

Understanding the performance of downscaled global climate model precipitation data: A
cautionary tale for watershed modeling applications

by

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Abstract

There is a growing demand for accurate predictions of climate variables across various spatial and temporal scales, as the Earth's climate has entered a period of rapid change that outpaces any historical experience of human civilizations (Kotamarthi et al., 2021; USGCRP, 2018). Climate models are the primary tools utilized for understanding climate patterns of the past and potential changes in future patterns as a result of decisions and choices made today (Edwards, 2011; Flato et al., 2013). At a large scale, global climate models (GCMs) can reasonably represent the interactions of climate variables throughout the climate system. However, global climate models lack the ability to reproduce climate variables, such as precipitation, at a scale that is applicable for specific hydrological regional or local assessments (Bastola and Misra, 2014; Cooney, 2012). Downscaling methods and techniques aim to refine the resolution of GCM outputs in order to provide more impactful and locally relevant climate projections for stakeholders and decision makers across regions, states, and cities.

The intent of this research is to improve upon the current understanding and use of downscaled GCMs' precipitation data for watershed modeling application and water resource management in the Blue River Watershed (BRW), an urbanizing watershed located within the Central United States Midwest region. Precipitation data was obtained from 18 downscaled GCMs under two different statistical downscaling methods: Localized Constructed Analogs (LOCA) and Multivariate Adaptive Constructed Analogs (MACA), for a total of 36 downscaled GCMs. Precipitation data from the 36 downscaled GCMs was statistically compared to precipitation data observed at six National Oceanic and Atmospheric Administration (NOAA) stations located throughout the BRW. From the statistical point comparison seven models were selected to assess spatial grid-surface comparisons of downscaled GCM data to the gridded

spatial precipitation datasets obtained from Parameter-elevation Regressions on Independent Slopes Model (PRISM). The results from the point statistical analysis demonstrated that seven models performed better as compared to the whole group of 36 models assessed for the BRW. The performance of the seven downscaled GCMs were further assessed, by comparing modeled monthly data to observed monthly data across gridded surfaces, utilizing the Kolmogorov-Smirnov (KS) test and the SPAtial EFficiency metric. This further investigation emphasized that the selected downscaled GCM precipitation monthly comparisons had a poor performance in capturing the monthly magnitude and distribution of precipitation for the given selected models, downscaling methods, time period, and surface extents assessed throughout this study. Overall, this research stresses the importance of approaching the application of downscaled GCMs precipitation outputs, at the watershed scale, cautiously. Understanding the uncertainties and variability that remain in downscaled GCM precipitation outputs is critical for effectively incorporating into water resource management designs and decisions, as well as continually advancing the capabilities of climate scientist tools for application.

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List of Abbreviations

BRW	Blue River Watershed
CMIP5	Coupled Model Intercomparison Project Phase 5
Corr	Correlation
CV	Coefficient of Variation
DEM	Digital Elevation Model
FHWA	Federal Highway Administration
GCMs	Global Climate Models
GDO	Green Data Oasis (Abbreviation used to identify LOCA downscaled models)
GIS	Geographic Information System
Histo Match	Histogram Match or Histogram Overlap
IPCC	Intergovernmental Panel on Climate Change
LOCA	Localized Constructed Analogs
MACA	Multivariate Adaptive Constructed Analogs
MARC	Mid-America Regional Council
NCEI	National Centers for Environmental Information
NetCDF	Network Common Data Form
NOAA	National Oceanic and Atmospheric Administration
PRISM	Parameter-elevation Regressions on Independent Slopes Model
RCPs	Representative Concentration Pathways
SPAEF	SPAtial EFficiency metric

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Dedication

I dedicate this thesis to my mother, father, and sister.

Thank you for always encouraging me to overcome any obstacle with enthusiasm and determination. Without your love and support I would not be where I am today.

Chapter 1 - Introduction

1.1 Problem Statement

There is a growing demand for accurate predictions of climate variables across various spatial and temporal scales, as the Earth's climate has entered a period of rapid change that outpaces any historical experience of human civilizations (Kotamarthi et al., 2021; USGCRP, 2018). Thus, the need for tools to serve as a predictor of future conditions is needed as historical data records can no longer be relied upon (Cook et al., 2017; USGCRP, 2018). Scientists and engineers often utilize models to understand complex systems and understand the processes, interactions, and influences occurring around the globe. Climate models are of particular importance as they are used for understanding climate patterns of the past and potential changes of future patterns as a result of decisions and choices made today (Edwards, 2011; Flato et al., 2013). Global climate models are built upon the global patterns in the ocean and atmosphere and utilized for completing long-term, multi-decadal assessments in assessing variations of climate system parameters.

Global climate models set the stage for potential analyses at local, regional, national, and international levels. At a large scale, global climate models can reasonably represent multiple climate variables throughout the climate system. However, global climate models lack the ability to reproduce climate variables, such as precipitation, at a scale that is applicable for specific hydrological regional or local assessments (Bastola and Misra, 2014; Cooney, 2012). Therefore, downscaling methods have become an important aspect for incorporating possible future climate projections in water resource management assessments. Downscaling of global climate models aim to produce a finer resolution product for climate projection (Abatzoglou and Brown, 2012; Navarro-Racines et al., 2020; Pierce et al., 2014). Despite many improvements to global climate

models and downscaling methods, continued advancements in refining the resolution of model outputs and further understanding of model uncertainties are required to bridge the gap between climate scientist tools and applications in water resource management. Efforts to bridge this gap will provide improved understandings of plausible future climate projections that can be incorporated effectively by water resource managers to inform designs and decisions needed for promoting resilient water management systems.

1.2 Objectives

The overall goal of this research is to understand how modeled precipitation data from downscaled GCMs perform when compared to observed precipitation data at the watershed scale. This research aims to improve the current understanding of, and the use of, downscaled GCMs' precipitation data for watershed modeling application and water resource management in the Central United States Midwest region. This research will answer the following questions:

1. Can downscaled GCMs be utilized to capture and represent changes in variable precipitation patterns in the Central United States Midwest region at the watershed scale?
2. How well does historically simulated downscaled GCM precipitation data perform spatially across the watershed when compared to observational based precipitation data?

1.3 Significance of Work

Water is essential for humans, crops, livestock, ecosystems, infrastructure, and industry. Small changes to the amount and distribution of precipitation received in a particular area over time can have major impacts to the immediate area and areas located downstream. Across the Missouri River Basin, approximately an 8% increase in precipitation has been observed since 1895, with primarily the spring and autumn seasons driving this increase (Kluck et al., 2020). As indicated within the Fourth National Climate Assessment, over the 21st century, there is high

confidence that the frequency and intensity of heavy precipitation events will increase across the United States (Easterling et al., 2017; USGCRP, 2017). Projected changes in precipitation, across the United States, will vary by regional and seasonal differences. A regional assessment for the Kansas City area, under current greenhouse gas emission trends without reduction, projected a 147.3 mm (5.8 in) increase in the average annual precipitation to 1132.8 mm/year (44.6 in/year) by 2100 (Anderson and Walker, 2015). As well as an increase, from 5.0 to 9.3, in the number of days with precipitation over 38.1 mm (1.5in) (Anderson and Walker, 2015). Changes in climate variables including the alteration of the amount and timing of precipitation are expected to amplify current risks related to climate and contribute to stress put on individuals and systems subjected to variable precipitation.

This research is a component of an overall research effort (McDonough, 2018; Stanton, 2020; Thomas, 2020), by water resource engineers, to attempt to understand how changes in climate affect transportation systems and exploring ways of better managing the associated effects in an urbanizing watershed, within the Kansas City region. This research effort contributes to projects and planning endeavors of the Federal Highway Administration (FHWA) and the Mid-America Regional Council (MARC) in utilizing available tools and resources to assess the vulnerability and risk of transportation systems and to increase system climate change resilience. Assessing the available tools and resources, specifically related to climate change projection capabilities of precipitation, is an important aspect of better understanding the potential risks to transportation systems for a site-specific watershed study in the central region of the United States.

Chapter 2 - Literature Review

2.1 Changes in Precipitation

The Earth's hydrologic cycle is a dynamic system that is greatly influenced by any modification to individual cycle components. Changing one cycle component affects the entire cycle. For example, an increase in temperature can lead to higher rates of evaporation from soil profiles and open bodies of water, then the warmer air and increased water vapor give way to intense precipitation events and high potential for runoff. The rates and distribution of water across the globe is a result of the connections between the hydrologic cycle system components. Natural and human-influenced changes to the hydrologic cycle have modified the rates and distribution of water, influencing the occurrence of extreme events such as droughts and floods. Natural influences such as topography, atmospheric circulation patterns, and solar energy variations have and will continue to impact the hydrologic cycle and climate system. However, human-influenced changes as a result of increased emissions of greenhouse gasses; land use and landcover changes; and increased dependency and manipulation of natural resources, have been linked to influencing the rate of change and increased variability of temperature and precipitation (Huntington, 2006; USGCRP, 2018).

Average annual temperatures have increased by 0.7 degree Celsius (1.2 degree Fahrenheit) across the contiguous United States from 1986-2016 and is expected to continue increasing in the future ranging from a 1.7 to 6.7 degree Celsius (3 to 12 degree Fahrenheit) increase, depending upon rates of greenhouse emission (USGCRP, 2018). Increases in water-holding capacity due to increased temperature, increases atmospheric water vapor which is followed by an expected increase in intensity of precipitation events, as individual storms are supplied with an increased level of moisture (Meehl et al., 2005; Trenberth, 2011). According to

the Clausius-Clapeyron relationship, the water holding capacity increases by approximately 7% per 1 degree Celsius temperature increase (Prein et al., 2017; Trenberth, 2011; Ummenhofer and Meehl, 2017). As seen across most parts of the contiguous United States, the average annual precipitation and the frequency of and intensity of heavy precipitation events has increased since 1901 (Easterling et al., 2017; USGCRP, 2018) and continued increases are projected for the future (Janssen et al., 2014; USGCRP, 2018). These observed and projected increases, however, are not occurring at equal distributions across geographical space, wet areas are expected to get wetter while dry areas get drier (Held and Soden, 2006; Putnam and Broecker, 2017; Trenberth, 2011). The increase of extreme events is expected to be accompanied by longer dry periods between the heavy and intense precipitation events (Trenberth, 2011; Ummenhofer and Meehl, 2017). Longer dry periods lead to drought or drought-like conditions that can stress the local environment and set up conditions for increased risk of flooding caused by intense precipitation events.

The number of weather and climate disasters, such as floods and droughts, are on the rise across the United States and the associated damages caused by these disasters is costly. The year of 2020 set a new annual record of 22 weather/climate disaster events, each with losses exceeding \$1 billion affecting the United States. Of the 22 events that occurred in 2020, the largest category was severe storm events, with 13 events. The total combined costs of the 22 events resulted in \$95 billion in damages (NOAA-NCEI, 2021). The increase in weather and climate disaster events is attributed to the combination of increased exposure of assets, increased vulnerability to associated event hazards and increased frequency of extremes due to changes in climate (NOAA-NCEI, 2021; USGCRP, 2018). Convective precipitation, due to thunderstorms propelled by the transport of moisture via the Great Plains Low Level Jet, drives the variability

in precipitation across the Great Plains and Midwest regions of the United States. Within these regions, historic severe droughts (e.g., 1930s, 1950s, 1988 and 2012) and floods (e.g., 1993, 2008 and 2011) have resulted in substantial economic losses (Harding et al., 2013). A study completed to evaluate the amount of rainfall produced by thunderstorms from 1950-1994, indicated that a station in Kansas City averaged 52 thunderstorm days per year with thunderstorms producing 66% of the total annual precipitation and the variability found in the station's total precipitation could be explained by 86% of the thunderstorm rainfall (Changnon, 2001). Contributing to the understanding that thunderstorms are an influencing factor in the amount of annual precipitation received in the central regions of the United States, especially in the warmer, summer seasons and this type of precipitation should be well accounted for in assessments within the region. However, completely understanding convective precipitation and how it might change across the Central United States remains a troubling uncertainty due to the difficulty and lack of ability to reasonably simulate the spatial variability and precipitation amounts associated with convective precipitation events within global climate models (Dai, 2006; Harding et al., 2013). To potentially overcome the lack of convective precipitation presence in large grid cells of global climate models, downscaling methods can assist in improving upon the level of detailed atmospheric processes occurring within a finer grid cell size. However, such downscaling methods are associated with limitations and bias which can contribute to the uncertainty of simulating future precipitation (Harding et al., 2013).

2.2 Understanding Global Climate Models and Downscaling

Throughout history many efforts have been made to understand the global climate system's relationships and functions of transport. With improvements in technology and expanding knowledge, climate science tools have built upon the initial isolated cycle conceptual

and mathematical models to develop improved comprehensive and coupled computer-based model simulations (Edwards, 2011). Improving the ability to assess and forecast large-scale dynamics within the climate system. As noted by Lynch (2008), one of the finest achievements of meteorology in the 20th century was the development of comprehensive models.

Numerical, computer-based models such as global climate models (GCMs), also known as general circulation models or Earth system models (ESMs), are used to simulate Earth's climate system. GCMs divide the Earth's surface into three-dimensional grid cells to characterize how energy and matter interact across the ocean, atmosphere, and land. GCMs utilize mathematical equations to quantify variables, physical processes, and fundamental laws that drive the Earth's system processes (Edwards, 2011; NOAA, n.d.; Setzer, n.d.). Mathematical equations including Newton's laws of motion, the hydrodynamic state equation, mass conversion, and the thermodynamic energy equations. The computer models use the system of mathematical equations to evaluate and simulate the climate and physical processes at each grid point. The number of climate variables and physical processes incorporated in GCMs has greatly increased over the years, largely due to increased computing power and refinements of solving numerical equations (Figure 2.1). For example, the variables in GCMs in the mid-1970s included rainfall and carbon dioxide emission whereas with continued model development the water cycle, carbon cycle, ocean interactions and land interactions are among the variables and processes included (Edwards, 2011; IPCC, 2007).

Major efforts from three groups including the Geophysical Fluid Dynamics Laboratory (GFDL), University of California Los Angeles (UCLA) Department of Meteorology, and the United States National Center for Atmospheric Research (NCAR) began early climate model development and influenced creation of additional modeling groups. GCMs today are uniquely

developed by many different agencies and institutions around the globe, such as Britain's Hadley Centre and Japan's Earth Simulator Centre (Edwards, 2011). During model development, climate model variables and parameters are adjusted and aim to match observed climate system behaviors. GCMs are commonly tested through comparison with each other or with observational data through a "hindcasting" process that runs a model from a current time back into the past (Edwards, 2011; NOAA, n.d.). With hindcasting, the model results are then compared with the matching modeled time frame's climate and weather observations to assess the model performance and determine if adjustments are needed. If the hindcasting comparisons performance is similar, then the climate model results for simulating future projections is assumed to be valid. Representative Concentration Pathways (RCPs) climate forcing scenarios are applied to climate models to project future climate conditions. RCPs scenarios indicate the possible trajectories, various levels of impact, and climate response to potential levels of greenhouse gasses in the atmosphere in 2100, as well as provide climate models with additional information about land use and cover (Moss et al., 2010; van Vuuren et al., 2011).

The Intergovernmental Panel on Climate Change (IPCC) and the World Climate Research Programme's (WCRP) Working Group on Coupled Modelling (WGCM) have large impacts in the role of bringing together climate researchers for defining and establishing climate forcing scenarios, as well as model testing and evaluation (Edwards, 2011; van Vuuren et al., 2011). The Coupled Model Intercomparison Project Phase 5 (CMIP5) represents the most recent efforts of modeling groups, organized by the WCRP, to examine and test various climate modeling experiments. Including assessment of long-term and near-term climate modeling prediction experiments. The CMIP5 experiments inform the latest IPCC assessment report and provide access to latest model improvements to further advance climate research and climate

science understandings. CMIP5 builds upon previous CMIP experiments and includes a broader set of climate models with generally better spatial resolution than previous models (Flato et al., 2013; Taylor et al., 2012; D. Wuebbles et al., 2014). Improvements in computational power allowed for improvements in spatial resolution of climate models used in each IPCC assessment report. Overtime with increased computational power, GCMs include more climate variables and the spatial and temporal resolution of the models has seen much improvement (Figure 2.1). Model spatial resolution is defined by the three-dimensional grid cells that divide up the Earth's surface. Increasing the model's grid cell resolution corresponds to an increase in the level of detail and more grid cells that span the Earth's surface. Temporal resolution, or the time step for which a GCM is run, is an additional factor that impacts the level of detail and calculating time of a model. Early 1990s climate models, generally referenced a spatial resolution with a horizontal grid of 500km x 500km (5 degrees) and nine to ten vertical layers. Most recent global climate models tend to have a horizontal resolution of 100km or finer and more than 30 vertical layers (IPCC, 2007; Kotamarthi et al., 2021; NOAA, n.d.; Russell, 2010; Setzer, n.d.). Climate modeling is still a computational-intensive process. Even with much improvement in computational capabilities, producing finer resolution or more detailed model results is accompanied with increased time needed to perform the climate run.

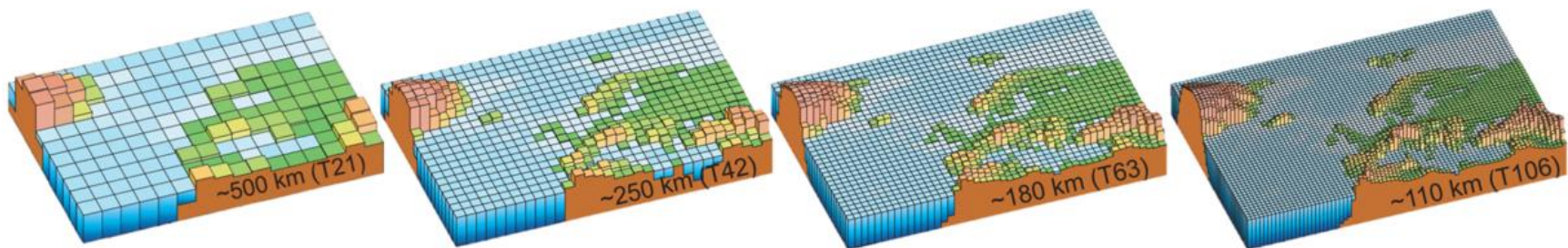
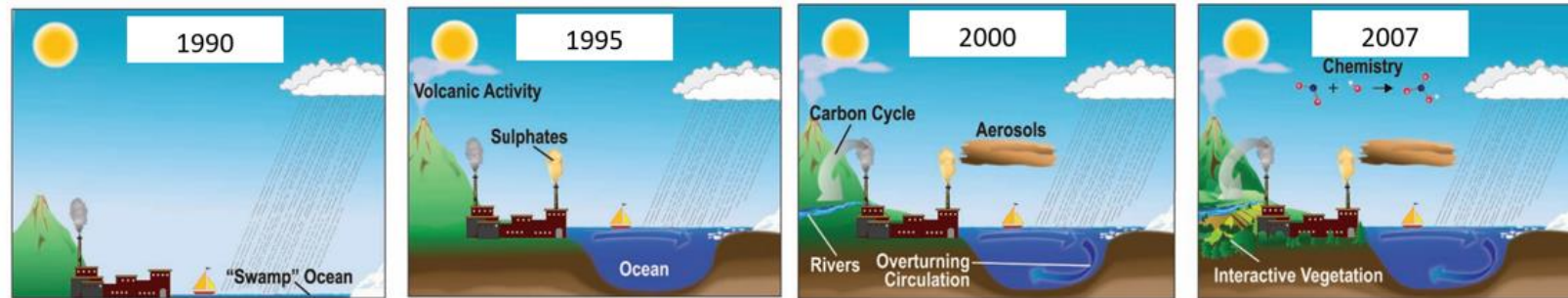


Figure 2.1. Visual representations of the significant advancements in global climate model (GCM) climate variables, model parameters, and spatial resolution from 1990 to 2007 (adapted from IPCC, 2007).

2.2.1 Downscaling of Global Climate Models

GCMs are developed to understand the changes in climate across large spatial (global) and temporal (decades) scales. While these models are accurate for global scale application, the resolution is not sufficient to fully capture the climate variabilities and behaviors that occur across local or regional scales. This insufficiency is due to a variety of climate variables which are driven by factors that differ across spatial scales including terrain, land use and landcover changes, and hydrological characteristics of a particular area. Scientific communities have recognized the need for regional and local scale assessments; however, the mismatch of spatial and temporal scales requires the development of higher resolution downscaling techniques for climate analysis. Downscaled modeling horizontal grid spatial resolutions can range from 25km x 25km grids down to 1km x 1km in some cases (Cooney, 2012; Kotamarthi et al., 2021). Overall, downscaling methods aim to provide more impactful and locally relevant climate projections for stakeholders and decision makers across regions, states, and cities.

Several approaches have been taken in respect to downscaling GCMs including dynamic and statistical downscaling. Dynamic downscaling utilizes high-resolution regional climate models (RCMs) to bias-correct and downscale GCM output to simulate dynamics of the regional climate system. Dynamic downscaling considers the boundary and initial conditions from a GCM and a nested RCM covers a limited geographic area providing greater detail to capture the regional climate characteristics. Dynamic downscaling technique involves a high level of detail that strains computations to short temporal model runs, hindering the ability to capture century-long model simulations for local and regional conditions (Cooney, 2012; Kotamarthi et al., 2021; Navarro-Racines et al., 2020). In contrast, statistical downscaling is considered more computationally efficient and an easier method to convert global-scale model output to high

spatial resolution for regional and local scale conditions. Statistical downscaling involves identifying statistical relationships linking local climate variables and large-scale predictors, then deriving downscaled outputs from GCMs based on the statistical relationships. Statistical downscaling approaches assume changes in climate will occur at coarse scales and the relationships between variables remain relatively constant at the local scale (Abatzoglou and Brown, 2012; Navarro-Racines et al., 2020). There are a variety of statistical downscaling methods but bias correction with spatial disaggregation (BCSD) and constructed analog (CA) based techniques have been widely applied over the western continental United States. The CA method aligns more closely with first principles of meteorology, more apt to model regionally complex meteorological phenomena, and more computationally efficient, as a comparison to other statistical interpolation based downscaling methods (Abatzoglou and Brown, 2012; Pierce et al., 2014). Statistical downscaling methods, Multivariate Adaptive Constructed Analogs (MACA) (Abatzoglou and Brown, 2012) and Localized Constructed Analogs (LOCA) (Pierce et al., 2014), build upon the CA method. The MACA statistical downscaling methods improve upon physical relationships between variables as compared to considering variables independently and incorporates a post-downscaling bias correction to reduce some of the errors in underestimating variables and the spatial-temporal variability in extreme events. MACA averages together multiple days to construct a final downscaled field, whereas, the LOCA method uses a slightly more intense computational method of selecting a single analog day in the local region about to be downscaled (Abatzoglou and Brown, 2012; Pierce et al., 2014). While these methods have unique statistical approaches, they both provide improvements to the current downscaling tools available and can be utilized in climate assessments. For example, LOCA downscaled models were utilized in The Fourth US National Climate Assessment. Both MACA

and LOCA downscaling methods, provide access to gridded climate data for 18 common GCMs that are downscaled to a finer spatial resolution.

2.3 Spatial and Temporal needs for Hydrologic and Watershed Applications

Changes in climate are impacting and will continue to affect water resource management systems. Within the Central United States, climate change has the potential to greatly impact productive agricultural systems, ecosystems, water resources, and human health and welfare (D. J. Wuebbles and Hayhoe, 2004). In addition, pressures from the expanding human population, growing economy and urbanization expansion compounds the impact and stresses placed on resources in the region. Nearly 85% of the total United States population in 2015, about 275 million people, lived in metropolitan areas (USGCRP, 2018). Many urban areas have aging stormwater infrastructure and critical transportation infrastructure that is at an increased risk of being overwhelmed and failing with the projected increases in precipitation events. Increases in urbanization and conversion of natural areas or floodplains to impervious surfaces modifies the watershed dynamics and affects the amount of surface runoff that water infrastructure systems need to handle (D. J. Wuebbles and Hayhoe, 2004).

Water resource management, infrastructure planning and risk assessments depend upon multiple decades of historical flood and rainfall data. However, solely considering historical data can result in the assumption of stationarity or no significant change of precipitation events in the future leading to underrepresentation of future risks that will impact infrastructure systems and society (Cook et al., 2017; USGCRP, 2018). The United States Global Change Research Program Fourth National Climate Assessment described learning to plan for plausible future climate conditions as a central challenge for water planning and management (USGCRP, 2018). Planning for plausible future climate conditions will assist in assuring reliable and resilient

infrastructure. However, this will require evaluating several possible future scenarios, updating policy, adjusting engineering standards, and incorporating available monitoring and forecasting tools (Lopez-Cantu et al., 2020; Revi et al., 2014; USGCRP, 2018). Tools such as downscaled global climate models, have been incorporated by stakeholders and modelers to assist in analysis and planning for future climate conditions (Chen et al., 2011; Lopez-Cantu et al., 2020; Rosenberg et al., 2010). Water resource management at regional and local levels requires high spatial and temporal resolution data inputs, ranging from basin to point spatial scales and seasonal to sub-hourly temporal scales (Cook et al., 2017). While downscaling methods of global climate models have led to significant improvements in refining the spatial and temporal resolution of global climate model data outputs, uncertainties and mismatch of scales still remain a challenge for appropriately incorporating downscaled output data into regional or local engineering applications (Chen et al., 2011; Cook et al., 2017; Lopez-Cantu et al., 2020; Varis et al., 2004). Specifically, the trend and magnitude of precipitation downscaled data varies widely across models, downscaling methods and geographic regions (Chen et al., 2011; Cook et al., 2017). Thus, when applying outputs from downscaled global climate models consideration of the number of models included in analysis; characteristics of downscaling method- assumptions, data storage and data resolution; and potential associated uncertainties are needed for appropriate application and interpretation of results (Chen et al., 2011; Cook et al., 2017). Continued improvements in downscaled global climate model projections and improved methods of applying model projections at local and regional scales will be vital to continuing to bridge the gap between tools in climate sciences and application in water resources.

Chapter 3 - Methods

3.1 Study Area

The study area for this research focuses on the Blue River Watershed (BRW). The Blue River Watershed is located in the Central United States Midwest region along the Kansas and Missouri border. The watershed spans across three Kansas Counties: Johnson, Miami, and Wyandotte and two Missouri counties: Cass and Jackson (Figure 3.1). Included within the greater Missouri River Basin, the Blue River Watershed (HUC #1030010101) drains from the headwaters in southern Johnson County and outlets in the Missouri River in the northwest part of Jackson County. The total drainage area of this watershed is 701 square kilometers (173,162 acres).

In 2013 the BRW was described, by the Heartland Conservation Alliance, as one of the most rapidly developing and urbanizing areas in the Kansas City region (Heartland Conservation Alliance, 2013). The headwaters of the watershed consist of mostly less-developed agricultural areas and moving toward the outlet the land use shifts to more commercial, residential, and urbanized areas. With projected increases in population growth, urban development will likely expand into the less developed areas in the headwaters of the BRW. Stormwater runoff and flooding has long been a major concern for the BRW with several historical flooding events, such as the floods of 1928, 1929 and 1961, and much effort has been spent on flood control measures in already developed portions of the watershed (Mid-America Regional Council, n.d.). Increases in urbanization and impervious surfaces throughout the watershed will continue to threaten water quality conditions, runoff volumes, and flood potentials. The amplification and variability of climate related events also contribute to the potential impacts on the watershed and what risks may be associated with overwhelmed structures and water management systems. The

year of 2019 was recorded as the third-wettest year for the Missouri River Basin (Kluck et al., 2020). The combination of high snowmelt and wide-spread heavy thunderstorms resulted in many areas along the Missouri River to experience flooding conditions in March 2019 (Liberto, 2019). Later in May of 2019, additional heavy precipitation events and flooding conditions of area streams, creeks, and rivers impacted many Kansas City communities and resulted in road and interstate closures as floodwaters overtopped the roads (Cronkleton and Rice, 2019). The extent of impacts associated with amplified and variable precipitation events will fluctuate throughout the watershed due to the varying levels of development and variability of climate events. Careful considerations will be required as the watershed develops in order to minimize potential risk to the Blue River Watershed's ecosystems, communities, and infrastructure.

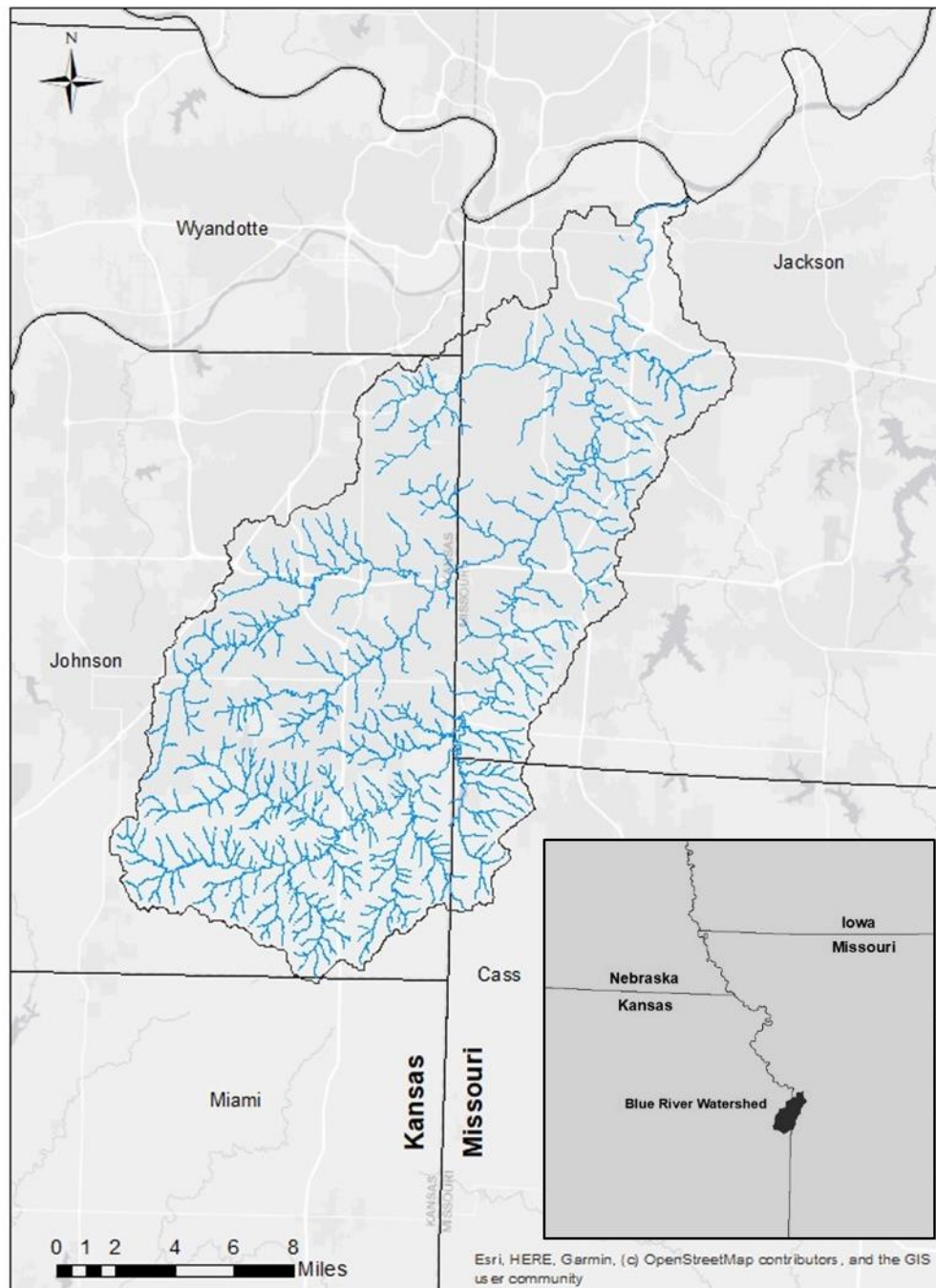


Figure 3.1. Location of the Blue River Watershed (BRW) along the Kansas and Missouri state line and spanning across 5 counties.

3.2 Data Collection

3.2.1 NOAA Stations

National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) works to provide free access to high-value environmental data and information via data center interfaces for the scientific community and general public (NOAA-NCEI, n.d.). The online data center and tools provide access to observation station information and archives of global historical weather and climate data. NOAA-NCEI observation stations measure meteorological information at a specific site or location in which the station and instrumentation is installed. Length of record and the availability of variables varies depending on the station's observation recording equipment or volunteer observers recording the data.

Continuous, historical, daily precipitation data summaries were obtained from 14 NOAA-NCEI precipitation stations located within and surrounding the BRW (Figure 3.2). All 14 stations were within 30 km (19 mi) of the watershed edge. The furthest station from the watershed edge, at approximately 29.5km (18.3mi), was Kearney3 (station label m). Using NOAA's Climate Data Online Find-a-Station data tool, station location and precipitation records were viewed and assessed online before selection for download (NOAA-NCEI, n.d.). The stations were selected based on their proximity to the study area, length of coverage and availability (Table 3.1). The length of coverage and the completeness of records vary; however, the selected stations were determined to have the most available and complete historical daily precipitation station data in, or within, close proximity of the BRW available to freely access and download. Complete step-by-step download instructions are included in Appendix A - .

Stations labeled a-f (Table 3.1) were utilized in the point comparison and initial validation analysis; these stations are located within the BRW (stations a, d-f) or are less than 3

miles from the watershed edge (stations b, c), with decent coverage and availability of data. The additional stations g-n (Table 3.1) were reviewed for development of continuous, raster surfaces. Additional stations around the BRW were needed to provide “anchoring” points for developing continuous surfaces to minimize the boundary effects and prediction error in surface interpolation calculations. Surface interpolation methods such as Ordinary Kriging, Radial Basis Function and Inverse Distance Weighting were explored to develop a continuous surface precipitation data across the study area. However even with the addition of stations, the limitations in the number of stations and the amount of data coverage hindered the capabilities of developing good station surfaces for specifically the BRW area. Thus, leading to the decision of obtaining and utilizing gridded surface datasets from accessible data sources such as PRISM to ultimately compare surfaces of data rather than just points of data.

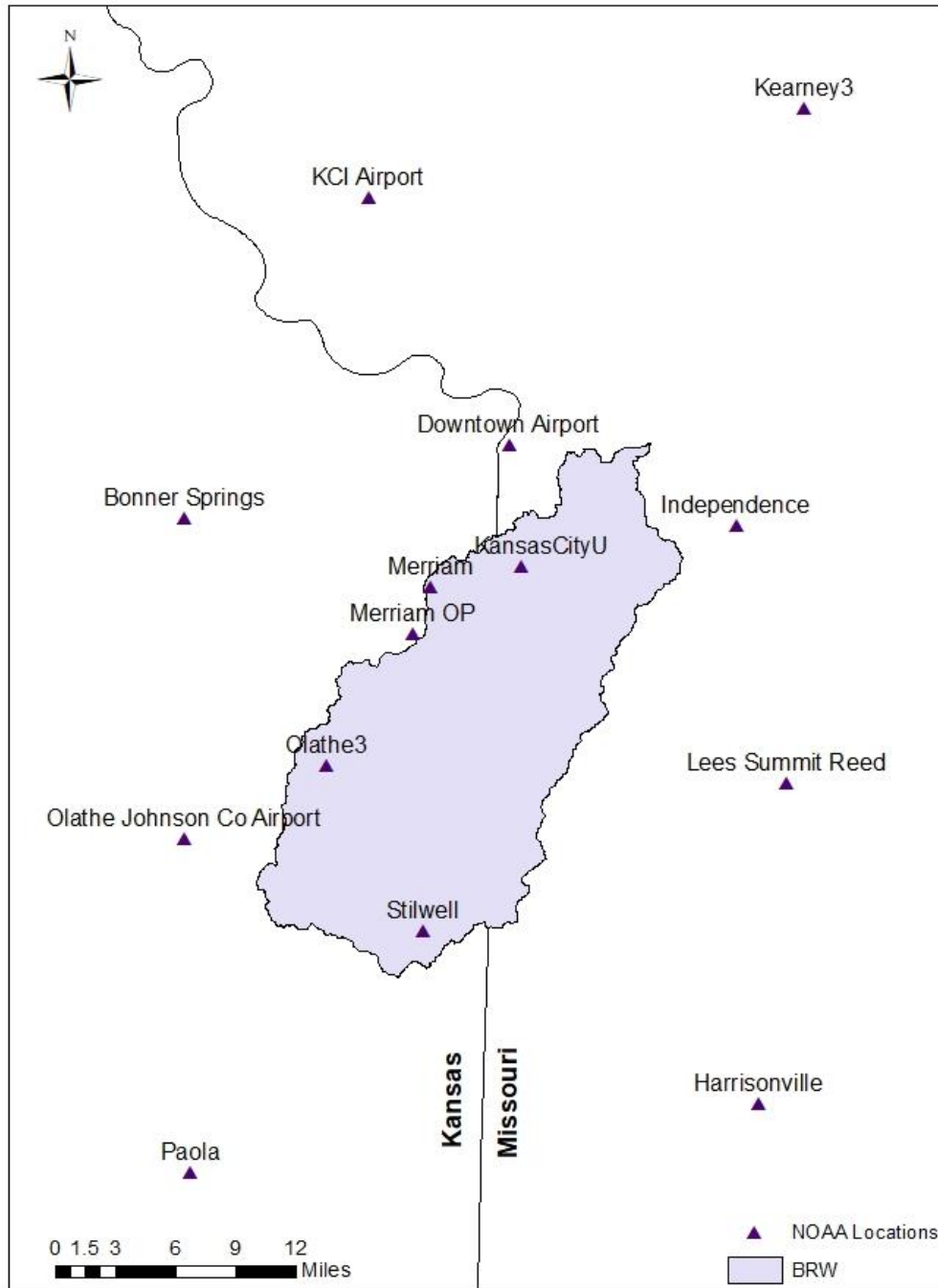


Figure 3.2. The 14 NOAA stations utilized within and surrounding the Blue River Watershed (BRW) (NOAA-NCEI, n.d.).

Table 3.1. The selected NOAA stations, locations and data record (NOAA-NCEI, n.d.).

Label	Station ID	Station Name	Latitude	Longitude	Availability	Coverage	Downloaded
a	USC00234379	Kansas City U of MO, MO US	39.03333	-94.58333	1/01/1950 to 5/31/1970	95%	1950-1970
b	USW00013988	Kansas City Downtown Airport, MO US	39.1208	-94.5969	1/01/1950 to 12/31/2010	91%	1950-2010
c	USC00145248	Merriam Overland Park, KS US	38.98333	-94.68333	8/17/1951 to 2/11/1965	96%	1951-1965
d	USC00145245	Merriam, KS US	39.01667	-94.66667	1/01/1950 to 2/28/1965	95%	1950-1965
e	USC00145972	Olathe 3 E, KS US	38.8875	-94.7602	1/01/1950 to 9/30/2009	96%	1950-2009
f	USC00147809	Stilwell, KS US	38.7695	-94.6682	1/01/1950 to 2/28/2010	90%	1950-2010
g	USW00093909	Olathe Johnson Co Industrial Airport, KS US	38.83167	-94.88972	3/01/1945 to 12/11/2018	61%	1950-2010
h	USC00140957	Bonner Springs, KS US	39.0636	-94.8959	1/01/1938 to 12/12/2018	99%	1950-2010
i	USC00233649	Harrisonville, MO US	38.6494	-94.3567	1/01/1893 to 12/23/2017	80%	1950-2010
j	USC00234850	Lees Summit Reed Wlr, MO US	38.8802	-94.3358	4/02/1962 to 11/21/2011	98%	1962-2010
k	USC00234154	Independence, MO US	39.0647	-94.3861	1/01/1990 to 12/07/2018	97%	1990-2010
l	USC00146209	Paola, KS US	38.5912	-94.8778	8/01/1895 to 8/31/2009	86%	1990-2009
m	USC00234382	Kearney 3 E, MO US	39.3667	-94.3294	7/01/1994 to 2/05/2019	92%	1994-2010
n	USW00003947	Kansas City International Airport, MO US	39.2972	-94.7306	10/01/1972 to 12/05/2018	100%	1973-2010

3.2.2 GCMs- GDO and MACA

Simulated precipitation data was collected from two statistically downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projection sources: GDO LOCA and MACA V2. Localized Constructed Analogs (LOCA) downscaled CMIP5 climate projection data requests are processed by the Lawrence Livermore National Laboratory's (LLNL) data storage network Green Data Oasis (GDO) ("Downscaled CMIP3 and CMIP5 climate and hydrology projections," n.d.; Pierce et al., 2014, 2015). LOCA and GDO were used interchangeably throughout this thesis and analysis in reference to the LOCA downscaled climate projection method. The Multivariate Adaptive Constructed Analogs (MACA) downscaled climate datasets are processed using a gallery of online data tools available from the Northwest Knowledge Network ("Data Tools," n.d.; Abatzoglou, 2013; Abatzoglou and Brown, 2012).

The downscaling methods GDO LOCA and MACA V2 use different statistical methods for downscaling GCMs to a higher resolution or finer grid cell size. GDO LOCA is downscaled to a $1/16^{\text{th}}$ degree grid cell spatial resolution (~6km by 6km). Whereas MACA V2 downscaling method has a grid cell spatial resolution of $1/24^{\text{th}}$ degree (~4km by 4km) (Figure 3.3). Precipitation data was downloaded for the historical/current time period of 1950-2005, near-future time period of 2021-2050 and far-future time period of 2070-2099 from each downscaling method and 18 GCMs (for a total of 36 GCMs) (Table 3.2). Daily data from GDO and MACA was downloaded at points corresponding to the NOAA stations labeled a-f (Table 3.1) for 1950-2005 and used in the initial validation comparisons of NOAA and the 36 GCMs. The point location value represents the grid cell value of the downscaled GCM product. GDO and MACA selected model data for historical, near-future and far-future time periods was obtained at 37 similar point locations that correspond to the GDO cell approximate centers or "centroids"

(Table A.6.1). Then, selected GDO model precipitation data was obtained for a complete gridded surface of 80 grid cells developed by using point locations at approximate centers of the GDO LOCA downscaled product grid cells (Table A.6.1 and Table A.6.2). In addition, for a complete surface of selected MACA models, monthly MACA downscaled precipitation data was downloaded in the form of a NetCDF file format over a gridded surface consisting of 396 grid cells (4kmx4km grid cell resolution).

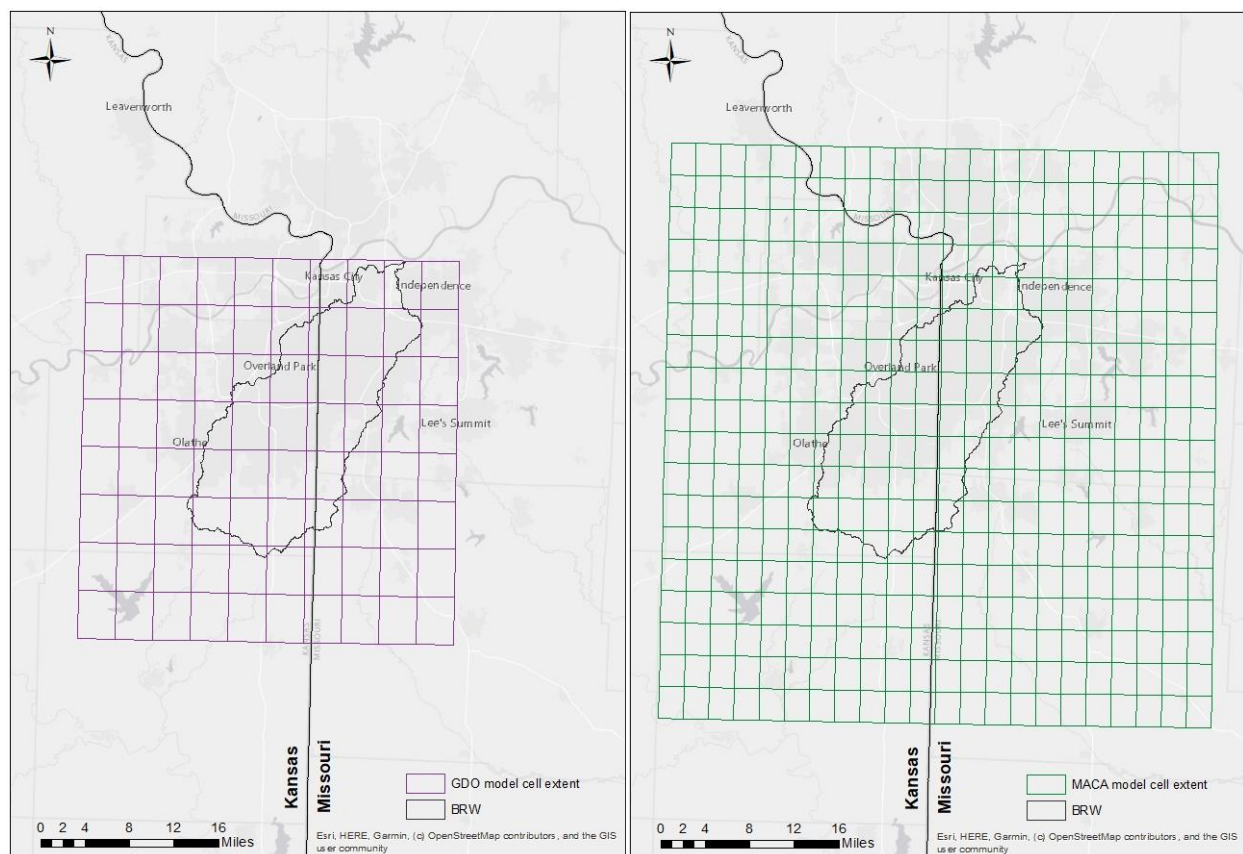


Figure 3.3. Downscaled global climate models (GCMs) GDO (left) and MACA (right) grid cell resolution and the downloaded extents across the Blue River Watershed (BRW).

Table 3.2. The 18 global climate models (GCMs) name and model agency in which data was obtained at the two downscaling methods.

GCM NAME	MODEL AGENCY
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration
BCC-CSM1-1-M	Beijing Climate Center, China Meteorological Administration
CANESM2	Canadian Centre for Climate Modeling and Analysis
CCSM4	National Center of Atmospheric Research, USA
CNRM-CM5	National Centre of Meteorological Research, France
CSIRO-MK3-6-0	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, USA
HADGEM2-CC365	Met Office HadleyCenter, UK
HADGEM2-ES365	Met Office HadleyCenter, UK
INMCM4	Institute for Numerical Mathematics, Russia
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France
IPSL-CM5A-MR	Institut Pierre Simon Laplace, France
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MIROC-ESM- CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MRI-CGCM3	Meteorological Research Institute, Japan
NORES1-M	Norwegian Climate Center, Norway

3.2.3 PRISM

Parameter-elevation Regressions on Independent Slopes Model (PRISM) is a computerized knowledge based climate mapping approach to provide access to estimates of spatial climate datasets. To develop gridded climate estimates, PRISM utilizes digital elevation models (DEMs) and point data to calculate a climate-elevation relationship (Daly et al., 1994, 2002, 2008). While PRISM was originally developed to suit complex terrain landscapes, such as mountainous regions, the mapped spatial datasets extend and are available for download across the contiguous United States. For this analysis, historical precipitation data was obtained at daily and monthly time series from 1981-2010 from the PRISM gridded spatial climate datasets (“PRISM Climate Group, Oregon State University,” 2004). Daily data was obtained at the same 37 point locations used for downloading the downscaled GCM datasets (Table A.6.1). Monthly gridded precipitation surfaces were also obtained in raster BIL file formats and in the PRISM grid cell spatial resolution of 1/24th degree (~4km by 4km).

3.3 Data Processing

3.3.1 Monthly and Yearly Aggregation

In order to perform similar comparisons at point locations and temporal scales, data was aggregated from daily values into monthly and yearly values. Monthly sums of the daily data collected from NOAA stations a-f were calculated using Excel for each station. GCM point daily datasets were aggregated to monthly and yearly values for historical, near-future and far-future time periods. Developed R code assisted in modifying the raw GCM data format and performing monthly and yearly calculations values. Monthly and yearly calculations included calculating the monthly and yearly summations; means; count of precipitation events greater than 3.00mm, 25.0mm and 38.5mm.

Chapter 4 - Aspatial Point to Point Comparison Approach

4.1 Station Point and GCM Comparison and Initial Validation

To begin understanding the usefulness of precipitation data from 36 downscaled GCMs, the modeled point values were compared to the observations from NOAA stations a-f within the historical time period of 1950-2005 on a monthly and annual basis using developed R code (Appendix B -). Several statistical parameters were utilized within the initial validation process to examine the performance of the historically projected GCM precipitation data against the observed NOAA datasets. Statistical analysis included the Mann-Kendall trend test (τ), Spearman's rank correlation coefficient (ρ), and root mean square error (RMSE). Once the statistical tests were completed, the trends and correlation of the models, as compared to the observed data, were assessed, and visually compared to identify the best performing models.

The Mann-Kendall non-parametric trend test was used to measure the strength, or correlation, of the relationship between the modeled and observed data. Tau (τ) indicates the trend by a positive or negative value of correlation. Positive trend values were used in selecting best performing GCMs as a positive correlation indicates both variables are increasing together. Spearman's rank correlation coefficient (ρ) assesses a degree of similarity or association between the interested variables. Spearman's rho (ρ) ranges from -1 to 1 determining if the correlation between the model and observed data was significantly different from 0. For this analysis, all models with a $\rho \geq 0.4$ were considered comparable to the observed data and were selected for further analysis. Root mean square error (RMSE) was also considered. RMSE is a measure of the spread in residuals or difference between the predicted and true value. Ideal performance would include a RMSE value close to zero, which indicates minimal error and accurate model simulation.

The combination of statistical results from the parameters described above assisted in selection of the best performing models for further analysis. Further analysis included methods to better visualize and compare how the selected models performed against each other, their location, and the observed precipitation using boxplots, Taylor diagrams and long-term trend plots.

4.2 Results and Discussion

From the original set of 36 downscaled GCMs, seven models were identified as the best performing models for the BRW following the statistical validation assessment comparing the downscaled GCM data to the observed NOAA stations a-f data over the historical time period (Table C.6.3). The seven selected models resulted in monthly precipitation sum comparison statistical performances with $\rho \geq 0.4$ and a positive τ , trend, at one or more of the NOAA locations. The average, maximum, and minimum Tau and Rho values for the seven selected models and all 36 models over the six NOAA locations show that the selected models' average Tau and average Rho statistical results were higher as compared to the whole group of 36 models (Table 4.1). This contributes to the determination that the selected models were the best performing models within the group of 36 models utilized in the statistical validation. The selected models included three models from the downscaling method GDO LOCA and four models from the downscaling method MACA V2 (Table 4.2). To further assess and visualize the validation performance of the selected models' boxplots, Taylor diagrams, and long-term trend line plots were developed to compare selected models to each other, location, and observed precipitation.

Table 4.1. Summary of monthly sum precipitation validation comparison statistics Mann-Kendall Tau and Spearman's rank correlation coefficient Rho for the seven selected downscaled global climate models (GCMs) and all 36 downscaled GCMs at NOAA stations a-f.

		Tau	Rho
Selected 7 models at stations a-f	Average	0.031	0.341
	Maximum	0.143	0.537
	Minimum	-0.013	-0.215
All 36 models at stations a-f	Average	0.004	0.298
	Maximum	0.143	0.537
	Minimum	-0.103	-0.357

Table 4.2. The seven selected downscaled global climate models (GCMs) and model agency.

GCM NAME	MODEL AGENCY
GDO_CCSM4	National Center of Atmospheric Research, USA
GDO_MRI-CGCM3	Meteorological Research Institute, Japan
GDO_NorESM1-M	Norwegian Climate Center, Norway
MACA_MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MACA_MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MACA_MRI-CGCM3	Meteorological Research Institute, Japan
MACA_NorESM1-M.	Norwegian Climate Center, Norway
*GDO LOCA GCM downloaded from: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ and MACA GCM downloaded from: https://climate.northwestknowledge.net/MACA/gallery_data.php	

Boxplots were used to visualize the dispersion, central tendency, and potential outliers of Spearman's correlation coefficient (ρ) values. Boxplots were developed for comparisons of GCM precipitation and observed precipitation for the monthly total and monthly maximum precipitation on both a location basis and a model basis. While mainly interested in the monthly sum precipitation comparison, examining the monthly maximum precipitation comparison gave

further insight in how the modeled data compared to the observed data. Comparing model performance on a location basis assisted in understanding the performance at the different point locations throughout the watershed, highlighting how each data group at a station compared to another. Similarly, the comparison on a model basis assisted in identifying any major differences among the seven models.

The boxplot shows comparatively how well the spread of correlation coefficients agree with each other. The median line depicts the middle or mid-point of the data values. The box size or interquartile range illustrates an overall level of agreement in data points between the 25th percentile and 75th percentile. Outliers (open dots) and whiskers (dotted upper lines) represent values that have a wider variability, indicating highest values, lowest values, and points falling outside the overall distribution of data values. Figure 4.1 shows the spread of correlation values between the monthly total precipitation of selected models and the observed precipitation at each location of the NOAA precipitation stations. From this figure, it was determined that the correlation coefficients performed similarly throughout the watershed at each of the NOAA locations, with one exception. The Merriam OP (Overland Park) had a lower validation performance, with a median $\rho < 0.3$ and wider range of correlation values as compared to other locations. Similarly, a boxplot was used to show correlation values of monthly maximum precipitation on a location basis (Figure 4.2). The median of correlation coefficients showed a stronger agreement for the maximum precipitation performing between 0.2 and 0.3 at each location, except for the Merriam OP location. As mentioned above the data length of coverage and availability at each station varies. The poorer validation performance on a location basis at the Merriam OP station is likely attributed to the shorter coverage of data available at this specific point location. Furthermore, boxplots were used to visualize the correlation coefficients

on a model basis for both the monthly total precipitation (Figure 4.3) and monthly maximum precipitation (Figure 4.4). The correlation coefficients were similarly dispersed and had similar median performances for each of the seven selected models.

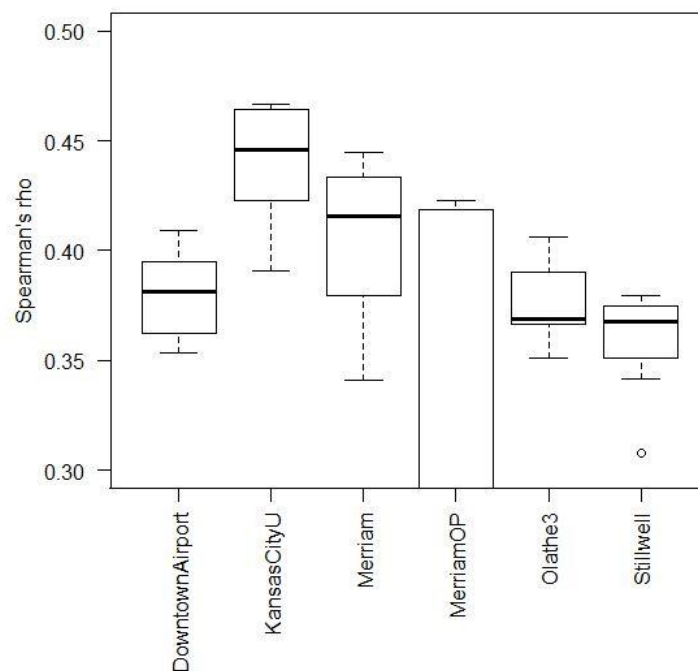


Figure 4.1. The correlation (ρ) between the monthly total downscaled global climate model (GCM) precipitation and historical, observed precipitation from NOAA stations on a location basis.

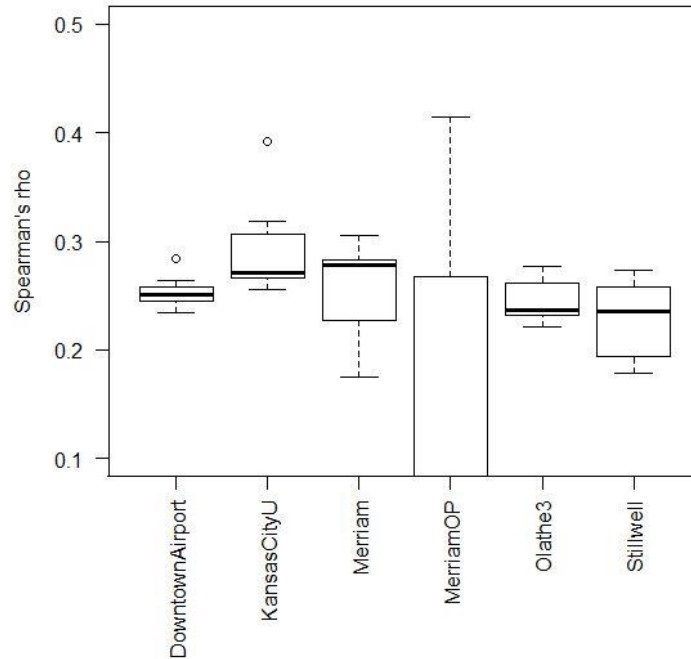


Figure 4.2. The correlation (ρ) between the monthly maximum downscaled global climate model (GCM) precipitation and historical, observed precipitation from NOAA stations on a location basis.

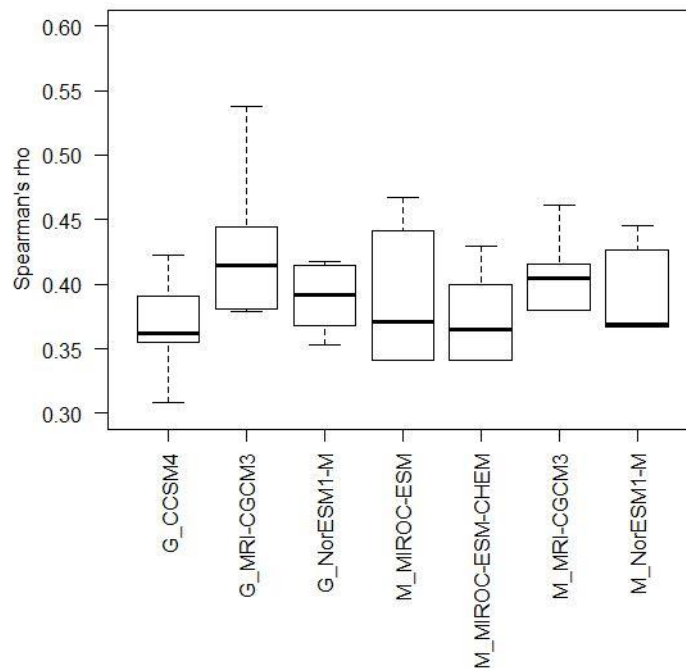


Figure 4.3. The correlation (ρ) between the monthly total downscaled global climate model (GCM) precipitation and historical, observed precipitation from NOAA stations for each of the seven selected downscaled GCMs. Model names with “G_” indicates the GDO LOCA downscaling method and “M_” indicates the MACA downscaling method.

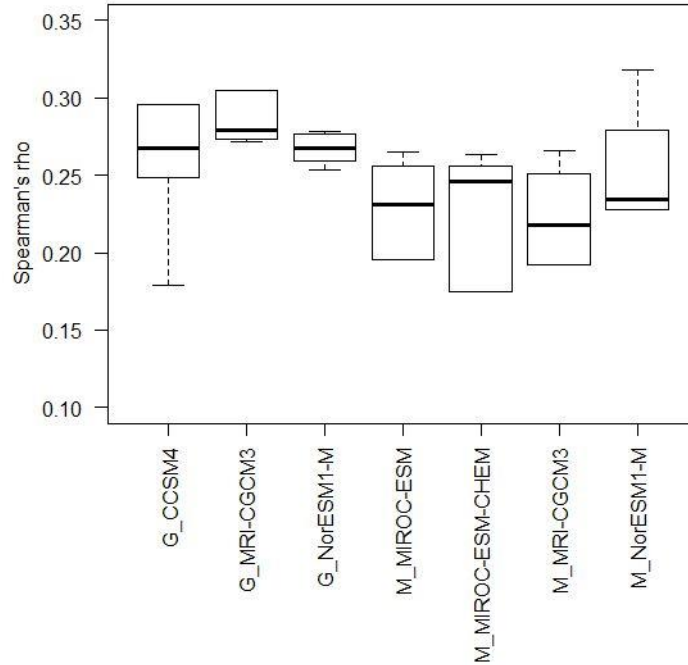


Figure 4.4. The correlation (ρ) between the monthly maximum downscaled global climate model (GCM) precipitation and historical, observed precipitation from NOAA stations for each of the seven selected downscaled GCMs. Model names with “G_” indicates the GDO LOCA downscaling method and “M_” indicates the MACA downscaling method.

Taylor diagrams were another method used to visualize the overall validation performance. These diagrams provide a concise statistical summary of multiple parameters including Spearman’s correlation coefficient, standard deviation, and RMSE difference used in the validation process (Taylor, 2001). The correlation coefficient is located along the curve relating to the angle from origin (black axis), standard deviation (blue axis) along the x-axis and root mean square difference (green field) is in a field that is proportional to the distance from the point on the x-axis representing the reference or observed point, detailed as a green square in the following diagrams. An ideal model performance would lie near the observed point on the x-axis. This would represent a model that has a low RMSE and high correlation and if the model lies on the same arc as the point then the model has a similar standard deviation, indicating an accurate representation of the observed conditions.

The overall validation performance by NOAA location is illustrated by a Taylor Diagram in Figure 4.5. Each NOAA location has seven colored triangles that represent the seven selected model performances at the given NOAA location. It was observed that the Merriam OP location had a poorer validation performance, as observed with some of the orange triangles lying further away from the rest of location comparisons and the optimal point value. This was expected as based on the boxplot visualizations and discussion above, the Merriam OP location had a higher spread of correlation values and a much lower median value as compared to other locations (Figure 4.1). However, all other locations had a comparable performance across the NOAA locations. Performing on the same standard deviation curve, correlation coefficient near 0.4 and similar RMSE.

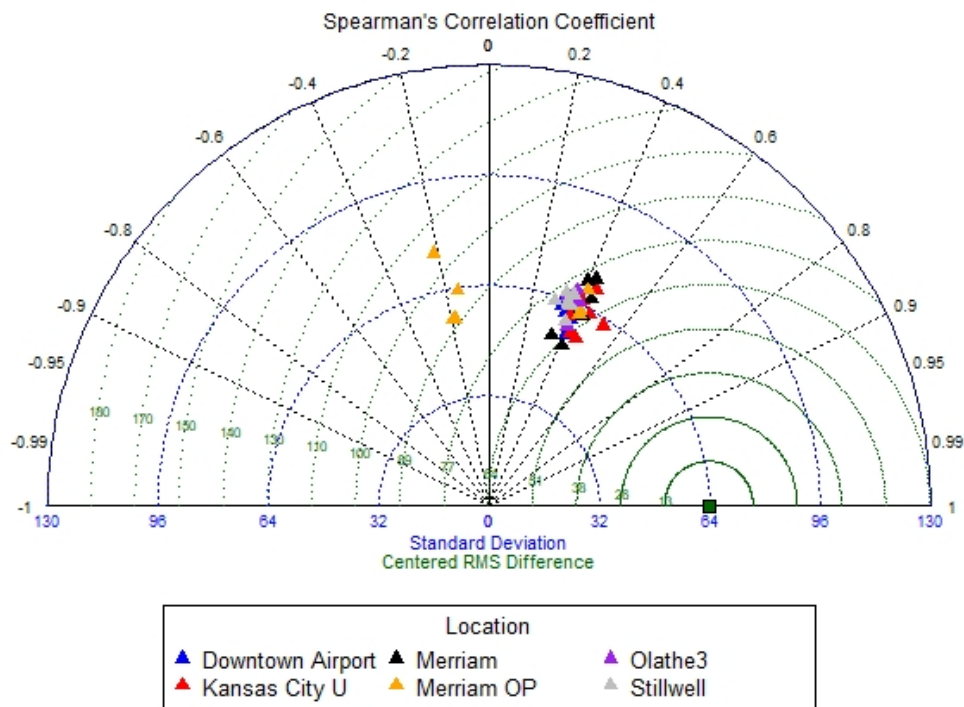


Figure 4.5. Taylor diagram illustrating the overall validation performance of the seven selected downscaled global climate models (GCMs) compared to observed NOAA precipitation stations by location of the NOAA stations.

A second Taylor Diagram (Figure 4.6) illustrates the overall validation performance by model. Each selected model is represented by six colored triangles corresponding to the NOAA locations. The selected model performances were comparable. Models GDO_CCSM4, GDO_MRI.CGCM3, GDO_NorESM1.M, and MACA_MIROC.ESM.CHEM can be observed to have a slightly better performance as these models were clustered along the same standard deviation curve, have a correlation coefficient of about 0.4, and similar RMSE.

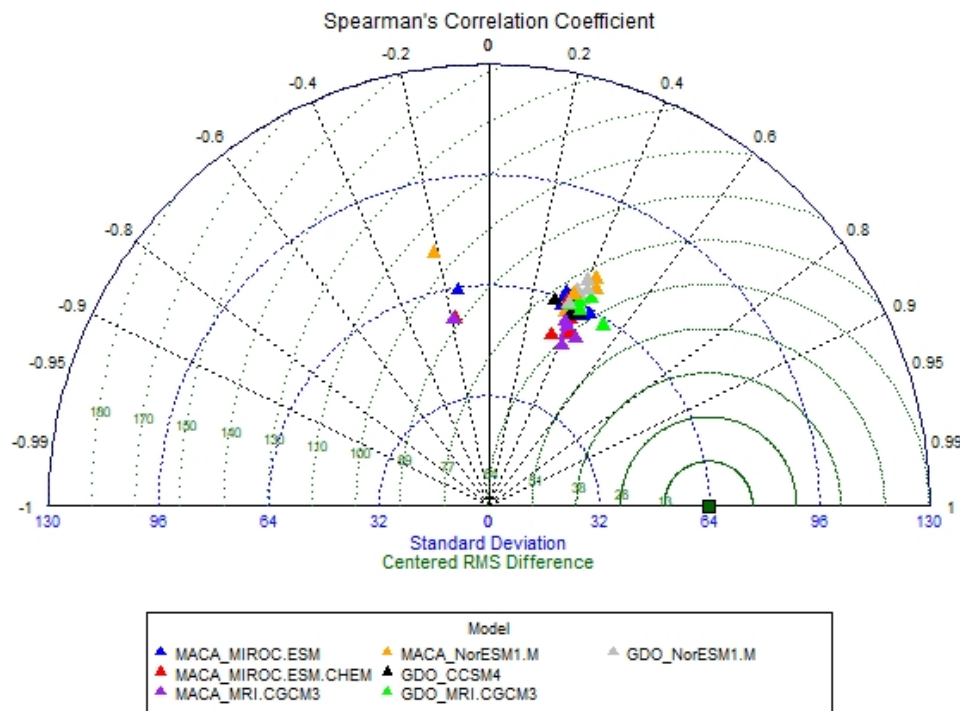


Figure 4.6. Taylor diagram illustrating the overall validation performance of the seven selected downscaled global climate models (GCMs) compared to observed NOAA precipitation stations by each GCM. Model names with “GDO_” indicates the GDO LOCA downscaling method and “MACA_” indicates the MACA downscaling method.

Lastly and separate from direct statistical result performance, long-term trend plots were used to visualize and compare the observed monthly precipitation to the modeled precipitation of the seven selected models for a specific year and location. These long-term plots allowed for a

whole year to be observed at once and for peaks in observed monthly precipitation and modeled monthly precipitation to be compared at one station. Figure 4.7 details monthly precipitation at the Downtown Airport location for the year 1950. The observed NOAA precipitation (NCEI black line) for 1950 peaked between the months of June and August; whereas the selected models followed a similar pattern, but a few models included an early season and late season peak in monthly precipitation totals. A similar plot was constructed for the Downtown Airport location for the year 2001 (Figure 4.8). In 2001, the MACA_MIROC-ESM-CHEM model appeared to depict the observed precipitation more accurately. While the GDO_NorESM1-M model peaked later in the year during September, not following the observed NOAA precipitation pattern as well.

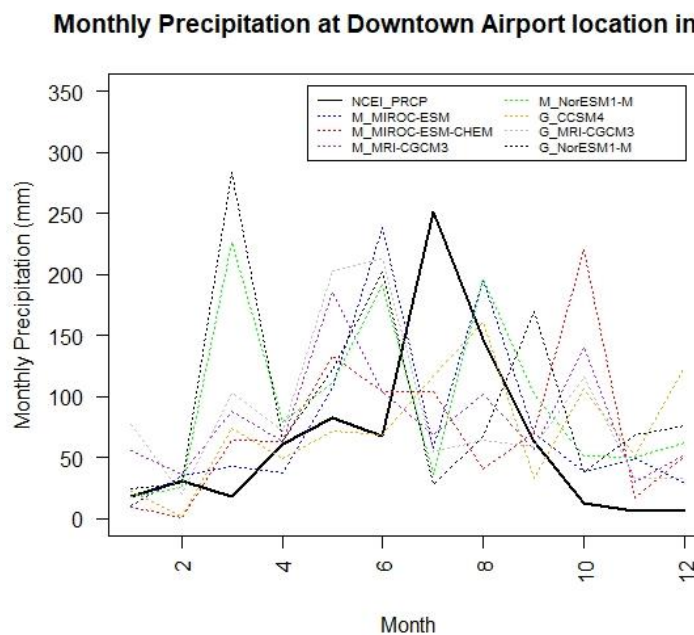


Figure 4.7. Long-term trend plot comparing observed, NOAA monthly precipitation at the Downtown Airport location (NCEI_PRCP) and the modeled monthly precipitation for the seven selected downscaled global climate models (GCMs) for the year 1950. Model names with “G_” indicates the GDO LOCA downscaling method and “M” indicates the MACA downscaling method.

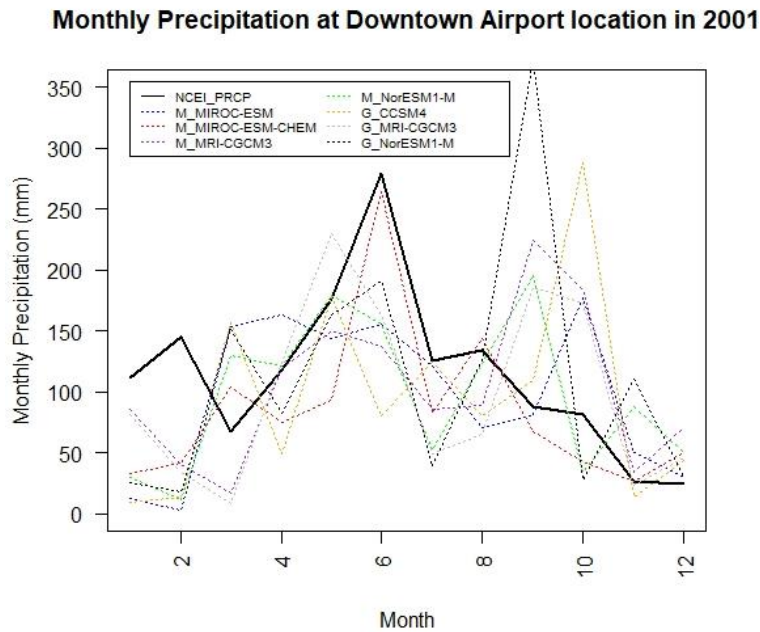


Figure 4.8. Long-term trend plot comparing the observed, NOAA monthly precipitation at the Downtown Airport location (NCEI_PRCP) and the modeled monthly precipitation for the seven selected downscaled global climate models (GCMs) for the year 2001. Model names with “G_” indicates the GDO LOCA downscaling method and “M” indicates the MACA downscaling method.

Through the statistical validation and visualization of the downscaled GCMs with the observed NOAA precipitation data, the original set of 36 downscaled GCMs was narrowed down to seven models. The seven selected models were identified as the better performing models for the BRW, based on the comparison of model and observed data with a $\rho \geq 0.4$ and a positive τ , trend, at one or more of the NOAA locations. While visualization of the validation statistics showed that the selected models had comparable performances to the observed location data, much variability still exists in the modeled monthly precipitation totals, from year-to-year and station-to-station, throughout the historical validation period as compared to the observed monthly precipitation totals for the study area.

Chapter 5 - Spatial Approach of Selected Model Surface

Comparison

The aspatial, point to point, comparisons described above refined the initial set of 36 downscaled GCMs to seven models that were comparable with the point station location and best performing in the BRW. To better assess the selected model spatial performances (cell by cell) across the BRW, rather than just at point locations, surfaces of selected modeled data were compared to the PRISM spatial dataset.

5.1 KS Test GDO GCM and PRISM Surface Comparison

Analysis of cell by cell surface comparison of selected GDO GCMs and PRISM used the Kolmogorov-Smirnov (KS) test. The two-sample KS test is a non-parametric method commonly used to compare probability distributions and the goodness of fit between two samples. Based on the empirical cumulative difference function (ECDF) and cumulative distribution function (CDF), the KS test derives the maximum vertical distance (D_n) between the two samples (Equation 5.1) (Fischer et al., 2012; Wang et al., 2008). A smaller D value and $p\text{-value} \geq 0.05$ indicates a better match of the two sample's distributions (samples drawn with the same distribution) whereas a larger D value, up to the value of 1, with $p\text{-value} < 0.05$ indicates the samples are different (drawn from different distributions). The KS test analysis served as an initial assessment of how monthly precipitation from the selected GDO GCMs compared to PRISM across a gridded surface of 37 cells. The KS test was completed using developed R code to run the test and generate CDF plots comparing the two samples for each month in the analysis period (Appendix D -).

$$D_n = \sup_x |F_n(x) - F(x)| \quad 5.1)$$

$$F_n(x) = \frac{1}{n} \sum_{i=1}^n I_{X_i \leq x}$$

Where: $F(x)$ represents the candidate cumulative distribution function

$\sup_x$ = the least upper bound of the set of distances

$I_{X_i \leq x}$ = indicator function, 1 if $X_i \leq x$ or 0 otherwise

5.1.1 Data Preprocessing

To prepare for the KS test analysis, the data for the selected GDO GCMs and PRISM was first preprocessed to gather monthly data for a 10-year period from 1995-2004 in similar formats and data resolution for cell to cell comparison. The KS-test used the downloaded precipitation data from the initial 37 grid cell centroids, at the 6kmx6km grid cell resolution, for three selected GDO downscaled GCMs. This data was formatted into monthly summaries for the analysis period of 1995-2004 and saved as a comma-separated values (csv) file format. Then, monthly gridded spatial dataset downloads from PRISM were preprocessed in ArcGIS. The PRISM download included separate monthly raster layers (.BIL file format) at a 4kmx4km grid cell resolution. The PRISM data was resampled within ArcGIS to the GDO 6kmx6km grid cell resolution and snapped to the GDO surface so each cell in the surface of PRISM would match with the cells in the GDO surfaces. Then the values at the PRISM grid cell centroids were extracted for each month to obtain the PRISM cell data at the same extent as the GDO surface. The resampled monthly PRISM cell data was exported to a csv file format for the 10-year analysis period.

Once the monthly data were formatted and obtained for the 10-year analysis period for the 37 grid cell surface, the KS test R code was run by using RStudio. The D test statistic and p-

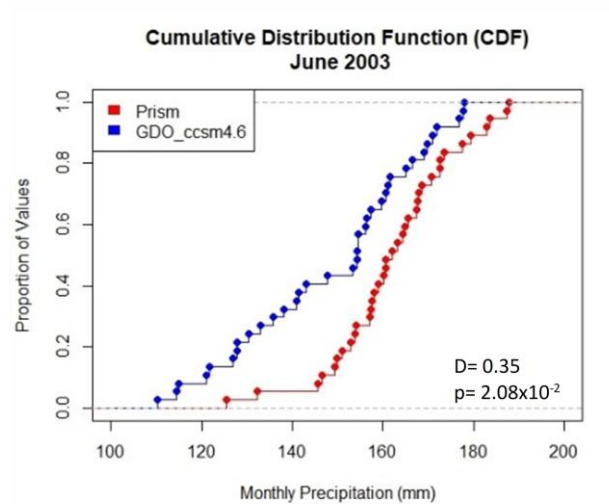
value for each month were recorded for each GDO model comparison to PRISM. The comparison CDF plots were also saved and compiled for GDO model comparison to PRISM.

5.1.2 Results and Discussion

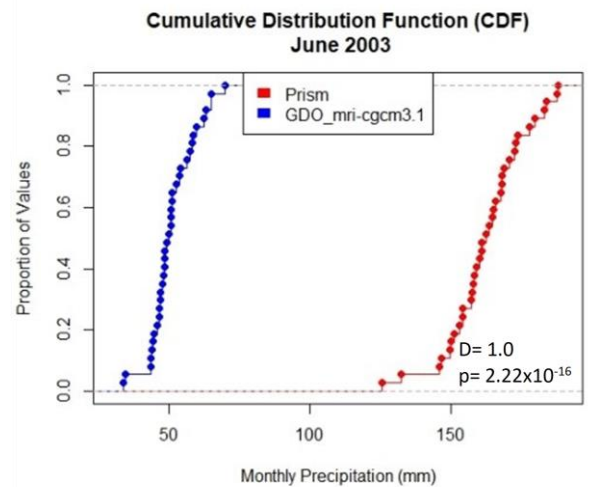
The KS test analysis for the historical period of 1995-2004 comparing the three GDO GCMs to PRISM resulted in very few comparisons with a D value ≤ 0.5 and a p-value > 0.05 (Table 5.1 and Table E.6.4). Figure 5.1 illustrates an example of generated CDF plots for the month of June 2003 from the 10-year analysis period. Figure 5.1a shows the comparison of GDOccsm to PRISM, this comparison result visually looks similar and has a low D value of 0.35, but the p-value of 2.08×10^{-2} is less than the significance level of 0.05 indicating the distributions are different. The comparison results of GDOmri to PRISM, Figure 5.1b, showed the distributions were different with a D value of 1.0 and p-value of 2.22×10^{-16} . Both Figure 5.1 a and b resulted in a significantly different comparison indicating that the samples compared are not drawn from the same distribution. Whereas the comparison of GDOnor to PRISM in Figure 5.1c, resulted in a similar comparison of the distributions with both the D and p-values, 0.24 and 0.224, respectively. The results of Figure 5.1c, show a KS test result that was not significant enough to specify the samples are drawn from different distributions. This was a preferred result in the analysis to identify that the comparison of GDO models to PRISM were drawn from similar distributions. However, a majority of the monthly comparisons for the entire 10-year period resulted in CDF comparisons similar to Figure 5.1b with D values near 1 and p-values less than the significance level of 0.05 overall indicating a difference in the compared distributions.

Table 5.1. Summary of Kolmogorov-Smirnov (KS) test monthly results for comparison of the three selected GDO downscaled global climate models (GCMs) (GDO LOCA model product, http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/) to PRISM (<https://prism.oregonstate.edu>) from 1995-2004 meeting the criteria levels for the D and p values (total number of months 120).

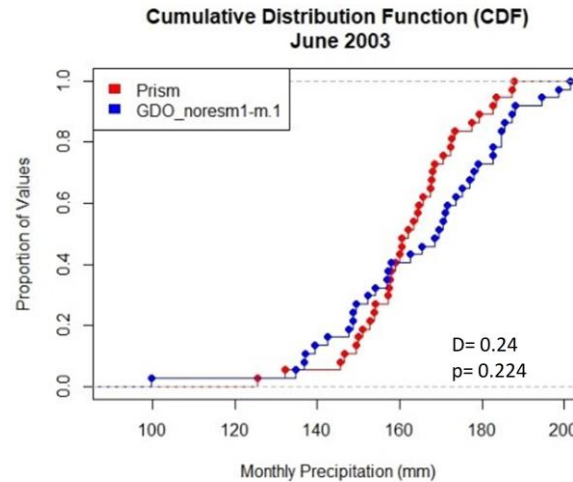
GDO Model Compared to PRISM	No. of Months meeting both $D \leq 0.5$ and $p > 0.05$
GDO_ccsm	2
GDO_mri	3
GDO_nor	8



a)



b)



c)

Figure 5.1. Kolmogorov-Smirnov (KS) test CDF plots for June 2003 for the three selected GDO downscaled global climate models (GCMs) (GDO LOCA model product, http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/) (blue) compared to PRISM (<https://prism.oregonstate.edu>) (red); a) GDOccsm with $D=0.35$ and $p=2.08 \times 10^{-2}$, b) GDOmri with $D=1.0$ and $p=2.22 \times 10^{-16}$, and c) GDOnor with $D=0.24$ and $p=0.224$.

The KS test results showed a difference in distributions of GDO GCMs to PRISM for the 10-year historical analysis. As an initial assessment of how monthly precipitation from the selected GDO GCMs compared to PRISM across a gridded surface of 37 cells, the KS test began to indicate that the historical comparisons were not performing similarly. The lack of similarity prompted further investigation of the selected GDO GCMs performance across a more complete surface as compared to PRISM, as well as assessing the selected MACA GCMs performance over a longer, 25-year analysis period. Further analysis examined the GDO and MACA GCMs at their respective downscaled grid cell resolution as compared to PRISM in a corresponding resolution and utilized a statistical metric that incorporates several statistics into one metric value.

5.2 SPAEF Seven Selected GCMs and PRISM Surface Comparison

To assess the spatial comparison of two gridded layers (simulated GCMs and observed PRISM) a multi-component spatial comparisons metric was utilized. Demirel et al. (2018) introduced the SPAtial EFficiency metric (SPAEF) as a novel, multiple-component spatial comparison metric for use in comparing spatial patterns of two maps (Equation 5.2). The SPAEF metric was developed after extensively testing other current spatial correlation comparison metrics and inspired by the multiple-component nature of the Kling-Gupta efficiency (Demirel et al., 2018). The SPAEF metric is characterized by three equally weighted components: correlation, coefficient of variation ratio, and histogram overlap. Multiple-component metrics allow for a more holistic and balanced assessment, as compared to stand-alone metrics. The resulting SPAEF values are in the range between $-\infty$ and 1, with an optimal value of 1 (Demirel et al., 2018; Koch et al., 2018).

$$SPAEF = 1 - \sqrt{(\alpha - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad 5.2)$$

$$\alpha = \rho(A, B) \text{ and } \beta = \frac{\left(\frac{\sigma_A}{\mu_A}\right)}{\left(\frac{\sigma_B}{\mu_B}\right)} \text{ and } \gamma = \frac{\sum_{j=1}^n \min(K_j, L_j)}{\sum_{j=1}^n K_j}$$

Where:

- α = Pearson correlation coefficient between the observed map (A) and simulated map (B)
- β = fraction (a ratio) of coefficient of variations
- γ = percentage of histogram intersection, calculated for a given histogram K of observed map (A) and histogram of simulated map (B) each containing n bins

Within the SPAEF metric, the correlation coefficient allows for the comparison of the strength of the linear relationship between observed and simulated variables. A comparison with a correlation value closer to 1 indicates a high correlation. Spatial variability is represented by the coefficient of variation (CV) and is a ratio of standard deviation to the mean, a smaller CV ratio corresponds with lower or lacking spatial variability. The CV ratio is the main spatial component within the SPAEF metric, representing the spatial differences and separation between the compared variables. Histogram match describes the intersection of observed and simulated histograms, reflecting the range of and the distribution of the comparison variable. The developed SPAEF metric source code and examples were obtained by open source download (Demirel, 2018). The SPAEF metric source code was modified for use for monthly spatial comparison of modeled GCM layers (simulated) with PRISM layers (observed) (Appendix F -).

The SPAEF modified python script was utilized to generate monthly, complete surface comparisons for a 25-year period from 1981-2005 of the simulated (GDO and MACA) data with the observed (PRISM) data. The 25-year period represents the complete time period with data availability from all three data sources: GDO, MACA and PRISM. The SPAEF script generates a histogram overlap plot detailing the overall SPAEF score and histomatch value; a scatter plot with a trend line detailing the correlation and CV ratio values; and grid surface maps showing the distribution of values across the observed and simulated surface extents and the percent map bias. The plots and maps, as well as, the statistical results including overall SPAEF score, histomatch, correlation, CV ratio and percent map bias were saved and recorded for each monthly comparison over the 25-year analysis period. The statistical results were then used to develop multidimensional scatterplots to show each model's SPAEF performance as compared to the optimal point. The multidimensional scatterplots include the three statistical components

on the main axes, the color of the markers indicates the overall SPAEF score and the four marker shapes represent the season. The optimal point for the spatial comparison, for a surface that would match cell by cell across the watershed, would result in the three statistical components near one and is marked on the plots at the point (1,1,1) with a filled in circle (●). Line plots were also generated to display individual statistical results across the three GDO and four MACA models, separately. The multiple visual representations of statistical results generated from the SPAEF comparison assisted in understanding the GCMs spatial performance as compared to PRISM.

5.2.1 Data Preprocessing

5.2.1.1 Selected GDO GCMs and PRISM

For each of the three selected GDO downscaled GCMs, the data downloaded from 80 cell centroids was first processed in ArcGIS and standalone Python scripts to prepare the data for monthly SPAEF surface comparisons. The GDO cell centroid data was originally downloaded in a comma-separated values (csv) file format. Each centroid location data was joined to the corresponding location in an ArcGIS location and grid cell polygon file. Individual monthly surfaces, that included the monthly value from each of the 80 grid cells, could then be generated in ArcGIS through the process of converting the polygon to a raster then to an ASCII file type. This process was replicated using created standalone python script that utilizes ArcGIS geoprocessing tools to complete the data type conversions for a complete year and was completed for the entire time period, 1981-2005, generating monthly surfaces at a 6kmx6km grid cell resolution for each of the selected models in ASCII file format.

PRISM data also was preprocessed in ArcGIS. The monthly PRISM gridded spatial dataset downloads included separate monthly raster layers (.BIL file format) at a 4kmx4km grid

cell resolution. In order to capture a complete cell by cell surface comparison with cells that match, the PRISM data was resampled within ArcGIS to the GDO 6kmx6km grid cell resolution and snapped to the GDO surface so each cell in the surface of PRISM would match with the cells in the GDO surfaces. In addition to the grid cell resolution, the projected coordinate system of PRISM was also checked during the resampling process to confirm the spatial references were both the same for PRISM and the GDO surfaces. Next, values at the PRISM grid cell centroids were extracted for each month to obtain the PRISM cell data at the same extent as the GDO surface. Then, extracted monthly values were converted to an ASCII file type using a similar process as detailed for the GDO ASCII file surfaces. Monthly surfaces for 1981-2005 of the PRISM data resampled at the 6kmx6km grid cell resolution were generated in the format needed to proceed for cell by cell comparison to the GDO surfaces.

5.2.1.2 Selected MACA GCMs and PRISM

Unlike the GDO GCMs, MACA GCM data could be obtained in a monthly gridded dataset in the form of a NetCDF. The downloaded NetCDF file stores the individual monthly layers for the defined surface extent, 396 grid cells, as subset time dimension layers. The time dimension layers were first extracted from the main NetCDF file to individual raster layers, resulting in raster layers for each month from 1981-2005 and in 4kmx4km grid cell resolution. Both MACA and original PRISM datasets have the same spatial grid cell resolution of 4kmx4km but have different coordinate systems. Therefore, the MACA monthly raster layers were reprojected to match the PRISM spatial coordinate system and snapped to the PRISM surface so the grid cells would match for spatial comparison. The projected MACA monthly raster values then were converted to an ASCII file format needed for the cell by cell comparison.

The original downloaded, monthly PRISM gridded spatial dataset included separate monthly raster layers (.BIL file format) at the same 4kmx4km grid cell resolution as the MACA GCM data, thus, no data resampling or projections processes were needed. Values at the PRISM grid cell centroids were extracted for each month to obtain the PRISM cell data at the same extent as the MACA 396 grid cell surface. Then, extracted monthly values were converted to an ASCII file type. Monthly surfaces for 1981-2005 of the PRISM data at the 4kmx4km grid cell resolution were generated in the format needed to proceed for cell by cell comparison to the MACA surfaces.

5.2.2 Results and Discussion

Comparing the selected GCMs to PRISM only resulted in a few months that generated positive SPAEF metric values. Throughout the 25-year analysis, there were no clear results in any model or season that had a better comparison performance. Overall, the SPAEF surface comparison analysis of selected downscaled GCMs compared to PRISM, supplemented to the findings of the GDO KS test comparison, indicates that the downscaled GCMs precipitation surface data does not similarly compare to PRISM datasets. Poor surface comparisons over the historical period suggest that the selected downscaling GCMs do not adequately capture or historically simulate precipitation across the extent of the watershed.

5.2.2.1 Selected GDO GCM and PRISM SPAEF Comparison Analysis

Across the historical monthly comparison time period, 1981-2005, overall SPAEF scores for the three selected GDO GCMs were low. The maximum overall SPAEF scores range from 0.37 to 0.43 for the three GDO GCMs, which still is a relatively low score (Table 5.2). The generated monthly histogram overlap plot, correlation scatterplot and the grid surface maps, provided a general overview of how each individual statistical component was contributing to

and influencing the overall SPAEF score. In general, months performing with a higher overall SPAEF score had individual statistical components approaching the optimal point range. However, even though some monthly comparisons resulted in a positive overall SPAEF score, examining the grid surface maps indicated variability in the magnitude and range of cell values (monthly precipitation) between the GDO GCMs and PRISM. For example, the monthly plot and map for the GDOmri model compared to PRISM for the month of March in the year of 1998 (Figure 5.2) and 2003 (Figure 5.3) show a decent and poor monthly comparison, respectively. Figure 5.2 for March 1998, resulted in a low, but positive overall SPAEF score. The low overall SPAEF score is influenced by lower performances of the histogram overlay and correlation components. The red and blue map of Figure 5.2 illustrates the surface grid cells compared. The range in magnitude of monthly precipitation for the surface grid cell values are fairly similar, but there is some spatial variability cell to cell especially on the right side of the map. Figure 5.3 for March 2003, resulted in a lower overall SPAEF score as compared to the March 1998 example. This negative and poor overall SPAEF score comparison was once again a result of low histogram overlay and correlation performance. However, the increased value of the CV ratio (away from the optimal value 1) also influences the low overall SPAEF score. The red and blue grid cell surface maps highlight this spatial variability from cell to cell as well as the mismatch in the range in magnitude of monthly precipitation (Figure 5.3).

Table 5.2. Summary of monthly SPAtial Efficiency (SPAEF) overall metric score comparison results for GDO downscaled global climate models (GCMs) and PRISM from 1981-2005 (300 total months). Overall, the number of positive SPAEF metric monthly comparisons (count ≥ 0) were low and fewer monthly comparisons that approach the optimal SPAEF value of 1 (counts ≥ 0.3).

	GDO ccsm	GDO mri	GDO nor
Count ≥ 0.0	49	77	62
Count ≥ 0.3	3	11	12
Average	-0.65	-0.53	-0.47
Maximum	0.37	0.43	0.42

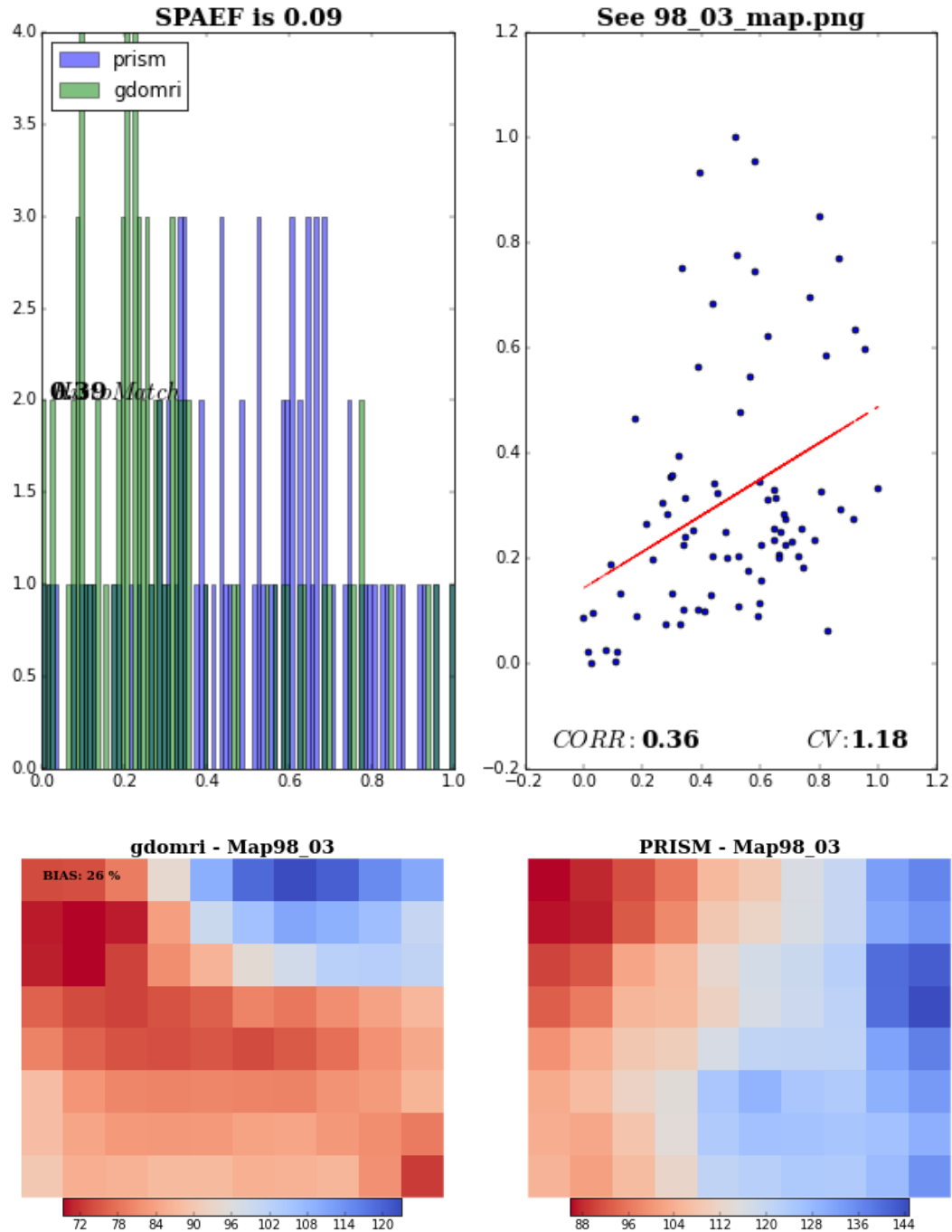


Figure 5.2. SPAtial EFficiency (SPAEF) analysis results for the GDOMri downscaled global climate model (GCM) to PRISM comparison for March 1998. This monthly result is a decent comparison with a low, positive overall SPAEF score that is influenced by the low performances of histogram overlap and correlation statistics.

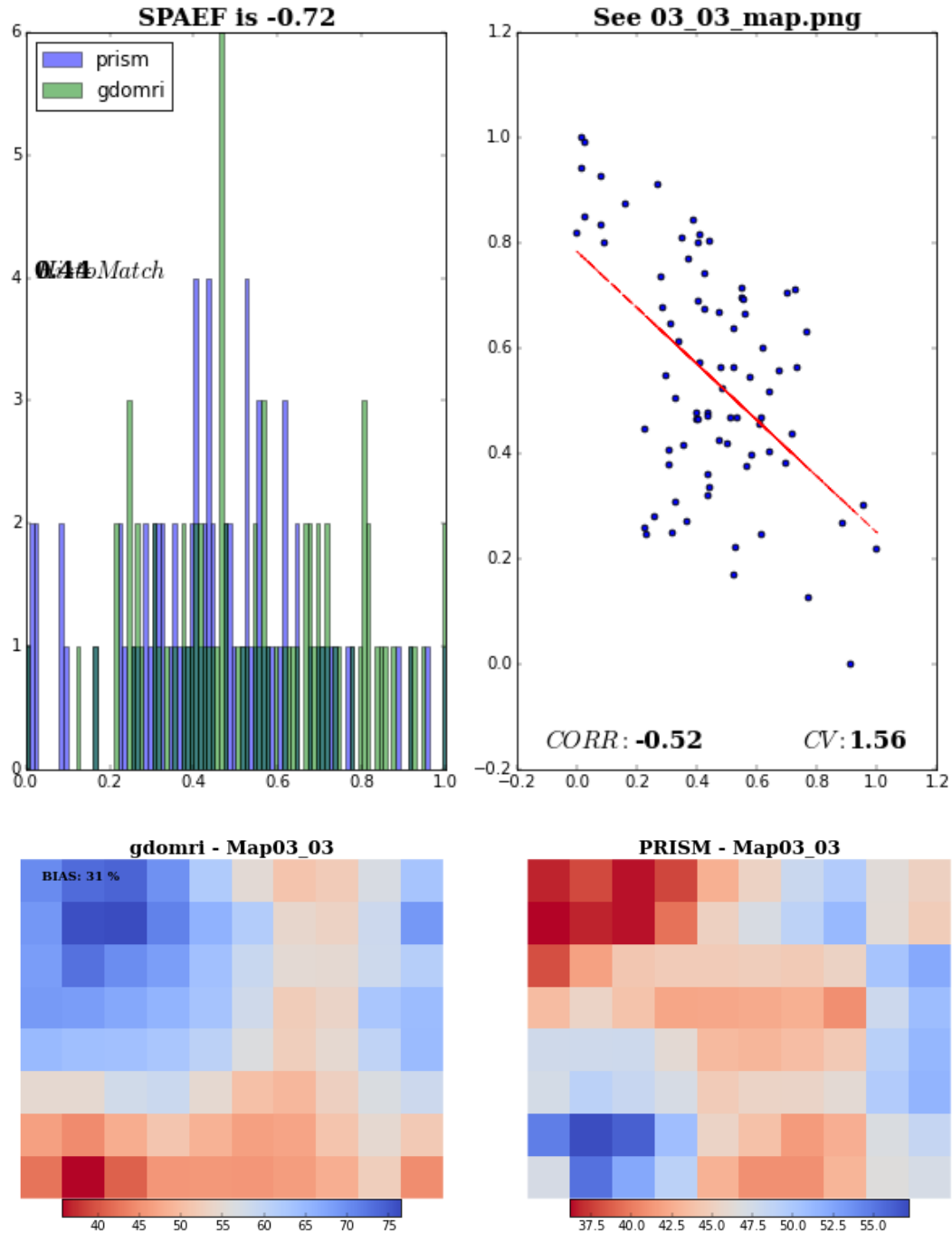


Figure 5.3. SPAtial Efficiency (SPAEF) analysis results for the GDOMri downscaled global climate model (GCM) to PRISM comparison for March 2003. The negative overall SPAEF indicates a poor monthly comparison.

The multidimensional plots contain the monthly values for 1981-2005 for each GDO GCM comparison. Figure 5.4 shows the multidimensional plot for the GDOccsm model SPAEF comparison, most of the monthly values are scattered along the histomatch line of 0.4 and below CV line of 5, however points for January 1989 and February 2000 have CV ratio values of 28.16 and 15.04, respectively. These values skew the overall SPAEF score weighting for those points. In the GDOmri model SPAEF comparison multidimensional plots, three points, January 1994, February 2000, and January 2002, with CV values of approximately 12 influence the negative overall SPAEF score (Figure 5.5). The point of January 2002 with a CV of about 9, lies further away from the rest of the points in the GDOnor model SPAEF comparison multidimensional plot (Figure 5.6).

Figure 5.7 shows the correlation values, an individual statistical component of the SPAEF score, over the 30-year analysis period. There was no clear trend in the correlation values over time and for this analysis period all three GDO models correlation values ranged from -0.9 to 0.9. For the histomatch values (Figure 5.8), the three GDO models had similar performances with values mainly in the range of 0.2 to 0.6 and averaging a histomatch value of 0.4. Figure 5.9 shows the CV ratio values and Figure 5.10 shows the overall SPAEF scores, these line plots show more variability in the range of values and show how different GDO models are peaking at different points in time throughout the analysis period.

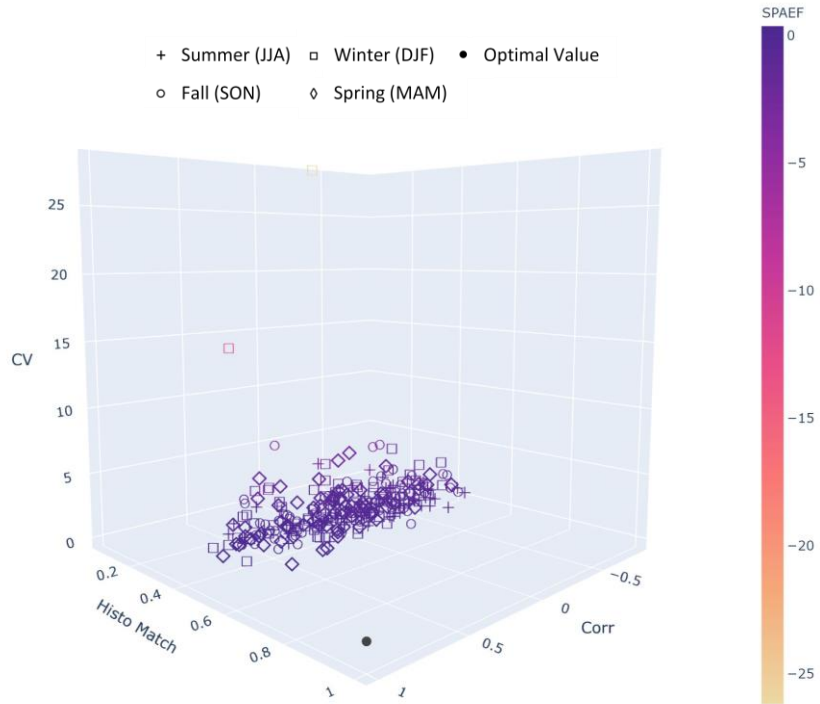


Figure 5.4. SPAtial EFficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the GDOccsm downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie far away from the optimal point (black dot).

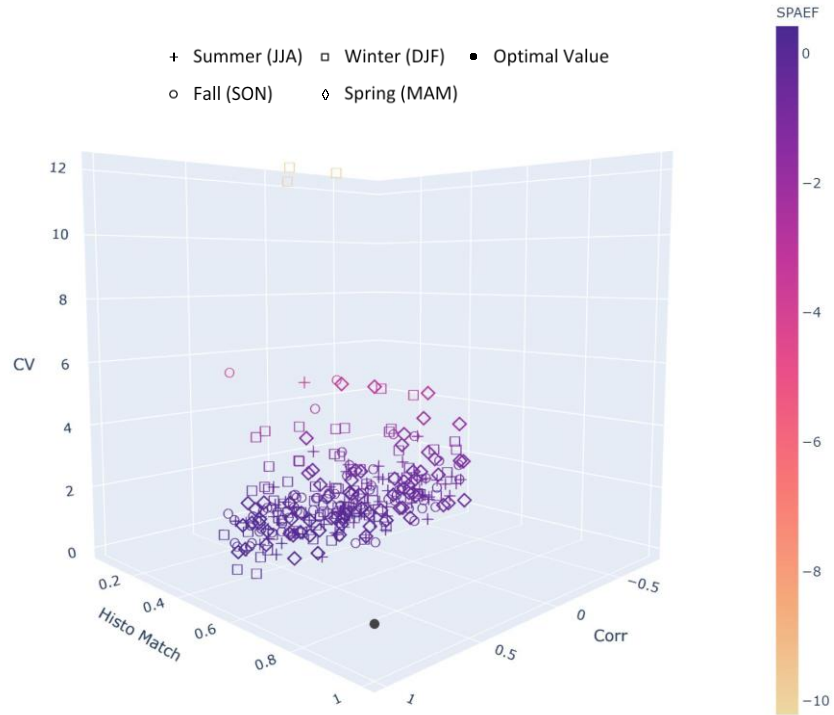


Figure 5.5. SPAtial EFficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the GDOMri downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie far away from the optimal point (black dot).

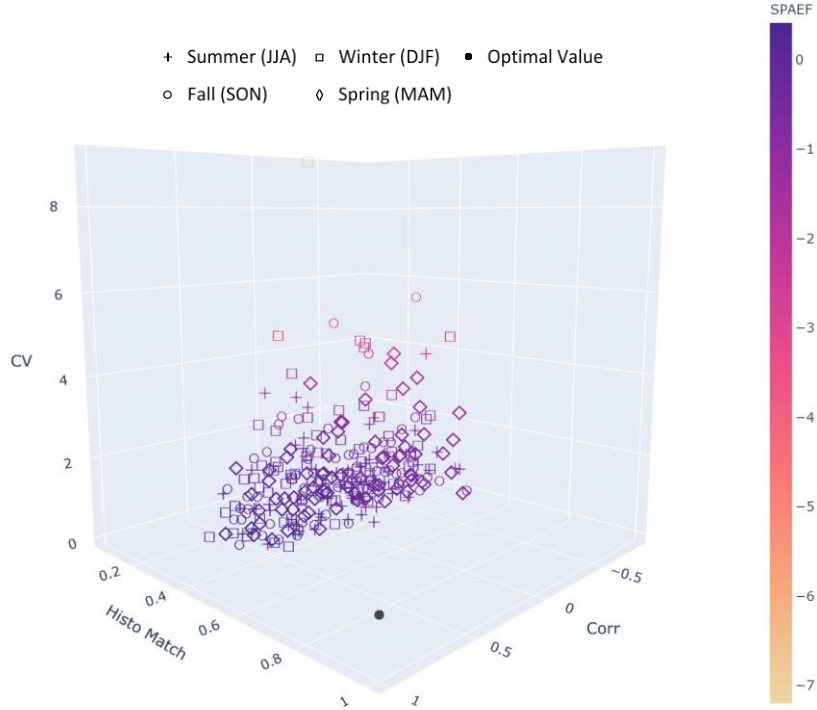


Figure 5.6. SPAtial EFficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the GDO nor downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie far away from the optimal point (black dot).

Correlation by GDO Model and Month from 1981-2005

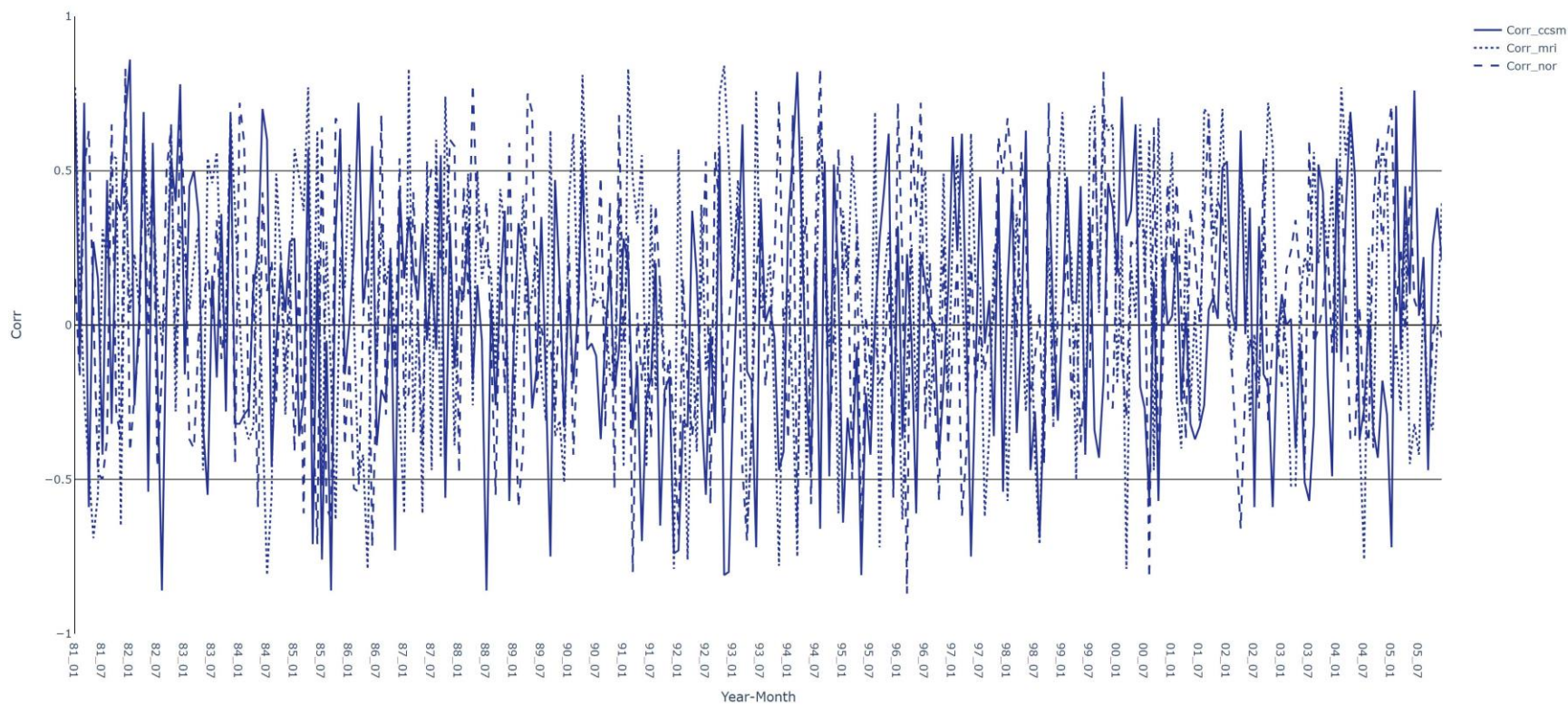


Figure 5.7. Correlation values for each GDO downscaled global climate model (GCM) over the SPAtial Efficiency (SPAEF) analysis period of 1981-2005. Correlation values ranged from -0.9 to 0.9 with no clear trend in any GDO model.

Histo Match by GDO Model and Month from 1981-2005

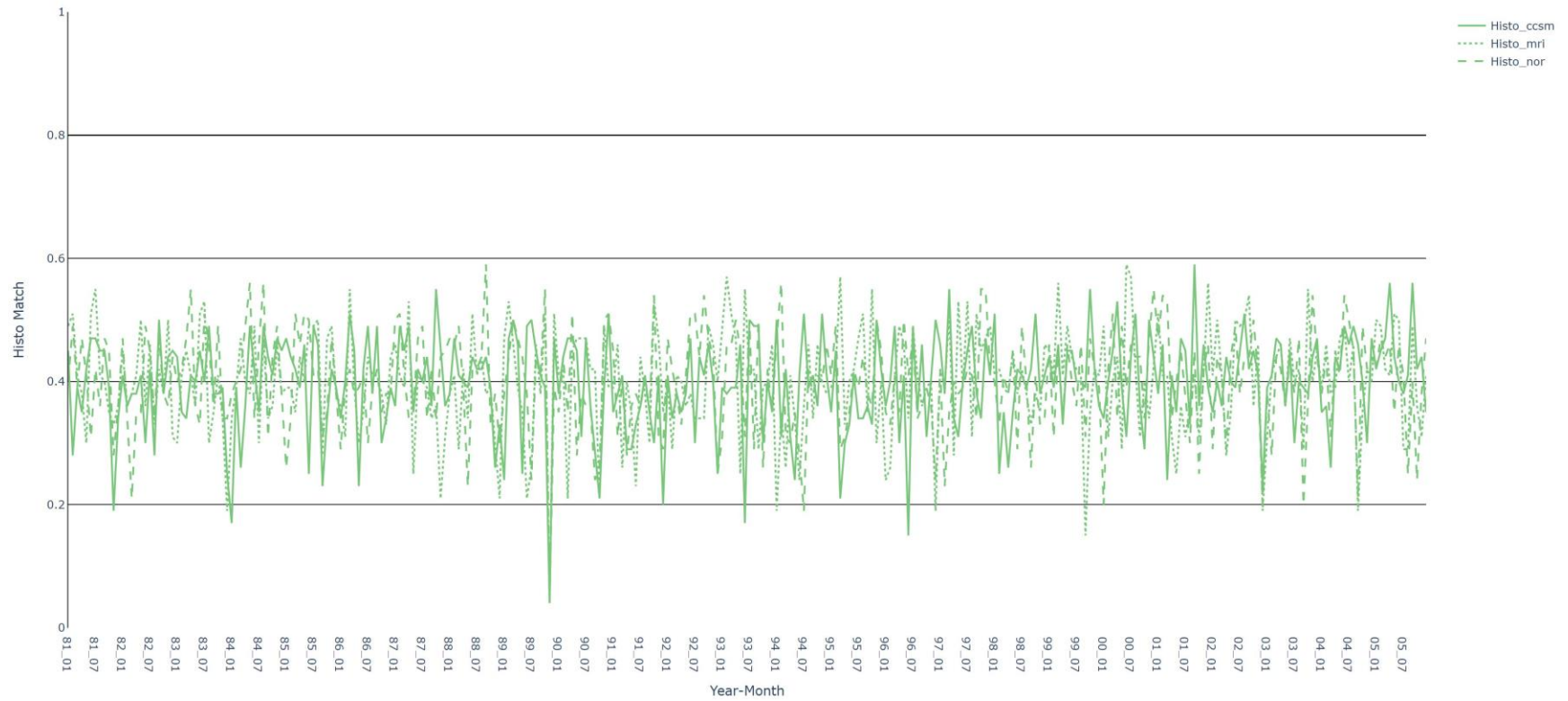


Figure 5.8. Histomatch values for each GDO downscaled global climate model (GCM) over the SPAtial Efficiency (SPAEF) analysis period of 1981-2005. The histomatch values for the three GDO models averaged at 0.4 and mainly ranged from 0.2 to 0.6.

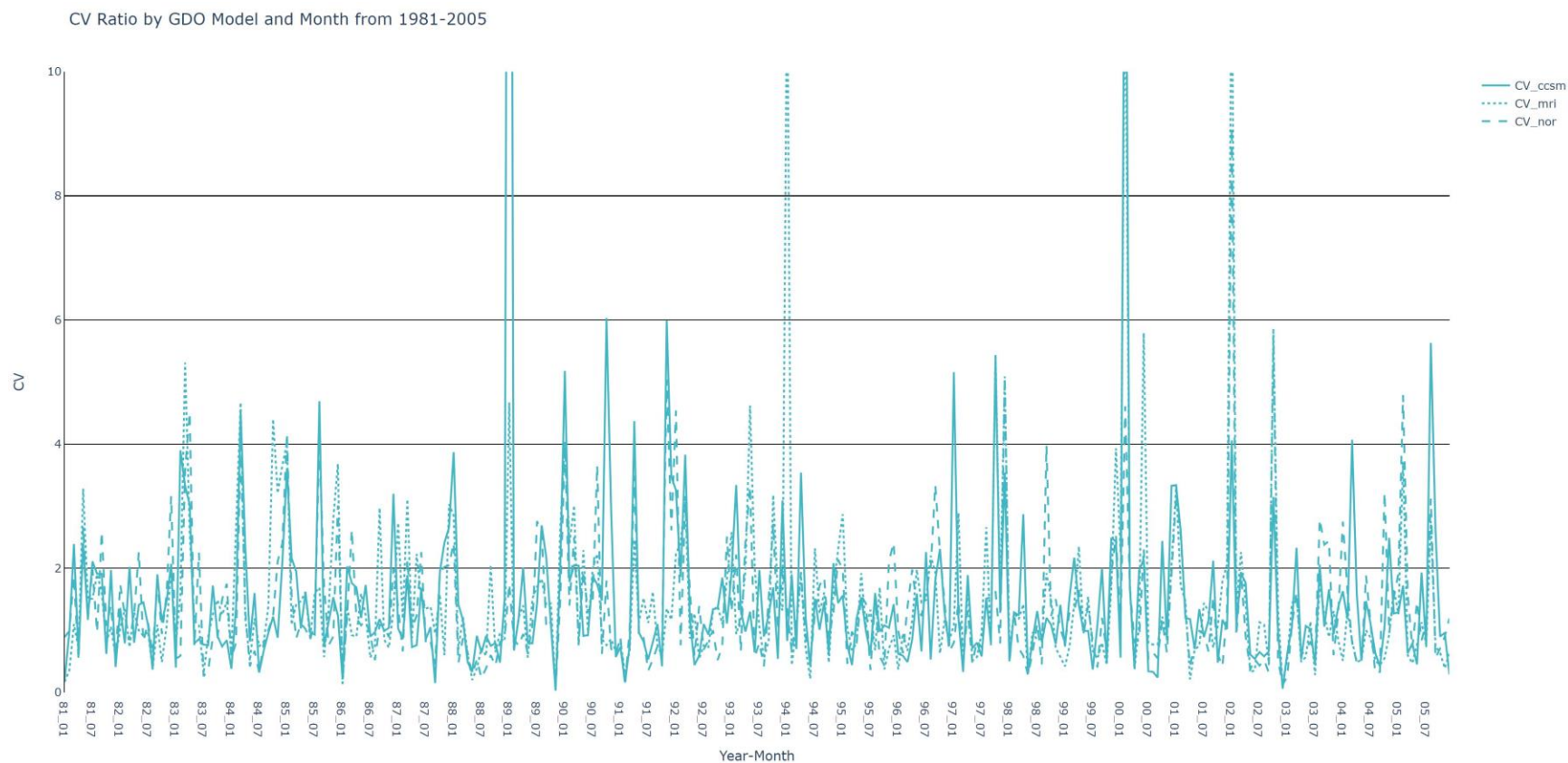


Figure 5.9. Coefficient of variation (CV) ratio values for each GDO downscaled global climate model (GCM) over the SPATial Efficiency (SPAEF) analysis period of 1981-2005. More variability in the CV ratio values was observed between models and months in a year.

SPAEF by GDO Model and Month from 1981-2005

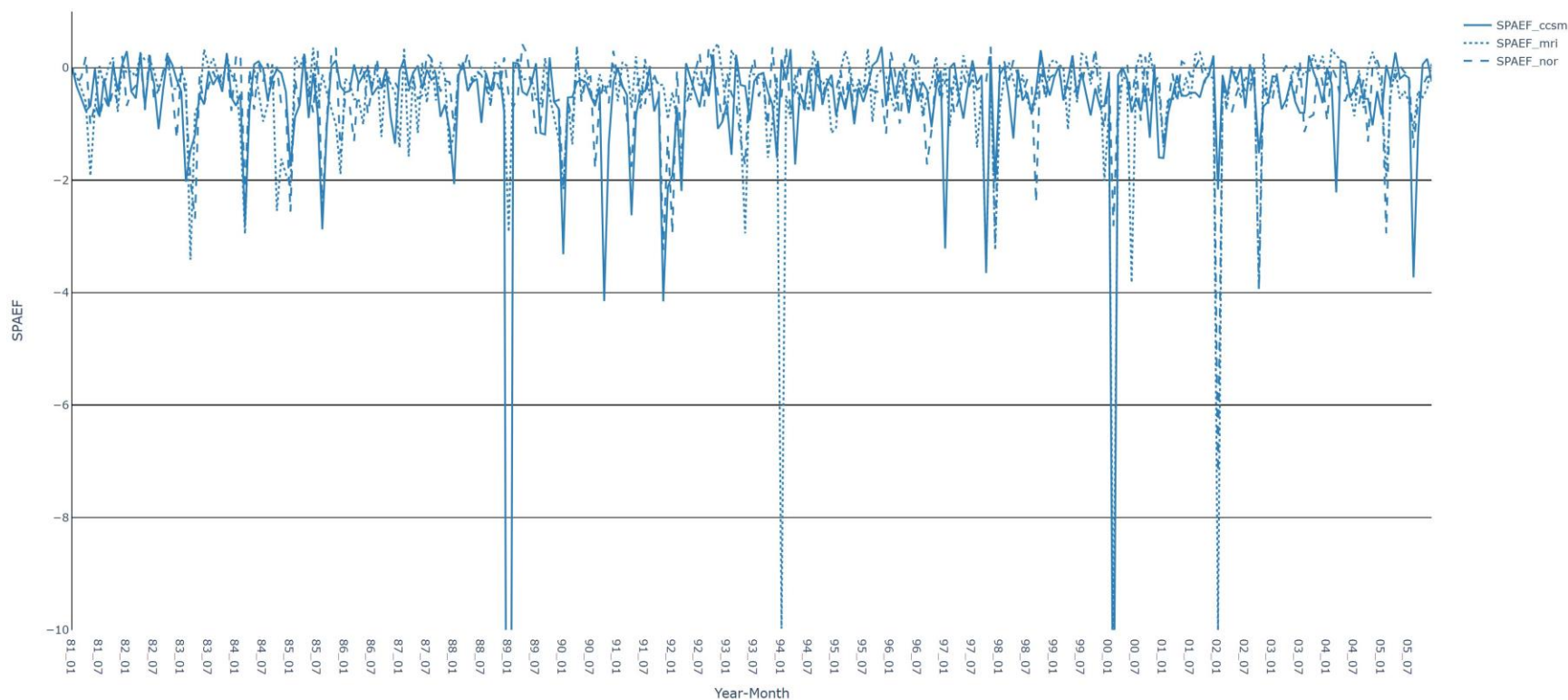


Figure 5.10. SPAtial Efficiency (SPAEF) metric overall scores for each GDO downscaled global climate model (GCM) over the analysis period of 1981-2005. The overall SPAEF metric weights the correlation, histomatch and CV ratio statistical components. The historical, monthly SPAEF analysis resulted in a poor comparison with low overall SPAEF scores.

5.2.2.2 Selected MACA GCM and PRISM SPAEF Comparison Analysis

SPAEF comparison results of the four MACA GCMs as compared to PRISM, at the 4kmx4km surface grid cell resolution, showed slightly improved results overall as compared to the GDO analysis. The four MACA models resulted in more months with a positive overall SPAEF score and the maximum SPAEF scores ranged from 0.61 to 0.63, across the four MACA models (Table 5.3). However, as observed with the GDO SPAEF comparison, even as some monthly comparisons result in a positive SPAEF, some grid surface maps show a fairly different magnitude and range of cell values. Figure 5.11 shows a good overall SPAEF comparison for MACAmri to PRISM with a SPAEF score of 0.56. The stronger performance of the three individual statistical components aided in this better overall performance and is illustrated well by the histogram and correlation plots. The red and blue surface maps show some similarities in the spatial variabilities cell to cell, but the range in magnitude of cell values is fairly different. Figure 5.12 is another example of low overall SPAEF comparison performance. Even though the histogram overlap is similar to that of Figure 5.11, the lower correlation and CV ratio components influence the poor SPAEF performance.

Table 5.3. Summary of monthly SPAtial Efficiency (SPAEF) overall metric score comparison results for MACA downscaled global climate models (GCMs) and PRISM from 1981-2005 (300 total months). Overall, the MACA monthly comparison saw a slight improvement as compared to the GDO analysis. However, the number of positive SPAEF monthly comparisons (count ≥ 0) were still low and monthly comparisons that approach the optimal SPAEF value of 1 (counts ≥ 0.3) were still low.

	MACA me	MACA mec	MACA mri	MACA nor
Count ≥ 0.0	119	130	125	112
Count ≥ 0.3	39	49	39	32
Average	-0.17	-0.12	-0.37	-0.14
Maximum	0.63	0.63	0.61	0.62

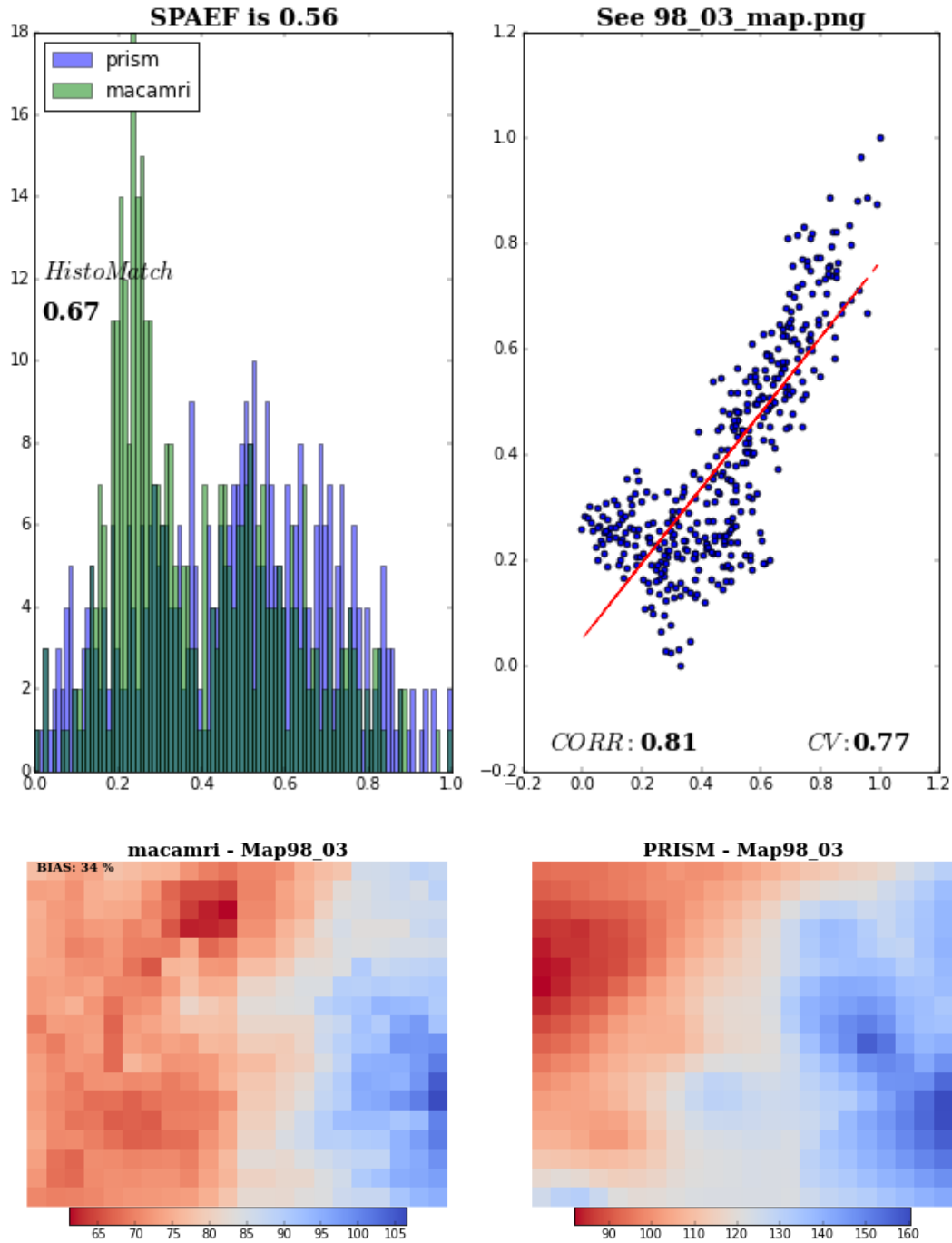


Figure 5.11. SPAtial EFFiciency (SPAEF) analysis results for the MACAmri downscaled global climate model (GCM) to PRISM comparison for March 1998. This is a good monthly comparison result for this analysis. The higher, positive overall SPAEF score is a result of the stronger performances of correlation, histomatch and coefficient of variation (CV) ratio.

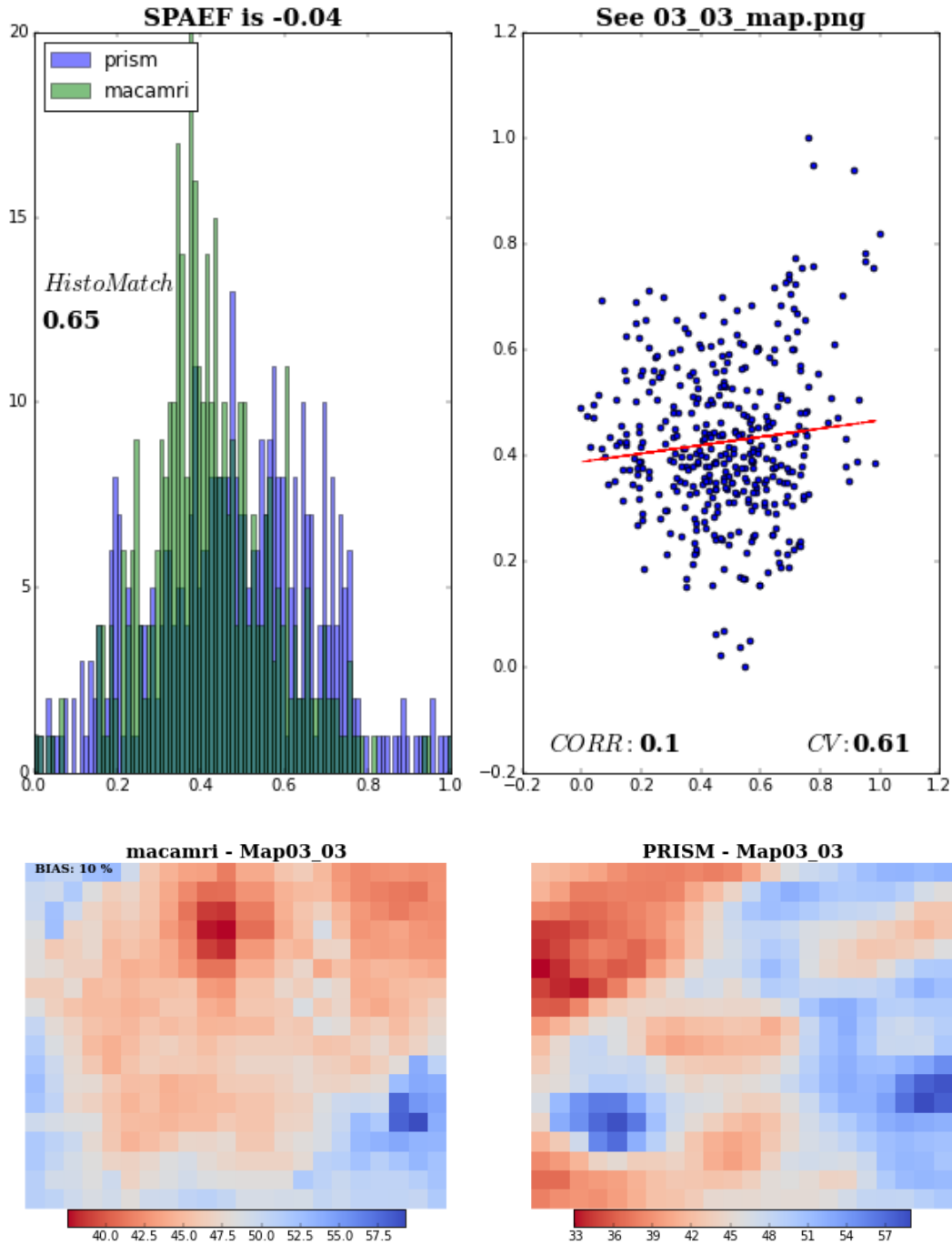


Figure 5.12. SPAtial EFFiciency (SPAEF) analysis results for the MACAmri downscaled global climate model (GCM) to PRISM comparison for March 2003. This monthly result is a poor comparison with a low, negative overall SPAEF score that is influenced by the performances of correlation and coefficient of variation (CV) ratio.

The multidimensional plots in Figure 5.13, Figure 5.14, Figure 5.15, Figure 5.16 contain the monthly values for the MACA GCM SPAEF comparison for the analysis period of 1981-2005. Each of the four MACA model's comparison values are slightly closer to the optimal point value than what was seen in the GDO model comparisons. One of the major outlying points for the MACA models is observed in the MACAmri comparison (Figure 5.15), the January 1994 point, with a CV ratio value of 72.35, influences the skewed nature of the overall SPAEF score. Without this point the MACAmri model performs similarly to the other MACA models.

Over the 30-year analysis period, the correlation statistical component values ranged from -0.8 to 0.9 and no clear trend was observed over the analysis period (Figure 5.17). The four MACA models averaged a histomatch value of 0.6 and over the 30-year time period mainly stayed in the range of 0.3 to 0.8 (Figure 5.18). The CV ratio line plot (Figure 5.19) and overall SPAEF score line plot (Figure 5.20) show more of the variability in values and points throughout the analysis period where models differ from one another, including the outlying January 1994 point for the MACAmri model.

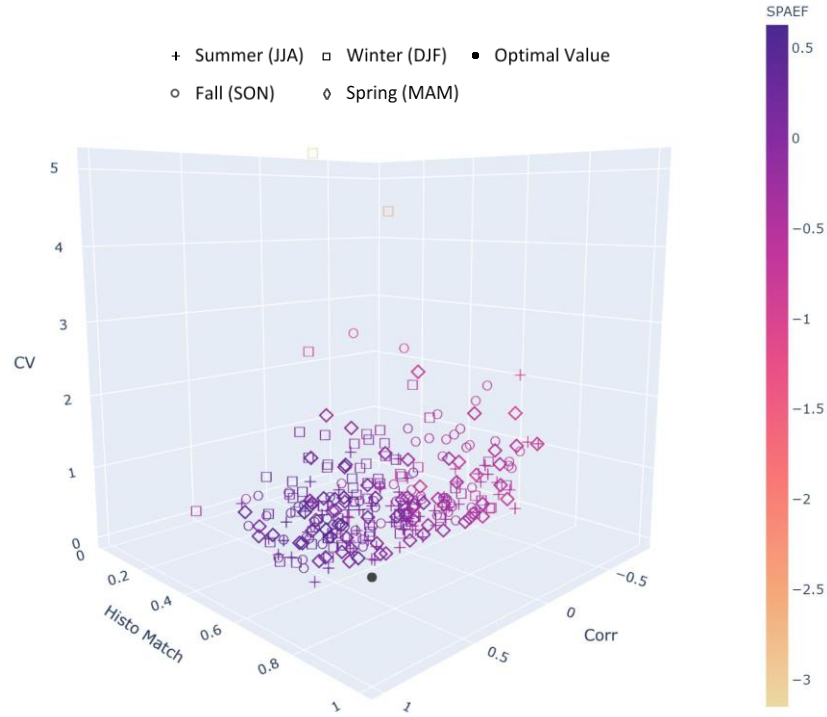


Figure 5.13. SPAtial Efficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the MACAmec downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie away from the optimal point (black dot).

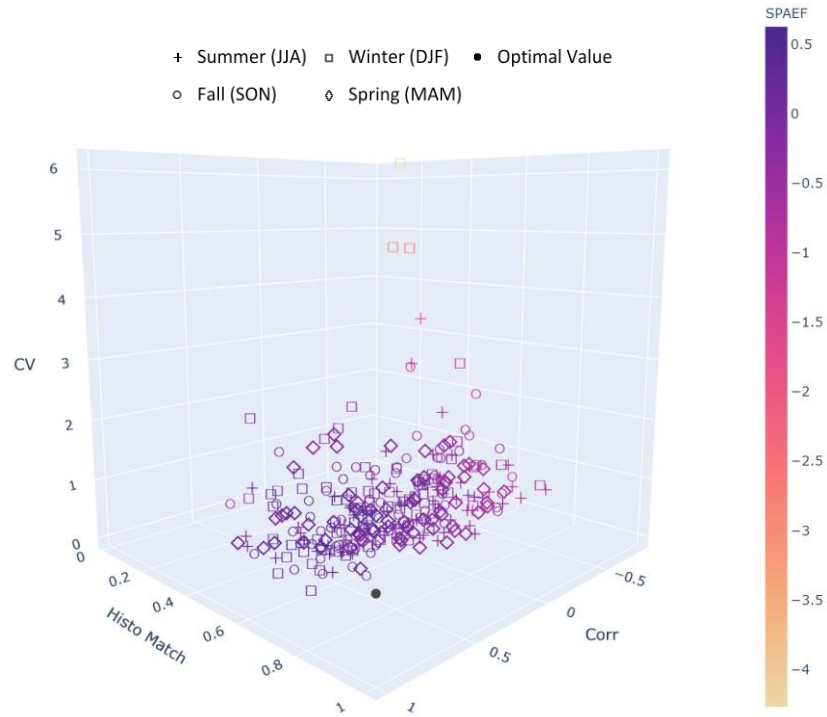


Figure 5.14. SPAtial Efficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the MACAm downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie away from the optimal point (black dot).

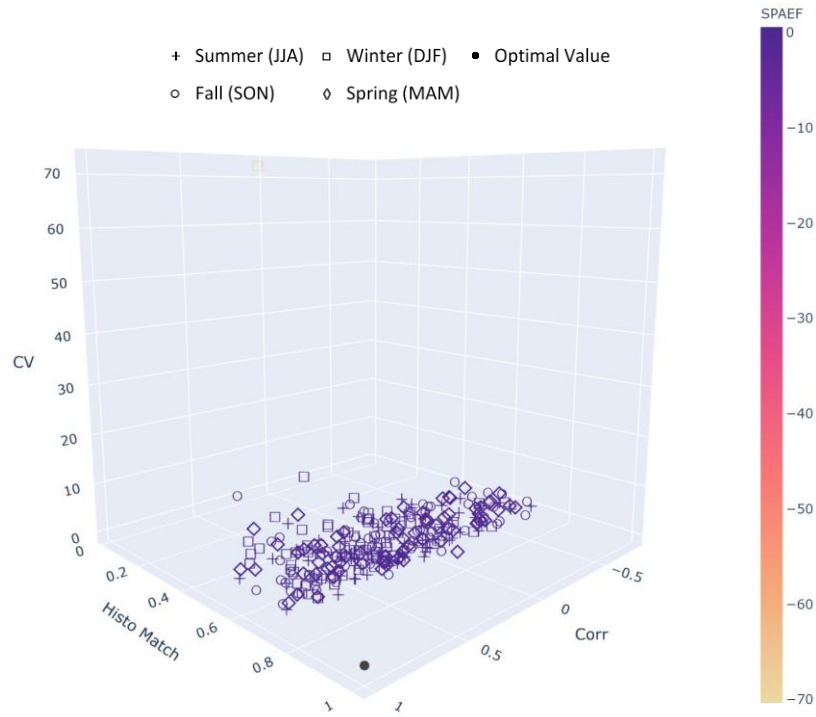


Figure 5.15. SPAtial Efficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the MACAmri downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie away from the optimal point (black dot).

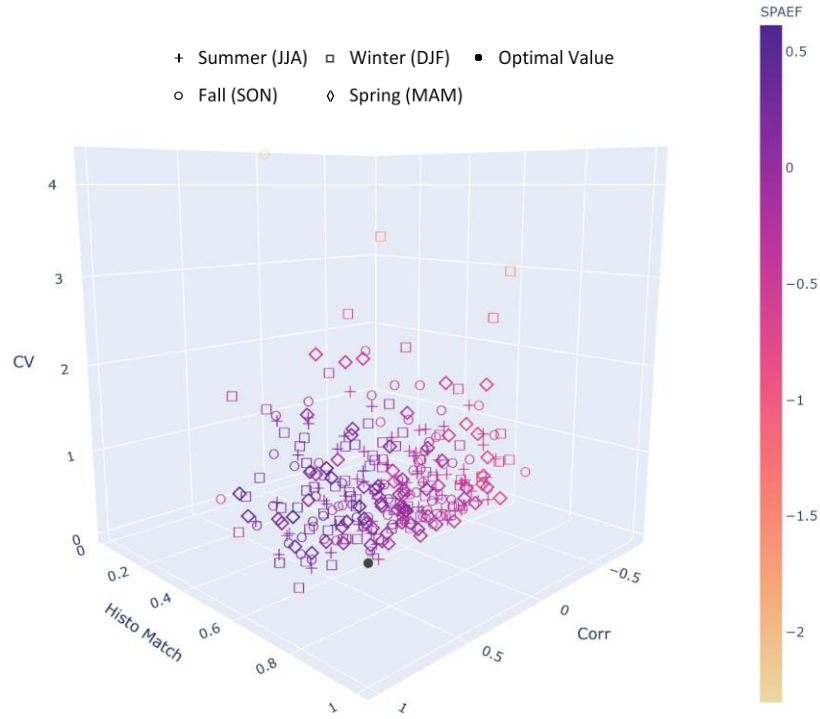


Figure 5.16. SPAtial Efficiency (SPAEF) multidimensional plot with monthly values from 1981-2005 for the MACAnor downscaled global climate model (GCM) to PRISM surface comparison. The SPAEF monthly comparisons are shown by seasonal shapes and colored by the SPAEF score gradient. Overall, monthly comparison results lie away from the optimal point (black dot).

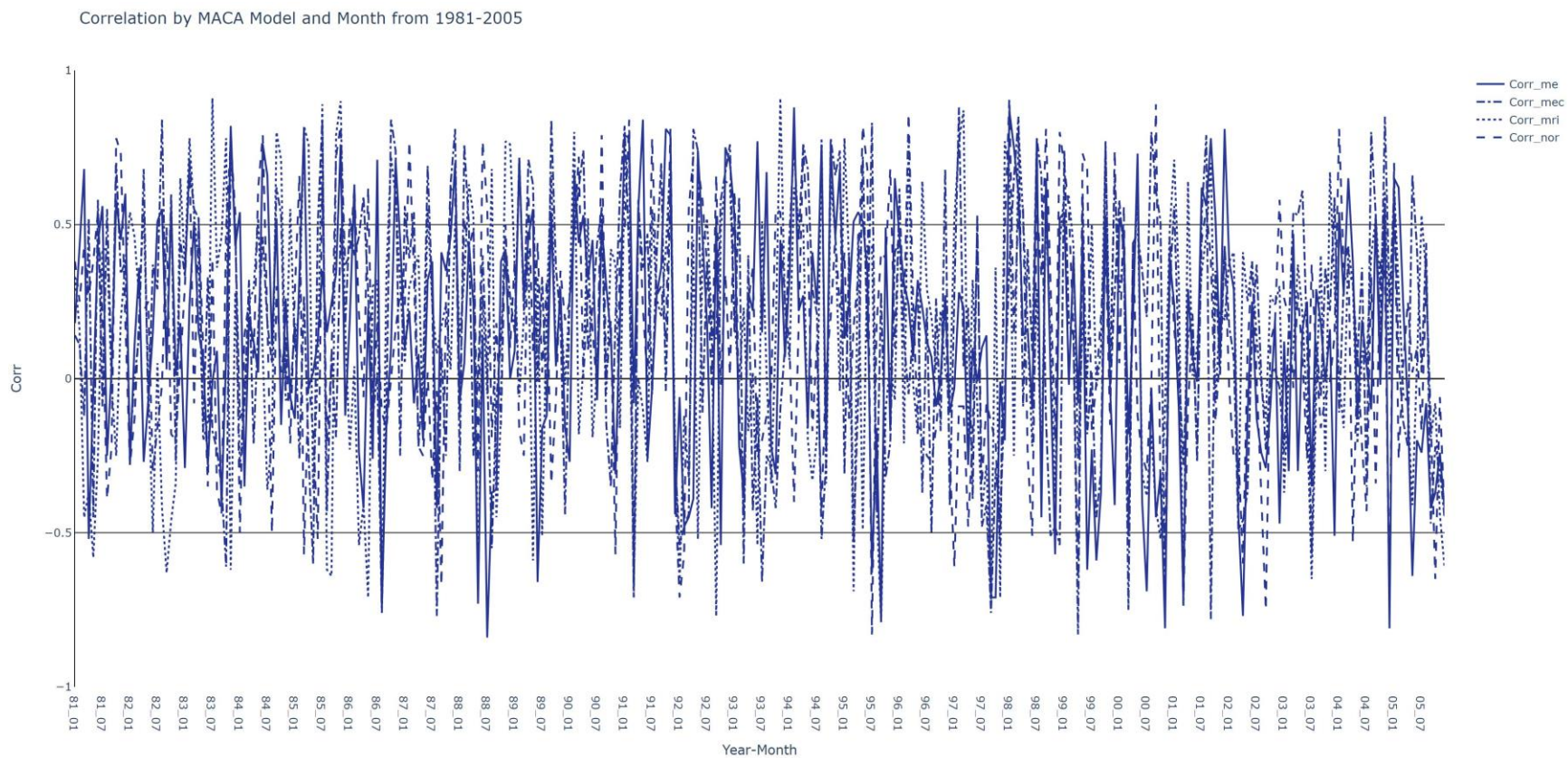


Figure 5.17. Correlation values for each MACA downscaled global climate model (GCM) over the SPAtial Efficiency (SPAEF) analysis period of 1981-2005. Correlation values ranged from -0.8 to 0.9 and no clear trend in any MACA model.

Histo Match by MACA Model and Month from 1981-2005

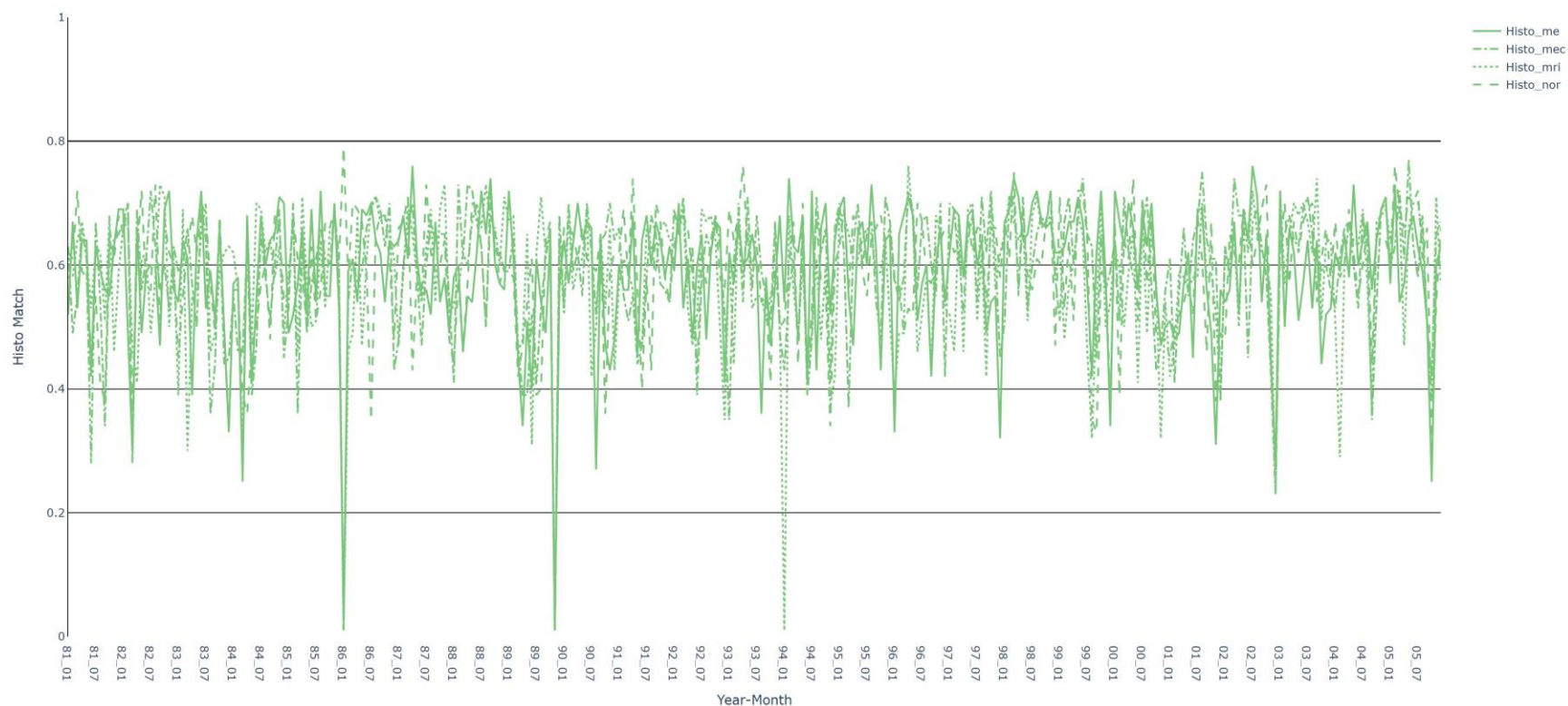


Figure 5.18. Histomatch values for each MACA downscaled global climate model (GCM) over the SPAtial Efficiency (SPAEF) analysis period of 1981-2005. The histomatch values for the four MACA models averaged at 0.6 and mainly ranged from 0.3 to 0.8

CV Ratio by MACA Model and Month from 1981-2005

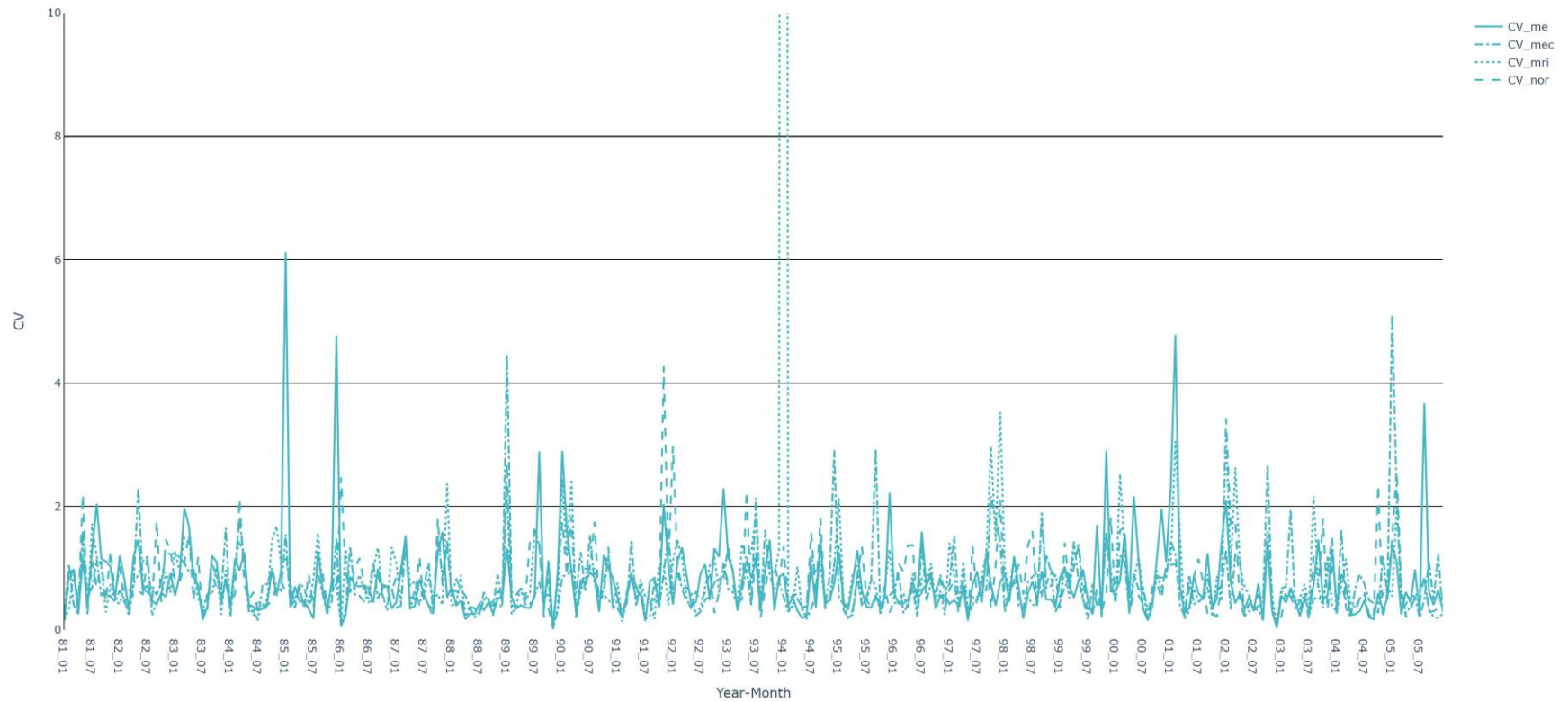


Figure 5.19. Coefficient of variation (CV) ratio values for each MACA downscaled global climate model (GCM) over the SPAtial Efficiency (SPAEF) analysis period of 1981-2005. More variability in the CV ratio values was observed between models and months in a year.

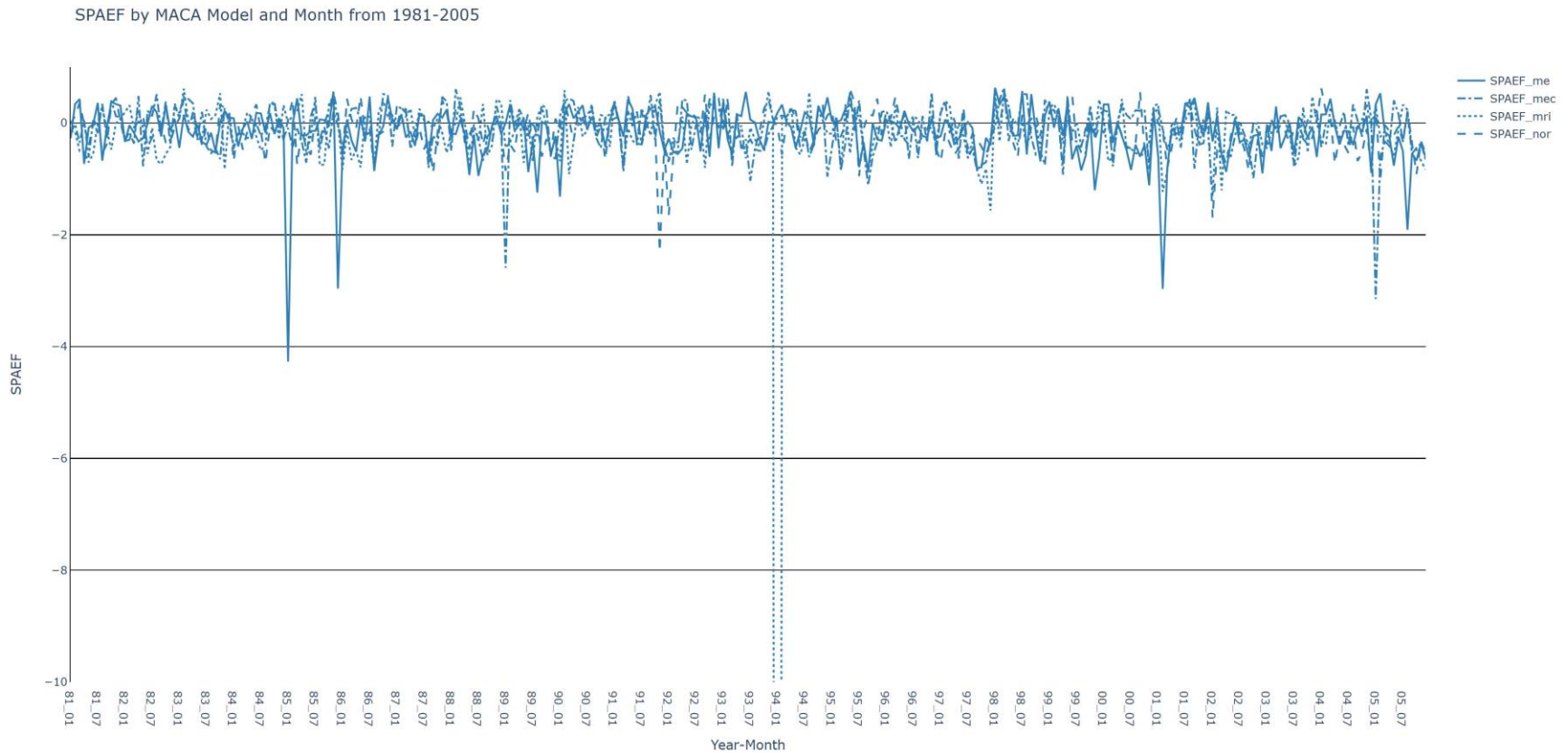


Figure 5.20. SPATial Efficiency (SPAEF) metric overall scores for each MACA downscaled global climate model (GCM) over the analysis period of 1981-2005. The overall SPAEF metric weights the correlation, histomatch and CV ratio statistical components. The historical, monthly SPAEF analysis resulted in a poor comparison with low overall SPAEF scores

Chapter 6 - Conclusions

This research set out to develop a better understanding of downscaled global climate models (GCMs) and determine if downscaled precipitation data could effectively be utilized within watershed modeling applications in the Central United States Midwest region, specifically across the Blue River Watershed (BRW). These goals were accomplished by assessing GCMs from two downscaling methods and comparing historically simulated precipitation data to corresponding spatial and temporal observational based precipitation data.

Precipitation data was obtained from 18 downscaled GCMs under two different statistical downscaling methods, Localized Constructed Analogs (LOCA, identified as GDO in the analysis) and Multivariate Adaptive Constructed Analogs (MACA), for a total of 36 downscaled GCMs. Precipitation data from the 36 downscaled GCMs was statistically compared to precipitation data observed at six National Oceanic and Atmospheric Administration (NOAA) stations located throughout the BRW. From the statistical point comparison, seven models were selected to assess spatial grid-surface comparisons of downscaled GCM data to the gridded spatial precipitation datasets obtained from Parameter-elevation Regressions on Independent Slopes Model (PRISM).

The results from the point statistical analysis demonstrated that seven models performed better as compared to the whole group of 36 models assessed for the BRW. However, further investigation of the seven downscaled GCMs across continuous, monthly gridded surfaces utilizing the KS Test and SPAtial EFficiency metric (SPAEF) emphasized that for the models, downscaling methods, time period, and surface extents assessed, the downscaled precipitation monthly comparisons had a poor performance in capturing the monthly magnitude and distribution of precipitation. The poor performance in comparison of historically simulated

downscaled GCM precipitation to observed data, calls to attention that future simulated downscaled GCM precipitation data should not be directly used in hydrological modeling applications. Watershed hydrological modeling applications require data with a high level of spatial and temporal resolution agreement in the input data. Given the poor historical performance of the downscaled GCMs, future simulations of downscaled GCM data may have additional uncertainty and inconsistencies for supplying an estimate of future amounts, magnitude, and distribution of precipitation for the study area. The poor comparative performance of historical downscaled GCM to observed data are similar to the results found in a comparative analysis completed in the Great Lakes Region, USA (Mehan et al., 2018). Mehan et al. (2018) ultimately performed and recommended further bias-correction to be completed on the downscaled climate model product to reduce uncertainty and have a more reliable climate database for application. Jiang and Yang (2012) examined historical downscaled model data performance across the state of Texas and found that the models capture the main features of the present-day climate but still observed great variability in performance of precipitation data from model to model. While this assessment and the previous examples indicate poor performance of downscaled precipitation data, the performances of some downscaling global climate methods can perform better in other locations and more reasonably capture the local climate with more confidence. For example, downscaled GCM approaches assessed in a Northeast USA study area resulted in similar simulations of the present-day climate, however with precipitation some uncertainties in heavy or extreme precipitation remained among the various model data approaches used (Hayhoe et al., 2008). In addition, downscaled historical modeled data was found to perform well in capturing the timing and distributions of precipitation ultimately providing more confidence in the capabilities of models to represent the Pacific Northwest USA

climate (Salathé, 2005). Even with better comparative performances of downscaled precipitation data, the spatial and temporal resolutions of modeled data remain a challenge to represent the fine scales needed for hydrological or stormwater modeling applications as indicated by Maimone et al. (2019).

While not the most desirable results for water modeling applications, this assessment provides important findings illustrating the state of downscaled GCM performances within the Central United States Midwest region. Stressing the importance of approaching the application of downscaled GCMs precipitation outputs, at the watershed scale, cautiously. While many improvements and advances have been made from the climate science point of view in GCM development and downscaling techniques, a gap still exists between the GCM tools and the ability to effectively utilize the data outputs from these tools in watershed modeling applications. Understanding the uncertainties and variabilities that remain in downscaled GCM precipitation outputs is critical for effectively incorporating modeled precipitation data into water resource management designs and decisions, as well as continually advancing the capabilities of climate scientist tools for application and planning for a variable future.

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Appendix A - Data Download Information and Instructions

NOAA Station Download Steps

1. Navigate to the NOAA Climate Data Online Data Tools: Find a Station website:
<https://www.ncdc.noaa.gov/cdo-web/datatools/findstation>
2. Enter Location: If station location is unknown enter an approximate location for desired station location. Ex: Kansas City, KS, USA Or, if station location is known type in exact location.
3. Select Dataset: Use the dropdown feature to select dataset. Ex: Daily Summaries
4. Select Date Range: Select desired date ranges using the calendar selection feature. Must select year and month drop downs then click on day for both start and end dates. Then, click apply. Ex: 1950-01-01 to 2005-12-31.
5. Data Categories: Check the desired categories for data download. Ex: Precipitation
6. Available stations, based on the information entered in steps 1-4, will be displayed with a blue icon in the Map located to the right of screen.
7. Select blue station icons to view station details window including station name, ID, Lat/Lon coordinates, period of record: length and coverage.
8. Full station details can be observed by selecting the blue full details button in which the data can be previewed, or the station data can be added to the download cart by selecting the orange add to cart button within the station details window.
9. Clicking add to cart will add that station data to the cart for download. Click the upper right corner to view all items in the cart.
10. Cart options/order:

- a. Select the output format for download: specify the format desired for data download Ex: Custom GHCN-Daily CSV
 - b. Select the data range: specify the desired data range for download, if different from what was entered in Step 3.
 - c. Review the items in your cart: review the stations selected
 - d. Continue (orange button)
 - e. Station detail and data flag options: check the desired output options and specify units. Ex: Station name, Geographic Location, Include Data Flags, Metric units
 - f. Select data types for custom output. Ex: Precipitation
 - g. Continue (orange button)
 - h. Review order and enter email address for data links to be sent.
 - i. Submit Order (orange button)
11. Order confirmation Wait for email containing data links and follow email download instructions. (click on download link in email)

Data Tools: Find a Station

Retrieve weather records from observing stations by entering the desired location, data set, data range, and data category. Location can be specified as city, county, state, country, or ZIP code.

Enter Location

Kansas City, KS, USA

Select Dataset

Daily Summaries

Select Date Range

1950-01-01 to 2005-12-31

Data Categories

- ☐ Air Temperature
- ☐ Evaporation
- ☐ Land
- ☒ Precipitation
- ☐ Sky cover & clouds

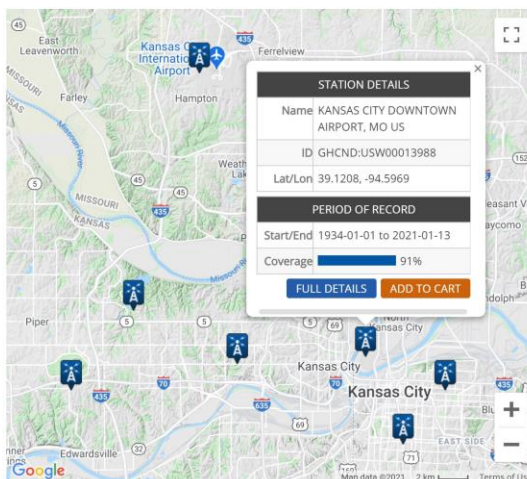


Figure A.6.1. NOAA's Find a Station Data Tool online interface (NOAA-NCEI, n.d.). Detailing Steps 1-9 from above.

■ Cart: Daily Summaries

Step 1: Choose Options

Step 2: Review Order

Step 3: Order Complete

Help

Have questions about the data? Need some assistance? Use the links below to quickly find the answers you need.

[Climate Data Online help](#)
[Check order status](#)
[Request assistance](#)

Need technical documentation or assistance with systems access?

[View data samples & documentation](#)
[NCDC Web Services](#)
[CDQ Web Services Documentation](#)

Select Cart Options

Specify the desired formatting options for the data added in the cart. These options allow more refined date selection, selection of the processed format, and the option to remove items from the cart.

Select the Output Format

Choose one option below to choose a type of format for download. Formats are a standard PDF format. Other formats are CSV (Comma Separated Value) and Text format, both of which can be opened with programs such as Microsoft Excel or OpenOffice Calc. Some formats have additional options which can be selected on the next page.

☐ **GHCN-Daily PDF**
DOC Certification Option
(Does not include all elements)
☐ Include Documentation

☒ **Custom GHCN-Daily CSV**
(Additional options available on next page)

☐ **Custom GHCN-Daily Text**
(Additional options available on next page)

Select the Date Range

Click to choose the date range below.

1950-01-01 to 2005-12-31

Review the items in your cart

[\[CLEAR CART\]](#)

KANSAS CITY DOWNTOWN AIRPORT, MO US

[View Full Details](#)

Station ID: GHCND:USW00013988
Period of Record: 1934-01-01 : 2021-01-13

Delete

CONTINUE

Figure A.6.2. NOAA's Find a Station Data Tool online interface (NOAA-NCEI, n.d.). Detailing Steps 10a-10d from above.

Custom Options: Daily Summaries

Step 1: Choose Options
Step 2: Review Order
Step 3: Order Complete

Data types are grouped by category for easier selection and can be selected as a group or individually. Selected data types will be included in the customized output.

Station Detail & Data Flag Options

Additional output options such as data flags (attributes), station names, and geographic location are also available.

☒ Station Name
☒ Geographic Location
☒ Include Data Flags
Units: Metric

Select data types for custom output

The items below are data types that can be added to the output. Expand the data type category headers to view the categorized data type names and descriptions.

Show All / Hide All | Select All / Deselect All

☒ Precipitation
☐ Sky cover & clouds
☐ Sunshine
☐ Air Temperature
☐ Water
☐ Wind
☐ Weather Type

BACK
CONTINUE

Downloads

Download full documentation for the Daily Summaries dataset/product. Includes full descriptions; format, observation, element and flag definitions.

Documentation (Word Format)
Documentation (PDF Format)

Help

Assistance

Climate Data Online help
Check order status
Request assistance

Documentation

View data samples & documentation
NCEP Web Services
CDQ Web Services Documentation

Figure A.6.3. NOAA’s Find a Station Data Tool online interface (NOAA-NCEI, n.d.). Detailing Steps 10e-11 from above.

GCM Point Locations

Table A.6.1. Centroid point locations and corresponding GDO LOCA GCM grid cell bounds. Data collected at these point locations for both GDO and MACA point comparisons.

Filename	Grid Cell Latitude Bounds	Grid Cell Longitude Bounds	“centroid” point used for data collection of the 37 cells and all models
loca5(1) / 1_16obs(1)	(38.875, 38.9375)	(-94.875, -94.8125)	(38.915425, -94.832755)
loca5(2) / 1_16obs(2)	(38.9375, 39.0)	(-94.75, -94.6875)	(38.960289, -94.717399)
loca5(3) / 1_16obs(3)	(39.0625, 39.125)	(-94.5625, -94.5)	(39.077655, -94.527885)
loca5(4) / 1_16obs(4)	(39.0625, 39.125)	(-94.8125, -94.75)	(39.079787, -94.802543)

loca5(5) / 1_16obs(5)	(39.0625, 39.125)	(-94.6875, -94.625)	(39.071258, -94.681693)
loca5(6) / 1_16obs(6)	(38.9375, 39.0)	(-94.5625, -94.5)	(38.970967, -94.560844)
loca5(7) / 1_16obs(7)	(39.0, 39.0625)	(-94.625, -94.5625)	(39.035756, -94.614977)
loca5(8) / 1_16obs(8)	(39.0, 39.0625)	(-94.5625, -94.5)	(39.017086, -94.531207)
loca5(9) / 1_16obs(9)	(39.0, 39.0625)	(-94.6875, -94.625)	(39.044289, -94.650683)
loca5(10) / 1_16obs(10)	(38.875, 38.9375)	(-94.75, -94.6875)	(38.92206, -94.700121)
loca5(11) / 1_16obs(11) / KC Downtown Airport (WBAN 13988)	(39.0625, 39.125)	(-94.625, -94.5625)	(39.094401, -94.606051)
loca5(12) / 1_16obs(12)	(38.875, 38.9375)	(-94.5625, -94.5)	(38.906032, -94.538073)
loca5(13) / 1_16obs(13)	(38.875, 38.9375)	(-94.625, -94.5625)	(38.914047, -94.586138)
loca5(14) / 1_16obs(14)	(38.9375, 39.0)	(-94.6875, -94.625)	(38.988805, -94.654803)
loca5(15) / 1_16obs(15)	(38.875, 38.9375)	(-94.6875, -94.625)	(38.915115, -94.657549)
loca5(16) / 1_16obs(16)	(38.875, 38.9375)	(-94.8125, -94.75)	(38.906032, -94.783754)
loca5(17) / 1_16obs(17)	(38.9375, 39.0)	(-94.625, -94.5625)	(38.969055, -94.592318)
loca5(18) / 1_16obs(18)	(38.8125, 38.875)	(-94.75, -94.6875)	(38.847507, -94.739809)
loca5(19) / 1_16obs(19)	(38.8125, 38.875)	(-94.8125, -94.75)	(38.863273, -94.781007)
loca5(20) / 1_16obs(20)	(38.75, 38.8125)	(-94.8125, -94.75)	(38.778488, -94.775514)

loca5(21) / 1_16obs(21)	(38.75, 38.8125)	(-94.75, -94.6875)	(38.770459, -94.717836)
loca5(22) / 1_16obs(22)	(38.75, 38.8125)	(-94.6875, -94.625)	(38.787053, -94.643678)
loca5(23) / 1_16obs(23)	(38.8125, 38.875)	(-94.6875, -94.625)	(38.84216, -94.662218)
loca5(24) / 1_16obs(24)	(38.75, 38.8125)	(-94.5625, -94.5)	(38.77503, -94.52535)
loca5(25) / 1_16obs(25)	(38.8125, 38.875)	(-94.875, -94.8125)	(38.847796, -94.854939)
loca5(26) / 1_16obs(26)	(38.75, 38.8125)	(-94.625, -94.5625)	(38.773959, -94.591268)
loca5(27) / 1_16obs(27)	(38.75, 38.8125)	(-94.875, -94.8125)	(38.776101, -94.852193)
loca5(28) / 1_16obs(28)	(38.6875, 38.75)	(-94.75, -94.6875)	(38.716121, -94.732717)
loca5(29) / 1_16obs(29)	(38.6875, 38.75)	(-94.6875, -94.625)	(38.734334, -94.662679)
loca5(30) / 1_16obs(30)	(38.9375, 39.0)	(-94.5, -94.4375)	(38.980295, -94.477284)
loca5(31) / 1_16obs(31)	(39.0, 39.0625)	(-94.5, -94.4375)	(39.037919, -94.462178)
loca5(32) / 1_16obs(32)	(38.9375, 39.0)	(-94.8125, -94.75)	(38.97389, -94.786275)
loca5(33) / 1_16obs(33)	(39.0, 39.0625)	(-94.4375, -94.375)	(39.037919, -94.407247)
loca5(34) / 1_16obs(34)	(38.8125, 38.875)	(-94.625, -94.5625)	(38.847796, -94.607747)
loca5(35) / 1_16obs(35)	(39.0625, 39.125)	(-94.4375, -94.375)	(39.089101, -94.405873)

loca5(36) / 1_16obs(36) / KC Richards Gebaur Airport (WBAN 03929)	(38.8125, 38.875)	(-94.5625, -94.5)	(38.853143, -94.532216)
loca5(37) / 1_16obs(37)	(39.0625, 39.125)	(-94.5, -94.4375)	(39.107219, -94.474538)

Table A.6.2. Centroid point locations and corresponding GDO LOCA GCM grid cell bounds. Data collected at these grid cells for completing the 80 cell GDO surface for surface comparisons.

Filename	Grid Cell Latitude Bounds	Grid Cell Longitude Bounds	“centroid” point used for data collection for completing GDO surface
loca5(38)	(39.0625, 39.125)	(-95.0, -94.9375)	(39.100524, -94.964276)
loca5(39)	(39.0625, 39.125)	(-94.9375, -94.875)	(39.100965, -94.905818)
loca5(40)	(39.0625, 39.125)	(-94.875, -94.8125)	(39.095670, -94.839730)
loca5(41)	(39.0625, 39.125)	(-94.75, -94.6875)	(39.094409, -94.713926)
loca5(42)	(39.0, 39.0625)	(-95.0, -94.9375)	(39.025862, -94.962208)
loca5(43)	(39.0, 39.0625)	(-94.9375, -94.875)	(39.027415, -94.900444)
loca5(44)	(39.0, 39.0625)	(-94.875, -94.8125)	(39.035279, -94.839521)
loca5(45)	(39.0, 39.0625)	(-94.8125, -94.75)	(39.033662, -94.772912)
loca5(46)	(39.0, 39.0625)	(-94.75, -94.6875)	(39.033406, -94.719244)
loca5(47)	(38.9375, 39.0)	(-95.0, -94.9375)	(38.971725, -94.968178)
loca5(48)	(38.9375, 39.0)	(-94.9375, -94.875)	(38.974835, -94.908539)
loca5(49)	(38.9375, 39.0)	(-94.875, -94.8125)	(38.972197, -94.841959)
loca5(50)	(38.9375, 39.0)	(-94.4375, -94.375)	(38.967716, -94.402084)
loca5(51)	(38.875, 38.9375)	(-95.0, -94.9375)	(38.904429, -94.969030)
loca5(52)	(38.875, 38.9375)	(-94.9375, -94.875)	(38.903920, -94.903927)

loca5(53)	(38.875, 38.9375)	(-94.5, -94.4375)	(38.908106, -94.467363)
loca5(54)	(38.875, 38.9375)	(-94.4375, -94.375)	(38.912051, -94.405057)
loca5(55)	(38.8125, 38.875)	(-95.0, -94.9375)	(38.840874, -94.967954)
loca5(56)	(38.8125, 38.875)	(-94.9375, -94.875)	(38.841411, -94.903614)
loca5(57)	(38.8125, 38.875)	(-94.5, -94.4375)	(38.843964, -94.470109)
loca5(58)	(38.8125, 38.875)	(-94.4375, -94.375)	(38.843738, -94.402357)
loca5(59)	(38.75, 38.8125)	(-95.0, -94.9375)	(38.781531, -94.968351)
loca5(60)	(38.75, 38.8125)	(-94.9375, -94.875)	(38.778856, -94.906010)
loca5(61)	(38.75, 38.8125)	(-94.5, -94.4375)	(38.778318, -94.466053)
loca5(62)	(38.75, 38.8125)	(-94.4375, -94.375)	(38.778585, -94.401080)
loca5(63)	(38.6875, 38.75)	(-95.0, -94.9375)	(38.712622, -94.970517)
loca5(64)	(38.6875, 38.75)	(-94.9375, -94.875)	(38.718011, -94.901011)
loca5(65)	(38.6875, 38.75)	(-94.875, -94.8125)	(38.723783, -94.838268)
loca5(66)	(38.6875, 38.75)	(-94.8125, -94.75)	(38.717778, -94.781309)
loca5(67)	(38.6875, 38.75)	(-94.625, -94.5625)	(38.716226, -94.595301)
loca5(68)	(38.6875, 38.75)	(-94.5625, -94.5)	(38.716034, -94.530377)
loca5(69)	(38.6875, 38.75)	(-94.5, -94.4375)	(38.717413, -94.464131)
loca5(70)	(38.6875, 38.75)	(-94.4375, -94.375)	(38.718697, -94.402615)
loca5(71)	(38.625, 38.6875)	(-95.0, -94.9375)	(38.652174, -94.973588)
loca5(72)	(38.625, 38.6875)	(-94.9375, -94.875)	(38.652202, -94.908053)
loca5(73)	(38.625, 38.6875)	(-94.875, -94.8125)	(38.654862, -94.841234)
loca5(74)	(38.625, 38.6875)	(-94.8125, -94.75)	(38.653726, -94.777694)
loca5(75)	(38.625, 38.6875)	(-94.75, -94.6875)	(38.654075, -94.718920)
loca5(76)	(38.625, 38.6875)	(-94.6875, -94.625)	(38.658188, -94.654151)
loca5(77)	(38.625, 38.6875)	(-94.625, -94.5625)	(38.654274, -94.592575)
loca5(78)	(38.625, 38.6875)	(-94.5625, -94.5)	(38.657726, -94.532513)
loca5(79)	(38.625, 38.6875)	(-94.5, -94.4375)	(38.655397, -94.466246)
loca5(80)	(38.625, 38.6875)	(-94.4375, -94.375)	(38.651359, -94.406706)

GDO LOCA GCMs Download Steps

1. Navigate to the GDO UCLLNL Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections website and select the Projections: Subset Request tab: https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html
2. Page 1 Temporal and Spatial Extent tab:
 - a. Step 1.1: Time period- Select the desired time period using the month and year drop down selection buttons. Ex: Jan 1950 through Dec 2005.
 - b. Step 1.2: Domain- Select desired domain NLDAS or Basin Specific. Ex: Basin Specific and drop down select Missouri Basin.
 - c. Step 1.3: Spatial extent selection method-Select desired spatial extent selection method Tributary Area, Rectangular Area, or Location. Ex: Select Location and type in Latitude and Longitude coordinates. Then, select the Map Location button.
 - d. Confirm location on the map
3. Page 2 Products, Variables, Projections tab:
 - a. Step 2.4: Select Projection Set Ex: LOCA-CMIP5-daily
 - b. Step 2.5: Select Products and Variables Ex: Products- 1/16 degree LOCA projections Variables- Precipitation Rate (mm/day)
 - c. Step 2.6: Select Emission Scenarios, Climate Models and Runs Ex: noresen1-m, RCP4.5
4. Page 3 Analysis, Format, and Notification tab:
 - a. Step 3.7: Analysis- Select desired analysis. Ex: No analysis (extract time series only)

- b. Step 3.8: Select Output format NetCDF or ASCII text, comma-delimited (csv).
Ex: csv
 - c. Step 3.9: Notification when Processing is Complete- Enter email address and label for request
 - d. Step 3.10: Usage Information- Select entity, application, sectors in which the information obtained will be used.
- 5. Confirm that the form status bar at the top of the page is green for all steps.
 - 6. Submit Request
 - 7. Wait for email containing data links and follow email download instructions. (click on download link in email)



Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections

This site is best viewed with [Chrome](#) (recommended) or [Firefox](#). Some features are unavailable when using Internet Explorer. Requires JavaScript to be enabled.

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Feedback
Links

Specify a customized data retrieval by using the form below, spread among three tabs ("Page 1: Temporal & Spatial Extent", "Page 2: Products, Variables, Projections", "Page 3: Analysis, Format, & Notification"). The form permits specification of projection subsets according to user selections for products, variables, models, emissions scenarios, time periods, geographical areas, series versus statistical output, and output format. Submissions are constrained so that the resulting file download size does not exceed approximately 1 gigabytes. The form tracks user selections and indicates whether the specified request is within this size constraint. Requests are queued at LLNL Green Data Oasis for processing. When the request has been processed and made ready for download, the user is notified via the email submitted in the form below (sub-tab "Page 3: Analysis, Format, & Notification"). A video illustrating the process of retrieving projections data is available [here](#).

Enter specifications on three page form below. Then press 'Submit Request'.
?

Submit Request

Form Status (completed == green)

1.1

1.2

1.3

2.4

2.5

2.6

3.7

3.8

3.9

3.10

Size (% , 100 max): 1

Page 1: Temporal & Spatial Extent

Page 2: Products, Variables, Projections

Page 3: Analysis, Format, & Notification

Step 1.1: Time Period
?

Period Jan 1950 through Dec 2005

Step 1.2: Domain
?

☐ NLDAS
☒ Basin Specific Missouri

Step 1.3: Spatial extent selection method
?

☐ Tributary Area
38.038862 -122.265747
Map Outlet Location

☐ Rectangular Area
Latitude 43 .9375 to 43 .9375 N
Longitude -102 .0625 to -102 .0625 E

☒ Location
38.9154 -94.8328
Map Location

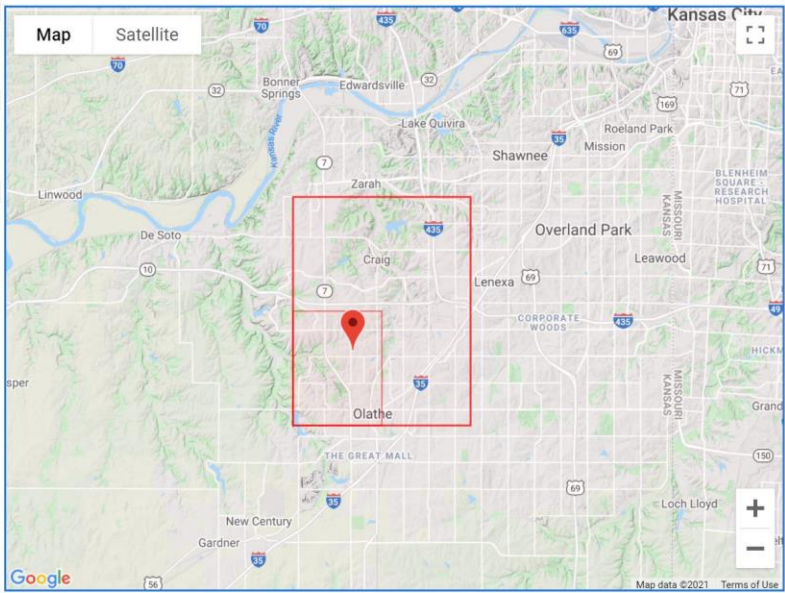
Lat: 38.7949 Lon: -94.7816

Map

Satellite

Kansas

Missouri



Map data ©2021 Terms of Use

UGRL WEB 230256
Last modified August 2020

[Privacy and Legal Notice](#)
[Comments/Questions](#)

Figure A.6.4. GDO LOCA GCM projection subset request interface (“Downscaled CMIP3 and CMIP5 climate and hydrology projections,” n.d.). Detailing Steps 1-2 from above.

95

Enter specifications on three page form below. Then press 'Submit Request'. ?

Submit Request Form Status (completed == green) Size (% , 100 max): 2

Page 1: Temporal & Spatial Extent Page 2: Products, Variables, Projections Page 3: Analysis, Format, & Notification

Step 2.4: Select Projection Set (Green text indicates projection set form completed) ?

☐ BCSD-CMIP3-Climate-monthly
☐ BCCAv2-CMIP3-Climate-daily
☐ BCSD-CMIP3-Hydrology-monthly
☐ BCSD-CMIP5-Climate-monthly
☐ BCCAv2-CMIP5-Climate-daily
☐ BCSD-CMIP5-Hydrology-monthly
☒ LOCA-CMIP5-Climate-daily
☐ LOCA-CMIP5-Hydrology-daily

BCSD-CMIP3-Climate-monthly BCCAv2-CMIP3-Climate-daily BCSD-CMIP3-Hydrology-monthly BCSD-CMIP5-Climate-monthly BCCAv2-CMIP5-Climate-daily BCSD-CMIP5-Hydrology-monthly **LOCA-CMIP5-Climate-daily** LOCA-CMIP5-Hydrology-daily

Step 2.5: Products & Variables -- daily projections ?

Products
☒ 1/16 degree LOCA projections
☐ 1/16 degree Observed data (1950-2005)
☐ 1 degree LOCA projections

Variables
☒ Precipitation Rate (mm/day)
☐ Min Surface Air Temperature (deg C)
☐ Max Surface Air Temperature (deg C)

Step 2.6: Emissions Scenarios, Climate Models and Runs ?

De-select all runs	None	None	None	None
Select all runs	All	All	All	All
Climate Models:	Emissions Path: RCP2.6	Emissions Path: RCP4.5	Emissions Path: RCP6.0	Emissions Path: RCP8.5
access1-0	☐	☐	☐	☐
access1-3	☐	☐	☐	☐
bcc-csm1-1	☐	☐	☐	☐
bcc-csm1-1-m	☐	☐	☐	☐
canesm2	☐	☐	☐	☐
ccsm4	☐	☐	☐	☐
cesm1-bgc	☐	☐	☐	☐
cesm1-cam5	☐	☐	☐	☐
cmcc-cm	☐	☐	☐	☐
cmcc-cms	☐	☐	☐	☐
cnrm-cm5	☐	☐	☐	☐
csiro-mk3-6-0	☐	☐	☐	☐
ec-earth	☐	☐	☐	☐
fgoals-g2	☐	☐	☐	☐
gfdl-cm3	☐	☐	☐	☐
gfdl-esm2g	☐	☐	☐	☐
gfdl-esm2m	☐	☐	☐	☐
giss-e2-h	☐	☐	☐	☐
giss-e2-r	☐	☐	☐	☐
hadgem2-ao	☐	☐	☐	☐
hadgem2-cc	☐	☐	☐	☐
hadgem2-es	☐	☐	☐	☐
inmcm4	☐	☐	☐	☐
ipsl-cm5a-lr	☐	☐	☐	☐
ipsl-cm5a-mr	☐	☐	☐	☐
miroc-esm	☐	☐	☐	☐
miroc-esm-chem	☐	☐	☐	☐
miroc5	☐	☐	☐	☐
mpi-esm-lr	☐	☐	☐	☐
mpi-esm-mr	☐	☐	☐	☐
mri-cgcm3	☐	☐	☐	☐
noresm1-m	☐	☒	☐	☐

Figure A.6.5. GDO LOCA GCM projection subset request interface (“Downscaled CMIP3 and CMIP5 climate and hydrology projections,” n.d.). Detailing Steps 3 from above.

Enter specifications on three page form below. Then press 'Submit Request'. ?

Submit Request Form Status (completed == green) Size (% , 100 max): 2

1.1 1.2 1.3 2.4 2.5 2.6 3.7 3.8 3.9 3.10

Page 1: Temporal & Spatial Extent Page 2: Products, Variables, Projections Page 3: Analysis, Format, & Notification

Step 3.7: Analysis ?

☒ No Analysis (Extracting Time Series only)

☐ Statistics

☐ Period Mean

☐ Period Standard Deviation

☐ Spatial Mean

☐ Spatial Standard Deviation

Step 3.8: Output Format ?

☐ NetCDF

☒ ASCII text, comma-delimited (csv)

Step 3.9: Notification when Processing is Complete ?

Email Address

Email Address Confirm

Tag/Label for request (Optional, characters may be letters, numbers, or '_')

Step 3.10: Usage Information

Please specify usage information below. This information will help LLNL and Reclamation track how this archive is serving various sectors and entities in the user community. For entity and application lists, please make one selection. For sector, please make one or multiple selections.

Entity	Application	Sector(s)
☐ Govt. - Federal	☐ Research	☐ Water Quantity
☐ Govt. - State	☐ Environmental Documentation	☐ Water Quality
☐ Govt. - Regional/Local	☐ Endangered Species consultation	☐ Flood Management
☐ Research Institution	☐ Vulnerability Assessment	☐ Energy
☐ Academic Institution	☐ Adaptation Planning	☐ Air Quality
☐ Private Sector	☐ Other	☐ Ecosystem - Land
☐ Non-Govt. Organization		☐ Ecosystem - Aquatic
☐ Other		☐ Social Systems
		☐ Other

Figure A.6.6. GDO LOCA GCM projection subset request interface (“Downscaled CMIP3 and CMIP5 climate and hydrology projections,” n.d.). Detailing Steps 4-7 from above.

MACA GCMs Download Steps

1. Navigate to the MACA Statistical Downscaling website and select get the data tab:
 - a. For csv format: https://climate.northwestknowledge.net/MACA/data_csv.php
 - b. For NetCDF format:

https://climate.northwestknowledge.net/MACA/data_portal.php

2. CSV format steps:

- a. Step 1: Select time frequency and time range of Desired Data- Ex: Daily Data, 1950-2005
- b. Step 2: Select Point Location for data- Ex: type in Latitude and Longitude coordinates
- c. Confirm location on the map
- d. Step 3: Select Number of Variables for CSV columns- Ex: 4, column for each of the chosen models.
- e. Step 4: Select Desired Data for each column- Ex: Select MACA V2- METADATA (1/24 deg grid cell size), select desired models, select precipitation variable.
- f. Step 5: Click the show csv button to process the data request and wait for results to be displayed.
- g. Download csv and save data to desired folder.

3. NetCDF format steps

- a. Step 1: Select MACA Product- Ex: MACA V2- METADATA
- b. Step 2: Select time frequency- Ex: monthly
- c. Step 3: Select variables- Ex: precipitation, pr
- d. Step 4: Select CMIP5 Models- Ex: noresm1-m
- e. Step 5: Select CMIP5 Scenarios and time period- Ex: historical (1950-2005)
- f. Step 6: Specify domain- Ex: rectangular subset- NE corner: 39.2298N,-94.1652E; SW corner: 38.5264N,-95.0253E
- g. Confirm domain range on the map

- h. Step 7: Specify Download format- Ex: NetCDF data downloads and files of URLs for downloading data
- i. Step 8: Click the download file button. Wait for download to complete. Open downloaded file and follow URL links to download files one-by-one.

Design your Own CSV File of MACA Point Data

STEP ONE:

Select Frequency of Desired Data:

☒ Return all days in years
☐ Return only the following days:
 to

Select Scenario:

Year Start: Year End:

STEP TWO:

Select Point Location for data: ?

Point Location: N, E

STEP THREE:

Select Number of Variables for CSV Columns:

Map

Note: the data extracted corresponds to the average over the grid cell that contains your selected point. Click the following to show/hide the 2 different grids about your point (you might need to zoom in).

☒ 1/24-deg METDATA grid cell ☐ 1/16-deg LIVNEH grid cell

Show domain overlay MACAv2-METDATA

Figure A.6.7. MACA GCM projection subset request interface (“Data Tools,” n.d.). Detailing steps for CSV format, 2a- 2d above.

STEP FOUR:

Select Desired Data For Each Column:

COLUMN 1	COLUMN 2	COLUMN 3	COLUMN 4	COLUMN 5
Time (YYYY-MM-DD)	MACAv2-METDATA (Climate) ▾ MIROC-ESM (Japan) ▾ pr(Precipitation) ▾	MACAv2-METDATA (Climate) ▾ MIROC-ESM-CHEM (Japan) ▾ pr(Precipitation) ▾	MACAv2-METDATA (Climate) ▾ MRI-CGCM3 (Japan) ▾ pr(Precipitation) ▾	MACAv2-METDATA (Climate) ▾ NorESM1-M (Norway) ▾ pr(Precipitation) ▾

STEP FIVE:

Click the Button to Process the Request

SHOW CSV

DATA RESULTS:

DOWNLOAD CSV

```
#Variables:
#pr_MIROC-ESM_historical(mm):Precipitation
#pr_MIROC-ESM-CHEM_historical(mm):Precipitation
#pr_MRI-CGCM3_historical(mm):Precipitation
#pr_NorESM1-M_historical(mm):Precipitation
#Data Extracted for Average over Grid Cell w/ center: 38.8962 Latitude, -94.8143 Longitude (closest value to Latitude:38.915425, Longitude:-94.832755)
#Original Data File(s):
#agg_macav2metdata_pr_MIROC-ESM_r1i1p1_historical_1950_2005_CONUS_daily.nc
#agg_macav2metdata_pr_MIROC-ESM-CHEM_r1i1p1_historical_1950_2005_CONUS_daily.nc
#agg_macav2metdata_pr_MRI-CGCM3_r1i1p1_historical_1950_2005_CONUS_daily.nc
#agg_macav2metdata_pr_NorESM1-M_r1i1p1_historical_1950_2005_CONUS_daily.nc
#=====
1950-01-01,0.000000,0.000000,0.000000,0.000000
1950-01-02,0.000000,0.000000,2.497194,0.000000
1950-01-03,0.000000,0.000000,0.333061,0.000000
1950-01-04,0.315062,0.000000,0.428569,0.000000
-----
```

**Figure A.6.8. MACA GCM projection subset request interface (“Data Tools,” n.d.).
Detailing steps for CSV format, 2e-2g above.**

MACA Data Portal

[Welcome](#)
[Introduction](#)
[Get Started](#)
[Best Practices](#)
[Join Mailing List](#)
[Data Portal Issues](#)
[netCDF Data Extraction Issues](#)

Welcome to the MACA data portal. This tool helps you to access MACA data that is hosted on [NKN](#). If you download data, check 'best practices' and join the mailing list.

Download File

MACA PRODUCT ☐ ? ☒ MACAv2-LIVNEH ☐ MACAv1-METDATA ☐ MACAv2-METDATA	Domain: Rectangular Subset NE corner: 39.2298 N -94.1652 E SW corner: 38.5264 N -95.0253 E	Download Format: netCDF data downloads files of URLs for downloading data
TIME FREQUENCY ☐ daily ☒ monthly		
VARIABLES Select All DeSelect All ☐ huss (Specific Humidity) ☒ pr (Precipitation) ☐ rsds (Downwelling Solar Radiation) ☐ tasmin (Minimum Air Temperature) ☐ tasmax (Maximum Air Temperature) ☐ was (Wind Speed Near Surface)		
CMIP5 MODELS Select All DeSelect All		

Figure A.6.9. MACA GCM projection subset request interface (“Data Tools,” n.d.). Detailing steps for NetCDF format, 3a-3c & 3f-3i above.

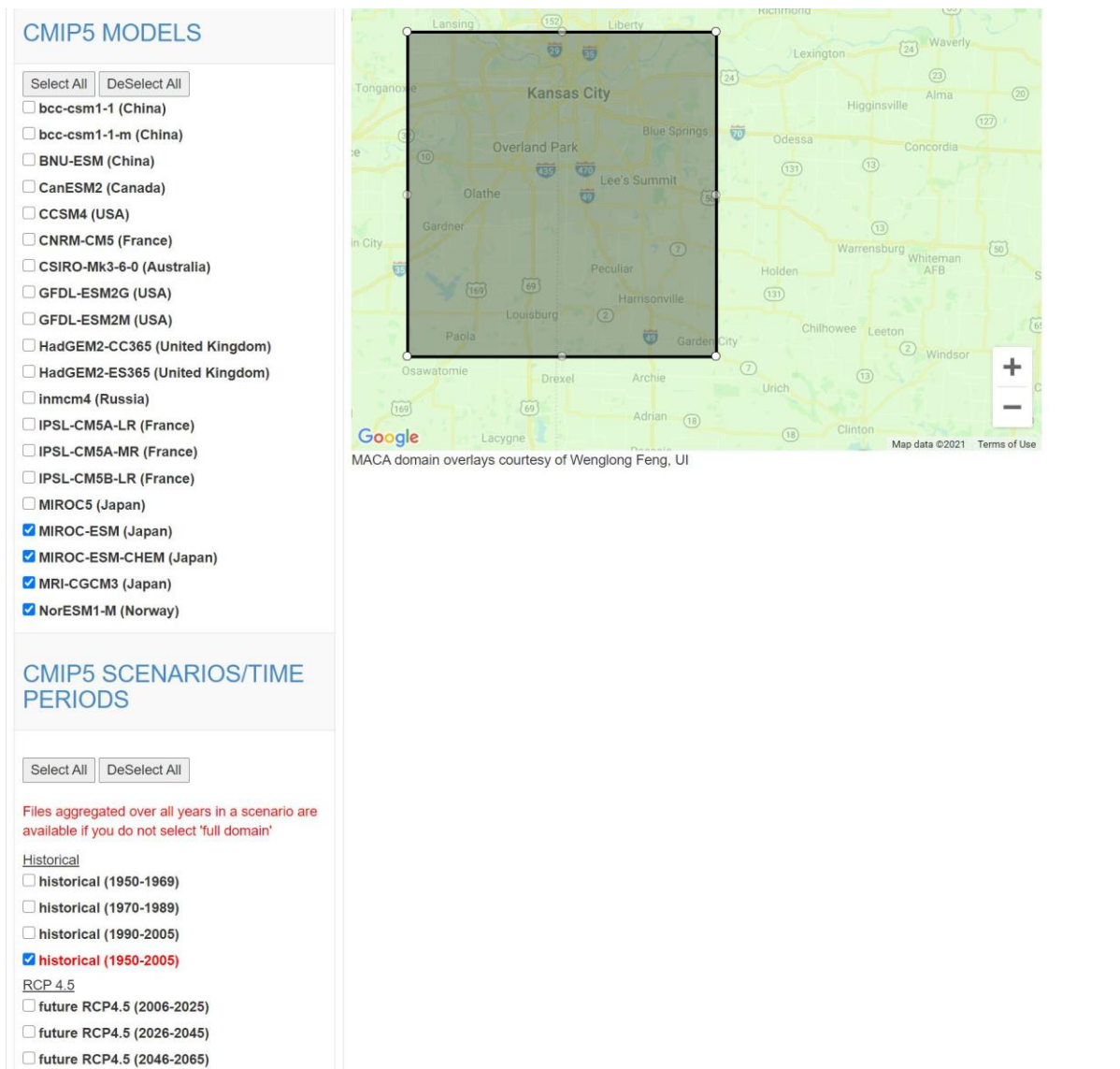


Figure A.6.10. MACA GCM projection subset request interface (“Data Tools,” n.d.). Detailing steps for NetCDF format, 3d-3e above.

PRISM Download Steps

1. Navigate to the PRISM Climate Group website Recent Years tab
<https://prism.oregonstate.edu/recent/> or the Data Explorer tab
<https://prism.oregonstate.edu/explorer/>
2. Recent Years tab (gridded data formats)

- a. Select climate variable- Ex: Precipitation
 - b. Select temporal period- Ex: Monthly data, annual values
 - c. Select download format option- Ex: Download all data for all years (.bil) (1981-2020)
 - d. Wait for requested download zip file to complete, then unzip files and open with ArcGIS
3. Data Explorer tabs allows for download at individual locations (single or multiple)
- a. Download data from multiple locations or single- location- Ex: select link to go to multiple locations or do not select to stay on the single location request
 - b. Single-location request: specify location- Ex: type in latitude and longitude coordinates, select zoom to location to view and confirm location on map
 - c. Data settings: select variable, temporal period and specify units- Ex: Precipitation, Daily values use drop down arrows to specify start and end dates (01/Jan/1981-31/Dec/2010), SI (metric) units
 - d. Select the Retrieve Time Series button confirm the loaded information at bottom of page
 - e. Select the Download Time Series button: wait for download request to complete and then open the downloaded csv file



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[What's new](#) at PRISM

Recent Years (Jan 1981 - Jun 2020)

Time series datasets since 1981 are modeled using climatologically-aided interpolation (CAI), which uses the long-term average pattern (i.e., the 30-year normals) as first-guess of the spatial pattern of climatic conditions for a given month or day. CAI is robust to wide variations in station data density, which is necessary when modeling long time series.

The datasets are available based on either **monthly or daily** modeling. As with any averaging technique, the yearly average obtained from monthly values may not exactly match that based on daily values. Moreover, since 1 January 2002, the precipitation observations used for daily modeling includes radar measurements, which monthly modeling does not take into account. This may cause dramatic local differences between the two datasets in monthly/annual totals for areas east of the Rocky Mountains.

These datasets use all of the station networks and data sources ingested by the PRISM Climate Group, not just those that have existed for long periods of time. See [PRISM datasets](#) for more information; the data available from this page is "AN81m" (monthly) or "AN81d" (daily). Note that individual grids contain non-climatic variations due to station equipment and location changes, stations openings and closings, and varying observation times. **These datasets should be considered "stable"** (unlikely to change until a major version change). Datasets from 1895-1980 will be found in the Historical Data section. For information on when the grids were most recently updated, see [calendar of PRISM data updates](#).

Download size: approx. 12MB per data file; 300KB per full-size image

Climate variable:

☒ precipitation
☐ mean dewpoint temperature

☐ mean temperature
☐ minimum vapor pressure deficit

☐ minimum temperature
☐ maximum vapor pressure deficit

☐ maximum temperature

Temporal period:

☒ monthly data
☐ annual values
☐ monthly values for January

Choose year ▼

Choose month ▼

Choose day ▼

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[Download All Data for Year \(.asc\)](#)
[Download All Data for All Years \(.bil\)](#)

☐ daily data

Choose year ▼

Choose month ▼

Choose day ▼

[Download Data \(.bil\)](#)
[View/Download Metadata](#)

[Download All Data for Month \(.bil\)](#)
[Download All Data for Month \(.asc\)](#)
[Download All Data for Year \(.bil\)](#)

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Figure A.6.11. PRISM data subset request interface (“PRISM Climate Group, Oregon State University,” 2004). Detailing steps for gridded .bil format, 2a- 2d above

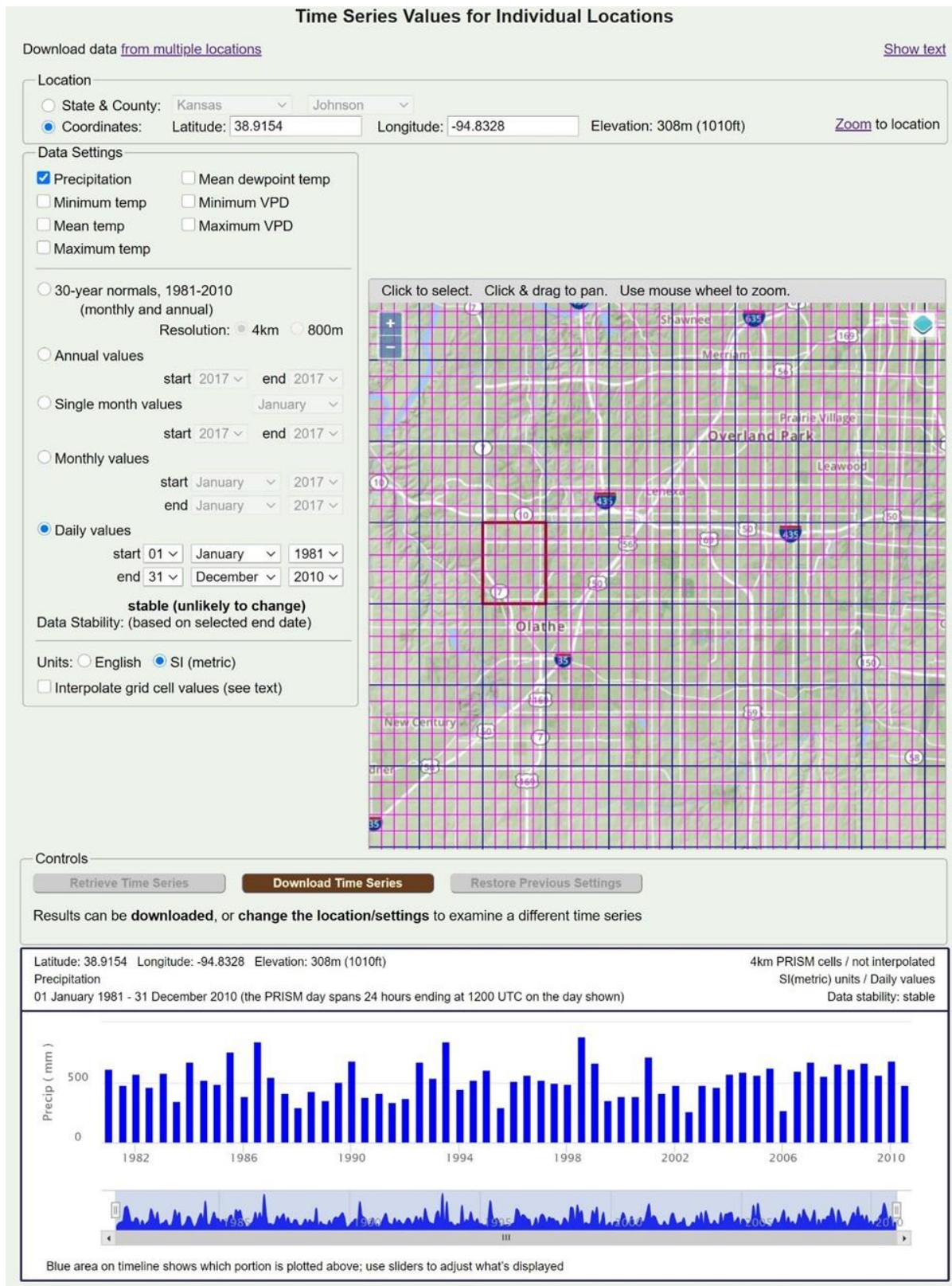


Figure A.6.12. PRISM data subset request interface (“PRISM Climate Group, Oregon State University,” 2004). Detailing steps for single location CSV format, 3a-3e above.

Appendix B - Point Comparison Statistical Validation and Visualization R code

The following R code for statistical validation and visualization was developed and modified with the assistance of Dr. Kelsey McDonough.

Statistical Validation R Code

```
#####Code for validation of downscaled GCM precipitation data#####
##Created by and Modified by Kelsey R. McDonough & Laura J. Krueger on August 11, 2018##

#####Set up your workspace and load your files#####
##Get working directory
getwd()

##Set working directory
setwd('D:/Datasets/CMIP5/Validation') #This should be the path to the folder wherever your files
are located

##Double check your working directory
getwd() #This should now represent the path to the folder where your files are

##Read your files into R
loca1 = read.csv('KansasCityU.csv', sep=",", header=TRUE) #Name of the file that includes
Station and GCM data.

#See data columns
head(loca1)

##This code will use the following libraries. Please install each package using install.packages(),
if not already done.
#For more information about the zoo package: https://cran.r-
project.org/web/packages/zoo/zoo.pdf
library(zoo)
#For more information about the hydroGOF package: https://cran.r-
project.org/web/packages/hydroGOF/hydroGOF.pdf
library(hydroGOF)
#For more information about the Kendall package: https://cran.r-
project.org/web/packages/Kendall/Kendall.pdf
library(Kendall)

##Turn your file into a 'zoo' series for timeseries analysis
zoo1 = read.zoo(loca1, format = "%m/%d/%Y")
```

```
#Daily validation & assessment of the GCM data vs. NOAA NCEI LCD Station observed data#
#Assess the trend of each column of data using the Mann-Kendall test
df2 <- data.frame(zoo1)
```

```
MannKendall(df2$NCEI_PRCP)
MannKendall(df2$MACA_bcc.csm1.1)
MannKendall(df2$MACA_bcc.csm1.1.m)
MannKendall(df2$MACA_CanESM2)
MannKendall(df2$MACA_CCSM4)
MannKendall(df2$MACA_CNRM.CM5)
MannKendall(df2$MACA_CSIRO.Mk3.6.0)
MannKendall(df2$MACA_GFDL.ESM2M)
MannKendall(df2$MACA_GFDL.ESM2G)
MannKendall(df2$MACA_HadGEM2.CC365)
MannKendall(df2$MACA_HadGEM2.ES365)
MannKendall(df2$MACA_inmcm4)
MannKendall(df2$MACA_IPSL.CM5A.LR)
MannKendall(df2$MACA_IPSL.CM5A.MR)
MannKendall(df2$MACA_MIROC5)
MannKendall(df2$MACA_MIROC.ESM)
MannKendall(df2$MACA_MIROC.ESM.CHEM)
MannKendall(df2$MACA_MRI.CGCM3)
MannKendall(df2$MACA_NorESM1.M)
```

```
MannKendall(df2$GDO_bcc.csm1.1)
MannKendall(df2$GDO_bcc.csm1.1.m)
MannKendall(df2$GDO_CanESM2)
MannKendall(df2$GDO_CCSM4)
MannKendall(df2$GDO_CNRM.CM5)
MannKendall(df2$GDO_CSIRO.Mk3.6.0)
MannKendall(df2$GDO_GFDL.ESM2M)
MannKendall(df2$GDO_GFDL.ESM2G)
MannKendall(df2$GDO_HadGEM2.CC365)
MannKendall(df2$GDO_HadGEM2.ES365)
MannKendall(df2$GDO_inmcm4)
MannKendall(df2$GDO_IPSL.CM5A.LR)
MannKendall(df2$GDO_IPSL.CM5A.MR)
MannKendall(df2$GDO_MIROC5)
MannKendall(df2$GDO_MIROC.ESM)
MannKendall(df2$GDO_MIROC.ESM.CHEM)
MannKendall(df2$GDO_MRI.CGCM3)
MannKendall(df2$GDO_NorESM1.M)
```

```
#####Monthly validation of the GCM data vs. observed data#####
```

```
##Get the monthly sum for each month/year over the entire time period
```

```

MSum1 = aggregate(zoo1, as.yearmon, sum)
df3 <- data.frame(MSum1)

##Get the monthly average for each month/year over the entire time period
MAvg1 = aggregate(zoo1, as.yearmon, mean)
df4 <- data.frame(MAvg1)

##Get the monthly maximum for each month/year over the entire time period
MMax1 = aggregate(zoo1, as.yearmon, max)
df5 <- data.frame(MMax1)

#Assess the trend of each column of data using the Mann-Kendall test #run df3,4,5
MannKendall(df3$NCEI_PRCP)
MannKendall(df3$MACA_bcc.csm1.1)
MannKendall(df3$MACA_bcc.csm1.1.m)
MannKendall(df3$MACA_CanESM2)
MannKendall(df3$MACA_CCSM4)
MannKendall(df3$MACA_CNRM.CM5)
MannKendall(df3$MACA_CSIRO.Mk3.6.0)
MannKendall(df3$MACA_GFDL.ESM2M)
MannKendall(df3$MACA_GFDL.ESM2G)
MannKendall(df3$MACA_HadGEM2.CC365)
MannKendall(df3$MACA_HadGEM2.ES365)
MannKendall(df3$MACA_inmcm4)
MannKendall(df3$MACA_IPSL.CM5A.LR)
MannKendall(df3$MACA_IPSL.CM5A.MR)
MannKendall(df3$MACA_MIROC5)
MannKendall(df3$MACA_MIROC.ESM)
MannKendall(df3$MACA_MIROC.ESM.CHEM)
MannKendall(df3$MACA_MRI.CGCM3)
MannKendall(df3$MACA_NorESM1.M)

MannKendall(df4$NCEI_PRCP)
MannKendall(df4$MACA_bcc.csm1.1)
MannKendall(df4$MACA_bcc.csm1.1.m)
MannKendall(df4$MACA_CanESM2)
MannKendall(df4$MACA_CCSM4)
MannKendall(df4$MACA_CNRM.CM5)
MannKendall(df4$MACA_CSIRO.Mk3.6.0)
MannKendall(df4$MACA_GFDL.ESM2M)
MannKendall(df4$MACA_GFDL.ESM2G)
MannKendall(df4$MACA_HadGEM2.CC365)
MannKendall(df4$MACA_HadGEM2.ES365)
MannKendall(df4$MACA_inmcm4)
MannKendall(df4$MACA_IPSL.CM5A.LR)
MannKendall(df4$MACA_IPSL.CM5A.MR)

```

MannKendall(df4\$MACA_MIROC5)
MannKendall(df4\$MACA_MIROC.ESM)
MannKendall(df4\$MACA_MIROC.ESM.CHEM)
MannKendall(df4\$MACA_MRI.CGCM3)
MannKendall(df4\$MACA_NorESM1.M)

MannKendall(df5\$NCEI_PRCP)
MannKendall(df5\$MACA_bcc.csm1.1)
MannKendall(df5\$MACA_bcc.csm1.1.m)
MannKendall(df5\$MACA_CanESM2)
MannKendall(df5\$MACA_CCSM4)
MannKendall(df5\$MACA_CNRM.CM5)
MannKendall(df5\$MACA_CSIRO.Mk3.6.0)
MannKendall(df5\$MACA_GFDL.ESM2M)
MannKendall(df5\$MACA_GFDL.ESM2G)
MannKendall(df5\$MACA_HadGEM2.CC365)
MannKendall(df5\$MACA_HadGEM2.ES365)
MannKendall(df5\$MACA_inmcm4)
MannKendall(df5\$MACA_IPSL.CM5A.LR)
MannKendall(df5\$MACA_IPSL.CM5A.MR)
MannKendall(df5\$MACA_MIROC5)
MannKendall(df5\$MACA_MIROC.ESM)
MannKendall(df5\$MACA_MIROC.ESM.CHEM)
MannKendall(df5\$MACA_MRI.CGCM3)
MannKendall(df5\$MACA_NorESM1.M)

MannKendall(df3\$GDO_bcc.csm1.1)
MannKendall(df3\$GDO_bcc.csm1.1.m)
MannKendall(df3\$GDO_CanESM2)
MannKendall(df3\$GDO_CCSM4)
MannKendall(df3\$GDO_CNRM.CM5)
MannKendall(df3\$GDO_CSIRO.Mk3.6.0)
MannKendall(df3\$GDO_GFDL.ESM2M)
MannKendall(df3\$GDO_GFDL.ESM2G)
MannKendall(df3\$GDO_HadGEM2.CC365)
MannKendall(df3\$GDO_HadGEM2.ES365)
MannKendall(df3\$GDO_inmcm4)
MannKendall(df3\$GDO_IPSL.CM5A.LR)
MannKendall(df3\$GDO_IPSL.CM5A.MR)
MannKendall(df3\$GDO_MIROC5)
MannKendall(df3\$GDO_MIROC.ESM)
MannKendall(df3\$GDO_MIROC.ESM.CHEM)
MannKendall(df3\$GDO_MRI.CGCM3)
MannKendall(df3\$GDO_NorESM1.M)

```

MannKendall(df4$GDO_bcc.csm1.1)
MannKendall(df4$GDO_bcc.csm1.1.m)
MannKendall(df4$GDO_CanESM2)
MannKendall(df4$GDO_CCSM4)
MannKendall(df4$GDO_CNRM.CM5)
MannKendall(df4$GDO_CSIRO.Mk3.6.0)
MannKendall(df4$GDO_GFDL.ESM2M)
MannKendall(df4$GDO_GFDL.ESM2G)
MannKendall(df4$GDO_HadGEM2.CC365)
MannKendall(df4$GDO_HadGEM2.ES365)
MannKendall(df4$GDO_inmcm4)
MannKendall(df4$GDO_IPSL.CM5A.LR)
MannKendall(df4$GDO_IPSL.CM5A.MR)
MannKendall(df4$GDO_MIROC5)
MannKendall(df4$GDO_MIROC.ESM)
MannKendall(df4$GDO_MIROC.ESM.CHEM)
MannKendall(df4$GDO_MRI.CGCM3)
MannKendall(df4$GDO_NorESM1.M)

```

```

MannKendall(df5$GDO_bcc.csm1.1)
MannKendall(df5$GDO_bcc.csm1.1.m)
MannKendall(df5$GDO_CanESM2)
MannKendall(df5$GDO_CCSM4)
MannKendall(df5$GDO_CNRM.CM5)
MannKendall(df5$GDO_CSIRO.Mk3.6.0)
MannKendall(df5$GDO_GFDL.ESM2M)
MannKendall(df5$GDO_GFDL.ESM2G)
MannKendall(df5$GDO_HadGEM2.CC365)
MannKendall(df5$GDO_HadGEM2.ES365)
MannKendall(df5$GDO_inmcm4)
MannKendall(df5$GDO_IPSL.CM5A.LR)
MannKendall(df5$GDO_IPSL.CM5A.MR)
MannKendall(df5$GDO_MIROC5)
MannKendall(df5$GDO_MIROC.ESM)
MannKendall(df5$GDO_MIROC.ESM.CHEM)
MannKendall(df5$GDO_MRI.CGCM3)
MannKendall(df5$GDO_NorESM1.M)

```

```

#get Spearman's rho (correlation) #run df3,4,5
rho=cor.test(df3$NCEI_PRCP, df3$MACA_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df3$NCEI_PRCP, df3$MACA_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$MACA_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df3$NCEI_PRCP, df3$MACA_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df4$NCEI_PRCP, df4$MACA_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_MIROC5, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df4$NCEI_PRCP, df4$MACA_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$MACA_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df5$NCEI_PRCP, df5$MACA_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_inmcm4, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df5$NCEI_PRCP, df5$MACA_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$MACA_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df3$NCEI_PRCP, df3$GDO_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df3$NCEI_PRCP, df3$GDO_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df3$NCEI_PRCP, df3$GDO_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df4$NCEI_PRCP, df4$GDO_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df4$NCEI_PRCP, df4$GDO_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df4$NCEI_PRCP, df4$GDO_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df5$NCEI_PRCP, df5$GDO_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df5$NCEI_PRCP, df5$GDO_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df5$NCEI_PRCP, df5$GDO_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho

```

```
rho=cor.test(df5$NCEI_PRCP, df5$GDO_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho
```

```
#Create a Q-Q plot to visually assess whether the two datasets have the same distribution.
#If they do, the dots should match up roughly along the 45 degree line
qqplot(df3$NCEI_PRCP, df3$MACA_bcc.csm1.1, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1) #adds 45 degree line to the plot
qqplot(df3$NCEI_PRCP, df3$MACA_bcc.csm1.1.m, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_CanESM2, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_CCSM4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_CNRM.CM5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_CSIRO.Mk3.6.0, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_GFDL.ESM2M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_GFDL.ESM2G, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_HadGEM2.CC365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_HadGEM2.ES365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_inmcm4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_IPSL.CM5A.LR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_IPSL.CM5A.MR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_MIROC5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_MIROC.ESM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_MIROC.ESM.CHEM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_MRI.CGCM3, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$MACA_NorESM1.M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

qqplot(df4$NCEI_PRCP, df4$MACA_bcc.csm1.1, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_bcc.csm1.1.m, ylim=c(0,50), xlim=c(0,50))
```

```

abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_CanESM2, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_CCSM4, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_CNRM.CM5, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_CSIRO.Mk3.6.0, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_GFDL.ESM2M, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_GFDL.ESM2G, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_HadGEM2.CC365, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_HadGEM2.ES365, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_inmcm4, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_IPSL.CM5A.LR, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_IPSL.CM5A.MR, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_MIROC5, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_MIROC.ESM, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_MIROC.ESM.CHEM, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_MRI.CGCM3, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$MACA_NorESM1.M, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)

qqplot(df5$NCEI_PRCP, df5$MACA_bcc.csm1.1, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_bcc.csm1.1.m, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_CanESM2, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_CCSM4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_CNRM.CM5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_CSIRO.Mk3.6.0, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

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```

qqplot(df5$NCEI_PRCP, df5$MACA_GFDL.ESM2M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_GFDL.ESM2G, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_HadGEM2.CC365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_HadGEM2.ES365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_inmcm4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_IPSL.CM5A.LR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_IPSL.CM5A.MR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_MIROC5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_MIROC.ESM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_MIROC.ESM.CHEM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_MRI.CGCM3, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$MACA_NorESM1.M, ylim=c(0,200), xlim=c(0,200))
abline(a=0, b=1)

qqplot(df3$NCEI_PRCP, df3$GDO_bcc.csm1.1, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_bcc.csm1.1.m, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_CanESM2, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_CCSM4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_CNRM.CM5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_CSIRO.Mk3.6.0, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_GFDL.ESM2M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_GFDL.ESM2G, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_HadGEM2.CC365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_HadGEM2.ES365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_inmcm4, ylim=c(0,400), xlim=c(0,400))

```

```

abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_IPSL.CM5A.LR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_IPSL.CM5A.MR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_MIROC5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_MIROC.ESM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_MIROC.ESM.CHEM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_MRI.CGCM3, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df3$NCEI_PRCP, df3$GDO_NorESM1.M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

qqplot(df4$NCEI_PRCP, df4$GDO_bcc.csm1.1, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_bcc.csm1.1.m, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_CanESM2, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_CCSM4, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_CNRM.CM5, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_CSIRO.Mk3.6.0, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_GFDL.ESM2M, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_GFDL.ESM2G, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_HadGEM2.CC365, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_HadGEM2.ES365, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_inmcm4, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_IPSL.CM5A.LR, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_IPSL.CM5A.MR, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_MIROC5, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_MIROC.ESM, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)

```

```

qqplot(df4$NCEI_PRCP, df4$GDO_MIROC.ESM.CHEM, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_MRI.CGCM3, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)
qqplot(df4$NCEI_PRCP, df4$GDO_NorESM1.M, ylim=c(0,50), xlim=c(0,50))
abline(a=0, b=1)

qqplot(df5$NCEI_PRCP, df5$GDO_bcc.csm1.1, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_bcc.csm1.1.m, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_CanESM2, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_CCSM4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_CNRM.CM5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_CSIRO.Mk3.6.0, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_GFDL.ESM2M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_GFDL.ESM2G, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_HadGEM2.CC365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_HadGEM2.ES365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_inmcm4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_IPSL.CM5A.LR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_IPSL.CM5A.MR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_MIROC5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_MIROC.ESM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_MIROC.ESM.CHEM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_MRI.CGCM3, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df5$NCEI_PRCP, df5$GDO_NorESM1.M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

#get coefficient of determination (R2)
r2=br2(df3$MACA_bcc.csm1.1, df3$NCEI_PRCP, na.rm=TRUE)

```

```

r2
r2=br2(df3$MACA_bcc.csm1.1.m, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_CanESM2, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_CCSM4, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_CNRM.CM5, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_CSIRO.Mk3.6.0, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_GFDL.ESM2M, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_GFDL.ESM2G, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_HadGEM2.CC365, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_HadGEM2.ES365, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_inmcm4, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_IPSL.CM5A.LR, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_IPSL.CM5A.MR, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_MIROC5, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_MIROC.ESM, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_MIROC.ESM.CHEM, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_MRI.CGCM3, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$MACA_NorESM1.M, df3$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df4$MACA_bcc.csm1.1, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_bcc.csm1.1.m, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_CanESM2, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_CCSM4, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_CNRM.CM5, df4$NCEI_PRCP, na.rm=TRUE)
r2

```

```

r2=br2(df4$MACA_CSIRO.Mk3.6.0, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_GFDL.ESM2M, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_GFDL.ESM2G, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_HadGEM2.CC365, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_HadGEM2.ES365, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_inmcm4, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_IPSL.CM5A.LR, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_IPSL.CM5A.MR, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_MIROC5, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_MIROC.ESM, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_MIROC.ESM.CHEM, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_MRI.CGCM3, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$MACA_NorESM1.M, df4$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df5$MACA_bcc.csm1.1, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_bcc.csm1.1.m, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_CanESM2, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_CCSM4, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_CNRM.CM5, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_CSIRO.Mk3.6.0, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_GFDL.ESM2M, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_GFDL.ESM2G, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_HadGEM2.CC365, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_HadGEM2.ES365, df5$NCEI_PRCP, na.rm=TRUE)

```

```

r2
r2=br2(df5$MACA_inmcm4, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_IPSL.CM5A.LR, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_IPSL.CM5A.MR, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_MIROC5, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_MIROC.ESM, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_MIROC.ESM.CHEM, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_MRI.CGCM3, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$MACA_NorESM1.M, df5$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df3$GDO_bcc.csm1.1, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_bcc.csm1.1.m, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_CanESM2, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_CCSM4, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_CNRM.CM5, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_CSIRO.Mk3.6.0, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_GFDL.ESM2M, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_GFDL.ESM2G, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_HadGEM2.CC365, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_HadGEM2.ES365, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_inmcm4, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_IPSL.CM5A.LR, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_IPSL.CM5A.MR, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_MIROC5, df3$NCEI_PRCP, na.rm=TRUE)
r2

```

```

r2=br2(df3$GDO_MIROC.ESM, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_MIROC.ESM.CHEM, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_MRI.CGCM3, df3$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df3$GDO_NorESM1.M, df3$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df4$GDO_bcc.csm1.1, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_bcc.csm1.1.m, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_CanESM2, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_CCSM4, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_CNRM.CM5, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_CSIRO.Mk3.6.0, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_GFDL.ESM2M, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_GFDL.ESM2G, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_HadGEM2.CC365, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_HadGEM2.ES365, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_inmcm4, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_IPSL.CM5A.LR, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_IPSL.CM5A.MR, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_MIROC5, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_MIROC.ESM, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_MIROC.ESM.CHEM, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_MRI.CGCM3, df4$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df4$GDO_NorESM1.M, df4$NCEI_PRCP, na.rm=TRUE)
r2

```

```

r2=br2(df5$GDO_bcc.csm1.1, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_bcc.csm1.1.m, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_CanESM2, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_CCSM4, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_CNRM.CM5, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_CSIRO.Mk3.6.0, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_GFDL.ESM2M, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_GFDL.ESM2G, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_HadGEM2.CC365, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_HadGEM2.ES365, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_inmcm4, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_IPSL.CM5A.LR, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_IPSL.CM5A.MR, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_MIROC5, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_MIROC.ESM, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_MIROC.ESM.CHEM, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_MRI.CGCM3, df5$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df5$GDO_NorESM1.M, df5$NCEI_PRCP, na.rm=TRUE)
r2

#get RMSE value
RMSE=round(rmse(sim=df3$MACA_bcc.csm1.1, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_bcc.csm1.1.m, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_CanESM2, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_CCSM4, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df3$MACA_CNRM.CM5, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_CSIRO.Mk3.6.0, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_GFDL.ESM2M, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_GFDL.ESM2G, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_HadGEM2.CC365, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_HadGEM2.ES365, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_inmcm4, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_IPSL.CM5A.LR, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_IPSL.CM5A.MR, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_MIROC5, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_MIROC.ESM, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_MIROC.ESM.CHEM, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_MRI.CGCM3, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$MACA_NorESM1.M, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df4$MACA_bcc.csm1.1, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_bcc.csm1.1.m, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_CanESM2, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_CCSM4, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_CNRM.CM5, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df4$MACA_CSIRO.Mk3.6.0, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_GFDL.ESM2M, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_GFDL.ESM2G, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_HadGEM2.CC365, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_HadGEM2.ES365, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_inmcm4, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_IPSL.CM5A.LR, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_IPSL.CM5A.MR, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_MIROC5, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_MIROC.ESM, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_MIROC.ESM.CHEM, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_MRI.CGCM3, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$MACA_NorESM1.M, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df5$MACA_bcc.csm1.1, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_bcc.csm1.1.m, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_CanESM2, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_CCSM4, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_CNRM.CM5, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_CSIRO.Mk3.6.0, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df5$MACA_GFDL.ESM2M, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_GFDL.ESM2G, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_HadGEM2.CC365, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_HadGEM2.ES365, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_inmcm4, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_IPSL.CM5A.LR, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_IPSL.CM5A.MR, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_MIROC5, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_MIROC.ESM, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_MIROC.ESM.CHEM, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_MRI.CGCM3, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$MACA_NorESM1.M, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df3$GDO_bcc.csm1.1, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_bcc.csm1.1.m, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_CanESM2, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_CCSM4, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_CNRM.CM5, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_CSIRO.Mk3.6.0, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_GFDL.ESM2M, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_GFDL.ESM2G, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df3$GDO_HadGEM2.CC365, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_HadGEM2.ES365, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_inmcm4, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_IPSL.CM5A.LR, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_IPSL.CM5A.MR, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_MIROC5, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_MIROC.ESM, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_MIROC.ESM.CHEM, obs=df3$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_MRI.CGCM3, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df3$GDO_NorESM1.M, obs=df3$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df4$GDO_bcc.csm1.1, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_bcc.csm1.1.m, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_CanESM2, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_CCSM4, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_CNRM.CM5, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_CSIRO.Mk3.6.0, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_GFDL.ESM2M, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_GFDL.ESM2G, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_HadGEM2.CC365, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_HadGEM2.ES365, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df4$GDO_inmcm4, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_IPSL.CM5A.LR, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_IPSL.CM5A.MR, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_MIROC5, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_MIROC.ESM, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_MIROC.ESM.CHEM, obs=df4$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_MRI.CGCM3, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df4$GDO_NorESM1.M, obs=df4$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df5$GDO_bcc.csm1.1, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_bcc.csm1.1.m, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_CanESM2, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_CCSM4, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_CNRM.CM5, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_CSIRO.Mk3.6.0, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_GFDL.ESM2M, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_GFDL.ESM2G, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_HadGEM2.CC365, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_HadGEM2.ES365, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_inmcm4, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_IPSL.CM5A.LR, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_IPSL.CM5A.MR, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df5$GDO_MIROC5, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_MIROC.ESM, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_MIROC.ESM.CHEM, obs=df5$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_MRI.CGCM3, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df5$GDO_NorESM1.M, obs=df5$NCEI_PRCP, na.rm=TRUE),4)
RMSE

```

```

#calculate percent bias
pbias=pbias(sim=df3$MACA_bcc.csm1.1, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_bcc.csm1.1.m, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_CanESM2, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_CCSM4, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_CNRM.CM5, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_CSIRO.Mk3.6.0, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_GFDL.ESM2M, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_GFDL.ESM2G, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_HadGEM2.CC365, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_HadGEM2.ES365, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_inmcm4, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_IPSL.CM5A.LR, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_IPSL.CM5A.MR, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_MIROC5, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_MIROC.ESM, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_MIROC.ESM.CHEM, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$MACA_MRI.CGCM3, obs=df3$NCEI_PRCP, na.rm=TRUE)

```

```

pbias
pbias=pbias(sim=df3$MACA_NorESM1.M, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df4$MACA_bcc.csm1.1, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_bcc.csm1.1.m, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_CanESM2, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_CCSM4, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_CNRM.CM5, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_CSIRO.Mk3.6.0, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_GFDL.ESM2M, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_GFDL.ESM2G, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_HadGEM2.CC365, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_HadGEM2.ES365, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_inmcm4, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_IPSL.CM5A.LR, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_IPSL.CM5A.MR, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_MIROC5, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_MIROC.ESM, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_MIROC.ESM.CHEM, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_MRI.CGCM3, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$MACA_NorESM1.M, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df5$MACA_bcc.csm1.1, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_bcc.csm1.1.m, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_CanESM2, obs=df5$NCEI_PRCP, na.rm=TRUE)

```

```

pbias
pbias=pbias(sim=df5$MACA_CCSM4, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_CNRM.CM5, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_CSIRO.Mk3.6.0, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_GFDL.ESM2M, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_GFDL.ESM2G, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_HadGEM2.CC365, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_HadGEM2.ES365, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_inmcm4, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_IPSL.CM5A.LR, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_IPSL.CM5A.MR, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_MIROC5, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_MIROC.ESM, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_MIROC.ESM.CHEM, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_MRI.CGCM3, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$MACA_NorESM1.M, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df3$GDO_bcc.csm1.1, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_bcc.csm1.1.m, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_CanESM2, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_CCSM4, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_CNRM.CM5, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_CSIRO.Mk3.6.0, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_GFDL.ESM2M, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias

```

```

pbias=pbias(sim=df3$GDO_GFDL.ESM2G, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_HadGEM2.CC365, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_HadGEM2.ES365, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_inmcm4, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_IPSL.CM5A.LR, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_IPSL.CM5A.MR, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_MIROC5, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_MIROC.ESM, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_MIROC.ESM.CHEM, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_MRI.CGCM3, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df3$GDO_NorESM1.M, obs=df3$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df4$GDO_bcc.csm1.1, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_bcc.csm1.1.m, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_CanESM2, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_CCSM4, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_CNRM.CM5, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_CSIRO.Mk3.6.0, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_GFDL.ESM2M, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_GFDL.ESM2G, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_HadGEM2.CC365, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_HadGEM2.ES365, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_inmcm4, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_IPSL.CM5A.LR, obs=df4$NCEI_PRCP, na.rm=TRUE)

```

```

pbias
pbias=pbias(sim=df4$GDO_IPSL.CM5A.MR, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_MIROC5, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_MIROC.ESM, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_MIROC.ESM.CHEM, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_MRI.CGCM3, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df4$GDO_NorESM1.M, obs=df4$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df5$GDO_bcc.csm1.1, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_bcc.csm1.1.m, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_CanESM2, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_CCSM4, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_CNRM.CM5, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_CSIRO.Mk3.6.0, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_GFDL.ESM2M, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_GFDL.ESM2G, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_HadGEM2.CC365, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_HadGEM2.ES365, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_inmcm4, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_IPSL.CM5A.LR, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_IPSL.CM5A.MR, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_MIROC5, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_MIROC.ESM, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_MIROC.ESM.CHEM, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias

```

```

pbias=pbias(sim=df5$GDO_MRI.CGCM3, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df5$GDO_NorESM1.M, obs=df5$NCEI_PRCP, na.rm=TRUE)
pbias

#####Annual validation of the GCM data vs. observed data#####
#Skipped Merriam Overland Park due to missing data both MACA and GDO (not enough)

#Create a function to analyze the time series on a yearly basis
as.year <- function(x) as.numeric(floor(as.yearmon(x)))

##Get the yearly sum for each year over the entire time period
YSum1 = aggregate(zoo1, as.year, sum)
df6 <- data.frame(YSum1)

##Get the yearly average for each year over the entire time period
YAvg1 = aggregate(zoo1, as.year, mean)
df7 <- data.frame(YAvg1)

##Get the yearly maximum for each year over the entire time period
YMax1 = aggregate(zoo1, as.year, max)
df8 <- data.frame(YMax1)

#get Spearman's rho (correlation)
rho=cor.test(df6$NCEI_PRCP, df6$MACA_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df6$NCEI_PRCP, df6$MACA_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$MACA_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df7$NCEI_PRCP, df7$MACA_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_CCSM4, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df7$NCEI_PRCP, df7$MACA_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$MACA_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df8$NCEI_PRCP, df8$MACA_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df8$NCEI_PRCP, df8$MACA_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df8$NCEI_PRCP, df8$MACA_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$MACA_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df6$NCEI_PRCP, df6$GDO_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df6$NCEI_PRCP, df6$GDO_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df6$NCEI_PRCP, df6$GDO_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df7$NCEI_PRCP, df7$GDO_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df7$NCEI_PRCP, df7$GDO_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df7$NCEI_PRCP, df7$GDO_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

rho=cor.test(df8$NCEI_PRCP, df8$GDO_bcc.csm1.1, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_bcc.csm1.1.m, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_CanESM2, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_CCSM4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_CNRM.CM5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_CSIRO.Mk3.6.0, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_GFDL.ESM2M, use="complete.obs",
method=c("spearman"))
rho

```

```

rho=cor.test(df8$NCEI_PRCP, df8$GDO_GFDL.ESM2G, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_HadGEM2.CC365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_HadGEM2.ES365, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_inmcm4, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_IPSL.CM5A.LR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_IPSL.CM5A.MR, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_MIROC5, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_MIROC.ESM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_MIROC.ESM.CHEM, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_MRI.CGCM3, use="complete.obs",
method=c("spearman"))
rho
rho=cor.test(df8$NCEI_PRCP, df8$GDO_NorESM1.M, use="complete.obs",
method=c("spearman"))
rho

```

```

#Create a Q-Q plot to visually assess whether the two datasets have the same distribution.
#If they do, the dots should match up roughly along the 45 degree line
qqplot(df6$NCEI_PRCP, df6$MACA_bcc.csm1.1, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_bcc.csm1.1.m, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_CanESM2, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_CCSM4, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_CNRM.CM5, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)

```

```

qqplot(df6$NCEI_PRCP, df6$MACA_CSIRO.Mk3.6.0, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_GFDL.ESM2M, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_GFDL.ESM2G, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_HadGEM2.CC365, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_HadGEM2.ES365, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_inmcm4, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_IPSL.CM5A.LR, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_IPSL.CM5A.MR, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_MIROC5, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_MIROC.ESM, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_MIROC.ESM.CHEM, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_MRI.CGCM3, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$MACA_NorESM1.M, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)

qqplot(df7$NCEI_PRCP, df7$MACA_bcc.csm1.1, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_bcc.csm1.1.m, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_CanESM2, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_CCSM4, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_CNRM.CM5, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_CSIRO.Mk3.6.0, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_GFDL.ESM2M, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_GFDL.ESM2G, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_HadGEM2.CC365, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_HadGEM2.ES365, ylim=c(0,20), xlim=c(0,20))

```

```

abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_inmcm4, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_IPSL.CM5A.LR, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_IPSL.CM5A.MR, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_MIROC5, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_MIROC.ESM, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_MIROC.ESM.CHEM, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_MRI.CGCM3, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$MACA_NorESM1.M, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)

qqplot(df8$NCEI_PRCP, df8$MACA_bcc.csm1.1, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_bcc.csm1.1.m, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_CanESM2, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_CCSM4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_CNRM.CM5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_CSIRO.Mk3.6.0, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_GFDL.ESM2M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_GFDL.ESM2G, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_HadGEM2.CC365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_HadGEM2.ES365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_inmcm4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_IPSL.CM5A.LR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_IPSL.CM5A.MR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_MIROC5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

```

```

qqplot(df8$NCEI_PRCP, df8$MACA_MIROC.ESM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_MIROC.ESM.CHEM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_MRI.CGCM3, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$MACA_NorESM1.M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

```

```

qqplot(df6$NCEI_PRCP, df6$GDO_bcc.csm1.1, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_bcc.csm1.1.m, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_CanESM2, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_CCSM4, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_CNRM.CM5, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_CSIRO.Mk3.6.0, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_GFDL.ESM2M, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_GFDL.ESM2G, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_HadGEM2.CC365, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_HadGEM2.ES365, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_inmcm4, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_IPSL.CM5A.LR, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_IPSL.CM5A.MR, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_MIROC5, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_MIROC.ESM, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_MIROC.ESM.CHEM, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_MRI.CGCM3, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)
qqplot(df6$NCEI_PRCP, df6$GDO_NorESM1.M, ylim=c(0,1600), xlim=c(0,1600))
abline(a=0, b=1)

```

```

qqplot(df7$NCEI_PRCP, df7$GDO_bcc.csm1.1, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_bcc.csm1.1.m, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_CanESM2, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_CCSM4, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_CNRM.CM5, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_CSIRO.Mk3.6.0, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_GFDL.ESM2M, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_GFDL.ESM2G, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_HadGEM2.CC365, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_HadGEM2.ES365, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_inmcm4, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_IPSL.CM5A.LR, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_IPSL.CM5A.MR, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_MIROC5, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_MIROC.ESM, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_MIROC.ESM.CHEM, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_MRI.CGCM3, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)
qqplot(df7$NCEI_PRCP, df7$GDO_NorESM1.M, ylim=c(0,20), xlim=c(0,20))
abline(a=0, b=1)

qqplot(df8$NCEI_PRCP, df8$GDO_bcc.csm1.1, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_bcc.csm1.1.m, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_CanESM2, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_CCSM4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_CNRM.CM5, ylim=c(0,400), xlim=c(0,400))

```

```

abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_CSIRO.Mk3.6.0, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_GFDL.ESM2M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_GFDL.ESM2G, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_HadGEM2.CC365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_HadGEM2.ES365, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_inmcm4, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_IPSL.CM5A.LR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_IPSL.CM5A.MR, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_MIROC5, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_MIROC.ESM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_MIROC.ESM.CHEM, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_MRI.CGCM3, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)
qqplot(df8$NCEI_PRCP, df8$GDO_NorESM1.M, ylim=c(0,400), xlim=c(0,400))
abline(a=0, b=1)

#get coefficient of determination (R2)
r2=br2(df6$MACA_bcc.csm1.1, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_bcc.csm1.1.m, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_CanESM2, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_CCSM4, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_CNRM.CM5, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_CSIRO.Mk3.6.0, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_GFDL.ESM2M, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_GFDL.ESM2G, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_HadGEM2.CC365, df6$NCEI_PRCP, na.rm=TRUE)

```

```

r2
r2=br2(df6$MACA_HadGEM2.ES365, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_inmcm4, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_IPSL.CM5A.LR, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_IPSL.CM5A.MR, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_MIROC5, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_MIROC.ESM, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_MIROC.ESM.CHEM, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_MRI.CGCM3, df6$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df6$MACA_NorESM1.M, df6$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df7$MACA_bcc.csm1.1, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_bcc.csm1.1.m, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_CanESM2, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_CCSM4, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_CNRM.CM5, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_CSIRO.Mk3.6.0, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_GFDL.ESM2M, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_GFDL.ESM2G, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_HadGEM2.CC365, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_HadGEM2.ES365, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_inmcm4, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_IPSL.CM5A.LR, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_IPSL.CM5A.MR, df7$NCEI_PRCP, na.rm=TRUE)
r2

```

```

r2=br2(df7$MACA_MIROC5, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_MIROC.ESM, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_MIROC.ESM.CHEM, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_MRI.CGCM3, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$MACA_NorESM1.M, df7$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df8$MACA_bcc.csm1.1, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_bcc.csm1.1.m, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_CanESM2, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_CCISM4, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_CNRM.CM5, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_CSIRO.Mk3.6.0, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_GFDL.ESM2M, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_GFDL.ESM2G, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_HadGEM2.CC365, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_HadGEM2.ES365, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_inmcm4, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_IPSL.CM5A.LR, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_IPSL.CM5A.MR, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_MIROC5, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_MIROC.ESM, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_MIROC.ESM.CHEM, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_MRI.CGCM3, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$MACA_NorESM1.M, df8$NCEI_PRCP, na.rm=TRUE)

```

r2

r2=br2(df6\$GDO_bcc.csm1.1, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_bcc.csm1.1.m, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_CanESM2, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_CCSM4, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_CNRM.CM5, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_CSIRO.Mk3.6.0, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_GFDL.ESM2M, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_GFDL.ESM2G, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_HadGEM2.CC365, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_HadGEM2.ES365, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_inmcm4, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_IPSL.CM5A.LR, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_IPSL.CM5A.MR, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_MIROC5, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_MIROC.ESM, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_MIROC.ESM.CHEM, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_MRI.CGCM3, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df6\$GDO_NorESM1.M, df6\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df7\$GDO_bcc.csm1.1, df7\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df7\$GDO_bcc.csm1.1.m, df7\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df7\$GDO_CanESM2, df7\$NCEI_PRCP, na.rm=TRUE)

r2

r2=br2(df7\$GDO_CCSM4, df7\$NCEI_PRCP, na.rm=TRUE)

```

r2
r2=br2(df7$GDO_CNRM.CM5, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_CSIRO.Mk3.6.0, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_GFDL.ESM2M, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_GFDL.ESM2G, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_HadGEM2.CC365, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_HadGEM2.ES365, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_inmcm4, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_IPSL.CM5A.LR, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_IPSL.CM5A.MR, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_MIROC5, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_MIROC.ESM, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_MIROC.ESM.CHEM, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_MRI.CGCM3, df7$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df7$GDO_NorESM1.M, df7$NCEI_PRCP, na.rm=TRUE)
r2

r2=br2(df8$GDO_bcc.csm1.1, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_bcc.csm1.1.m, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_CanESM2, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_CCSM4, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_CNRM.CM5, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_CSIRO.Mk3.6.0, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_GFDL.ESM2M, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_GFDL.ESM2G, df8$NCEI_PRCP, na.rm=TRUE)
r2

```

```

r2=br2(df8$GDO_HadGEM2.CC365,df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_HadGEM2.ES365, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_inmcm4, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_IPSL.CM5A.LR, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_IPSL.CM5A.MR, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_MIROC5, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_MIROC.ESM, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_MIROC.ESM.CHEM, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_MRI.CGCM3, df8$NCEI_PRCP, na.rm=TRUE)
r2
r2=br2(df8$GDO_NorESM1.M, df8$NCEI_PRCP, na.rm=TRUE)
r2

```

#get RMSE value

```

RMSE=round(rmse(sim=df6$MACA_bcc.csm1.1, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_bcc.csm1.1.m, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_CanESM2, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_CCSM4, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_CNRM.CM5, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_CSIRO.Mk3.6.0, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_GFDL.ESM2M, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_GFDL.ESM2G, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_HadGEM2.CC365, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_HadGEM2.ES365, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_inmcm4, obs=df6$NCEI_PRCP, na.rm=TRUE),4)

```

```

RMSE
RMSE=round(rmse(sim=df6$MACA_IPSL.CM5A.LR, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_IPSL.CM5A.MR, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_MIROC5, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_MIROC.ESM, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_MIROC.ESM.CHEM, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_MRI.CGCM3, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$MACA_NorESM1.M, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df7$MACA_bcc.csm1.1, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_bcc.csm1.1.m, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_CanESM2, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_CCSM4, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_CNRM.CM5, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_CSIRO.Mk3.6.0, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_GFDL.ESM2M, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_GFDL.ESM2G, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_HadGEM2.CC365, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_HadGEM2.ES365, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_inmcm4, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_IPSL.CM5A.LR, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)

```

```

RMSE
RMSE=round(rmse(sim=df7$MACA_IPSL.CM5A.MR, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_MIROC5, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_MIROC.ESM, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_MIROC.ESM.CHEM, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_MRI.CGCM3, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$MACA_NorESM1.M, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df8$MACA_bcc.csm1.1, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_bcc.csm1.1.m, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_CanESM2, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_CCSM4, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_CNRM.CM5, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_CSIRO.Mk3.6.0, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_GFDL.ESM2M, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_GFDL.ESM2G, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_HadGEM2.CC365, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_HadGEM2.ES365, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_inmcm4, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_IPSL.CM5A.LR, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_IPSL.CM5A.MR, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)

```

```

RMSE
RMSE=round(rmse(sim=df8$MACA_MIROC5, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_MIROC.ESM, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_MIROC.ESM.CHEM, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_MRI.CGCM3, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$MACA_NorESM1.M, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df6$GDO_bcc.csm1.1, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_bcc.csm1.1.m, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_CanESM2, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_CCSM4, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_CNRM.CM5, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_CSIRO.Mk3.6.0, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_GFDL.ESM2M, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_GFDL.ESM2G, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_HadGEM2.CC365, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_HadGEM2.ES365, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_inmcm4, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_IPSL.CM5A.LR, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_IPSL.CM5A.MR, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_MIROC5, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_MIROC.ESM, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE

```

```

RMSE=round(rmse(sim=df6$GDO_MIROC.ESM.CHEM, obs=df6$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_MRI.CGCM3, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df6$GDO_NorESM1.M, obs=df6$NCEI_PRCP, na.rm=TRUE),4)
RMSE

RMSE=round(rmse(sim=df7$GDO_bcc.csm1.1, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_bcc.csm1.1.m, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_CanESM2, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_CCSM4, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_CNRM.CM5, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_CSIRO.Mk3.6.0, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_GFDL.ESM2M, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_GFDL.ESM2G, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_HadGEM2.CC365, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_HadGEM2.ES365, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_inmcm4, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_IPSL.CM5A.LR, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_IPSL.CM5A.MR, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_MIROC5, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_MIROC.ESM, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_MIROC.ESM.CHEM, obs=df7$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_MRI.CGCM3, obs=df7$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df7$GDO_NorESM1.M, obs=df7$NCEI_PRCP, na.rm=TRUE),4)

```

RMSE

```
RMSE=round(rmse(sim=df8$GDO_bcc.csm1.1, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_bcc.csm1.1.m, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_CanESM2, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_CCSM4, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_CNRM.CM5, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_CSIRO.Mk3.6.0, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_GFDL.ESM2M, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_GFDL.ESM2G, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_HadGEM2.CC365, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_HadGEM2.ES365, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_inmcm4, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_IPSL.CM5A.LR, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_IPSL.CM5A.MR, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_MIROC5, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_MIROC.ESM, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_MIROC.ESM.CHEM, obs=df8$NCEI_PRCP,
na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_MRI.CGCM3, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
RMSE=round(rmse(sim=df8$GDO_NorESM1.M, obs=df8$NCEI_PRCP, na.rm=TRUE),4)
RMSE
```

#calculate percent bias

```
pbias=pbias(sim=df6$MACA_bcc.csm1.1, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_bcc.csm1.1.m, obs=df6$NCEI_PRCP, na.rm=TRUE)
```

```

pbias
pbias=pbias(sim=df6$MACA_CanESM2, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_CCSM4, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_CNRM.CM5, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_CSIRO.Mk3.6.0, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_GFDL.ESM2M, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_GFDL.ESM2G, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_HadGEM2.CC365, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_HadGEM2.ES365, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_inmcm4, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_IPSL.CM5A.LR, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_IPSL.CM5A.MR, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_MIROC5, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_MIROC.ESM, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_MIROC.ESM.CHEM, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_MRI.CGCM3, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$MACA_NorESM1.M, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df7$MACA_bcc.csm1.1, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_bcc.csm1.1.m, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_CanESM2, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_CCSM4, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_CNRM.CM5, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_CSIRO.Mk3.6.0, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias

```

```

pbias=pbias(sim=df7$MACA_GFDL.ESM2M, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_GFDL.ESM2G, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_HadGEM2.CC365, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_HadGEM2.ES365, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_inmcm4, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_IPSL.CM5A.LR, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_IPSL.CM5A.MR, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_MIROC5, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_MIROC.ESM, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_MIROC.ESM.CHEM, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_MRI.CGCM3, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$MACA_NorESM1.M, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df8$MACA_bcc.csm1.1, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_bcc.csm1.1.m, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_CanESM2, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_CCSM4, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_CNRM.CM5, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_CSIRO.Mk3.6.0, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_GFDL.ESM2M, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_GFDL.ESM2G, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_HadGEM2.CC365, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_HadGEM2.ES365, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_inmcm4, obs=df8$NCEI_PRCP, na.rm=TRUE)

```

```

pbias
pbias=pbias(sim=df8$MACA_IPSL.CM5A.LR, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_IPSL.CM5A.MR, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_MIROC5, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_MIROC.ESM, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_MIROC.ESM.CHEM, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_MRI.CGCM3, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$MACA_NorESM1.M, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df6$GDO_bcc.csm1.1, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_bcc.csm1.1.m, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_CanESM2, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_CCSM4, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_CNRM.CM5, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_CSIRO.Mk3.6.0, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_GFDL.ESM2M, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_GFDL.ESM2G, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_HadGEM2.CC365, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_HadGEM2.ES365, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_inmcm4, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_IPSL.CM5A.LR, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_IPSL.CM5A.MR, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_MIROC5, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_MIROC.ESM, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias

```

```

pbias=pbias(sim=df6$GDO_MIROC.ESM.CHEM, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_MRI.CGCM3, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df6$GDO_NorESM1.M, obs=df6$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df7$GDO_bcc.csm1.1, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_bcc.csm1.1.m, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_CanESM2, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_CCSM4, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_CNRM.CM5, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_CSIRO.Mk3.6.0, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_GFDL.ESM2M, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_GFDL.ESM2G, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_HadGEM2.CC365, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_HadGEM2.ES365, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_inmcm4, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_IPSL.CM5A.LR, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_IPSL.CM5A.MR, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_MIROC5, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_MIROC.ESM, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_MIROC.ESM.CHEM, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_MRI.CGCM3, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df7$GDO_NorESM1.M, obs=df7$NCEI_PRCP, na.rm=TRUE)
pbias

pbias=pbias(sim=df8$GDO_bcc.csm1.1, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias

```

```

pbias=pbias(sim=df8$GDO_bcc.csm1.1.m, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_CanESM2, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_CCSM4, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_CNRM.CM5, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_CSIRO.Mk3.6.0, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_GFDL.ESM2M, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_GFDL.ESM2G, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_HadGEM2.CC365, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_HadGEM2.ES365, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_inmcm4, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_IPSL.CM5A.LR, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_IPSL.CM5A.MR, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_MIROC5, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_MIROC.ESM, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_MIROC.ESM.CHEM, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_MRI.CGCM3, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias
pbias=pbias(sim=df8$GDO_NorESM1.M, obs=df8$NCEI_PRCP, na.rm=TRUE)
pbias

```

Point Validation Visualization R Code

Figure Code- Boxplot and Line plot

```

#####Figure Code for validation results of selected downscaled GCM precipitation data#####
##Created by and Modified by Kelsey R. McDonough & Laura J. Krueger on October 30, 2018#
#####
#Check your working directory
getwd()
#If you need to set your working directory to a new folder, use setwd("pathname_here")

```

```
#####Create boxplots showing validation results by location and by model#####
#Load dataset with compiled validation results for all locations and models
data = read.csv('MonthlyData.csv', sep=",", header=TRUE)
head(data)

#Create a boxplot to show correlation coeff. (sum) results by location
boxplot(S_Rho~Location, data=data, las=2, ylab="Spearman's rho", ylim=c(0.3,0.5),
xlim=c(0.5,6.5), pars=list(par(mar=c(8,5,0.5,1))))
##>>> to show all data, change the values in the ylim command

#Create a boxplot to show correlation coeff. (sum) results by model
boxplot(S_Rho~Model, data=data, las=2, ylab="Spearman's rho", ylim=c(0.3,0.6),
xlim=c(0.5,7.5), pars=list(par(mar=c(10,5,0.5,1))))
##>>>> need to shorten some of the model names so they all fit on the plot

#Create a boxplot to show correlation coeff. (max) results by location
boxplot(M_Rho~Location, data=data, las=2, ylab="Spearman's rho", ylim=c(0.1,0.5),
xlim=c(0.5,6.5), pars=list(par(mar=c(8,5,0.5,1))))
##>>> to show all data, change the values in the ylim command

#Create a boxplot to show correlation coeff. (max) results by model
boxplot(M_Rho~Model, data=data, las=2, ylab="Spearman's rho", ylim=c(0.1,0.35),
xlim=c(0.5,7.5), pars=list(par(mar=c(10,5,0.5,1))))
##>>>> need to shorten some of the model names so they all fit on the plot

#####Create a line plot of one year at one location, monthly precipitation#####
library(ggplot2)
#Load dataset with location sums of modeled and observed data
data1=read.csv('MSum1_DowntownAirport.csv', sep=",", header=TRUE)
head(data1)
df1 <- data.frame(data1) #create a dataframe
head(df1)

#Create year subsets
y1<-df1[1:12,] #Creates a subset only containing year 1950#
y2<-df1[613:624,] #Creates a subset only containing year 2001#

##Create your line plot for 1950
plot(y1$Month, y1$NCEI_PRCP, type="l", col="black", lty=1, lwd=2, las=2, ylim=c(0,350),
xlab="Month", ylab="Monthly Precipitation (mm)", main="Monthly Precipitation at Downtown
Airport location in 1950")
lines(y1$Month, y1$MACA_MIROC.ESM, lty=3, col="blue", lwd=1.5)
lines(y1$Month, y1$MACA_MIROC.ESM.CHEM, lty=3, col="red", lwd=1.5)
lines(y1$Month, y1$MACA_MRI.CGCM3, lty=3, col="purple", lwd=1.5)
lines(y1$Month, y1$MACA_NorESM1.M, lty=3, col="green", lwd=1.5)
lines(y1$Month, y1$GDO_CCSM4, lty=3, col="orange", lwd=1.5)
```

```

lines(y1$Month, y1$GDO_MRI.CGCM3, lty=3, col="gray", lwd=1.5)
lines(y1$Month, y1$GDO_NorESM1.M, lty=3, col="black", lwd=1.5)
legend(4.5, 355, legend=c("NCEI_PRCP", "M_MIROC-ESM", "M_MIROC-ESM-CHEM",
"M_MRI-CGCM3", "M_NorESM1-M", "G_CCSM4", "G_MRI-CGCM3", "G_NorESM1-M"),
col=c("black", "blue", "red", "purple", "green", "orange", "gray", "black"), lty=c(1, 3, 3, 3, 3, 3,
3, 3), cex=0.6, ncol=2)

```

##Create your line plot for 2001

```

plot(y2$Month, y2$NCEI_PRCP, type="l", col="black", lty=1, lwd=2, las=2, ylim=c(0,350),
xlab="Month", ylab="Monthly Precipitation (mm)", main="Monthly Precipitation at Downtown
Airport location in 2001")
lines(y2$Month, y2$MACA_MIROC.ESM, lty=3, col="blue", lwd=1.5)
lines(y2$Month, y2$MACA_MIROC.ESM.CHEM, lty=3, col="red", lwd=1.5)
lines(y2$Month, y2$MACA_MRI.CGCM3, lty=3, col="purple", lwd=1.5)
lines(y2$Month, y2$MACA_NorESM1.M, lty=3, col="green", lwd=1.5)
lines(y2$Month, y2$GDO_CCSM4, lty=3, col="orange", lwd=1.5)
lines(y2$Month, y2$GDO_MRI.CGCM3, lty=3, col="gray", lwd=1.5)
lines(y2$Month, y2$GDO_NorESM1.M, lty=3, col="black", lwd=1.5)
legend(1, 355, legend=c("NCEI_PRCP", "M_MIROC-ESM", "M_MIROC-ESM-CHEM",
"M_MRI-CGCM3", "M_NorESM1-M", "G_CCSM4", "G_MRI-CGCM3", "G_NorESM1-M"),
col=c("black", "blue", "red", "purple", "green", "orange", "gray", "black"), lty=c(1, 3, 3, 3, 3, 3,
3, 3), cex=0.6, ncol=2)

```

#####

#Create a line plot for another location

```

library(ggplot2)
data1=read.csv('MSum1_KansasCityU.csv', sep=";", header=TRUE)
head(data1)
df1 <- data.frame(data1) #create a dataframe
head(df1)

```

y1<-df1[1:12,] #Creates a subset only containing year 1950#

##Create your line plot for 1950

```

plot(y1$Month, y1$NCEI_PRCP, type="l", col="black", lty=1, lwd=2, las=2, ylim=c(0,350),
xlab="Month", ylab="Monthly Precipitation (mm)", main="Monthly Precipitation at Kansas
City U location in 1950")
lines(y1$Month, y1$MACA_MIROC.ESM, lty=3, col="blue", lwd=1.5)
lines(y1$Month, y1$MACA_MIROC.ESM.CHEM, lty=3, col="red", lwd=1.5)
lines(y1$Month, y1$MACA_MRI.CGCM3, lty=3, col="purple", lwd=1.5)
lines(y1$Month, y1$MACA_NorESM1.M, lty=3, col="green", lwd=1.5)
lines(y1$Month, y1$GDO_CCSM4, lty=3, col="orange", lwd=1.5)
lines(y1$Month, y1$GDO_MRI.CGCM3, lty=3, col="gray", lwd=1.5)
lines(y1$Month, y1$GDO_NorESM1.M, lty=3, col="black", lwd=1.5)
legend(4.5, 355, legend=c("NCEI_PRCP", "M_MIROC-ESM", "M_MIROC-ESM-CHEM",
"M_MRI-CGCM3", "M_NorESM1-M", "G_CCSM4", "G_MRI-CGCM3", "G_NorESM1-M"),

```

```
col=c("black", "blue", "red", "purple", "green", "orange", "gray", "black"), lty=c(1, 3, 3, 3, 3, 3, 3, 3), cex=0.6, ncol=2)
```

```
#####
```

Figure Code- Taylor Diagram

```
#Taylor Diagram Code to display validation results of selected downscaled GCM precipitation data#
```

```
#####Adapted by Kelsey R. McDonough & Laura J. Krueger on October 30, 2018#####
```

```
#####
```

```
##Note: recommend running this in R, rather than in RStudio
```

```
##Set working directory
```

```
setwd('C:/Users/lkrueger4/Desktop/Validation/Figures')
```

```
#####
```

```
# Display a Taylor diagram
```

```
# Taylor K.E. (2001)
```

```
# Summarizing multiple aspects of model performance in a single diagram
```

```
# Journal of Geophysical Research, 106: 7183-7192.
```

```
# version 1.0
```

```
# progr. Olivier.Etterradosi, 12/2007
```

```
# 2007-01-12 - modifications and Anglicizing - Jim Lemon
```

```
# version 2.0
```

```
# progr. initiale OLE, 8/01/2007
```

```
# rev. OLE 3/09/2008 : remove samples with NA's from mean, sd and cor calculations
```

```
# 2008-09-04 - integration and more anglicizing - Jim Lemon
```

```
# 2008-12-09 - added correlation radii, sd arcs to the pos.cor=FALSE routine
```

```
# and stopped the pos.cor=FALSE routine from calculating arcs for zero radius
```

```
# Jim Lemon
```

```
# 2010-4-30 - added the gamma.col argument for pos.cor=TRUE plots - Jim Lemon
```

```
# 2010-6-24 - added mar argument to pos.cor=TRUE plots - Jim Lemon
```

```
# 2012-1-31 - added the cex.axis argument - Jim Lemon
```

```
taylor.diagram<-function(ref,model,add=FALSE,col="red",pch=19,pos.cor = TRUE,
  xlab = "", ylab = "", main = "Taylor Diagram", show.gamma = TRUE,
  ngamma = 3, gamma.col = 8, sd.arcs = 1, ref.sd = FALSE, sd.method =
```

```
"sample",
```

```
  grad.corr.lines = c(0.2, 0.4, 0.6, 0.8, 0.9), pcex = 1, cex.axis = 1,
```

```
  normalize = FALSE, mar = c(5, 4, 6, 6), ...) {
```

```
  grad.corr.full <- c(0, 0.2, 0.4, 0.6, 0.8, 0.9, 0.95, 0.99, 1)
```

```
  # convert any list elements or data frames to vectors
```

```
  R <- cor(ref, model, method = "spearman", use = "pairwise.complete.obs")
```

```
  if (is.list(ref))
```

```
    ref <- unlist(ref)
```

```
  if (is.list(model))
```

```
    ref <- unlist(model)
```

```
  SD <- function(x, subn) {
```

```

meanx <- mean(x, na.rm = TRUE)
devx <- x - meanx
ssd <- sqrt(sum(devx * devx, na.rm = TRUE)/(length(x[!is.na(x)]) -
                                     subn))

return(ssd)
}
subn <- sd.method != "sample"
sd.r <- SD(ref, subn)
sd.f <- SD(model, subn)
if (normalize) {
  sd.f <- sd.f/sd.r
  sd.r <- 1
}
maxsd <- 1.5 * max(sd.f, sd.r)
oldpar <- par("mar", "xpd", "xaxs", "yaxs")
if (!add) {
  # display the diagram
  if (pos.cor) {
    if (nchar(ylab) == 0)
      ylab = "Standard deviation"
    par(mar = mar)
    plot(0, xlim = c(0, maxsd), ylim = c(0, maxsd), xaxs = "i",
         yaxs = "i", axes = FALSE, main = main, xlab = xlab,
         ylab = ylab, type = "n", cex = cex.axis, ...)
    if (grad.corr.lines[1]) {
      for (gcl in grad.corr.lines) lines(c(0, maxsd *
                                           gcl), c(0, maxsd * sqrt(1 - gcl^2)), lty = 3)
    }
    # add the axes
    segments(c(0, 0), c(0, 0), c(0, maxsd), c(maxsd,
                                                0))
    axis.ticks <- pretty(c(0, maxsd))
    axis.ticks <- axis.ticks[axis.ticks <= maxsd]
    axis(1, at = axis.ticks, cex.axis = cex.axis)
    axis(2, at = axis.ticks, cex.axis = cex.axis)
    if (sd.arcs[1]) {
      if (length(sd.arcs) == 1)
        sd.arcs <- axis.ticks
      for (sdarc in sd.arcs) {
        xcurve <- cos(seq(0, pi/2, by = 0.03)) * sdarc
        ycurve <- sin(seq(0, pi/2, by = 0.03)) * sdarc
        lines(xcurve, ycurve, col = "blue", lty = 3)
      }
    }
  }
  if (show.gamma[1]) {
    # if the user has passed a set of gamma values, use that

```

```

if (length(show.gamma) > 1) gamma <- show.gamma
# otherwise make up a set
else gamma <- pretty(c(0, maxsd), n = ngamma)[-1]
if (gamma[length(gamma)] > maxsd)
  gamma <- gamma[-length(gamma)]
labelpos <- seq(45, 70, length.out = length(gamma))
# do the gamma curves
for (gindex in 1:length(gamma)) {
  xcurve <- cos(seq(0, pi, by = 0.03)) * gamma[gindex] + sd.r
  # find where to clip the curves
  endcurve <- which(xcurve < 0)
  endcurve <- ifelse(length(endcurve), min(endcurve) -
    1, 105)
  ycurve <- sin(seq(0, pi, by = 0.03)) * gamma[gindex]
  maxcurve <- xcurve * xcurve + ycurve * ycurve
  startcurve <- which(maxcurve > maxsd * maxsd)
  startcurve <- ifelse(length(startcurve), max(startcurve) +
    1, 0)
  lines(xcurve[startcurve:endcurve], ycurve[startcurve:endcurve],
    col = gamma.col)
  if (xcurve[labelpos[gindex]] > 0)
    boxed.labels(xcurve[labelpos[gindex]], ycurve[labelpos[gindex]],
      gamma[gindex], border = FALSE)
}
}
# the outer curve for correlation
xcurve <- cos(seq(0, pi/2, by = 0.01)) * maxsd
ycurve <- sin(seq(0, pi/2, by = 0.01)) * maxsd
lines(xcurve, ycurve)
bigtickangles <- acos(seq(0.1, 0.9, by = 0.1))
medtickangles <- acos(seq(0.05, 0.95, by = 0.1))
smltickangles <- acos(seq(0.91, 0.99, by = 0.01))
segments(cos(bigtickangles) * maxsd, sin(bigtickangles) *
  maxsd, cos(bigtickangles) * 0.97 * maxsd, sin(bigtickangles) *
  0.97 * maxsd)
par(xpd = TRUE)
# the inner curve for reference SD
if (ref.sd) {
  xcurve <- cos(seq(0, pi/2, by = 0.01)) * sd.r
  ycurve <- sin(seq(0, pi/2, by = 0.01)) * sd.r
  lines(xcurve, ycurve)
}
points(sd.r, 0, cex = pcex)
text(cos(c(bigtickangles, acos(c(0.95, 0.99)))) *
  1.05 * maxsd, sin(c(bigtickangles, acos(c(0.95,
    0.99)))) * 1.05 * maxsd, c(seq(0.1, 0.9, by = 0.1),

```

```

                                0.95, 0.99))
text(maxsd * 0.8, maxsd * 0.8, "Correlation", srt = 315)
segments(cos(medtickangles) * maxsd, sin(medtickangles) *
maxsd, cos(medtickangles) * 0.98 * maxsd, sin(medtickangles) *
0.98 * maxsd)
segments(cos(smltickangles) * maxsd, sin(smltickangles) *
maxsd, cos(smltickangles) * 0.99 * maxsd, sin(smltickangles) *
0.99 * maxsd)
}
else {
  x <- ref
  y <- model
  R <- cor(x, y, use = "pairwise.complete.obs")
  E <- mean(x, na.rm = TRUE) - mean(y, na.rm = TRUE)
  xprime <- x - mean(x, na.rm = TRUE)
  yprime <- y - mean(y, na.rm = TRUE)
  sumofsquares <- (xprime - yprime)^2
  Eprime <- sqrt(sum(sumofsquares)/length(complete.cases(x)))
  E2 <- E^2 + Eprime^2
  if (add == FALSE) {
    # pourtour du diagramme (display the diagram)
    maxray <- 2 * max(sd.f, sd.r) #change highlighted value to make plot bigger
    plot(c(-maxray, maxray), c(0, maxray), type = "n",
asp = 1, bty = "n", xaxt = "n", yaxt = "n",
xlab = xlab, ylab = ylab, main = main, cex = cex.axis)
    discrete <- seq(180, 0, by = -1)
    listepoints <- NULL
    for (i in discrete) {
      listepoints <- cbind(listepoints, maxray *
cos(i * pi/180), maxray * sin(i * pi/180))
    }
    listepoints <- matrix(listepoints, 2, length(listepoints)/2)
    listepoints <- t(listepoints)
    lines(listepoints[, 1], listepoints[, 2])
    # axes x,y
    lines(c(-maxray, maxray), c(0, 0))
    lines(c(0, 0), c(0, maxray))
    # lignes radiales jusque R = +/- 0.8
    for (i in grad.corr.lines) {
      lines(c(0, maxray * i), c(0, maxray * sqrt(1 -
i^2)), lty = 3)
      lines(c(0, -maxray * i), c(0, maxray * sqrt(1 -
i^2)), lty = 3)
    }
    # texte radial
    for (i in grad.corr.full) {

```

```

text(1.05 * maxray * i, 1.05 * maxray * sqrt(1 -
                                     i^2), i, cex = 0.6)
text(-1.05 * maxray * i, 1.05 * maxray * sqrt(1 -
                                     i^2), -i, cex = 0.6)
}
# sd concentriques autour de la reference
seq.sd <- seq.int(0, 2 * maxray, by = (maxray/10))[-1]
for (i in seq.sd) {
  xcircle <- sd.r + (cos(discrete * pi/180) *
                    i)
  ycircle <- sin(discrete * pi/180) * i
  for (j in 1:length(xcircle)) {
    if ((xcircle[j]^2 + ycircle[j]^2) < (maxray^2)) {
      points(xcircle[j], ycircle[j], col = "darkgreen",
            pch = ".")
      if (j == 10)
        text(xcircle[j], ycircle[j], signif(i,
            2), cex = 0.52, col = "darkgreen")
    }
  }
}
# sd concentriques autour de l'origine
seq.sd <- seq.int(0, maxray, length.out = 5)
for (i in seq.sd) {
  xcircle <- (cos(discrete * pi/180) * i)
  ycircle <- sin(discrete * pi/180) * i
  if (i)
    lines(xcircle, ycircle, lty = 3, col = "blue")
  text(min(xcircle), -0.03 * maxray, signif(i,
            2), cex = 0.55, col = "blue")
  text(max(xcircle), -0.03 * maxray, signif(i,
            2), cex = 0.55, col = "blue")
}
text(0, -0.08 * maxray, "Standard Deviation",
     cex = 0.7, col = "blue")
text(0, -0.12 * maxray, "Centered RMS Difference",
     cex = 0.7, col = "darkgreen")
points(sd.r, 0, pch = 22, bg = "darkgreen", cex = 1.1)
text(0, 1.1 * maxray, "Spearman's Correlation Coefficient",
     cex = 0.75)
}
S <- (2 * (1 + R))/(sd.f + (1/sd.f))^2
# Taylor<-S
}
}
# display the points

```

```

points(sd.f * R, sd.f * sin(acos(R)), pch = pch, col = col,
      cex = pcex)
invisible(oldpar)
}
#####
##Now add datapoints to your Taylor Diagram
library(plotrix)
#####
##This set of data will plot by location
##You can change the colors of the points plotted
##You can change the shape of the points by adjusting the pch code

#Blue dots are for the Downtown Airport location
data_sum1 = read.csv('MSum1_DowntownAirport.csv', sep="," , header=TRUE)
ref<-data_sum1$NCEI_PRCP
model<-data_sum1$MACA_MIROC.ESM
taylor.diagram(ref,model,pos.cor=FALSE, add=FALSE, col='blue', pch=17)

ref1<-data_sum1$NCEI_PRCP
model1<-data_sum1$MACA_MIROC.ESM.CHEM
taylor.diagram(ref1,model1,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref2<-data_sum1$NCEI_PRCP
model2<-data_sum1$MACA_MRI.CGCM3
taylor.diagram(ref2,model2,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref3<-data_sum1$NCEI_PRCP
model3<-data_sum1$MACA_NorESM1.M
taylor.diagram(ref3,model3,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref4<-data_sum1$NCEI_PRCP
model4<-data_sum1$GDO_CCSM4
taylor.diagram(ref4,model4,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref5<-data_sum1$NCEI_PRCP
model5<-data_sum1$GDO_MRI.CGCM3
taylor.diagram(ref5,model5,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref6<-data_sum1$NCEI_PRCP
model6<-data_sum1$GDO_NorESM1.M
taylor.diagram(ref6,model6,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

#Red dots are for the KansasCityU location
data_sum2 = read.csv('MSum1_KansasCityU.csv', sep="," , header=TRUE)
ref7<-data_sum2$NCEI_PRCP
model7<-data_sum2$MACA_MIROC.ESM

```

```

taylor.diagram(ref7,model7,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref8<-data_sum2$NCEI_PRCP
model8<-data_sum2$MACA_MIROC.ESM.CHEM
taylor.diagram(ref8,model8,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref9<-data_sum2$NCEI_PRCP
model9<-data_sum2$MACA_MRI.CGCM3
taylor.diagram(ref9,model9,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref10<-data_sum2$NCEI_PRCP
model10<-data_sum2$MACA_NorESM1.M
taylor.diagram(ref10,model10,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref11<-data_sum2$NCEI_PRCP
model11<-data_sum2$GDO_CCSM4
taylor.diagram(ref11,model11,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref12<-data_sum2$NCEI_PRCP
model12<-data_sum2$GDO_MRI.CGCM3
taylor.diagram(ref12,model12,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref13<-data_sum2$NCEI_PRCP
model13<-data_sum2$GDO_NorESM1.M
taylor.diagram(ref13,model13,pos.cor=FALSE, add=TRUE, col='red', pch=17)

#Green dots are for the Merriam location
data_sum3 = read.csv('MSum1_Merriam.csv', sep=",", header=TRUE)
ref14<-data_sum3$NCEI_PRCP
model14<-data_sum3$MACA_MIROC.ESM
taylor.diagram(ref14,model14,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref15<-data_sum3$NCEI_PRCP
model15<-data_sum3$MACA_MIROC.ESM.CHEM
taylor.diagram(ref15,model15,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref16<-data_sum3$NCEI_PRCP
model16<-data_sum3$MACA_MRI.CGCM3
taylor.diagram(ref16,model16,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref17<-data_sum3$NCEI_PRCP
model17<-data_sum3$MACA_NorESM1.M
taylor.diagram(ref17,model17,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref18<-data_sum3$NCEI_PRCP
model18<-data_sum3$GDO_CCSM4

```

```

taylor.diagram(ref18,model18,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref19<-data_sum3$NCEI_PRCP
model19<-data_sum3$GDO_MRI.CGCM3
taylor.diagram(ref19,model19,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref20<-data_sum3$NCEI_PRCP
model20<-data_sum3$GDO_NorESM1.M
taylor.diagram(ref20,model20,pos.cor=FALSE, add=TRUE, col='black', pch=17)

#Orange dots are for the MerriamOP location
data_sum4 = read.csv('MSum1_MerriamOP.csv', sep=",", header=TRUE)
ref21<-data_sum4$NCEI_PRCP
model21<-data_sum4$MACA_MIROC.ESM
taylor.diagram(ref21,model21,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref22<-data_sum4$NCEI_PRCP
model22<-data_sum4$MACA_MIROC.ESM.CHEM
taylor.diagram(ref22,model22,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref23<-data_sum4$NCEI_PRCP
model23<-data_sum4$MACA_MRI.CGCM3
taylor.diagram(ref23,model23,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref24<-data_sum4$NCEI_PRCP
model24<-data_sum4$MACA_NorESM1.M
taylor.diagram(ref24,model24,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref25<-data_sum4$NCEI_PRCP
model25<-data_sum4$GDO_CCSM4
taylor.diagram(ref25,model25,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref26<-data_sum4$NCEI_PRCP
model26<-data_sum4$GDO_MRI.CGCM3
taylor.diagram(ref26,model26,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref27<-data_sum4$NCEI_PRCP
model27<-data_sum4$GDO_NorESM1.M
taylor.diagram(ref27,model27,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

#Purple dots are for the Olathe3 location
data_sum5 = read.csv('MSum1_Olathe3.csv', sep=",", header=TRUE)
ref28<-data_sum5$NCEI_PRCP
model28<-data_sum5$MACA_MIROC.ESM
taylor.diagram(ref28,model28,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

```

```

ref29<-data_sum5$NCEI_PRCP
model29<-data_sum5$MACA_MIROC.ESM.CHEM
taylor.diagram(ref29,model29,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref30<-data_sum5$NCEI_PRCP
model30<-data_sum5$MACA_MRI.CGCM3
taylor.diagram(ref30,model30,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref31<-data_sum5$NCEI_PRCP
model31<-data_sum5$MACA_NorESM1.M
taylor.diagram(ref31,model31,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref32<-data_sum5$NCEI_PRCP
model32<-data_sum5$GDO_CCSM4
taylor.diagram(ref32,model32,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref33<-data_sum5$NCEI_PRCP
model33<-data_sum5$GDO_MRI.CGCM3
taylor.diagram(ref33,model33,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref34<-data_sum5$NCEI_PRCP
model34<-data_sum5$GDO_NorESM1.M
taylor.diagram(ref34,model34,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

#Gray dots are for the Stillwell location
data_sum6 = read.csv('MSum1_Stillwell.csv', sep=",", header=TRUE)
ref35<-data_sum6$NCEI_PRCP
model35<-data_sum6$MACA_MIROC.ESM
taylor.diagram(ref35,model35,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

ref36<-data_sum6$NCEI_PRCP
model36<-data_sum6$MACA_MIROC.ESM.CHEM
taylor.diagram(ref36,model36,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

ref37<-data_sum6$NCEI_PRCP
model37<-data_sum6$MACA_MRI.CGCM3
taylor.diagram(ref37,model37,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

ref38<-data_sum6$NCEI_PRCP
model38<-data_sum6$MACA_NorESM1.M
taylor.diagram(ref38,model38,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

ref39<-data_sum6$NCEI_PRCP
model39<-data_sum6$GDO_CCSM4
taylor.diagram(ref39,model39,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

```

```

ref40<-data_sum6$NCEI_PRCP
model40<-data_sum6$GDO_MRI.CGCM3
taylor.diagram(ref40,model40,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

ref41<-data_sum6$NCEI_PRCP
model41<-data_sum6$GDO_NorESM1.M
taylor.diagram(ref41,model41,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

legend("bottom", title="Location",cex=0.8,pt.cex=1,legend=c("Downtown Airport","Kansas
City U","Merriam", "Merriam OP", "Olathe3", "Stillwell"),pch=c(17, 17, 17, 17, 17,
17),col=c("blue","red","black","orange","purple", "gray"), ncol=3)
#####
##This set of data will plot by CMIP5 model
##You can change the colors of the points plotted
##You can change the shape of the points by adjusting the pch code

#Blue dots are for the MACA_MIROC.ESM model
#Red dots are for the MACA_MIROC.ESM.CHEM model
#Purple dots are for the MACA_MRI.CGCM3 model
#Orange dots are for the MACA_NorESM1.M model
#Black dots are for the GDO_CCSM4 model
#Green dots are for the GDO_MRI.CGCM3 model
#Gray dots are for the GDO_NorESM1.M model

data_sum1 = read.csv('MSum1_DowntownAirport.csv', sep=",", header=TRUE)
ref<-data_sum1$NCEI_PRCP
model<-data_sum1$MACA_MIROC.ESM
taylor.diagram(ref,model,pos.cor=FALSE, add=FALSE, col='blue', pch=17)

ref1<-data_sum1$NCEI_PRCP
model1<-data_sum1$MACA_MIROC.ESM.CHEM
taylor.diagram(ref1,model1,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref2<-data_sum1$NCEI_PRCP
model2<-data_sum1$MACA_MRI.CGCM3
taylor.diagram(ref2,model2,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref3<-data_sum1$NCEI_PRCP
model3<-data_sum1$MACA_NorESM1.M
taylor.diagram(ref3,model3,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref4<-data_sum1$NCEI_PRCP
model4<-data_sum1$GDO_CCSM4
taylor.diagram(ref4,model4,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref5<-data_sum1$NCEI_PRCP

```

```

model5<-data_sum1$GDO_MRI.CGCM3
taylor.diagram(ref5,model5,pos.cor=FALSE, add=TRUE, col='green', pch=17)

ref6<-data_sum1$NCEI_PRCP
model6<-data_sum1$GDO_NorESM1.M
taylor.diagram(ref6,model6,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

data_sum2 = read.csv('MSum1_KansasCityU.csv', sep=",", header=TRUE)
ref7<-data_sum2$NCEI_PRCP
model7<-data_sum2$MACA_MIROC.ESM
taylor.diagram(ref7,model7,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref8<-data_sum2$NCEI_PRCP
model8<-data_sum2$MACA_MIROC.ESM.CHEM
taylor.diagram(ref8,model8,pos.cor=FALSE, add=TRUE, col='red', pch=17)

ref9<-data_sum2$NCEI_PRCP
model9<-data_sum2$MACA_MRI.CGCM3
taylor.diagram(ref9,model9,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref10<-data_sum2$NCEI_PRCP
model10<-data_sum2$MACA_NorESM1.M
taylor.diagram(ref10,model10,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref11<-data_sum2$NCEI_PRCP
model11<-data_sum2$GDO_CCSM4
taylor.diagram(ref11,model11,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref12<-data_sum2$NCEI_PRCP
model12<-data_sum2$GDO_MRI.CGCM3
taylor.diagram(ref12,model12,pos.cor=FALSE, add=TRUE, col='green', pch=17)

ref13<-data_sum2$NCEI_PRCP
model13<-data_sum2$GDO_NorESM1.M
taylor.diagram(ref13,model13,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

data_sum3 = read.csv('MSum1_Merriam.csv', sep=",", header=TRUE)
ref14<-data_sum3$NCEI_PRCP
model14<-data_sum3$MACA_MIROC.ESM
taylor.diagram(ref14,model14,pos.cor=FALSE, add=TRUE, col='blue', pch=17)

ref15<-data_sum3$NCEI_PRCP
model15<-data_sum3$MACA_MIROC.ESM.CHEM
taylor.diagram(ref15,model15,pos.cor=FALSE, add=TRUE, col='red', pch=17)

```

```
ref16<-data_sum3$NCEI_PRCP
model16<-data_sum3$MACA_MRI.CGCM3
taylor.diagram(ref16,model16,pos.cor=FALSE, add=TRUE, col='purple', pch=17)
```

```
ref17<-data_sum3$NCEI_PRCP
model17<-data_sum3$MACA_NorESM1.M
taylor.diagram(ref17,model17,pos.cor=FALSE, add=TRUE, col='orange', pch=17)
```

```
ref18<-data_sum3$NCEI_PRCP
model18<-data_sum3$GDO_CCSM4
taylor.diagram(ref18,model18,pos.cor=FALSE, add=TRUE, col='black', pch=17)
```

```
ref19<-data_sum3$NCEI_PRCP
model19<-data_sum3$GDO_MRI.CGCM3
taylor.diagram(ref19,model19,pos.cor=FALSE, add=TRUE, col='green', pch=17)
```

```
ref20<-data_sum3$NCEI_PRCP
model20<-data_sum3$GDO_NorESM1.M
taylor.diagram(ref20,model20,pos.cor=FALSE, add=TRUE, col='gray', pch=17)
```

```
data_sum4 = read.csv('MSum1_MerriamOP.csv', sep=",", header=TRUE)
ref21<-data_sum4$NCEI_PRCP
model21<-data_sum4$MACA_MIROC.ESM
taylor.diagram(ref21,model21,pos.cor=FALSE, add=TRUE, col='blue', pch=17)
```

```
ref22<-data_sum4$NCEI_PRCP
model22<-data_sum4$MACA_MIROC.ESM.CHEM
taylor.diagram(ref22,model22,pos.cor=FALSE, add=TRUE, col='red', pch=17)
```

```
ref23<-data_sum4$NCEI_PRCP
model23<-data_sum4$MACA_MRI.CGCM3
taylor.diagram(ref23,model23,pos.cor=FALSE, add=TRUE, col='purple', pch=17)
```

```
ref24<-data_sum4$NCEI_PRCP
model24<-data_sum4$MACA_NorESM1.M
taylor.diagram(ref24,model24,pos.cor=FALSE, add=TRUE, col='orange', pch=17)
```

```
ref25<-data_sum4$NCEI_PRCP
model25<-data_sum4$GDO_CCSM4
taylor.diagram(ref25,model25,pos.cor=FALSE, add=TRUE, col='black', pch=17)
```

```
ref26<-data_sum4$NCEI_PRCP
model26<-data_sum4$GDO_MRI.CGCM3
taylor.diagram(ref26,model26,pos.cor=FALSE, add=TRUE, col='green', pch=17)
```

```
ref27<-data_sum4$NCEI_PRCP
model27<-data_sum4$GDO_NorESM1.M
taylor.diagram(ref27,model27,pos.cor=FALSE, add=TRUE, col='gray', pch=17)
```

```
data_sum5 = read.csv('MSum1_Olathe3.csv', sep="," , header=TRUE)
ref28<-data_sum5$NCEI_PRCP
model28<-data_sum5$MACA_MIROC.ESM
taylor.diagram(ref28,model28,pos.cor=FALSE, add=TRUE, col='blue', pch=17)
```

```
ref29<-data_sum5$NCEI_PRCP
model29<-data_sum5$MACA_MIROC.ESM.CHEM
taylor.diagram(ref29,model29,pos.cor=FALSE, add=TRUE, col='red', pch=17)
```

```
ref30<-data_sum5$NCEI_PRCP
model30<-data_sum5$MACA_MRI.CGCM3
taylor.diagram(ref30,model30,pos.cor=FALSE, add=TRUE, col='purple', pch=17)
```

```
ref31<-data_sum5$NCEI_PRCP
model31<-data_sum5$MACA_NorESM1.M
taylor.diagram(ref31,model31,pos.cor=FALSE, add=TRUE, col='orange', pch=17)
```

```
ref32<-data_sum5$NCEI_PRCP
model32<-data_sum5$GDO_CCSM4
taylor.diagram(ref32,model32,pos.cor=FALSE, add=TRUE, col='black', pch=17)
```

```
ref33<-data_sum5$NCEI_PRCP
model33<-data_sum5$GDO_MRI.CGCM3
taylor.diagram(ref33,model33,pos.cor=FALSE, add=TRUE, col='green', pch=17)
```

```
ref34<-data_sum5$NCEI_PRCP
model34<-data_sum5$GDO_NorESM1.M
taylor.diagram(ref34,model34,pos.cor=FALSE, add=TRUE, col='gray', pch=17)
```

```
data_sum6 = read.csv('MSum1_Stillwell.csv', sep="," , header=TRUE)
ref35<-data_sum6$NCEI_PRCP
model35<-data_sum6$MACA_MIROC.ESM
taylor.diagram(ref35,model35,pos.cor=FALSE, add=TRUE, col='blue', pch=17)
```

```
ref36<-data_sum6$NCEI_PRCP
model36<-data_sum6$MACA_MIROC.ESM.CHEM
taylor.diagram(ref36,model36,pos.cor=FALSE, add=TRUE, col='red', pch=17)
```

```
ref37<-data_sum6$NCEI_PRCP
```

```

model37<-data_sum6$MACA_MRI.CGCM3
taylor.diagram(ref37,model37,pos.cor=FALSE, add=TRUE, col='purple', pch=17)

ref38<-data_sum6$NCEI_PRCP
model38<-data_sum6$MACA_NorESM1.M
taylor.diagram(ref38,model38,pos.cor=FALSE, add=TRUE, col='orange', pch=17)

ref39<-data_sum6$NCEI_PRCP
model39<-data_sum6$GDO_CCSM4
taylor.diagram(ref39,model39,pos.cor=FALSE, add=TRUE, col='black', pch=17)

ref40<-data_sum6$NCEI_PRCP
model40<-data_sum6$GDO_MRI.CGCM3
taylor.diagram(ref40,model40,pos.cor=FALSE, add=TRUE, col='green', pch=17)

ref41<-data_sum6$NCEI_PRCP
model41<-data_sum6$GDO_NorESM1.M
taylor.diagram(ref41,model41,pos.cor=FALSE, add=TRUE, col='gray', pch=17)

legend("bottom",
title="Model",cex=0.6,pt.cex=0.8,legend=c("MACA_MIROC.ESM","MACA_MIROC.ESM.C
HEM","MACA_MRI.CGCM3", "MACA_NorESM1.M", "GDO_CCSM4",
"GDO_MRI.CGCM3", "GDO_NorESM1.M"),pch=c(17, 17, 17, 17, 17,
17),col=c("blue","red","purple","orange","black", "green", "gray"), ncol=3)
#####

```

Appendix C - Point Comparison Statistical Validation Monthly Sum

Results

Table C.6.3. Monthly sum precipitation validation comparison statistics with highlighted Tau with positive trend with $Rho \geq 0.4$, all $Rho \geq 0.4$ and p values < 0.05 for all 36 models at each NOAA station a-f.

Station	Model Name	Tau	p value	rho	p value	R ²	RMSE	pbias
Downtown Airport	NCEI_PRCP	0.04	0.18					
	MACA_bcc-csm1-1	0.02	0.51	0.29	1.17E-12	0.03	79.59	1.30
	MACA_bcc-csm1-1-m	0.01	0.64	0.33	< 2.2e-16	0.06	74.24	2.00
	MACA_CanESM2	0.03	0.29	0.30	3.77E-13	0.06	78.69	2.50
	MACA_CCSM4	0.01	0.60	0.37	< 2.2e-16	0.08	72.25	3.60
	MACA_CNRM-CM5	-0.03	0.20	0.33	6.35E-16	0.05	77.40	4.20
	MACA_CSIRO-Mk3-6-0	0.02	0.51	0.30	2.36E-13	0.05	75.01	3.30
	MACA_GFDL-ESM2M	0.00	0.85	0.34	< 2.2e-16	0.05	75.42	3.80
	MACA_GFDL-ESM2G	0.00	0.90	0.29	7.48E-13	0.05	76.28	2.40
	MACA_HadGEM2-CC365	0.02	0.56	0.27	3.86E-11	0.03	83.06	3.80
	MACA_HadGEM2-ES365	-0.01	0.68	0.31	1.89E-14	0.09	80.65	2.90
	MACA_inmcm4	0.00	0.86	0.29	5.33E-13	0.06	77.91	4.90
	MACA_IPSL-CM5A-LR	-0.01	0.69	0.35	< 2.2e-16	0.06	74.55	1.30
	MACA_IPSL-CM5A-MR	0.00	0.87	0.28	1.25E-11	0.03	80.53	2.40
	MACA_MIROC5	0.00	0.94	0.36	< 2.2e-16	0.08	71.33	5.00
	MACA_MIROC-ESM	0.00	0.96	0.39	< 2.2e-16	0.09	72.32	3.40
	MACA_MIROC-ESM-CHEM	0.02	0.55	0.40	< 2.2e-16	0.10	69.81	3.40
	MACA_MRI-CGCM3	-0.01	0.61	0.41	< 2.2e-16	0.10	66.60	2.80
	MACA_NorESM1-M	0.02	0.47	0.37	< 2.2e-16	0.07	73.34	4.90
	GDO_bcc-csm1-1	0.03	0.29	0.33	5.50E-16	0.03	79.30	0.70
	GDO_bcc-csm1-1-m	0.01	0.79	0.32	5.88E-15	0.05	76.90	1.50
	GDO_CanESM2	0.04	0.12	0.28	9.98E-12	0.04	81.08	2.70

KansasCityU	GDO_CCSM4	0.02	0.50	0.36	< 2.2e-16	0.07	74.82	3.30
	GDO_CNRM-CM5	-0.04	0.17	0.32	6.64E-15	0.05	79.02	4.60
	GDO_CSIRO-Mk3-6-0	0.02	0.34	0.28	1.66E-11	0.04	77.68	3.80
	GDO_GFDL-ESM2M	0.01	0.62	0.29	3.29E-12	0.03	81.08	4.10
	GDO_GFDL-ESM2G	0.01	0.84	0.26	4.14E-10	0.04	81.98	2.70
	GDO_HadGEM2-CC365	0.01	0.80	0.31	4.59E-14	0.04	80.89	3.40
	GDO_HadGEM2-ES365	0.01	0.81	0.32	2.51E-15	0.08	78.31	1.70
	GDO_inmcm4	-0.03	0.29	0.33	6.13E-16	0.06	77.74	4.10
	GDO_IPSL-CM5A-LR	-0.01	0.62	0.34	< 2.2e-16	0.06	76.69	3.20
	GDO_IPSL-CM5A-MR	-0.02	0.34	0.23	1.64E-08	0.02	85.06	3.60
	GDO_MIROC5	-0.03	0.28	0.33	3.98E-16	0.06	78.34	5.00
	GDO_MIROC-ESM	0.01	0.77	0.35	< 2.2e-16	0.07	78.16	5.10
	GDO_MIROC-ESM-CHEM	0.03	0.24	0.34	< 2.2e-16	0.05	77.66	2.90
	GDO_MRI-CGCM3	0.00	0.92	0.38	< 2.2e-16	0.08	74.19	3.40
	GDO_NorESM1-M	0.01	0.66	0.35	< 2.2e-16	0.06	78.03	6.10
	NCEI_PRCP	0.04	0.45					
	MACA_bcc-csm1-1	-0.03	0.43	0.33	1.17E-06	0.03	80.46	14.60
	MACA_bcc-csm1-1-m	-0.01	0.87	0.38	2.24E-08	0.10	73.35	20.30
	MACA_CanESM2	0.03	0.51	0.34	6.27E-07	0.07	81.14	16.70
	MACA_CCSM4	0.00	1.00	0.37	2.48E-08	0.07	71.91	16.40
	MACA_CNRM-CM5	0.00	0.96	0.32	1.71E-06	0.06	83.86	29.70
	MACA_CSIRO-Mk3-6-0	0.02	0.61	0.26	1.43E-04	0.05	81.25	22.30
	MACA_GFDL-ESM2M	-0.01	0.73	0.36	7.32E-08	0.08	73.49	14.10
	MACA_GFDL-ESM2G	-0.02	0.72	0.33	7.68E-07	0.08	76.16	20.40
	MACA_HadGEM2-CC365	-0.08	0.07	0.35	1.55E-07	0.07	84.85	20.00
	MACA_HadGEM2-ES365	0.05	0.22	0.33	1.07E-06	0.12	91.79	29.40
	MACA_inmcm4	0.04	0.33	0.35	2.54E-07	0.12	72.21	18.30
	MACA_IPSL-CM5A-LR	-0.05	0.22	0.35	1.77E-07	0.07	77.95	23.80

Merriam	MACA_IPSL-CM5A-MR	-0.02	0.65	0.26	1.70E-04	0.06	74.94	15.30
	MACA_MIROC5	-0.03	0.45	0.37	5.44E-08	0.14	67.97	21.40
	MACA_MIROC-ESM	0.04	0.41	0.47	1.19E-12	0.17	67.38	19.30
	MACA_MIROC-ESM-CHEM	0.08	0.07	0.43	1.01E-10	0.11	65.54	15.80
	MACA_MRI-CGCM3	0.08	0.07	0.46	2.24E-12	0.14	65.66	21.80
	MACA_NorESM1-M	0.03	0.55	0.45	1.51E-11	0.10	78.83	21.80
	GDO_bcc-csm1-1	-0.02	0.56	0.37	3.93E-08	0.02	76.34	5.80
	GDO_bcc-csm1-1-m	-0.03	0.55	0.40	1.99E-09	0.09	71.51	12.30
	GDO_CanESM2	-0.03	0.55	0.34	5.77E-07	0.05	74.60	5.60
	GDO_CCSM4	0.01	0.89	0.39	5.36E-09	0.09	70.99	12.40
	GDO_CNRM-CM5	0.03	0.43	0.35	1.77E-07	0.08	78.87	23.30
	GDO_CSIRO-Mk3-6-0	0.04	0.31	0.24	5.89E-04	0.03	79.66	13.80
	GDO_GFDL-ESM2M	-0.03	0.43	0.33	1.30E-06	0.06	74.89	7.90
	GDO_GFDL-ESM2G	-0.04	0.35	0.30	1.07E-05	0.07	78.26	11.80
	GDO_HadGEM2-CC365	-0.06	0.14	0.41	9.98E-10	0.08	77.66	12.20
	GDO_HadGEM2-ES365	0.05	0.23	0.39	5.97E-09	0.12	82.69	20.10
	GDO_inmcm4	0.06	0.20	0.39	4.55E-09	0.09	73.52	15.30
	GDO_IPSL-CM5A-LR	-0.07	0.09	0.41	4.68E-10	0.10	70.35	16.50
	GDO_IPSL-CM5A-MR	0.00	0.98	0.27	8.24E-05	0.05	76.11	13.90
	GDO_MIROC5	-0.05	0.29	0.37	5.50E-08	0.12	70.21	18.70
	GDO_MIROC-ESM	-0.01	0.83	0.41	1.01E-09	0.14	70.45	12.90
	GDO_MIROC-ESM-CHEM	0.05	0.24	0.36	9.73E-08	0.05	72.75	10.50
	GDO_MRI-CGCM3	0.10	0.02	0.54	< 2.2e-16	0.19	61.90	14.50
	GDO_NorESM1-M	0.05	0.26	0.42	3.69E-10	0.09	74.97	16.80
	NCEI_PRCP	0.05	0.30					
	MACA_bcc-csm1-1	-0.05	0.33	0.31	2.79E-05	0.02	77.64	12.70
	MACA_bcc-csm1-1-m	0.01	0.91	0.35	2.34E-06	0.07	73.28	11.80
	MACA_CanESM2	0.01	0.82	0.30	5.23E-05	0.04	79.68	7.20
	MACA_CCSM4	0.00	0.99	0.35	2.95E-06	0.07	71.41	15.80
	MACA_CNRM-CM5	0.04	0.41	0.34	4.44E-06	0.11	79.16	24.60

MACA_CSIRO-Mk3-6-0	0.00	0.96	0.31	3.67E-05	0.07	72.20	12.10
MACA_GFDL-ESM2M	0.00	0.97	0.36	9.45E-07	0.08	70.80	11.40
MACA_GFDL-ESM2G	0.03	0.49	0.32	2.22E-05	0.09	74.33	20.10
MACA_HadGEM2-CC365	-0.05	0.33	0.30	8.08E-05	0.08	79.60	16.70
MACA_HadGEM2-ES365	0.03	0.53	0.31	4.24E-05	0.14	86.87	17.00
MACA_inmcm4	0.03	0.62	0.33	1.03E-05	0.13	71.23	15.20
MACA_IPSL-CM5A-LR	-0.08	0.11	0.37	4.54E-07	0.09	72.68	16.30
MACA_IPSL-CM5A-MR	0.02	0.74	0.28	2.50E-04	0.08	67.49	9.00
MACA_MIROC5	-0.08	0.09	0.35	2.19E-06	0.14	65.79	16.40
MACA_MIROC-ESM	0.03	0.57	0.44	1.58E-09	0.15	65.85	13.20
MACA_MIROC-ESM-CHEM	0.03	0.49	0.34	5.07E-06	0.04	68.56	3.20
MACA_MRI-CGCM3	0.08	0.12	0.42	1.60E-08	0.10	63.99	12.50
MACA_NorESM1-M	0.01	0.79	0.43	6.30E-09	0.08	79.72	17.40
GDO_bcc-csm1-1	-0.04	0.37	0.39	1.25E-07	0.02	77.32	6.90
GDO_bcc-csm1-1-m	0.00	0.95	0.36	1.80E-06	0.05	77.02	11.90
GDO_CanESM2	-0.03	0.56	0.29	1.52E-04	0.03	76.28	2.10
GDO_CCSM4	0.00	0.97	0.36	1.89E-06	0.08	70.95	9.40
GDO_CNRM-CM5	0.06	0.26	0.38	3.11E-07	0.16	73.34	20.10
GDO_CSIRO-Mk3-6-0	0.03	0.53	0.27	3.28E-04	0.04	74.89	7.50
GDO_GFDL-ESM2M	0.01	0.80	0.37	6.41E-07	0.09	75.34	13.70
GDO_GFDL-ESM2G	-0.03	0.60	0.26	6.39E-04	0.07	83.72	18.50
GDO_HadGEM2-CC365	-0.05	0.31	0.36	1.23E-06	0.09	73.55	9.30
GDO_HadGEM2-ES365	0.00	0.96	0.35	2.69E-06	0.13	81.84	8.00
GDO_inmcm4	0.06	0.23	0.35	2.21E-06	0.12	72.25	12.30
GDO_IPSL-CM5A-LR	-0.09	0.08	0.41	2.95E-08	0.10	71.74	17.00
GDO_IPSL-CM5A-MR	0.03	0.57	0.28	2.14E-04	0.06	72.04	11.20
GDO_MIROC5	-0.07	0.17	0.38	2.53E-07	0.14	70.50	18.40

GDO_MIROC-ESM	0.00	0.99	0.35	2.50E-06	0.15	69.67	10.30
GDO_MIROC-ESM-CHEM	0.01	0.80	0.27	4.52E-04	0.01	76.91	0.20
GDO_MRI-CGCM3	0.11	0.03	0.44	1.12E-09	0.10	66.96	9.00
GDO_NorESM1-M	0.03	0.60	0.40	4.26E-08	0.08	78.59	15.60
NCEI_PRCP	0.06	0.30					
MACA_bcc-csm1-1	-0.08	0.14	0.32	2.21E-04	0.02	77.21	9.40
MACA_bcc-csm1-1-m	0.05	0.36	-0.18	3.72E-02	0.02	94.06	22.20
MACA_CanESM2	0.00	0.97	-0.34	5.59E-05	0.05	104.60	16.40
MACA_CCSM4	0.03	0.61	-0.22	1.12E-02	0.03	95.79	23.70
MACA_CNRM-CM5	0.06	0.24	-0.23	7.51E-03	0.04	111.60	36.20
MACA_CSIRO-Mk3-6-0	0.02	0.73	-0.36	2.48E-05	0.06	100.35	18.50
MACA_GFDL-ESM2M	0.04	0.49	-0.14	9.88E-02	0.02	91.80	17.20
MACA_GFDL-ESM2G	0.02	0.71	-0.21	1.69E-02	0.03	94.97	17.50
MACA_HadGEM2-CC365	-0.03	0.56	-0.28	8.89E-04	0.05	109.17	23.20
MACA_HadGEM2-ES365	0.03	0.61	-0.11	2.10E-01	0.01	118.63	20.20
MACA_inmcm4	0.02	0.73	-0.29	6.37E-04	0.04	98.52	12.40
MACA_IPSL-CM5A-LR	-0.08	0.12	-0.24	5.02E-03	0.03	102.36	24.50
MACA_IPSL-CM5A-MR	-0.02	0.75	-0.03	6.91E-01	0.00	81.91	8.50
MACA_MIROC5	-0.08	0.11	-0.24	5.23E-03	0.03	90.11	18.60
MACA_MIROC-ESM	0.03	0.63	-0.14	9.84E-02	0.01	89.87	15.20
MACA_MIROC-ESM-CHEM	0.06	0.26	-0.18	4.08E-02	0.02	86.62	12.90
MACA_MRI-CGCM3	0.10	0.07	-0.19	3.03E-02	0.03	89.04	15.50
MACA_NorESM1-M	0.05	0.35	-0.21	1.31E-02	0.03	105.88	22.80
GDO_bcc-csm1-1	-0.09	0.09	0.40	1.36E-06	0.04	73.41	5.00
GDO_bcc-csm1-1-m	-0.04	0.51	0.35	3.84E-05	0.07	72.70	13.30
GDO_CanESM2	-0.05	0.37	0.33	1.23E-04	0.05	72.04	0.40
GDO_CCSM4	0.01	0.83	0.42	4.05E-07	0.13	63.56	10.50

Olathe3	GDO_CNRM-CM5	0.03	0.63	0.32	1.85E-04	0.12	71.90	11.80
	GDO_CSIRO-Mk3-6-0	-0.02	0.74	0.37	1.35E-05	0.10	70.58	14.60
	GDO_GFDL-ESM2M	-0.02	0.64	0.35	4.16E-05	0.09	72.57	13.20
	GDO_GFDL-ESM2G	0.02	0.66	0.32	2.08E-04	0.04	75.42	6.00
	GDO_HadGEM2-CC365	-0.09	0.07	0.37	1.32E-05	0.05	71.79	2.30
	GDO_HadGEM2-ES365	-0.05	0.38	0.32	1.46E-04	0.11	80.08	9.80
	GDO_inmcm4	0.09	0.09	0.32	2.19E-04	0.06	75.33	12.80
	GDO_IPSL-CM5A-LR	-0.10	0.05	0.41	1.31E-06	0.11	70.67	16.30
	GDO_IPSL-CM5A-MR	0.05	0.39	0.24	5.87E-03	0.02	71.98	5.90
	GDO_MIROC5	-0.05	0.36	0.37	1.43E-05	0.13	65.28	8.60
	GDO_MIROC-ESM	0.02	0.75	0.33	8.81E-05	0.08	68.90	8.00
	GDO_MIROC-ESM-CHEM	0.04	0.48	0.28	1.23E-03	0.02	70.36	-3.00
	GDO_MRI-CGCM3	0.14	0.01	0.42	4.08E-07	0.07	72.48	7.80
	GDO_NorESM1-M	0.06	0.23	0.41	6.84E-07	0.09	73.88	10.40
	NCEI_PRCP	0.05	0.04					
	MACA_bcc-csm1-1	0.02	0.41	0.30	8.01E-15	0.04	84.81	2.80
	MACA_bcc-csm1-1-m	0.01	0.59	0.31	< 2.2e-16	0.07	79.02	2.70
	MACA_CanESM2	0.03	0.32	0.33	< 2.2e-16	0.08	81.08	3.10
	MACA_CCSM4	0.02	0.48	0.33	< 2.2e-16	0.07	76.56	2.70
	MACA_CNRM-CM5	-0.03	0.19	0.30	1.34E-15	0.05	82.86	3.30
	MACA_CSIRO-Mk3-6-0	0.02	0.48	0.31	4.27E-16	0.05	79.42	3.30
	MACA_GFDL-ESM2M	0.00	0.94	0.33	< 2.2e-16	0.06	79.19	2.90
	MACA_GFDL-ESM2G	0.01	0.67	0.29	1.64E-14	0.04	81.60	3.00
	MACA_HadGEM2-CC365	0.01	0.64	0.29	1.72E-14	0.05	85.71	3.00
	MACA_HadGEM2-ES365	-0.01	0.61	0.30	4.55E-15	0.09	84.98	2.20
	MACA_inmcm4	-0.01	0.73	0.28	8.39E-14	0.06	81.24	3.50
	MACA_IPSL-CM5A-LR	-0.01	0.57	0.33	< 2.2e-16	0.06	80.82	3.00
	MACA_IPSL-CM5A-MR	0.00	0.96	0.26	3.99E-12	0.03	85.13	3.00

Stillwell	MACA_MIROC5	0.00	0.96	0.35	< 2.2e-16	0.08	74.10	2.90
	MACA_MIROC-ESM	0.01	0.77	0.35	< 2.2e-16	0.09	76.19	3.20
	MACA_MIROC-ESM-CHEM	0.01	0.64	0.37	< 2.2e-16	0.08	75.41	3.50
	MACA_MRI-CGCM3	0.00	0.89	0.40	< 2.2e-16	0.10	70.80	2.90
	MACA_NorESM1-M	0.02	0.40	0.37	< 2.2e-16	0.07	77.96	3.00
	GDO_bcc-csm1-1	0.03	0.24	0.36	< 2.2e-16	0.04	83.07	-1.50
	GDO_bcc-csm1-1-m	0.01	0.64	0.38	< 2.2e-16	0.07	78.25	-1.40
	GDO_CanESM2	0.03	0.22	0.38	< 2.2e-16	0.08	75.78	-1.20
	GDO_CCSM4	0.02	0.35	0.37	< 2.2e-16	0.08	75.99	-1.70
	GDO_CNRM-CM5	-0.02	0.43	0.35	< 2.2e-16	0.07	79.97	-1.00
	GDO_CSIRO-Mk3-6-0	0.02	0.48	0.33	< 2.2e-16	0.05	81.17	-1.00
	GDO_GFDL-ESM2M	0.01	0.69	0.35	< 2.2e-16	0.06	79.31	-1.50
	GDO_GFDL-ESM2G	0.01	0.79	0.32	< 2.2e-16	0.04	83.62	-1.40
	GDO_HadGEM2-CC365	0.01	0.57	0.37	< 2.2e-16	0.07	80.22	-0.90
	GDO_HadGEM2-ES365	-0.01	0.63	0.37	< 2.2e-16	0.09	77.54	-2.00
	GDO_inmcm4	-0.02	0.40	0.35	< 2.2e-16	0.06	81.23	-0.70
	GDO_IPSL-CM5A-LR	-0.01	0.65	0.35	< 2.2e-16	0.06	81.30	-1.20
	GDO_IPSL-CM5A-MR	-0.02	0.48	0.30	2.78E-15	0.04	84.44	-1.50
	GDO_MIROC5	0.00	0.97	0.35	< 2.2e-16	0.08	78.99	-1.10
	GDO_MIROC-ESM	0.01	0.72	0.38	< 2.2e-16	0.09	76.73	-1.10
	GDO_MIROC-ESM-CHEM	0.02	0.54	0.38	< 2.2e-16	0.07	75.93	-0.60
	GDO_MRI-CGCM3	0.00	0.95	0.41	< 2.2e-16	0.08	76.19	-1.20
	GDO_NorESM1-M	0.01	0.63	0.38	< 2.2e-16	0.06	80.04	-1.40
	NCEI_PRCP	0.05	0.09					
	MACA_bcc-csm1-1	0.02	0.39	0.29	1.42E-13	0.03	87.32	3.50
	MACA_bcc-csm1-1-m	0.02	0.47	0.32	3.15E-16	0.06	81.50	2.40
	MACA_CanESM2	0.03	0.32	0.30	1.95E-14	0.06	84.95	3.10
	MACA_CCSM4	0.02	0.55	0.28	4.11E-13	0.05	81.38	3.30
	MACA_CNRM-CM5	-0.03	0.18	0.30	2.78E-14	0.04	85.12	2.80
	MACA_CSIRO-Mk3-6-0	0.02	0.46	0.29	4.59E-14	0.05	81.23	3.50

MACA_GFDL-ESM2M	0.01	0.83	0.35	< 2.2e-16	0.06	80.55	3.70
MACA_GFDL-ESM2G	0.01	0.68	0.28	8.78E-13	0.04	83.09	3.40
MACA_HadGEM2-CC365	0.02	0.56	0.32	3.37E-16	0.06	85.52	3.10
MACA_HadGEM2-ES365	-0.01	0.61	0.28	2.23E-13	0.08	88.41	3.00
MACA_inmcm4	-0.01	0.67	0.27	1.86E-12	0.05	82.79	2.50
MACA_IPSL-CM5A-LR	-0.02	0.46	0.33	< 2.2e-16	0.05	82.90	3.50
MACA_IPSL-CM5A-MR	0.00	0.88	0.26	3.23E-11	0.03	88.54	3.50
MACA_MIROC5	0.00	0.94	0.37	< 2.2e-16	0.09	74.40	3.50
MACA_MIROC-ESM	0.01	0.84	0.34	< 2.2e-16	0.08	78.25	3.80
MACA_MIROC-ESM-CHEM	0.01	0.62	0.36	< 2.2e-16	0.08	76.67	3.00
MACA_MRI-CGCM3	0.00	0.92	0.38	< 2.2e-16	0.08	73.75	3.40
MACA_NorESM1-M	0.02	0.39	0.37	< 2.2e-16	0.07	78.74	3.10
GDO_bcc-csm1-1	0.02	0.34	0.33	< 2.2e-16	0.04	84.33	-2.40
GDO_bcc-csm1-1-m	0.01	0.65	0.34	< 2.2e-16	0.06	79.00	-3.10
GDO_CanESM2	0.03	0.20	0.34	< 2.2e-16	0.05	81.70	-2.20
GDO_CCSM4	0.02	0.55	0.31	1.75E-15	0.05	79.21	-2.70
GDO_CNRM-CM5	-0.02	0.35	0.32	< 2.2e-16	0.05	81.81	-2.70
GDO_CSIRO-Mk3-6-0	0.03	0.33	0.30	9.68E-15	0.04	84.04	-2.20
GDO_GFDL-ESM2M	0.00	0.86	0.34	< 2.2e-16	0.06	79.28	-2.00
GDO_GFDL-ESM2G	0.01	0.56	0.28	2.20E-13	0.04	84.00	-2.50
GDO_HadGEM2-CC365	0.01	0.70	0.36	< 2.2e-16	0.07	79.83	-2.70
GDO_HadGEM2-ES365	-0.01	0.69	0.33	< 2.2e-16	0.08	79.52	-2.90
GDO_inmcm4	-0.02	0.51	0.31	1.02E-15	0.04	82.29	-3.10
GDO_IPSL-CM5A-LR	-0.01	0.73	0.33	< 2.2e-16	0.05	82.03	-2.30
GDO_IPSL-CM5A-MR	-0.03	0.32	0.28	7.21E-13	0.03	86.25	-2.30
GDO_MIROC5	-0.02	0.55	0.35	< 2.2e-16	0.07	77.15	-2.10
GDO_MIROC-ESM	0.01	0.77	0.34	< 2.2e-16	0.07	78.11	-1.40

GDO_MIROC-ESM-CHEM	0.02	0.42	0.36	< 2.2e-16	0.07	77.28	-2.10
GDO_MRI-CGCM3	0.01	0.73	0.38	< 2.2e-16	0.07	77.45	-2.20
GDO_NorESM1-M	0.01	0.61	0.37	< 2.2e-16	0.06	77.85	-2.70

Appendix D - Surface Comparison KS Test R Code

The following KS Test R code was set up and modified with the assistance of Dr. Shawn Hutchinson.

```
#####  
#####R Code for KS test of surface downscaled selected GDO GCM precipitation data#####  
##Created by and Modified by Dr. Shawn Hutchinson & Laura J. Krueger on March 25, 2020##  
  
#load required packages and import data file  
library(stats)  
library(psych)  
  
###Set your working directory. This is the path name to the folder wherever your datafile is  
saved.  
setwd("L:/WaterQuality/Krueger/KruegerInterpolation/Comparisons_2_points/Statistics")  
  
###Load the file that you are going to run your stats on  
prism <- read.csv(file="Export_GDOPrism.csv",header=TRUE, sep=",")  
ccsm <- read.csv(file="GDO_ccsm.csv",header=TRUE, sep=",")  
  
###Check to make sure that your data loaded properly  
head(prism) #This command will load the headers and first six lines of your document. Check to  
make sure that it looks correct  
head(ccsm)  
#####SAMPLE#####  
#run ks test using different phenometrics CHANGE VARIABLE  
ks.test(prism$gprs_95_1, ccsm$ccsm_95_1)  
  
#Two-sample Kolmogorov-Smirnov test  
#data: prism$gprs_95_1 and ccsm$ccsm_95_1  
#D = 1.0, p-value < 2.2e-16  
#alternative hypothesis: two-sided  
  
##The D value is the test statistic representing the maximum distance between the CDFs of the  
two samples  
##Reject the null hypothesis that the two samples were drawn from the same distribution if the p-  
value is less than your significance level.  
  
#use describe function to know min and max values for phenometrics  
describe(prism$gprs_95_1)  
describe(ccsm$ccsm_95_1)  
  
#create cumulative distribution function (CDF) plot CHANGE VARIABLE, X LABEL, and  
XLIM
```

```

prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_1), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n January 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(10,50))
plot(ecdf(ccsm$ccsm_95_1), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)

#####Monthly#####
#####January#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_1,ccsm$ccsm_95_1)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_1)
describe(ccsm$ccsm_95_1)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_1), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n January 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(10,50))
plot(ecdf(ccsm$ccsm_95_1), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####February#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_2,ccsm$ccsm_95_2)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_2)
describe(ccsm$ccsm_95_2)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_2), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n February 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(0,50))
plot(ecdf(ccsm$ccsm_95_2), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)

```

```
#####March#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_3,ccsm$ccsm_95_3)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_3)
describe(ccsm$ccsm_95_3)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_3), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n March 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(10,60))
plot(ecdf(ccsm$ccsm_95_3), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####April#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_4,ccsm$ccsm_95_4)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_4)
describe(ccsm$ccsm_95_4)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_4), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n April 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(40,130))
plot(ecdf(ccsm$ccsm_95_4), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####May#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_5,ccsm$ccsm_95_5)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_5)
describe(ccsm$ccsm_95_5)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
```

```

prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_5), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n May 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(250,400))
plot(ecdf(ccsm$ccsm_95_5), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####June#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_6,ccsm$ccsm_95_6)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_6)
describe(ccsm$ccsm_95_6)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_6), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n June 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(70,200))
plot(ecdf(ccsm$ccsm_95_6), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####July#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_7,ccsm$ccsm_95_7)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_7)
describe(ccsm$ccsm_95_7)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_7), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n July 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(40,200))
plot(ecdf(ccsm$ccsm_95_7), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####August#####
#run ks test using different phenometrics CHANGE VARIABLE

```

```

ks.test(prism$gprs_95_8,ccsm$ccsm_95_8)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_8)
describe(ccsm$ccsm_95_8)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_8), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n August 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(40,200))
plot(ecdf(ccsm$ccsm_95_8), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####September#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_9,ccsm$ccsm_95_9)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_9)
describe(ccsm$ccsm_95_9)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_9), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n September 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(20,100))
plot(ecdf(ccsm$ccsm_95_9), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####October#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_10,ccsm$ccsm_95_10)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_10)
describe(ccsm$ccsm_95_10)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)

```

```

plot(ecdf(prism$gprs_95_10), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n October 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(0,40))
plot(ecdf(ccsm$ccsm_95_10), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####November#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_11,ccsm$ccsm_95_11)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_11)
describe(ccsm$ccsm_95_11)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_11), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n November 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(10,60))
plot(ecdf(ccsm$ccsm_95_11), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####December#####
#run ks test using different phenometrics CHANGE VARIABLE
ks.test(prism$gprs_95_12,ccsm$ccsm_95_12)

#use describe function to know min and max values for phenometrics
describe(prism$gprs_95_12)
describe(ccsm$ccsm_95_12)

#create cumulative distribution function(CDF) plot CHANGE VARIABLE, X LABEL, and
XLIM
prismCDFcolor <- rgb(1,0,0)
ccsmCDFcolor <- rgb(0,0,1)
plot(ecdf(prism$gprs_95_12), verticals = TRUE, col=prismCDFcolor, main="Cumulative
Distribution Function (CDF)\n December 1995", xlab="Monthly Precipitation (mm)",
ylab="Proportion of Values", xlim=c(0,40))
plot(ecdf(ccsm$ccsm_95_12), verticals = TRUE, col=ccsmCDFcolor, add=TRUE)
legend("topleft", c("Prism", "GDO_ccsm4.6"), fill=c(prismCDFcolor, ccsmCDFcolor),
border=NA)
#####

```

Appendix E - Surface Comparison KS Test Results

Table E.6.4. Selected GDO LOCA GCMs surface comparison with PRISM KS Test results, with highlighted $D \leq 0.5$ and p value > 0.5 indicating results drawn from similar distributions.

Year	GDOccsm		GDOmri		GDOnor	
	D	p-value	D	p-value	D	p-value
95_1	1.00	2.22E-16	1.00	2.22E-16	0.41	4.57E-03
95_2	1.00	2.22E-16	0.78	2.69E-10	1.00	2.22E-16
95_3	0.92	5.40E-14	1.00	2.22E-16	0.95	8.33E-15
95_4	1.00	2.22E-16	0.97	1.22E-15	0.16	7.15E-01
95_5	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
95_6	0.62	1.24E-06	0.92	5.40E-14	1.00	2.22E-16
95_7	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
95_8	0.86	1.91E-12	0.95	8.33E-15	1.00	2.22E-16
95_9	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
95_10	0.30	7.60E-02	1.00	2.22E-16	0.97	1.22E-15
95_11	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
95_12	1.00	2.22E-16	0.59	4.17E-06	1.00	2.22E-16
96_1	0.59	4.17E-06	0.86	1.91E-12	1.00	2.22E-16
96_2	1.00	2.22E-16	0.97	1.22E-15	0.84	1.05E-11
96_3	1.00	2.22E-16	1.00	2.22E-16	0.95	8.33E-15
96_4	1.00	2.22E-16	1.00	2.22E-16	0.73	5.55E-09
96_5	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
96_6	0.76	1.26E-09	1.00	2.22E-16	1.00	2.22E-16
96_7	1.00	2.22E-16	1.00	2.22E-16	0.73	5.55E-09
96_8	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
96_9	1.00	2.22E-16	0.84	1.05E-11	1.00	2.22E-16
96_10	1.00	2.22E-16	0.95	8.33E-15	0.92	5.40E-14
96_11	1.00	2.22E-16	0.97	1.22E-15	1.00	2.22E-16
96_12	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
97_1	1.00	2.22E-16	1.00	2.22E-16	0.24	2.24E-01
97_2	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
97_3	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
97_4	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
97_5	0.81	5.46E-11	0.97	1.22E-15	1.00	2.22E-16
97_6	0.57	1.33E-05	1.00	2.22E-16	1.00	2.22E-16
97_7	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
97_8	1.00	2.22E-16	1.00	2.22E-16	0.95	8.33E-15
97_9	1.00	2.22E-16	1.00	2.22E-16	0.70	2.33E-08
97_10	1.00	2.22E-16	1.00	2.22E-16	0.95	8.33E-15
97_11	0.97	1.22E-15	1.00	2.22E-16	0.27	1.34E-01

97_12	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_1	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_2	0.51	1.16E-04	1.00	2.22E-16	0.95	8.33E-15
98_3	1.00	2.22E-16	0.73	5.55E-09	0.92	5.40E-14
98_4	0.81	5.46E-11	0.78	2.69E-10	0.81	5.46E-11
98_5	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_6	0.89	3.30E-13	1.00	2.22E-16	1.00	2.22E-16
98_7	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_8	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_9	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_10	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_11	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
98_12	0.92	5.40E-14	1.00	2.22E-16	1.00	2.22E-16
99_1	1.00	2.22E-16	1.00	2.22E-16	0.32	4.08E-02
99_2	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
99_3	0.97	1.22E-15	0.86	1.91E-12	0.49	3.15E-04
99_4	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
99_5	0.86	1.91E-12	1.00	2.22E-16	1.00	2.22E-16
99_6	0.95	8.33E-15	0.78	2.69E-10	0.76	1.26E-09
99_7	1.00	2.22E-16	1.00	2.22E-16	0.95	8.33E-15
99_8	0.95	8.33E-15	1.00	2.22E-16	0.97	1.22E-15
99_9	0.70	2.33E-08	0.89	3.30E-13	1.00	2.22E-16
99_10	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
99_11	0.65	3.47E-07	0.73	5.55E-09	0.76	1.26E-09
99_12	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
00_1	1.00	2.22E-16	0.86	1.91E-12	1.00	2.22E-16
00_2	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
00_3	0.97	1.22E-15	1.00	2.22E-16	1.00	2.22E-16
00_4	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
00_5	0.32	4.08E-02	0.65	3.47E-07	0.89	3.02E-14
00_6	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
00_7	1.00	2.22E-16	0.59	4.17E-06	1.00	2.22E-16
00_8	1.00	2.22E-16	1.00	2.22E-16	0.92	5.40E-14
00_9	1.00	2.22E-16	1.00	2.22E-16	0.97	1.22E-15
00_10	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
00_11	1.00	2.22E-16	1.00	2.22E-16	0.97	1.22E-15
00_12	0.89	3.30E-13	0.32	4.08E-02	1.00	2.22E-16
01_1	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
01_2	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
01_3	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
01_4	0.84	1.05E-11	0.76	1.26E-09	0.43	1.98E-03
01_5	0.89	3.30E-13	0.32	4.08E-02	0.27	1.34E-01
01_6	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16

01_7	0.92	5.40E-14	0.35	2.08E-02	1.00	2.22E-16
01_8	1.00	2.22E-16	0.95	8.33E-15	0.30	7.60E-02
01_9	0.86	1.91E-12	1.00	2.22E-16	1.00	2.22E-16
01_10	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
01_11	0.49	3.15E-04	0.97	1.22E-15	1.00	2.22E-16
01_12	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
02_1	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
02_2	1.00	2.22E-16	0.38	1.00E-02	1.00	2.22E-16
02_3	1.00	2.22E-16	0.43	1.98E-03	0.57	1.33E-05
02_4	1.00	2.22E-16	1.00	2.22E-16	0.27	1.34E-01
02_5	1.00	2.22E-16	1.00	2.22E-16	0.41	4.57E-03
02_6	1.00	2.22E-16	0.68	9.23E-08	0.62	1.24E-06
02_7	1.00	2.22E-16	0.59	4.17E-06	0.97	1.22E-15
02_8	1.00	2.22E-16	0.78	2.69E-10	0.24	2.24E-01
02_9	0.57	1.33E-05	1.00	2.22E-16	0.97	1.22E-15
02_10	1.00	2.22E-16	1.00	2.22E-16	0.97	1.22E-15
02_11	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
02_12	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
03_1	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
03_2	1.00	2.22E-16	0.30	7.60E-02	0.32	4.08E-02
03_3	1.00	2.22E-16	0.89	3.30E-13	0.84	1.05E-11
03_4	1.00	2.22E-16	0.86	1.91E-12	0.78	2.69E-10
03_5	0.46	8.11E-04	1.00	2.22E-16	0.89	3.30E-13
03_6	0.35	2.08E-02	1.00	2.22E-16	0.24	2.24E-01
03_7	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
03_8	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
03_9	0.65	3.47E-07	0.89	3.30E-13	1.00	2.22E-16
03_10	0.49	3.15E-04	1.00	2.22E-16	0.95	8.33E-15
03_11	0.70	2.33E-08	1.00	2.22E-16	0.97	1.22E-15
03_12	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
04_1	0.73	5.55E-09	0.30	7.60E-02	0.97	1.22E-15
04_2	0.51	1.16E-04	1.00	2.22E-16	0.57	1.33E-05
04_3	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
04_4	1.00	2.22E-16	0.27	1.34E-01	0.76	1.26E-09
04_5	0.95	8.33E-15	1.00	2.22E-16	0.73	5.55E-09
04_6	1.00	2.22E-16	0.92	5.40E-14	1.00	2.22E-16
04_7	0.70	2.33E-08	1.00	2.22E-16	1.00	2.22E-16
04_8	1.00	2.22E-16	1.00	2.22E-16	1.00	2.22E-16
04_9	0.89	3.30E-13	0.68	9.23E-08	0.81	5.46E-11
04_10	0.86	1.91E-12	0.32	4.08E-02	0.97	1.22E-15
04_11	1.00	2.22E-16	0.46	8.11E-04	0.68	9.23E-08
04_12	0.30	7.60E-02	0.76	1.26E-09	0.70	2.33E-08

Appendix F - Surface Comparison SPAEF Analysis Code

The following SPAEF metric code was obtained (Demirel, 2018) and modified, with the assistance of Dr. Shawn Hutchinson, for use for monthly spatial comparison of modeled GCM layers (simulated) with PRISM layers (observed).

SPAEF Metric Code

```
#####
#####Adapted by Laura J. Krueger & Dr. Shawn Hutchinson on August 31, 2020#####
#saved as file name- SPAEF_metric.py, referenced by code file name-
SPAEF_gprs_full_ccsm_LK.py
#####
#!/usr/bin/env python
# -*- coding: utf-8 -*-
"""
Created on Thu Sep 13 11:33:33 2017
@ authors:      Mehmet Cüneyd Demirel, Gorka Mendiguren, Julian Koch, Simon Stisen
and Fabio Oriani
@ author's website:  http://www.space.geus.dk/
@ author's webpage:  http://akademi.itu.edu.tr/demirelmc/
@ author's email id:  demirelmc@itu.edu.tr

A library with Python functions for calculation of spatial efficiency (SPAEF) metric.
Literature:
[1] Demirel, M. C., Mai, J., Mendiguren, G., Koch, J., Samaniego, L., & Stisen, S. (2017).
Combining satellite data and appropriate objective functions for improved spatial pattern
performance of a distributed hydrologic model. Hydrology and Earth System Sciences
Discussions, 1–22. https://doi.org/10.5194/hess-2017-570
[2] Koch, J., Demirel, M. C., & Stisen, S. (2017). On the importance of multiple-component
evaluation of spatial patterns for optimization of earth system models - A case study using mHM
v5.6 at catchment scale. Geoscientific Model Development Discussions, 1–25.
https://doi.org/10.5194/gmd-2017-238

function:
    SPAEF : spatial efficiency
    """

# import required modules
import numpy as np
from scipy.stats import variation, zscore
#####
def filter_nan(s,o):
```

```

data = np.transpose(np.array([s.flatten(),o.flatten()]))
data = data[~np.isnan(data).any(1)]
return data[:,0], data[:,1]
#####
def SPAEF(s, o, bins):
    #remove NaNs
    s,o = filter_nan(s,o)
    #compute ratio of CV
    alpha = variation(s)/variation(o)
    #compute zscore mean=0, std=1
    o=zscore(o)
    s=zscore(s)
    #compute histograms
    hobs,binobs = np.histogram(o,bins)
    hsim,bin sim = np.histogram(s,bins)
    #convert int to float, critical conversion for the result
    hobs=np.float64(hobs)
    hsim=np.float64(hsim)
    #find the overlapping of two histogram
    minima = np.minimum(hsim, hobs)
    #compute the fraction of intersection area to the observed histogram area, hist
intersection/overlap index
    hh = np.sum(minima)/np.sum(hobs)
    #compute corr coeff
    cc = np.corrcoef(s,o)[0,1]
    #compute SPAEF finally with three vital components
    spaef = 1- np.sqrt( (cc-1)**2 + (alpha-1)**2 + (hh-1)**2 )

    return spaef, cc, alpha, hh
#####
#####
#####
##### Adapted and modified by Laura J. Krueger for each model run#####
#saved as file name- figures_gprs_full_ccsm.py, referenced by code file name-
SPAEF_gprs_full_ccsm_LK.py
#####
#!/usr/bin/env python
# -*- coding: utf-8 -*-
"""

```

Created on Thu Sep 13 11:33:33 2017

@ author: Mehmet Cüneyd Demirel
 @ author's webpage: <http://akademi.itu.edu.tr/demirelmc/>
 @ author's email id: demirelmc@itu.edu.tr
 @ author's website: <http://www.space.geus.dk/>

A library with Python functions for calculation of spatial efficiency (SPAEF) metric.

```

function:
    SPAEF : spatial efficiency
"""
# import required modules
import os
import matplotlib.pyplot as plt
from matplotlib import gridspec
import numpy as np
#####
#####
def plot_SPAEFstats(gdoccsm,prism,SPAef, cc, alpha, histo, titlet):
    font = {'family': 'serif',
            'color': 'black',
            'weight': 'bold',
            'size': 18,
            }

    newpath = "L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\temp_Maps\\"
    if not os.path.exists(newpath):
        os.makedirs(newpath)

    prism=(prism-np.nanmin(prism))/(np.nanmax(prism)-np.nanmin(prism))
    gdoccsm=(gdoccsm-np.nanmin(gdoccsm))/(np.nanmax(gdoccsm)-np.nanmin(gdoccsm))

    bins =100# np.linspace(100, 350, 100)

    hprism,binprism = np.histogram(prism,bins)
    hgdoccsm,bingdoccsm = np.histogram(gdoccsm,bins)

    fig, (ax1, ax2) = plt.subplots(1, 2 ,figsize=(10,16))
    gs = gridspec.GridSpec(1, 2, width_ratios=[1, 1], height_ratios=[1, 1])
    ax1 = plt.subplot(gs[0])
    ax1.hist(prism, bins, alpha=0.5, label='prism')
    ax1.hist(gdoccsm, bins, alpha=0.5, label='gdoccsm')
    ax1.legend(loc='upper left')
    ax1.text(0.02, max(hgdoccsm)*2/3, r'$Histo Match$', fontdict=font)
    ax1.text(0.02, max(hgdoccsm)*2/3-max(hgdoccsm)/13, '{:.2f}'.format(round(histo, 2)),
fontdict=font)

    ax1.set_title("SPAEF is %.2f" %SPAef,fontdict=font)
    ax2 = plt.subplot(gs[1])
    ax2.scatter(prism,gdoccsm)

    ax2.text(-0.11, -0.16, r'$CORR: $', fontdict=font)

```

```

ax2.text(0.195,-0.16, np.around(cc,2), fontdict=font)
ax2.text(0.75, -0.16, r'$CV: $', fontdict=font)
ax2.text(0.91,-0.16, np.around(alpha,2), fontdict=font)
z = np.polyfit(prism, gdoccsm, 1)
p = np.poly1d(z)
ax2.plot(prism,p(prism),"r--")
ax2.set_title("See " + titlet+ "_map.png",fontdict=font)

plt.tight_layout()

fig.savefig(newpath+'/'+titlet+'.png', dpi=60,bbox_inches='tight')

plt.show()
plt.close(fig)

print('figure saved')

def plot_maps(gdoccsm,prism,titlet):

    prism2=prism#(prism-np.nanmin(prism))/(np.nanmax(prism)-np.nanmin(prism))
    gdoccsm2=gdoccsm#(gdoccsm-np.nanmin(gdoccsm))/(np.nanmax(gdoccsm)-
np.nanmin(gdoccsm))

    font = {'family': 'serif',
            'color': 'black',
            'weight': 'bold',
            'size': 18,
            }

    font2 = {'family': 'serif',
            'color': 'black',
            'weight': 'bold',
            'size': 12,
            }

    newpath = "L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\temp_Maps\\"
    if not os.path.exists(newpath):
        os.makedirs(newpath)

    fig = plt.figure(figsize=(16, 10))

    plt.subplot(1, 2, 1)

```

```

x=plt.imshow(gdoccsm2, interpolation='none',cmap='coolwarm_r')
plt.axis('off')
plt.colorbar(x,orientation ='horizontal',fraction=0.04, pad = 0.001, shrink=0.80)
plt.title('gdoccsm - '+title, fontdict=font)

plt.text(0,0,r'BIAS: %.0f ' %(100*np.around((np.nanmean(np.abs(gdoccsm-
prism))/np.nanmean(prism)),2))+'%', fontdict=font2)

plt.subplot(1, 2, 2)
y=plt.imshow(prism2, interpolation='none',cmap='coolwarm_r')
plt.axis('off')
plt.colorbar(y,orientation ='horizontal',fraction=0.04, pad = 0.001, shrink=0.80)
plt.title('PRISM - '+title, fontdict=font)

foldergdoccsm =
"L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\temp_Maps\\"
filenamegdoccsm=title+'.png'
fig.savefig(foldergdoccsm+'/'+filenamegdoccsm, dpi=60,bbox_inches='tight')

plt.close(fig)

print('figure saved')
#####
#####
#####
##### Adapted and modified by Laura J. Krueger for each model & year run#####
#saved as file name- SPAEF_gprs_full_ccsm_LK.py
#####
# -*- coding: utf-8 -*-

from __future__ import print_function
print(__doc__)

import numpy as np
import sys
import csv

sys.path.append("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\py_files\\")

from SPAEF_metric import SPAEF
from figures_gprs_full_ccsm import plot_SPAEFstats, plot_maps

mask_panel=
np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\gprs_80
_ext.asc") # X is an array

```

```

dpi = 60 # Arbitrary. The number of pixels in the image will always be identical
height, width = [12,18]*np.array(aET_sim.shape, dtype=float) / dpi
font = {"family": "serif",
        "color": "black",
        "weight": "bold",
        "size": 16,
        }

prism=[]
gdccsm=[]
##### 95_01 gPrism and GDO ccsm #####
prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_01.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_01.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_01, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAef95_01",SPAef95_01)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_01, cc, alpha, hh,"95_01") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_01") # first two inputs should be 2D matrix (not vector)

#####95_02 gPrism and GDO ccsm#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_02.asc")

```

```

gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\ccsm_95_02.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_02, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAef95_02",SPAef95_02)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_02, cc, alpha, hh,"95_02") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_02") # first two inputs should be 2D matrix (not vector)

#####95_03 gPrism and GDO ccs#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_03.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\ccsm_95_03.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

```

```

SPAef95_03, cc, alpha, hh = SPAEF(gdoccsmm,prismm,100)
print ("SPAEF_95_03",SPAef95_03)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdoccsmm,prismm,SPAef95_03, cc, alpha, hh,"95_03") # first two inputs
should be 1D vector

plot_maps(gdoccsm,prism,"Map95_03") # first two inputs should be 2D matrix (not vector)

#####95_04 gPrism and GDO ccsmm#####
prism=[]
gdoccsm=[]
prismm=[]
gdoccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_04.asc")
gdoccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_04.asc")

prism[mask_panel== -9999]=np.nan
gdoccsm[mask_panel== -9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdoccsmm=gdoccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdoccsmm=gdoccsmm[np.isnan(prismm)==False]

SPAef95_04, cc, alpha, hh = SPAEF(gdoccsmm,prismm,100)
print ("SPAEF_95_04",SPAef95_04)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdoccsmm,prismm,SPAef95_04, cc, alpha, hh,"95_04") # first two inputs
should be 1D vector

plot_maps(gdoccsm,prism,"Map95_04") # first two inputs should be 2D matrix (not vector)

#####95_05 gPrism and GDO ccsmm#####
prism=[]
gdoccsm=[]
prismm=[]

```

```

gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_05.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_05.asc")

prism[mask_panel== -9999]=np.nan
gdccsm[mask_panel== -9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_05, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAef95_05",SPAef95_05)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_05, cc, alpha, hh,"95_05") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_05") # first two inputs should be 2D matrix (not vector)

#####95_06 gPrism and GDO ccs#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_06.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_06.asc")

prism[mask_panel== -9999]=np.nan
gdccsm[mask_panel== -9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

```

```

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_06, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAEF_95_06",SPAef95_06)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_06, cc, alpha, hh,"95_06") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_06") # first two inputs should be 2D matrix (not vector)

#####95_07 gPrism and GDO ccsm#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_07.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_07.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_07, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAEF_95_07",SPAef95_07)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_07, cc, alpha, hh,"95_07") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_07") # first two inputs should be 2D matrix (not vector)

```

```
#####95_08 gPrism and GDO ccsm#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_08.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_08.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_08, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAEF_95_08",SPAef95_08)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_08, cc, alpha, hh,"95_08") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_08") # first two inputs should be 2D matrix (not vector)

#####95_09 gPrism and GDO ccsm#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_09.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_09.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan
```

```

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_09, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAef95_09",SPAef95_09)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_09, cc, alpha, hh,"95_09") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_09") # first two inputs should be 2D matrix (not vector)

#####95_10 gPrism and GDO ccs#####
prism=[]
gdccsm=[]
prismm=[]
gdccsmm=[]

prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAef\\SPAef_GDOPrism_full80\\map_files\\g
prs_95_10.asc")
gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAef\\SPAef_GDOPrism_full80\\map_file
s\\ccsm_95_10.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_10, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAef95_10",SPAef95_10)
#####
PLOT  MAPS and STATS

```

```
plot_SPAEFstats(gdoccsmm,prismm,SPAef95_10, cc, alpha, hh,"95_10") # first two inputs
should be 1D vector
```

```
plot_maps(gdoccsm,prism,"Map95_10") # first two inputs should be 2D matrix (not vector)
```

```
#####95_11 gPrism and GDO ccsm#####
```

```
prism=[]
gdoccsm=[]
prismm=[]
gdoccsmm=[]
```

```
prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_11.asc")
gdoccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_file
s\\ccsm_95_11.asc")
```

```
prism[mask_panel==-9999]=np.nan
gdoccsm[mask_panel==-9999]=np.nan
```

```
notnan=np.argwhere(np.isnan(prism)==False)
```

```
prismm=prism[notnan[:,0],notnan[:,1]]
gdoccsmm=gdoccsm[notnan[:,0],notnan[:,1]]
```

```
prismm=prismm[np.isnan(prismm)==False]
gdoccsmm=gdoccsmm[np.isnan(prismm)==False]
```

```
SPAef95_11, cc, alpha, hh = SPAEF(gdoccsmm,prismm,100)
print ("SPAef95_11",SPAef95_11)
```

```
#####
PLOT  MAPS and STATS
```

```
plot_SPAEFstats(gdoccsmm,prismm,SPAef95_11, cc, alpha, hh,"95_11") # first two inputs
should be 1D vector
```

```
plot_maps(gdoccsm,prism,"Map95_11") # first two inputs should be 2D matrix (not vector)
```

```
#####95_12 gPrism and GDO ccsm#####
```

```
prism=[]
gdoccsm=[]
prismm=[]
gdoccsmm=[]
```

```
prism=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\g
prs_95_12.asc")
```

```

gdccsm=np.loadtxt("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\map_files\\ccsm_95_12.asc")

prism[mask_panel==-9999]=np.nan
gdccsm[mask_panel==-9999]=np.nan

notnan=np.argwhere(np.isnan(prism)==False)

prismm=prism[notnan[:,0],notnan[:,1]]
gdccsmm=gdccsm[notnan[:,0],notnan[:,1]]

prismm=prismm[np.isnan(prismm)==False]
gdccsmm=gdccsmm[np.isnan(prismm)==False]

SPAef95_12, cc, alpha, hh = SPAEF(gdccsmm,prismm,100)
print ("SPAef95_12",SPAef95_12)
#####
PLOT  MAPS and STATS

plot_SPAEFstats(gdccsmm,prismm,SPAef95_12, cc, alpha, hh,"95_12") # first two inputs
should be 1D vector

plot_maps(gdccsm,prism,"Map95_12") # first two inputs should be 2D matrix (not vector)

#####Summarize Results#####
val=np.array(['ID','SPAEF'],[ '95_01',np.around(SPAef95_01,7)],['95_02',np.around(SPAef95_02,7)],['95_03',np.around(SPAef95_03,7)],['95_04',np.around(SPAef95_04,7)],['95_05',np.around(SPAef95_05,7)],['95_06',np.around(SPAef95_06,7)],['95_07',np.around(SPAef95_07,7)],['95_08',np.around(SPAef95_08,7)],['95_09',np.around(SPAef95_09,7)],['95_10',np.around(SPAef95_10,7)],['95_11',np.around(SPAef95_11,7)],['95_12',np.around(SPAef95_12,7)]])

csvfile = "SPAEF_95_results.out"

#Assuming res is a flat list
with open("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\results\\"+csvfile,
"w") as output:
    writer = csv.writer(output,delimiter = ' ', lineterminator='\n')
    for val in val:
        writer.writerow(val)

###
output.close()
#####
#####

```

SPAEF Result Visualization Code

Figure Code- Multidimensional Plot

```
#####
#####Created and modified by Laura J. Krueger, last edited February 8, 2021#####
###referenced and sourced partially from:
https://github.com/ostwalprasad/PythonMultiDimensionalPlots &
https://medium.com/@prasadostwal/multi-dimension-plots-in-python-from-2d-to-6d-
9a2bf7b8cc74 #####
#####
import pandas as pd
import plotly
import plotly.graph_objs as go
import sys, csv

sys.path.append("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_re
sults\\Result_figures")

#Read data from csv
data=pd.read_csv("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_r
esults\\Result_figures\\GDOccsm-gPrism_full_SPAEF3.csv")

#Set marker properties
markercolor = data['SPAEF']
markershape = data['Season'].replace("summer","cross").replace("fall","circle-
open").replace("winter","square-open").replace("spring","diamond-
open").replace("optimal","circle")

#Make Plotly figure
fig1 = go.Scatter3d(x=data['Corr'],
                    y=data['Histo Match'],
                    z=data['CV'],
                    marker=dict(color=markercolor,
                                symbol=markershape,
                                opacity=1,
                                reversescale=True,
                                colorscale='agsunset',
                                size=5,colorbar=dict(title='SPAEF',thickness=20)),
                    line=dict (width=0.02),
                    mode='markers')

#Make Plot.ly Layout
mylayout = go.Layout(scene=dict(xaxis=dict( title="Corr"),
                                       yaxis=dict( title="Histo Match"),
                                       zaxis=dict(title="CV")),)
```

```
#Plot and save html
plotly.offline.plot({"data": [fig1],
                    "layout": mylayout},
                    auto_open=True,

filename=("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\
Result_figures\\output\\GDOccsm-gPrs_full_3.html"))
#####
```

Figure Code- SPAEF line plots

```
#####
#####Created and modified by Laura J. Krueger, last edited April 13, 2021 #####
####referenced and sourced partially from:
https://towardsdatascience.com/getting-started-with-plot-ly-
3c73706a837c#:~:text=Plotly%20is%20a%20platform%20that,or%20%24%20sudo%20pip%20i
nstall%20plotly%20.####
#####
import pandas as pd
import plotly
import plotly.graph_objs as go
import plotly.io as pio
import sys,csv

sys.path.append("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_re
sults\\Result_figures")

#Read data from csv
data=pd.read_csv("L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_r
esults\\Result_figures\\3GDOSPAEF_full_compare.csv")

#####Line Plot#####
#####SPAEF by GDO Model and Month from 1981-2005#####
trace1 = go.Scatter(
    x = data['ID'],
    y = data['SPAEF_ccsm'],
    mode = "lines",
    name = "SPAEF_ccsm",
    marker = dict(color = 'rgb(44,127,184)'),
    line = dict(dash = 'solid'))

trace2 = go.Scatter(
    x = data['ID'],
    y = data['SPAEF_mri'],
    mode = "lines",
    name = "SPAEF_mri",
    marker = dict(color = 'rgb(44,127,184)'),
    line = dict(dash = 'dot'))
```

```

trace3 = go.Scatter(
    x = data['ID'],
    y = data['SPAEF_nor'],
    mode = "lines",
    name = "SPAEF_nor",
    marker = dict(color = 'rgb(44,127,184)'),
    line = dict(dash = 'dash'))

data2 = [trace1, trace2, trace3]

mylayout = go.Layout(title = 'SPAEF by GDO Model and Month from 1981-2005',
    xaxis= dict(title= 'Year-Month',tickmode='auto', nticks= 50, ticklen= 5,zeroline=
False,linewidth='rgb(255,255,255)'),
    yaxis= dict(title= 'SPAEF',ticklen= 5,zeroline= True, zerolinewidth=1,
zerolinecolor='rgb(0,0,0)',linewidth='rgb(0,0,0)', showgrid=True, gridwidth=1,
gridcolor='rgb(0,0,0)', range=[-10,1]),
    paper_bgcolor='rgb(255,255,255)', plot_bgcolor='rgb(255,255,255)'
)
fig = go.Figure(data = data2, layout = mylayout)

fig.show()
##plot interactive line plot in html format##
pio.write_html(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_SPAEFGDO_full_4.html", auto_open=True)

##plot static line plot in png format##
pio.write_image(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_SPAEFGDO_full_4.png",format="png")
#####Line Plot#####
#####Corr by GDO Model and Month from 1981-2005#####
trace1 = go.Scatter(
    x = data['ID'],
    y = data['Corr_ccsm'],
    mode = "lines",
    name = "Corr_ccsm",
    marker = dict(color = 'rgb(37,52,148)'),
    line = dict(dash = 'solid'))

trace2 = go.Scatter(
    x = data['ID'],
    y = data['Corr_mri'],
    mode = "lines",
    name = "Corr_mri",
    marker = dict(color = 'rgb(37,52,148)'),
    line = dict(dash = 'dot'))

```

```

trace3 = go.Scatter(
    x = data['ID'],
    y = data['Corr_nor'],
    mode = "lines",
    name = "Corr_nor",
    marker = dict(color = 'rgb(37,52,148)'),
    line = dict(dash = 'dash'))

data2 = [trace1, trace2, trace3]

mylayout = go.Layout(title = 'Correlation by GDO Model and Month from 1981-2005',
    xaxis= dict(title= 'Year-Month', tickmode='auto', nticks= 50, ticklen= 5,zeroline=
False,linewidth='rgb(255,255,255)'),
    yaxis= dict(title= 'Corr',ticklen= 5,zeroline= True, zerolinewidth=1,
zerolinecolor='rgb(0,0,0)',linewidth='rgb(0,0,0)', showgrid=True, gridwidth=1,
gridcolor='rgb(0,0,0)', range=[-1,1]),
    paper_bgcolor='rgb(255,255,255)', plot_bgcolor='rgb(255,255,255)'
)
fig = go.Figure(data = data2, layout = mylayout)

##fig.show()

##plot interactive line plot in html format##
pio.write_html(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_CorrGDO_full_4.html", auto_open=True)

##plot static line plot in png format##
pio.write_image(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_CorrGDO_full_4.png",format="png")
#####Line Plot#####
#####CV by GDO Model and Month from 1981-2005#####
trace1 = go.Scatter(
    x = data['ID'],
    y = data['CV_ccsm'],
    mode = "lines",
    name = "CV_ccsm",
    marker = dict(color = 'rgb(65,182,196)'),
    line = dict(dash = 'solid'))

trace2 = go.Scatter(
    x = data['ID'],
    y = data['CV_mri'],
    mode = "lines",
    name = "CV_mri",
    marker = dict(color = 'rgb(65,182,196)'),

```

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        line = dict(dash = 'dot'))
trace3 = go.Scatter(
    x = data['ID'],
    y = data['CV_nor'],
    mode = "lines",
    name = "CV_nor",
    marker = dict(color = 'rgb(65,182,196)'),
    line = dict(dash = 'dash'))

data2 = [trace1, trace2, trace3]

mylayout = go.Layout(title = 'CV Ratio by GDO Model and Month from 1981-2005',
    xaxis= dict(title= 'Year-Month', tickmode='auto', nticks= 50, ticklen= 5,zeroline=
False,linecolor='rgb(255,255,255)'),
    yaxis= dict(title= 'CV',ticklen= 5,zeroline= True, zerolinewidth=1,
zerolinecolor='rgb(0,0,0)',linecolor='rgb(0,0,0)', showgrid=True, gridwidth=1,
gridcolor='rgb(0,0,0)', range=[0,10]),
    paper_bgcolor='rgb(255,255,255)', plot_bgcolor='rgb(255,255,255)'
)
fig = go.Figure(data = data2, layout = mylayout)

##fig.show()

##plot interactive line plot in html format##
pio.write_html(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_CVGDO_full_4.html", auto_open=True)

##plot static line plot in png format##
pio.write_image(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_CVGDO_full_4.png",format="png")
#####Line Plot#####
#####Histo Match by GDO Model and Month from 1981-2005#####
trace1 = go.Scatter(
    x = data['ID'],
    y = data['Histo_ccsm'],
    mode = "lines",
    name = "Histo_ccsm",
    marker = dict(color = 'rgb(120,198,121)'),
    line = dict(dash = 'solid'))
trace2 = go.Scatter(
    x = data['ID'],
    y = data['Histo_mri'],
    mode = "lines",
    name = "Histo_mri",

```

```

        marker = dict(color = 'rgb(120,198,121)'),
                    line = dict(dash = 'dot'))
trace3 = go.Scatter(
    x = data['ID'],
    y = data['Histo_nor'],
    mode = "lines",
    name = "Histo_nor",
    marker = dict(color = 'rgb(120,198,121)'),
    line = dict(dash = 'dash'))

data2 = [trace1, trace2, trace3]

mylayout = go.Layout(title = 'Histo Match by GDO Model and Month from 1981-2005',
    xaxis= dict(title= 'Year-Month', tickmode='auto', nticks= 50, ticklen= 5,zeroline=
False,linecolor='rgb(255,255,255)'),
    yaxis= dict(title= 'Histo Match',ticklen= 5,zeroline= True, zerolinewidth=1,
zerolinecolor='rgb(0,0,0)',linecolor='rgb(0,0,0)', showgrid=True, gridwidth=1,
gridcolor='rgb(0,0,0)', range=[0,1]),
    paper_bgcolor='rgb(255,255,255)', plot_bgcolor='rgb(255,255,255)'
)
fig = go.Figure(data = data2, layout = mylayout)

##fig.show()

##plot interactive line plot in html format##
pio.write_html(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_HistoGDO_full_4.html", auto_open=True)

##plot static line plot in png format##
pio.write_image(fig,
file="L:\\WaterQuality\\Krueger\\SPAEF\\SPAEF_GDOPrism_full80\\Compiled_results\\Result
_figures\\output\\lineplot_scatter2d\\line_HistoGDO_full_4.png",format="png")
#####

```