayaannya untuk menghasilkan corak ruang bagi pemboleh ubah iklim yang berbeza. Kaedah Kecekapan Kling-Gupta (KGE) telah digunakan untuk menilai GCMs dalam mensimulasikan corak ruang tahunan Tmx, Tmn, dan hujan. Purata dan sisihan piawai KGE telah dipertimbangkan dalam membuat keputusan penyenaaran kedudukan GCMs dengan pendekatan berpelbagaian kriteria yang dikenali sebagai penunjuk prestasi global. Keempat, beberapa kaedah pembetulan bias dinilai untuk mengenal pasti kaedah yang bersesuaian dalam pengunjuran simulasi GCMs terpilih untuk unjuran data iklim bergrid pada resolusi tinggi. Hasil menunjukkan prestasi GSMaP secara relatifnya adalah lebih baik berbanding produk hujan berasaskan satelit yang lain. SU dan RF didapati sebagai kaedah yang cekap untuk menilai data iklim bulanan dengan mengelakkan kekeliruan yang timbul daripada keputusan yang bercanggah yang sering diperolehi daripada statistik konvensional. Aplikasi SU dan RF menunjukkan data hujan GPCC dan suhu UDel sebagai produk terbaik untuk Mesir. Pengesahan data pada grid beresolusi  $0.05^\circ \times 0.05^\circ$  CNE menunjukkan peningkatan yang luar biasa dalam mengreplikasi kebolehubahan ruang-masa dengan suhu yang direkodkan. Pendekatan nobel untuk pemilihan GCMs yang diperolehi menunjukkan MRI-CGCM3 memberikan prestasi terbaik diikuti oleh FGOALS-g2, GFDL-ESM2G, GFDL-CM3 dan terakhir MPI-ESM-MR. GCM terpilih, bersertakan senario terpilih, mengunjurkan peningkatan dalam Tmx dan Tmn, masing-masing dalam julat 2.42 hingga 4.20°C dan 2.34 hingga 4.43°C menjelang akhir abad ini. Suhu pada musim sejuk diunjurkan meningkat lebih tinggi daripada suhu musim panas. Bagi hujan, penurunan 62% adalah dijangkakan dalam kawasan zon pantai utara yang kini mengalami hujan paling banyak, manakala peningkatan hujan pula dijangkakan berlaku di zon kering di selatan. Kaedah penskalaan selari dan varians didapati sesuai untuk membangunkan unjuran pengembalian tinggi bebas kecerungan, masing-masing untuk hujan dan suhu. Bagi CNE pula, unjuran resolusi tinggi menunjukkan kenaikan suhu maksimum (1.80 hingga 3.48°C) dan minimum (1.88 hingga 3.49°C) dan perubahan kedalaman hujan (-96.04 hingga 36.51%) menjelang akhir abad, yang mungkin mempunyai implikasi yang buruk untuk rantau berpopulasi tinggi ini.

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## LIST OF ABBREVIATIONS

APHRODITE	-	Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation
AR5	-	Fifth Assessment Report
ARC	-	African Rainfall Climatology
BWh	-	Hot Desert Climate
CCD	-	Cold Cloud Duration
CDF	-	Cumulative Density Function
CFSR	-	Climate Forecast System Reanalysis
CHELSA	-	Climatologies at High-resolution for the Earth's Land Surface Areas
CHG	-	Climate Hazard Group
CHIRP	-	Climate Hazard group InfraRed Precipitation
CHIRPS	-	Climate Hazard group InfraRed Precipitation with Stations
CMIP	-	Coupled Model Intercomparison Project
CNE	-	Central North region of Egypt
CONUS	-	Conterminous United States
COOP	-	Cooperative Observer Network
CORDEX	-	COordinated Regional climate Downscaling Experiment
CPC	-	Climate Prediction Centre
CRU TS	-	Climate Research Unit Time Series
CSI	-	Critical Success Index
DTR	-	Diurnal Temperature Range
eCDF	-	Empirical Cumulative Density Function
EMA	-	Egyptian Meteorological Authority
E-OBS	-	European ensembles of gridded data
EQM	-	Empirical Quantile Mapping
ERA	-	European Centre for Medium-Range Weather Forecasts
ESGF	-	Earth System Grid Federation
FAO	-	Food and Agriculture Organization

FAR	-	False Alarm Ratio
GCM	-	Global Climate Model
GHCN+CAMS	-	Global Historical Climatology Network + Climate Anomaly Monitoring System
GHCN-D	-	Global Historical Climatology Network-Daily
GPCC	-	Global Precipitation Climatology Centre
GPI	-	Global Performance Indicator
GSMaP	-	Global Satellite Mapping of Precipitation
GSOD	-	Global Surface Summary of Day
GTS	-	Global Telecommunication System
IR	-	InfraRed
IDW	-	Inverse Distance Weighting
IMERG	-	Integrated Multi-satellite Retrievals for Global precipitation measurement
IPCC	-	Intergovernmental Panel on Climate Change
JAXA	-	Japan Aerospace Exploration Agency
JST	-	Japan Science and Technology Agency
KDDM	-	Kernel Density Distribution Mapping
KGE	-	Kling-Gupta Efficiency
LST	-	Land Surface Temperature
MENA	-	The Middle East and North Africa
MERRA	-	Modern-era Retrospective-analysis for Research and Applications
MFG	-	Meteosat First Generation
MI	-	Mutual Information
MME	-	Multi-Model Ensemble
MODIS	-	Moderate Resolution Imaging Spectroradiometer
MOS	-	Model Output Statistics
MSG	-	Meteosat Second Generation
mTm	-	Monthly Mean Temperature
mTmn	-	Monthly Mean of Minimum Temperature
mTmx	-	Monthly Mean of Maximum Temperature
NCAR	-	National Centre for Atmospheric Research

NCDC	-	National Climatic Data Center
NCEP	-	National Centres for Environmental Prediction
NDVI	-	Normalized Difference Vegetation Index
NOAA	-	National Oceanic and Atmospheric Administration
NRMSE	-	Normalized Root Mean Square Error
NSE	-	Nash–Sutcliffe Efficiency
P2P	-	Pear to Pear
PDF	-	Probability Distribution Function
PDFss	-	Probability Distribution Function skill score
PERSIANN-CCS	-	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Cloud Classification
PGF	-	Princeton Global Forcing
PMW	-	Passive Microwave
POD	-	Probability of Detection
PREC/L	-	Precipitation Reconstruction over Land
PRISM	-	Parameter-elevation Regression on Independent Slopes Model
PT	-	Power Transform
R	-	Rainfall
r	-	Correlation
R <sup>2</sup>	-	Co-efficient of determination
RCP	-	Representative Concentration Pathway
RF	-	Random Forest
RMSE	-	Root Mean Square Error
SC	-	Similarity Co-efficient
SD	-	Statistical Downscaling
Sdv	-	Standard Deviation
SR	-	Success Ratio
SS	-	Skill Score
SU	-	Symmetrical Uncertainty
T	-	Temperature

TAMSAT	-	Tropical Applications of Meteorology using Satellite data and ground-based observations
TIR	-	Thermal InfraRed
Tm	-	Mean Temperature
Tmn	-	Minimum Temperature
TMPA	-	Tropical rainfall measuring mission Multi-satellite Precipitation Analysis
Tmx	-	Maximum Temperature
TRMM	-	Tropical Rainfall Measuring Mission
UDel	-	University of Delaware
Var	-	Variance Scaling
WMO	-	World Meteorological Organization

## LIST OF SYMBOLS

$\text{W/m}^2$	-	Watt per square metre
%	-	Per cent

# CHAPTER 1

## INTRODUCTION

### 1.1 Background of the Study

The knowledge of the spatiotemporal distribution of precipitation and temperature is essential for most of the hydro-climatic studies (Beck et al., 2019, Tapiador et al., 2012). However, the unavailability of long-term quality-controlled observation data is one of the major obstacles for such studies (Prein and Gobiet, 2017). Even if gauge records are reliable and available for an adequately long period, the sparse spatial distribution hinders their use (Prakash et al., 2015a). With the development of remote-sensing technologies and climate modelling, the estimation of climatic variables based on the combination of station data and other multi-source data enabled the generation of more reliable climate data, particularly in areas where long-term reliable observation data is not available or the gauges are sparsely distributed (Maidment et al., 2017). These datasets are spatially gridded and often temporally complete. Several gridded climate datasets have been developed in the last decade on regional and global scales. The regional datasets were developed for specific regions or countries such as the datasets for Europe (Haylock et al., 2008b), Asia (Yatagai et al., 2012), South America (Liebmann and Allured, 2005), Spain (Herrera et al., 2019), and Switzerland (Schiemann et al., 2010). Also, several global datasets are available such as the Climate Research Unit Time Series (CRU TS) datasets (Harris et al., 2014), the Global Precipitation Climatology Centre (GPCC) (Schneider et al., 2014), and the Climate Hazards Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015).

In the context of global climate change, spatial datasets of historical climate and projections of climate change have become increasingly important for resource managers, scientists, and policy makers (Wang et al., 2011). Gridded data usually have longer, quality controlled, and complete records. Therefore, their use can achieve reliable analysis of climate over a longer period at local, regional and global scales.



Gridded datasets provide credible estimates of climate variables at locations away from observing stations, thereby allowing studies of local climate in data-sparse regions. Area average indices, often used for monitoring of climate change, are easier to calculate using data of equal-area grids. Global Climate Model (GCM) and Regional Climate Model (RCM) are most widely used for climate change analysis. The evaluation of GCM or RCM over a region can be better conducted using gridded climate data (Ahmed et al., 2019c). Projections of climate at regional scale using GCMs require correction of bias in GCM simulations which can be better achieved using gridded data. Besides, climate change impact assessment can be better conducted using gridded data.

The success of big data analytics in different fields recently has prompted the expectation in better modelling, and thus solving, the environmental and socio-economic problem arisen from climate change. The big data generated from different sources contain a large amount of useful information. A better understanding of the interactions of the climate system with its drivers is important for complete monitoring of climate. It is important to know that the changes in climate occur due to global warming and the changes in micro-climate due to the change in land use and cover, water bodies, local topography and land-sea interactions. Such analysis needs a very high-resolution gridded climate data. Besides, it is not only required to know the change in mean and variability of climate but also the changes in climatic extremes as the major effect of climate change in society and economy comes from climatic extremes. This urges the need for daily or sub-daily gridded data. High temporal resolution is essential for the calculation of many variables required for engineering and agricultural applications — such as growing degree-days or the length of the frost-free period — or the probability of extreme climate events that structures have to bear or that may jeopardize crop yield (Xie et al., 2019). High spatial resolution climate data are important for ecological research where species compositions may change considerably at fine scales and elevations (Thellmann et al., 2019). The importance of high-resolution daily gridded climate data has introduced the concept of big data in climate change research. The high-resolution gridded datasets can be used for providing data-driven evidence of climate change impacts and effectiveness of adaptation measures for decision making which can have breakthrough implications in finding solutions to climate change challenges.

## 1.2 Problem Statement

Knowledge of climatic characteristics in many regions is limited due to unavailability of in situ observations. Setting up a dense network of gauging stations or radar systems to provide adequate high-resolution data is costly for many emerging economies (Nikolopoulos et al., 2013). Several satellite-based rainfall datasets have recently emerged as an alternative source of dense observation data. However, these datasets often contain large uncertainties – errors – posing concerns for using them. The magnitude and structure of estimation errors vary between the available datasets (Dezfuli et al., 2017), thus identifying the datasets performance in data-scarce regions can increase the confidence in their use. Conventional statistical metrics are generally used for the assessment of the performance of gridded climate datasets by comparing them with reliable ground observation data. However, these metrics are designed to assess the ability of gridded datasets in replicating a particular characteristic such as variability, distribution and extremes of observed data, and thus, not enough to evaluate the similarity in all characteristic of a time series. Furthermore, the use of different metrics often results in contradictory conclusions which make the decision-making a difficult task (Salman et al., 2019, Beck et al., 2019). This highlights the need for a robust statistical tool for the assessment of the performances of gridded datasets.

Although global gridded temperature datasets provide long-term time series over large domains, they lack the fine spatial resolution required for regional and local scale analysis. Available reanalysis gridded temperature datasets show limitations in the representation of several weather patterns (Bosilovich et al., 2008) and the satellite datasets are often restricted by specific cloud cover conditions (Sharifnezhadazizi et al., 2019). Therefore, high-resolution datasets are often developed by interpolating temperature observations from a high-density network (Isotta et al., 2014). However, the lack of dense observation stations network in most countries restricts the development of gridded datasets with sufficient spatial resolution and temporal consistency. Therefore, the development of credible high spatial resolution gridded temperature dataset for station-sparse and -scarce region remains a great challenge in climate data science.

The assessment of climate and its change not only require high-resolution historical climate data but also high-resolution projections of future climate. A large number of GCMs are available for the projection of climate. Selection of an appropriate set of GCMs based on their capability to simulate the historical climate is one of the important steps for the reduction of uncertainty in climate projections of the region (Lutz et al., 2016). But, selection of GCMs is not straightforward (Lutz et al., 2016). Challenges originate from the fact that the credibility of GCMs varies with the evaluation metrics used, temporal (i.e., annual and seasonal) and spatial scales examined, and region under consideration (Weigel et al., 2010, McSweeney et al., 2015). Successive efforts have been made to assess GCM performance to simulate spatial climate variability. Studies emphasised the importance of simulating spatial patterns only considered the mean annual or seasonal spatial patterns and ignored annual variations. A fidelity assessment of the temporal variability of spatial patterns of climatic variables is necessary to study the impact of climate change on hydrology and water resource management in a given study area.

Climate change vulnerability assessments and adaptation planning at local or regional scales require high-resolution climate change projections (Sa'adi et al., 2017, Sachindra et al., 2018b). The coarse-resolution GCMs outputs are downscaled to a fine scale for this purpose. The reliability of high-resolution climate projections not only depends on the selected GCMs and the high-resolution historical climate datasets used but also on the downscaling method used. A robust downscaling method is expected to be able to correct all form of biases presented in GCM simulations including biases in the mean, variability, distribution and extremes. However, the selection of suitable downscaling method is a challenging task as their performance significantly varies according to climate variables, regional climate, and types of bias in GCMs. There is a lack of a robust methodological framework for the selection of suitable downscaling method for the reliable projection of climate at fine resolution.

### **1.3 Research Objectives**

The main objective of this study is to develop a methodological framework for the generation of high-resolution gridded historical and future climate projection of a data-scarce region. This main objective was achieved by fulfilling the following specific objectives:

1. To derive robust methods for the evaluation of the performance of existing gridded climate datasets.
2. To derive a methodology for the development of high-resolution daily gridded temperature dataset in a data-scarce region.
3. To develop a credible framework for the selection of GCMs based on their ability to simulate the changes in the historical climatic pattern of a region for the reliable projection of climate.
4. To generate high-resolution gridded climate projections using the most suitable downscaling method of GCM simulations.

### **1.4 Scope of the Study**

This study aimed at developing high-resolution historical and projection datasets for rainfall and temperatures for the data-scarce region. The developed methodologies can be applied for any part of the world, but the present study encompassed Egypt and its central-north region as study areas.

Several gridded temperature and precipitation data are available for hydro-climatic study in data-scarce region. The scope of this study is to evaluate the performance of high-resolution (i.e.  $\leq 0.1^\circ$ ) satellite-based daily rainfall gridded datasets, gauge-based daily temperature gridded datasets, and gauge-based monthly temperature and rainfall gridded datasets. The gridded datasets were limited to only those which has spatial coverage to the study areas and temporally spans for a sufficient period to the targeted purpose of use. Therefore, other products currently

available such as the Integrated Multi-satellite Retrievals for Global precipitation measurement (IMERG), was not included in this study due to its relatively short temporal span.

This temperature datasets developed in this study were spatially and temporally exclusive for the Central North region of Egypt (CNE) during 1981 – 2017 due to the limited availability of station data. However, the methodology proposed for the developed of the datasets can be applied elsewhere.

Out of more than forty-five CMIP5 GCMs, thirty-one GCMs which have daily estimations and projections for two Representative Concentration Pathway (RCP) scenarios namely 4.5 and 8.5 were considered for the selection of GCMs for Egypt. This criterion ensured the use of the highest number of GCMs having common characteristics.

The future projections of rainfall and temperatures generated in this study were spatially exclusive for the CNE due to the limited spatial coverage of the high-resolution gridded temperature datasets.

## **1.5 Significance of the Study**

This study evaluated different satellite-based datasets for the identification of the best-performing dataset to provide fine resolution measurements of rainfall for the study area. The ability to acquire reliable and high-resolution estimates of rainfall for a given study area is expected to significantly improve the to design and implement mitigation measures to counter water-stress and hydro-meteorological disasters (Abutaleb et al., 2018).

The present study proposed new methodologies for evaluation of monthly gauge-based gridded climate datasets which shall reduce the uncertainty in the selection of the best performing gridded dataset for a given region due to the contradictory results often obtained using different conventional statistics. The method

can be used for any other climatic variable for systemic assessment of the performance of gridded data. The identification of the best performing monthly rainfall and temperature datasets for the study area shall provide more confidence in their use for many applications such as assessment of the historical changes in climatic characteristics.

The methodology proposed in this study for the development of high-resolution data can be replicated in any region to solve the problem of data-scarcity. The developed datasets have a wide range of applications such as better understanding of temperatures extremes in the study area which can help policymakers to understand the vulnerable zones and planning adaptation measures. The range of application can be widened by combining the use of the developed temperatures datasets with high-resolution rainfall dataset for water resources management operations such as determining the optimum water allocation to crops, estimation of hydrological hazard potential, investigation of climatic water availability and agricultural potential, and planning and management of water resources.

This study proposed a new framework for the selection of GCMs in a systemic manner which can help in the reduction of uncertainty in the projection of climate change in any region. The GCMs selected in the present study can be used for climate change impact assessment in different sectors in the study area.

The methodologies proposed for downscaling of the rainfall and temperature would reduce uncertainty in projection of high-resolution climate. The downscaled climate for CNE would provide insights into the future possible changes in the characteristics of the climatic variables. The availability of projection datasets will open the way for more studies to understand the impacts of changing climate on various natural systems in a heavily populated region like the CNE. This will be significant in developing appropriate adaptation plans and mitigation measures for adaptation to climate change.

Overall, this study paved the way for future studies through the availability of historical and projected high-resolution gridded rainfall and temperature datasets with

different temporal scales. By this, the intention of the study which is to surpass of the scarcity of metrological data, for future research, by the generation of high-resolution gridded dataset was achieved.

## **1.6 Thesis Outline**

The thesis is divided into five chapters. Descriptions of the chapters are given below in brief.

Chapter 1 gives a general introduction comprising of the background of the study, problem statement, and the objectives, scope, and significance of the present study.

Chapter 2 provides a description of the study area followed by a review of available gridded climate datasets, development of high-resolution gridded datasets, factors affecting their quality and methods of their performance evaluation. Furthermore, this chapter explores the recent advances in GCM selection, climate downscaling and projection.

Chapter 3 presents the methods used in the study. The chapter describes the data used and their sources, the novel method proposed for the selection of gridded precipitation and temperature gridded datasets, the development of high-resolution temperature datasets, the novel approach developed for the selection of GCMs, statistical downscaling and projection of climate.

Chapter 4 presents the results obtained in the study followed by a critical discussion of the results. It includes the results of the performances of various temperature and precipitation gridded datasets, the validation of the newly developed dataset, selection of GCMs using a novel framework, the generation of high-resolution gridded climate projections through statistical downscaling of GCM projections.

Finally, the conclusions made from the study are given in Chapter 5. Future research points envisaged from the study are also recommended.



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