Evaluating the Performance of Gridded Rainfall Datasets for the Des Moines River Basin

Presented by

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Final Project – CE 5900

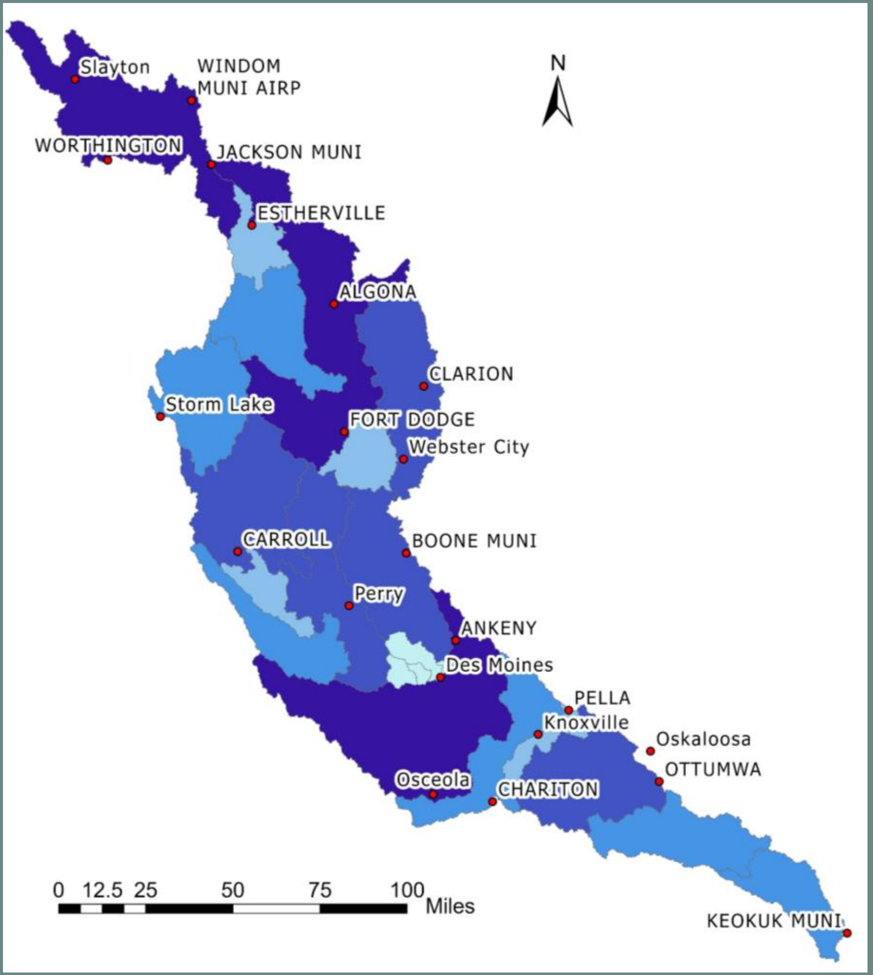
AI4CCEE

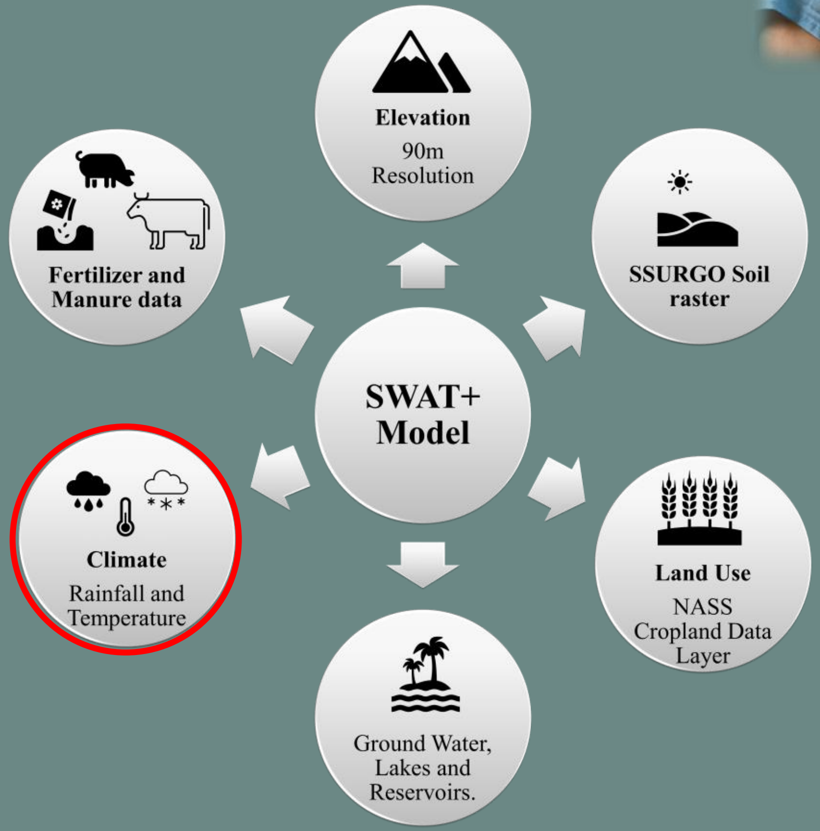
Flow of the presentation

1. Background
2. Need for the study
3. Methodology
4. Results
5. Conclusions
6. Future Work

Background

My thesis: Eco-hydrologic modeling of nutrient dynamics for sustainable drinking water protection in the Des Moines River basin.

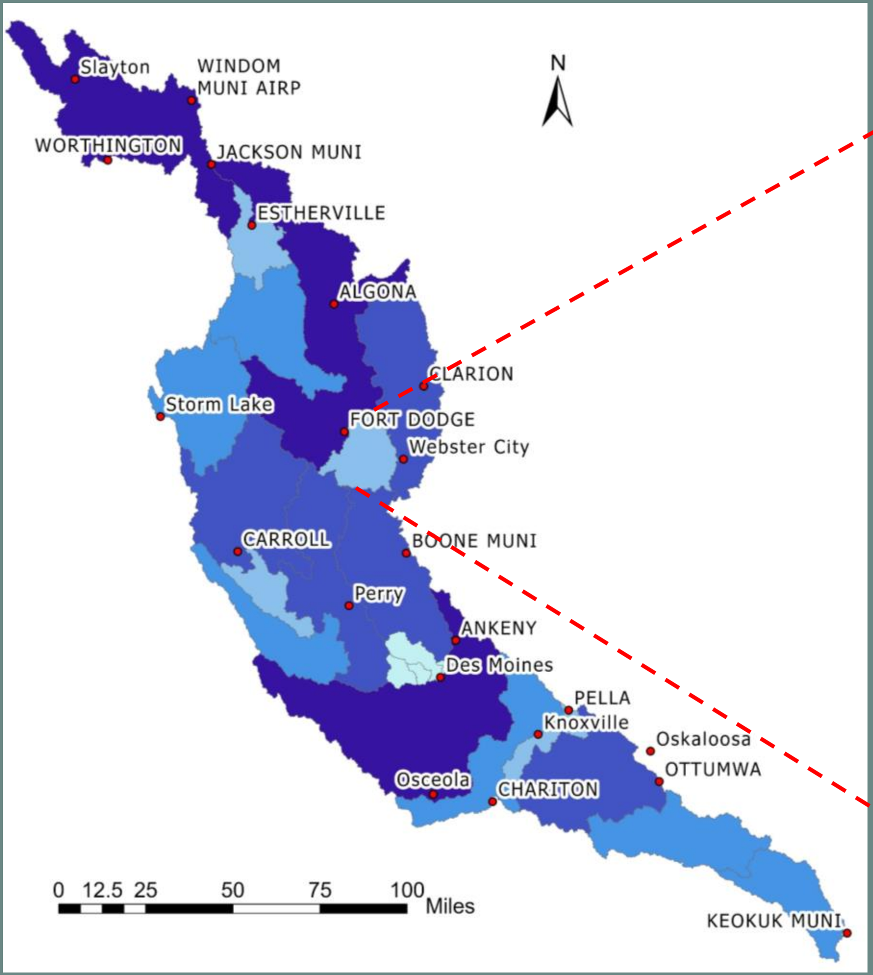


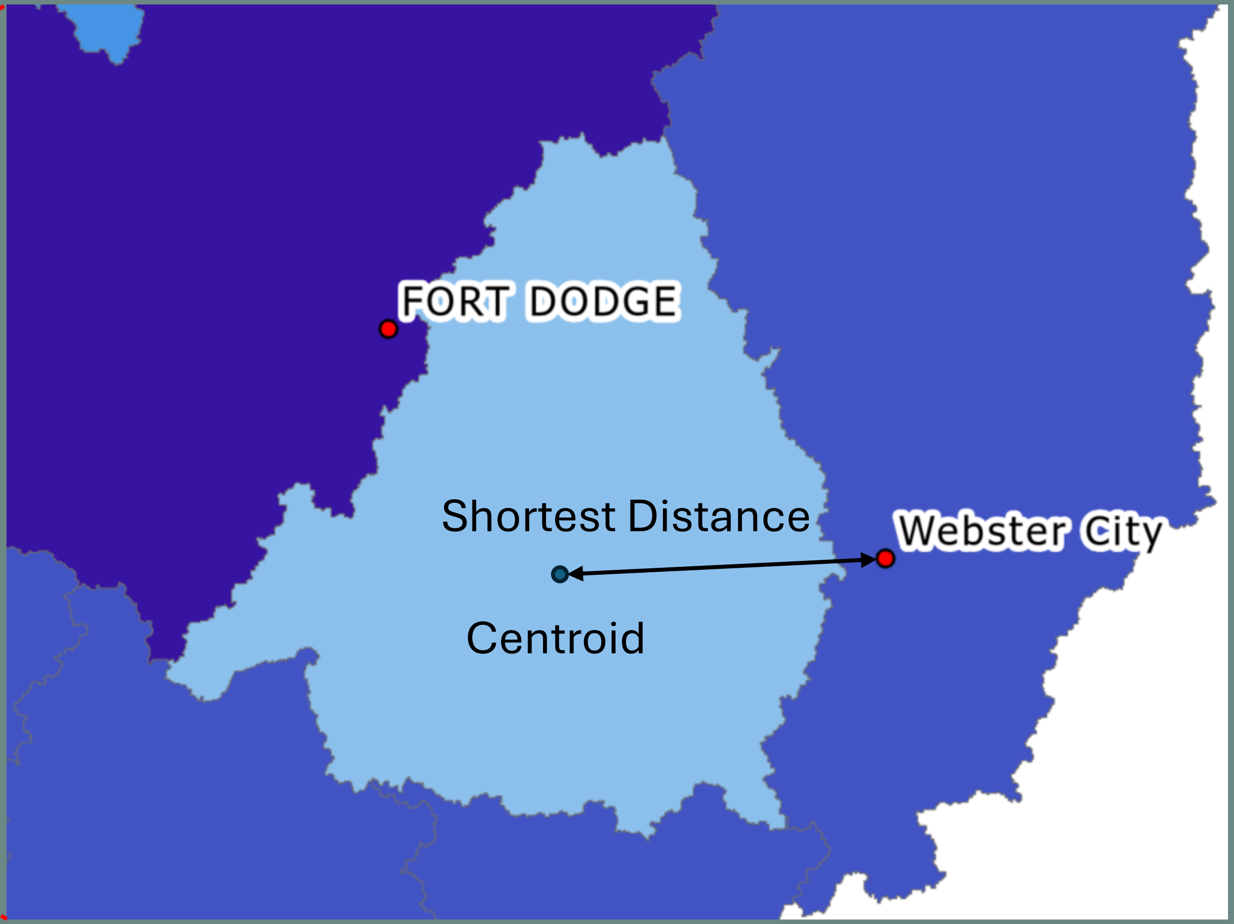


- Nutrient dynamics sensitive to rainfall.

Need for the study?

- Lack of consistently available field-observed data for the required time period.
- Trouble with SWAT+ rain gauge consideration.





Methodology

Extract gridded rainfall data → **Extract observed rainfall data** → **Perform data analysis**

Methodology

Extract gridded rainfall data

Extract observed rainfall data

Perform data analysis

Dataset:

- Earth Engine Data Catalog

Method:

- Google Earth Engine scripting with JavaScript

TermPaper_Myscript | Get Link | Save | Run | Reset | Apps

```
/**** Start of imports. If edited, may not auto-convert in the playground. ****/
var stanice_full = ee.FeatureCollection("projects/ee-revanthm81011/assets/StudyArea_RainGauges");
/***** End of imports. If edited, may not auto-convert in the playground. *****/
/*
###########################################################################################
Author: Revanth Mamidala
Inspired from the script of Daniel Paluba Daily_aggregates_GEE (palubad@natur.cuni.cz).
(contact: mrevanth@iastate.edu)
###########################################################################################
*/

// Set start and end dates
var startDate = '2016-01-01'; //'2006-01-01'
var endDate = '2024-11-01'; // '2016-01-01'

// Load the datasets
var ERA5_Land = ee.ImageCollection("ECMWF/ERA5_LAND/HOURLY").select('total_precipitation_hourly')
              .filterDate(startDate, endDate);

var CHIRPS = ee.ImageCollection("UCSB-CHG/CHIRPS/DAILY").select('precipitation')
              .filterDate(startDate, endDate);

var PERSIANN = ee.ImageCollection('NOAA/PERSIANN-CDR').select('precipitation')
              .filterDate(startDate, endDate);

var GPM = ee.ImageCollection('NASA/GPM_L3/IMERG_V07').select('precipitation')
              .filterDate(startDate, endDate);

var GSMAP = ee.ImageCollection('JAXA/GPM_L3/GSMaP/v8/operational')
              .filterDate(startDate, endDate).select('hourlyPrecipRate');

var GLDAS = ee.ImageCollection('NASA/GLDAS/V021/NOAH/G025/T3H')
              .filterDate(startDate, endDate).select('Rainf_f_tavg');
```

Methodology

Extract gridded rainfall data

↓

Extract observed rainfall data

↓

Perform data analysis

Dataset: Iowa Environmental Mesonet by ISU

(https://mesonet.agron.iastate.edu/request/daily.phtml)

Method: Data scraping using python script.

```python
# Base URL for scraping
base_url = "https://mesonet.agron.iastate.edu/cgi-bin/request/daily.py"

# Function to scrape and save data
def scrape_and_save(network, station_id):
    # Construct the query URL
    params = {
        "network": network,
        "stations": station_id,
        "year1": "2005",
        "month1": "9",
        "day1": "1",
        "year2": "2024",
        "month2": "9",
        "day2": "31",
        "var": ["max_temp_f", "min_temp_f", "precip_in", "avg_wind_speed_kts", "avg_rh", "srad_mj"],
        "na": "blank",
        "format": "csv"
    }

    # Request data
    response = requests.get(base_url, params=params)

    # Check if the request is successful
    if response.status_code == 200:
        # Save the data to a CSV file
        file_name = f"{network}_{station_id}.csv"
        file_path = os.path.join(output_folder, file_name)
        with open(file_path, "w") as file:
            file.write(response.text)
        print(f"Data for {network} {station_id} saved to {file_path}")
    else:
        print(f"Failed to fetch data for {network} {station_id}")
```

Methodology

Extract gridded rainfall data

↓

Extract observed rainfall data

↓

Perform data analysis

5. Perform Metrics Calculation

```python
# Perform metrics calculation for each station and gridded dataset
results = {}

# Loop through each gridded dataset
for name, df in dataframes.items():
    if name == "Observed":
        continue  # Skip the observed dataset

    station_metrics = {}
    for station in dataframes["Observed"].columns[1:]:  # Skip the 'Date' column
        if station in df.columns:
            # Merge observed and simulated on the 'Date' column
            merged = pd.merge(
                dataframes["Observed"][["Date", station]].dropna(),
                df[["Date", station]].dropna(),
                on="Date",
                suffixes=("_obs", "_sim")
            )
            if not merged.empty:
                observed = merged[f"{station}_obs"]
                simulated = merged[f"{station}_sim"]
                # Calculate metrics
                station_metrics[station] = calculate_metrics(observed, simulated)
    results[name] = station_metrics
```

Metrics: R^2, RMSE. MAE, rBias

Results

Observed Rain gauge data:

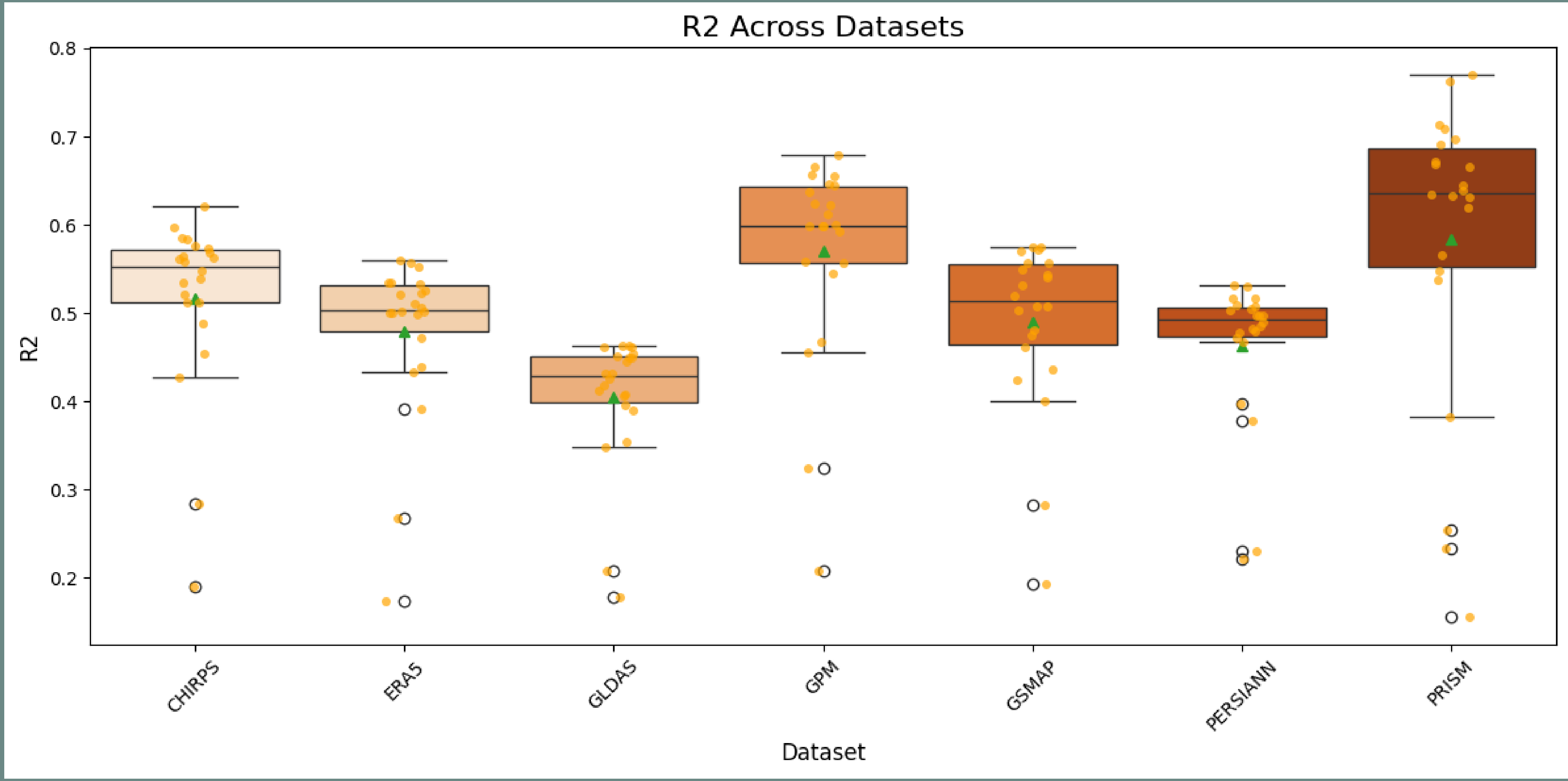
- **22** Rain gauge stations in and around the study area were selected for rainfall data between **2005-2024**.

Gridded Rain fall data:

- **7** datasets were considered in the study which were observed from Paluba et al. (2024), Rincón et al. (2022) and Banerjee et al. (2020).

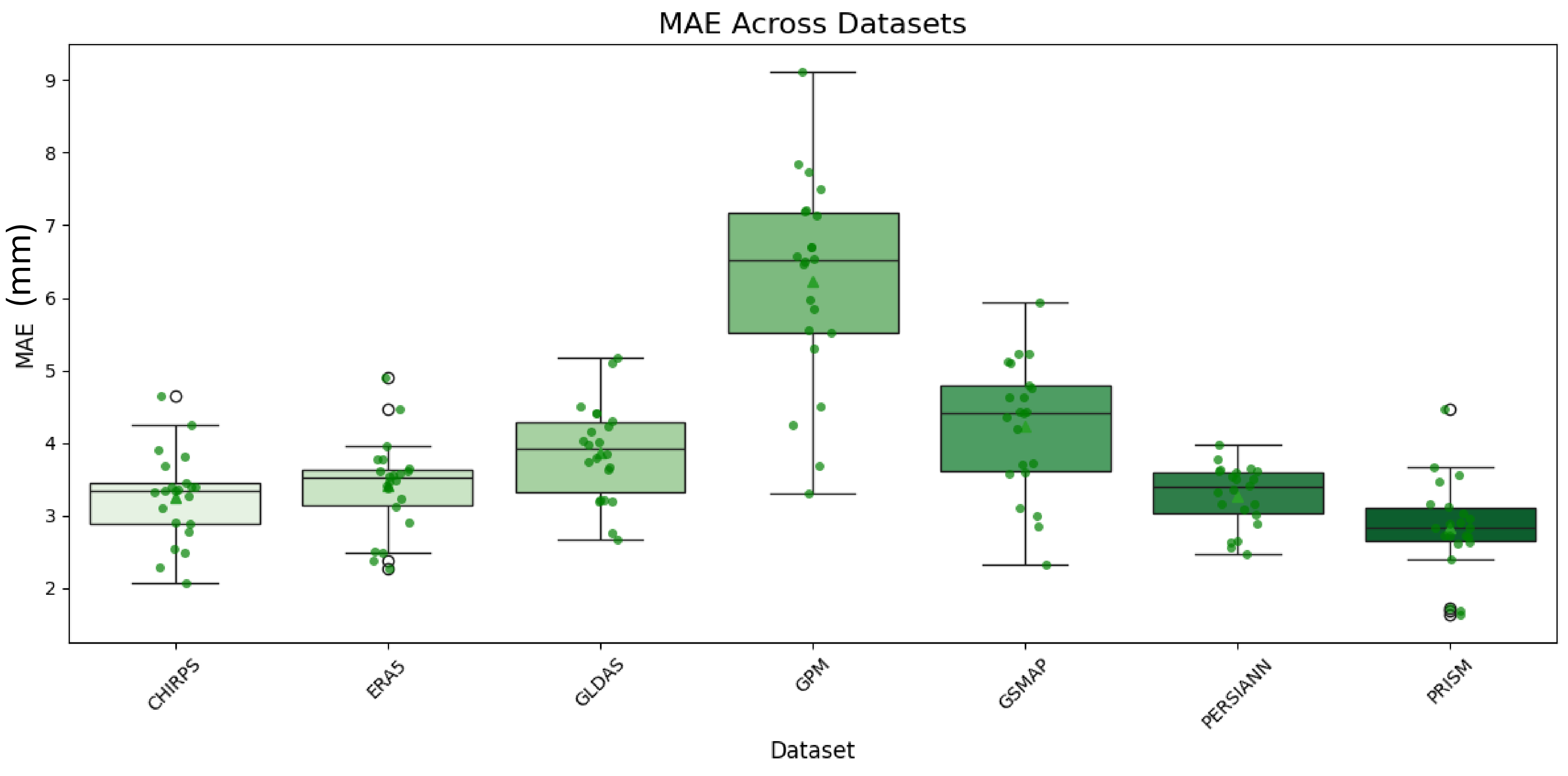
Dataset	Temporal resolution	Spatial Resolution	Availability period
CHIRPS	Daily	~0.05 deg (5.5km)	1981 – present
ERA5	Daily	~0.25 deg (31km)	1979 – present
GSMAP	Hourly	~0.1 deg (11km)	2000 – present
GPM	Hourly	~0.1 deg (11km)	2014 – present
PERSIANN	Daily	~0.25 deg (31km)	1983 – 2020
PRISM	Daily	~4km	1981 – present

Results



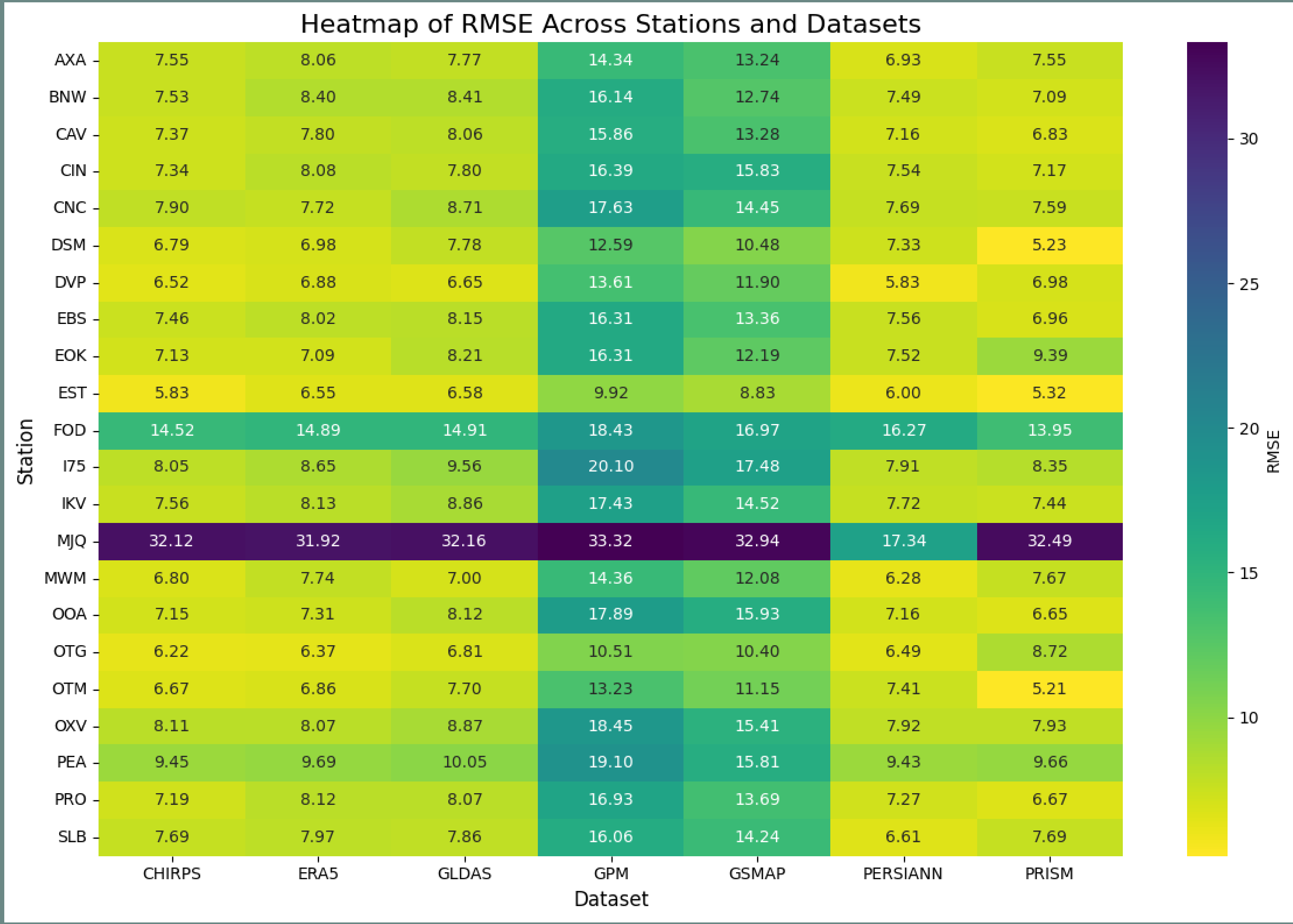
- PRISM Dataset has higher R^2 values when compared to other datasets.

Results



- GPM has highest mean absolute error in comparison with other datasets.

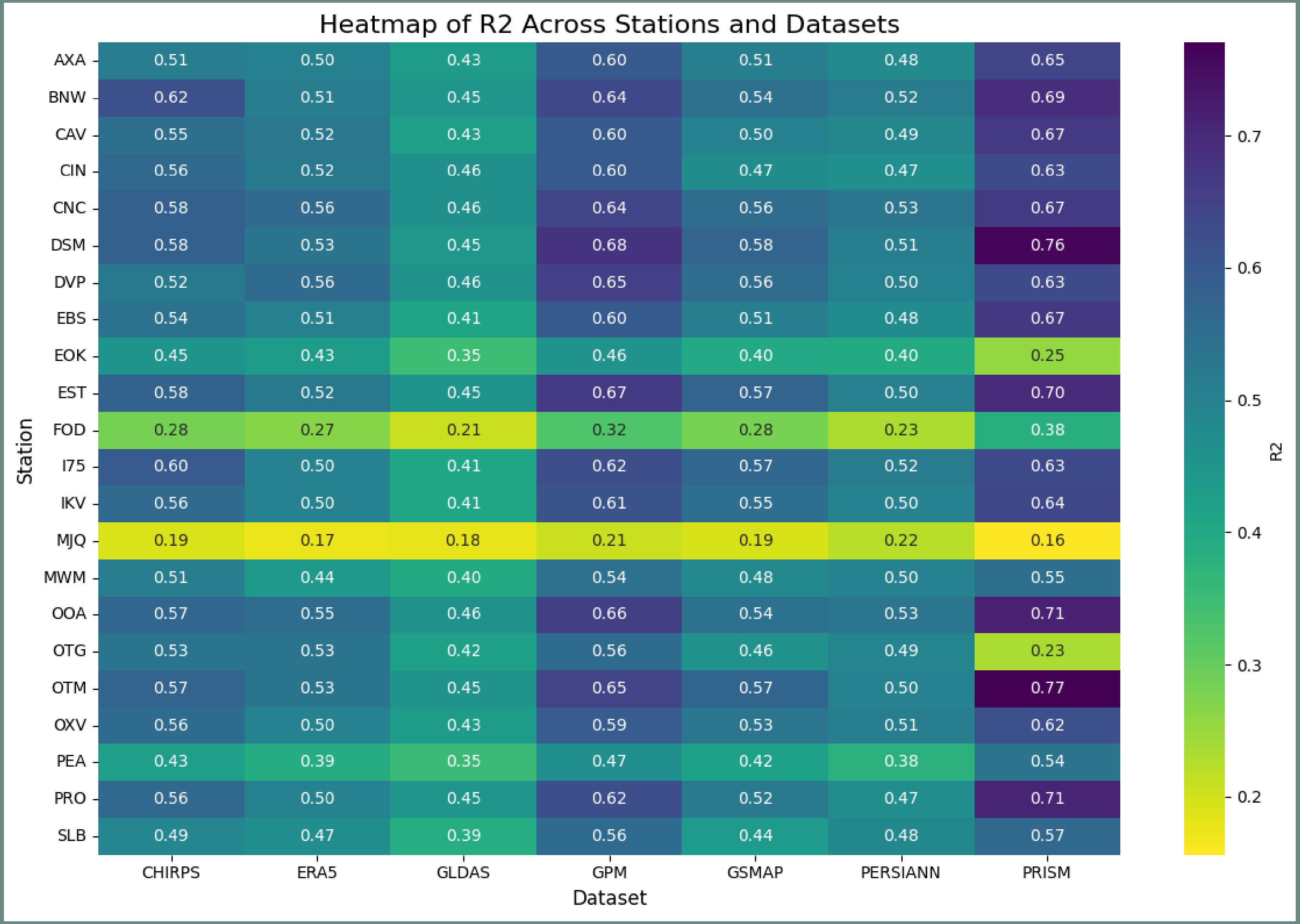
Results



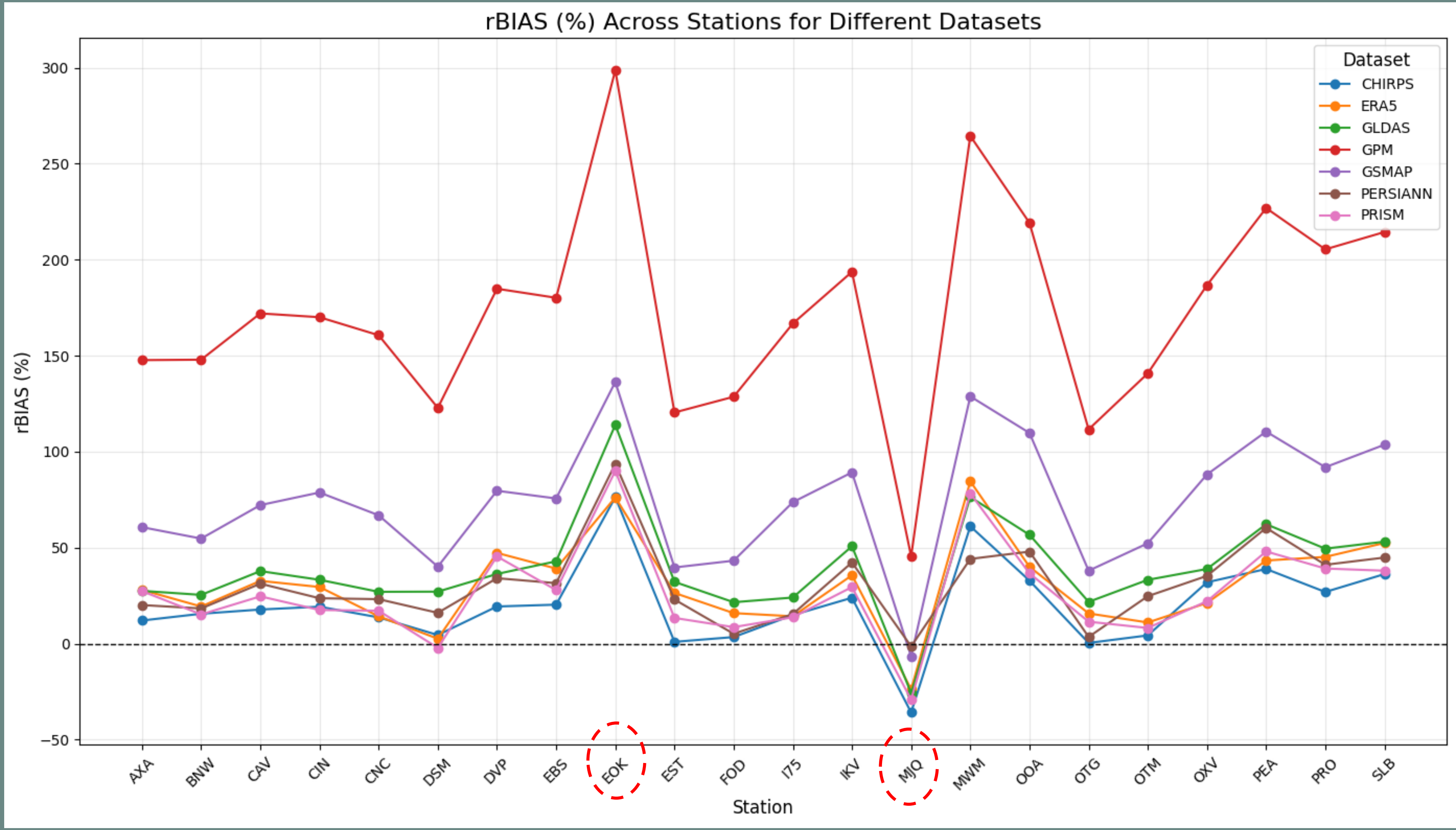
- Datasets **GPM** and **GSMAP** are not performing well.
- Rain gauge stations **FOD** and **MJQ** are major outliers in the study area.

Results

- R^2 heatmap reveals three rain gauge stations **FOD, EOK** and **MJQ** are major outliers in the study area.

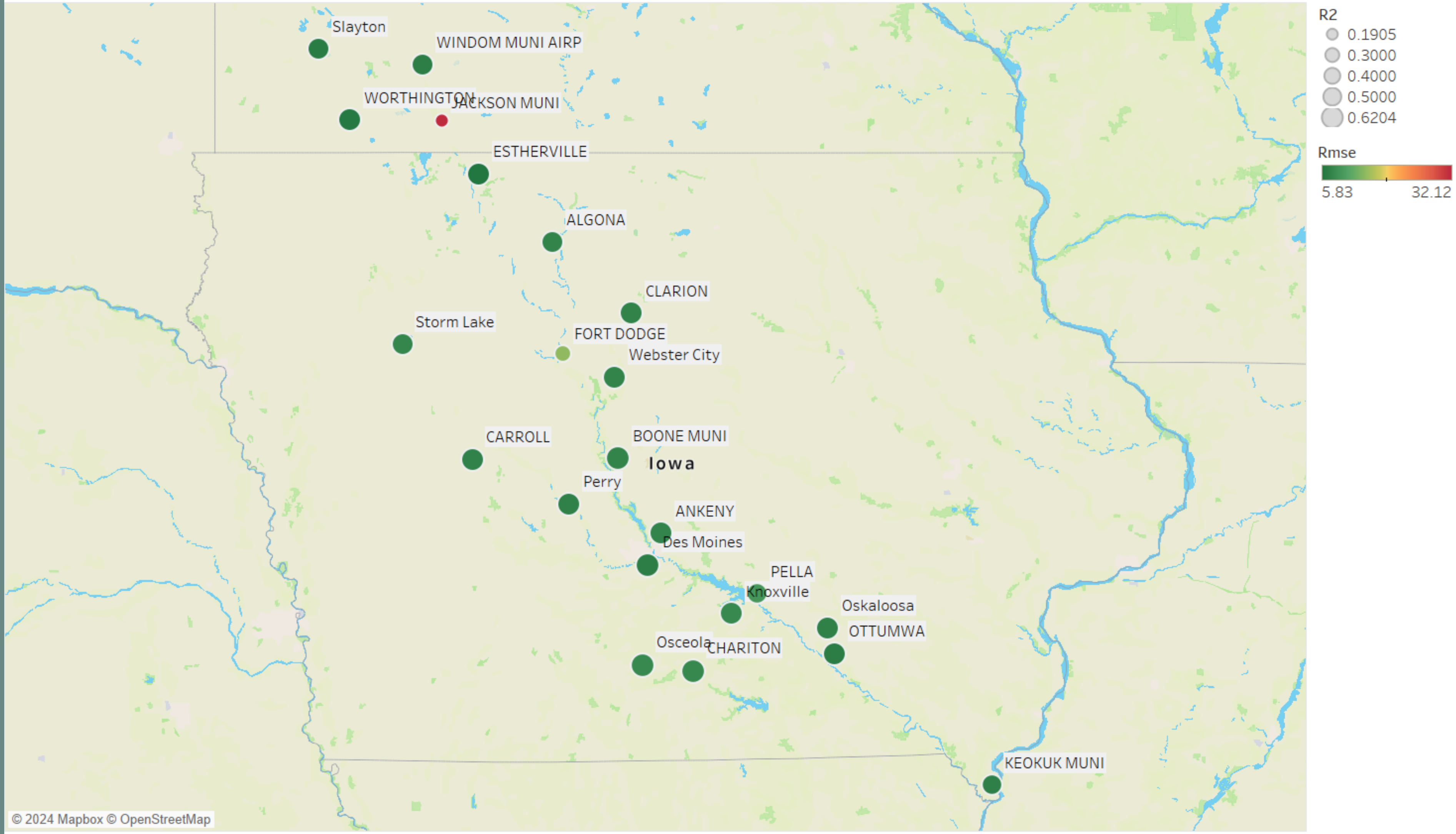


Results


rBIAS (%) Across Stations for Different Datasets
rBIAS (%)
300
250
200
150
100
50
0
−50
Station
AXA
BNW
CAV
CIN
CNC
DSM
DVP
EBS
EOK
EST
FOD
I75
IKV
MJQ
MWM
OOA
OTG
OTM
OXV
PEA
PRO
SLB
Dataset
CHIRPS
ERA5
GLDAS
GPM
GSMAP
PERSIANN
PRISM

Results

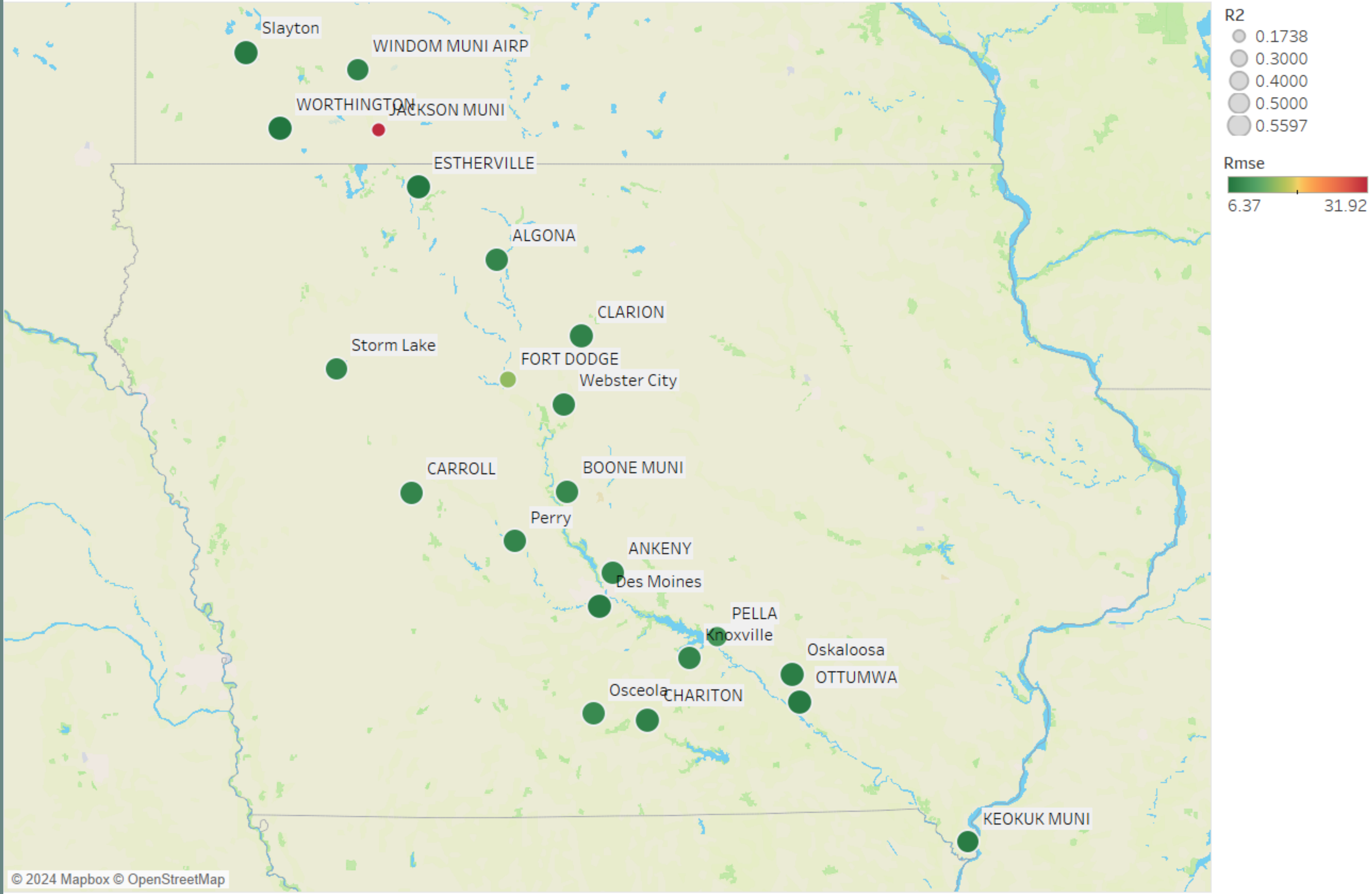
CHIRPS (Size by R2 and Color by RMSE)



Map based on Longitude and Latitude. Color shows Rmse as an attribute. Size shows details about R2. The marks are labeled by Name. The data is filtered on Dataset, which keeps CHIRPS.

Results

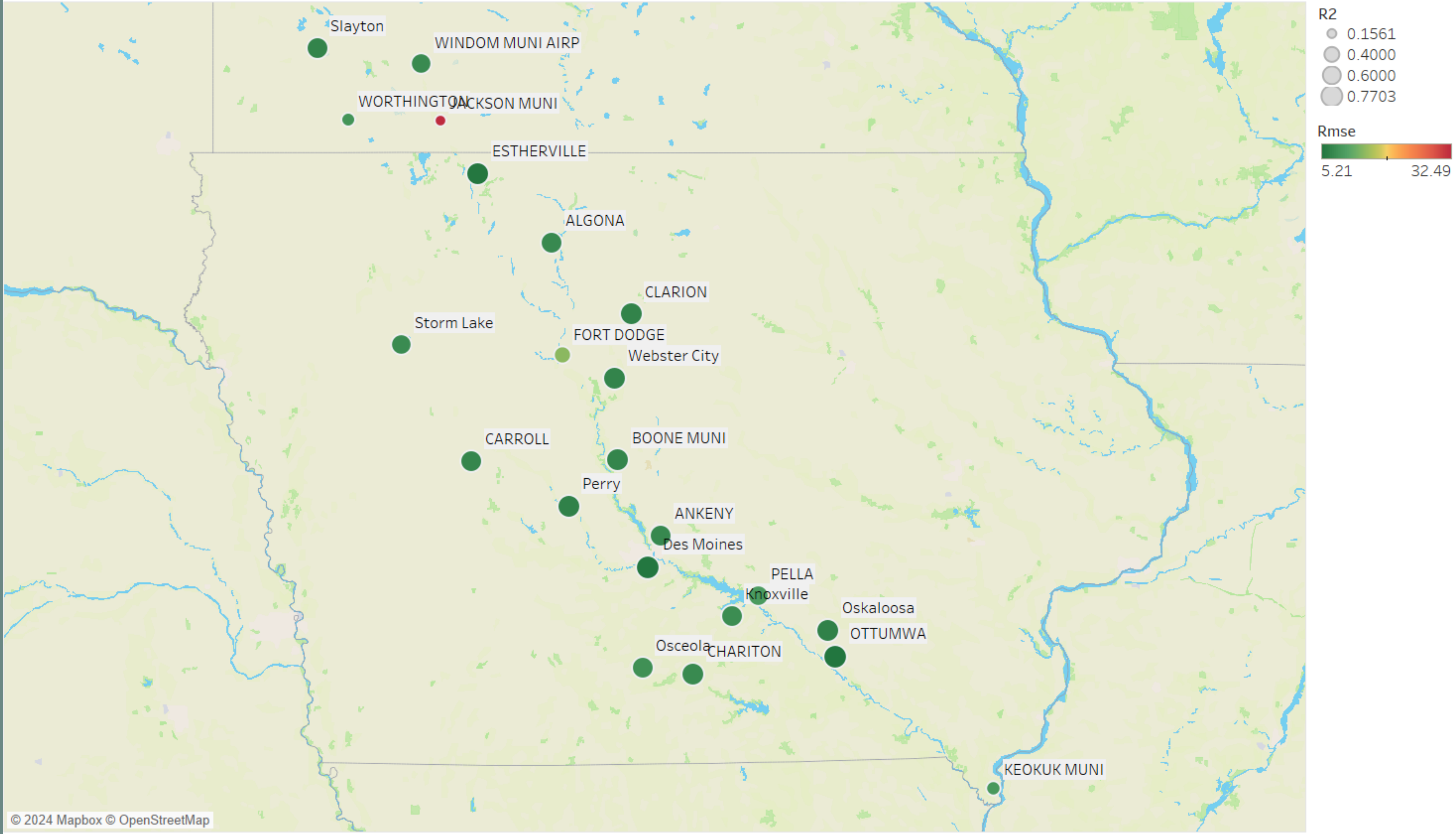
ERA5 (Size by R2 and Color by RMSE)



Map based on Longitude and Latitude. Color shows Rmse as an attribute. Size shows details about R2. The marks are labeled by Name. The data is filtered on Dataset, which keeps ERA5.

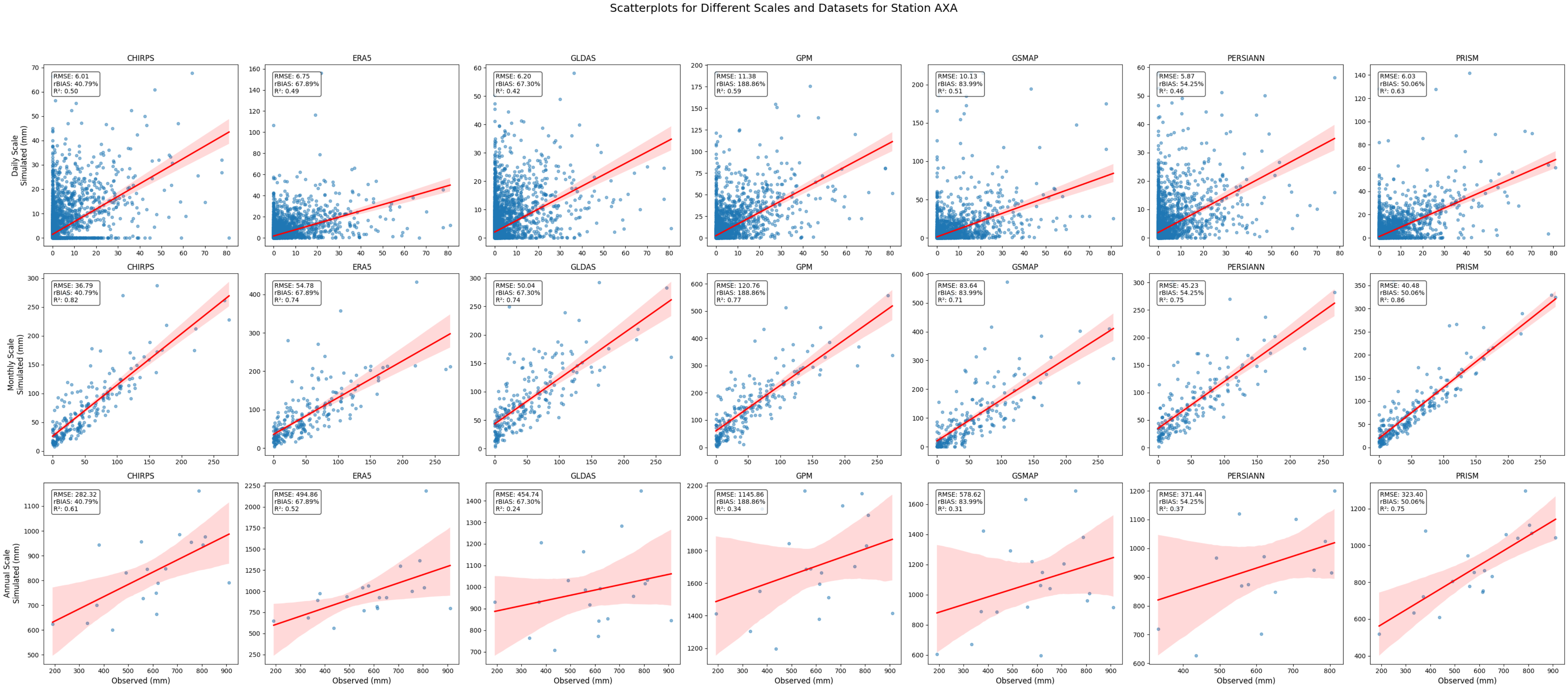
Results

PRISM (Size by R2 and Color by RMSE)



Map based on Longitude and Latitude. Color shows Rmse as an attribute. Size shows details about R2. The marks are labeled by Name. The data is filtered on Dataset, which keeps PRISM.

Results



Scatter plots to estimate the performance metrics at daily, monthly and annual scales.

Conclusions

Rain gauges:

- MJQ, EOK and FOD stations are stations with least correlation.

Gridded Rain fall data:

- GPM and GSMAP are observed to be poorly performing.
- PRISM and CHIRPS are relatively better representative gridded rainfall data.
- Finally, PRISM dataset is chosen as the most suitable source.

Outcomes

The methodology and the scripts developed in the study are scalable and applicable to other watersheds or states/counties.

Future Work

- The PRISM rainfall dataset is used to extract climate data
- The extracted data can be given as input into SWAT+ model.

References

- Paluba, D., Bližňák, V., Müller, M., & Štych, P. (2024). EVALUATION OF PRECIPITATION DATASETS AVAILABLE IN GOOGLE EARTH ENGINE ON A DAILY BASIS FOR CZECHIA.
- Rincón-Avalos, P., Khouakhi, A., Mendoza-Cano, O., Cruz, J. L. D. L., & Paredes-Bonilla, K. M. (2022). Evaluation of satellite precipitation products over Mexico using Google Earth Engine. Journal of Hydroinformatics, 24(4), 711-729.
- Banerjee, A., Chen, R., E. Meadows, M., Singh, R. B., Mal, S., & Sengupta, D. (2020). An analysis of long-term rainfall trends and variability in the uttarakhand himalaya using google earth engine. Remote Sensing, 12(4), 709.
- Fooladi, M., Golmohammadi, M. H., Rahimi, I., Safavi, H. R., & Nikoo, M. R. (2023). Assessing the changeability of precipitation patterns using multiple remote sensing data and an efficient uncertainty method over different climate regions of Iran. Expert Systems with Applications, 221, 119788.

Thank you!!

Any questions?

Dataset Abbreviations

- **ERA5**: ECMWF Climate Reanalysis
- **GLDAS**: Global Land Data Assimilation System
- IMERG V06 product from the **GPM**: Global Precipitation Measurement
- **GSMaP**: Global Satellite Mapping of Precipitation
- **CHIRPS**: Daily Climate Hazards Group InfraRed Precipitation With Station Data
- **PERSIANN**-CDR: Precipitation Estimation From Remotely Sensed Information Using Artificial Neural Networks-Climate Data Record.
- **PRISM**: Parameter-elevation Regressions on Independent Slopes Model

Supplementary Slide

0	Point	DVP	Slayton	MN_ASOS	########	43.9868	-95.7826
1	Point	MJQ	JACKSON MUNI	MN_ASOS	########	43.65	-94.9866
2	Point	MWM	WINDOM MUNI AIRP	MN_ASOS	########	43.9134	-95.1094
3	Point	OTG	WORTHINGTON	MN_ASOS	########	43.6551	-95.5792
4	Point	AXA	ALGONA	IA_ASOS	########	43.0796	-94.2724
5	Point	BNW	BOONE MUNI	IA_ASOS	########	42.0486	-93.8486
6	Point	CAV	CLARION	IA_ASOS	########	42.743	-93.7593
7	Point	CIN	CARROLL	IA_ASOS	########	42.0444	-94.7889
8	Point	CNC	CHARITON	IA_ASOS	########	41.0184	-93.3608
9	Point	DSM	Des Moines	IA_ASOS	########	41.534	-93.6531
10	Point	EBS	Webster City	IA_ASOS	########	42.4392	-93.8691
11	Point	EOK	KEOKUK MUNI	IA_ASOS	########	40.4615	-91.4274
12	Point	EST	ESTHERVILLE	IA_ASOS	########	43.4008	-94.7476
13	Point	FOD	FORT DODGE	IA_ASOS	########	42.5497	-94.2032
14	Point	I75	Osceola	IA_ASOS	########	41.0472	-93.6876
15	Point	IKV	ANKENY	IA_ASOS	########	41.6878	-93.5695
16	Point	OOA	Oskaloosa	IA_ASOS	########	41.2273	-92.4919
17	Point	OTM	OTTUMWA	IA_ASOS	########	41.1008	-92.4446
18	Point	OXV	Knoxville	IA_ASOS	########	41.2984	-93.1114
19	Point	PEA	PELLA	IA_ASOS	########	41.3989	-92.9431
20	Point	PRO	Perry	IA_ASOS	########	41.8278	-94.1637
21	Point	SLB	Storm Lake	IA_ASOS	########	42.5972	-95.2399

Things to cover in report.

- Check the time zone of each dataset
- Plot daily, monthly and yearly time series for the datasets
- Check if there is any shift in the time
- A gridded dataset from MESONET