Large-scale comparison of machine and statistical learning algorithms for blending gridded satellite and earth-observed precipitation data

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Abstract

An established way for improving the accuracy of gridded satellite precipitation products is to "correct" them by exploiting ground-based precipitation measurements, together with machine and statistical learning algorithms. Such corrections are made in regression settings, where the ground-based measurements are the dependent variable and the satellite data are predictor variables. Comparisons of machine and statistical learning algorithms in the direction of obtaining the most useful precipitation datasets by performing such corrections are regularly conducted in the literature. Nonetheless, in most of these comparisons, a small number of machine and statistical learning algorithms are considered. Also, small geographical regions and limited time periods are examined. Thus, the results provided tend to be of local importance and to not offer more general guidance. To provide results that are generalizable, we compared eight state-of-the-art machine and statistical learning algorithms in correcting satellite precipitation data for the entire contiguous United States and for a 15-year period. We used monthly data from the PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) gridded dataset and the Global Historical Climatology Network monthly database, version 2 (GHCNm). Our results suggest that extreme gradient boosting (XGBoost) and random forests are more accurate than the remaining algorithms, which can be ordered as follows from the best to the worst ones: Bayesian regularized feed-forward neural networks, multivariate adaptive polynomial splines (poly-MARS), gradient boosting machines (gbm), multivariate adaptive regression splines (MARS), feed-forward neural networks, linear regression.

This poster is based on Papacharalampous et al. (2023).

1. Previous studies on the topic

Study	Time scale	Spatial scale	Algorithms
He et al. (2016)	Hourly	South-western, central, north-eastern and south-eastern United States	Random forests
Meyer et al. (2016)	Daily	Germany	Random forests, artificial neural networks, support vector regression
Tao et al. (2016)	Daily	Central United States	Deep learning
Yang et al. (2016)	Daily	Chile	Quantile mapping
Baez-Villanueva et al. (2020)	Daily	Chile	Random forests
Chen et al. (2020a)	Daily	Dallas–Fort Worth in the United States	Deep learning
Chen et al. (2020b)	Daily	Xijiang basin in China	Geographically weighted ridge regression
Rata et al. (2020)	Annual	Chéliff watershed in Algeria	Kriging
Chen et al. (2021)	Monthly	Sichuan Province in China	Artificial neural networks, geographically weighted regression, kriging, random forests
Nguyen et al. (2021)	Daily	South Korea	Random forests
Shen and Yong (2021)	Annual	China	Gradient boosting decision trees, random forests, support vector regression
Zhang et al. (2021)	Daily	China	Artificial neural networks, extreme learning machines, random forests, support vector regression
Chen et al. (2022)	Daily	Coastal mountain region in the western United States	Deep learning
Fernandez-Palomino et al. (2022)	Daily	Ecuador and Peru	Random forests
Lin et al. (2022)	Daily	Three Gorges Reservoir area in China	Adaptive boosting decision trees, decision trees, random forests
Yang et al. (2022)	Daily	Kelantan river basin in Malaysia	Deep learning
Zandi et al. (2022)	Monthly	Alborz and Zagros mountain ranges in Iran	Artificial neural networks, locally weighted linear regression, random forests, stacked generalization, support vector regression
Militino et al. (2023)	Daily	Navarre in Spain	K-nearest neighbors, random forests, artificial neural networks

2. Summary of methods and metrics

Algorithms for spatial interpolation

- Linear regression (Hastie et al. 2009, pp 43–55)
- Multivariate adaptive regression splines (MARS; Friedman 1991, 1993)
- Multivariate adaptive polynomial splines (poly-MARS; Kooperberg et al. 1997, Stone et al. 1997)
- Random forests (Breiman 2001, Tyralis et al. 2019)
- Gradient boosting machines (gbm; Friedman 2001, Mayr et al. 2014, Tyralis and Papacharalampous 2021)
- Extreme gradient boosting (XGBoost; Chen and Guestrin 2016 , Tyralis and Papacharalampous 2021)
- Feed-forward neural networks (Ripley 1996, pp 143–180)
- Feed-forward neural networks with Bayesian regularization (MacKay 1992)

Variable importance metric

Random forests' permutation importance

Evaluation metrics

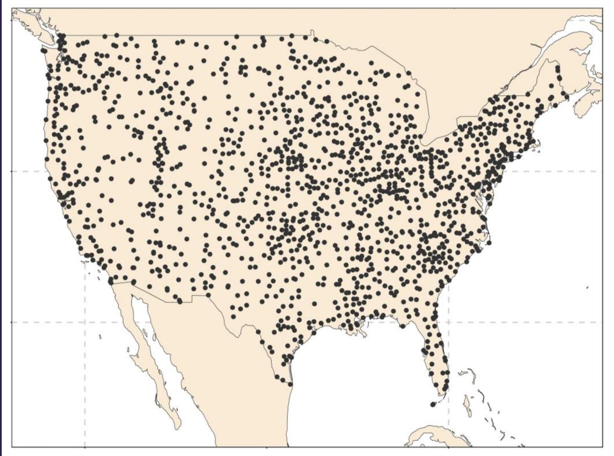
Median squared error → rankings, mean relative improvements, mean rankings

The comparison is made in a five-fold cross-validation setting.

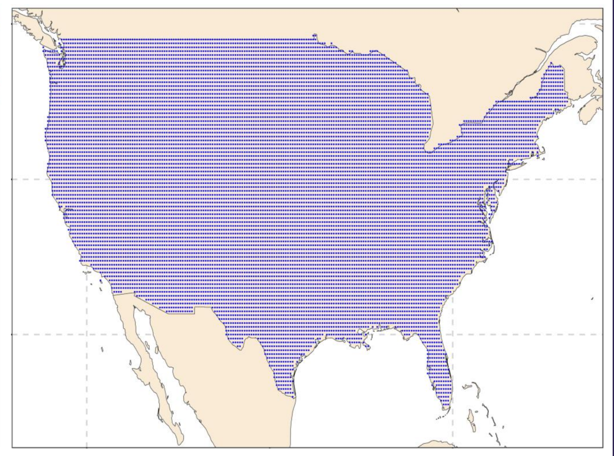
3. Summary of data

- **Total monthly precipitation data** from:
  - a) the Global Historical Climatology Network monthly database, version 2 (GHCNm; Peterson and Vose 1997); and
  - b) daily precipitation data of the current operational PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) system.
- **Elevation data** from the Amazon Web Services (AWS) Terrain Tiles application.

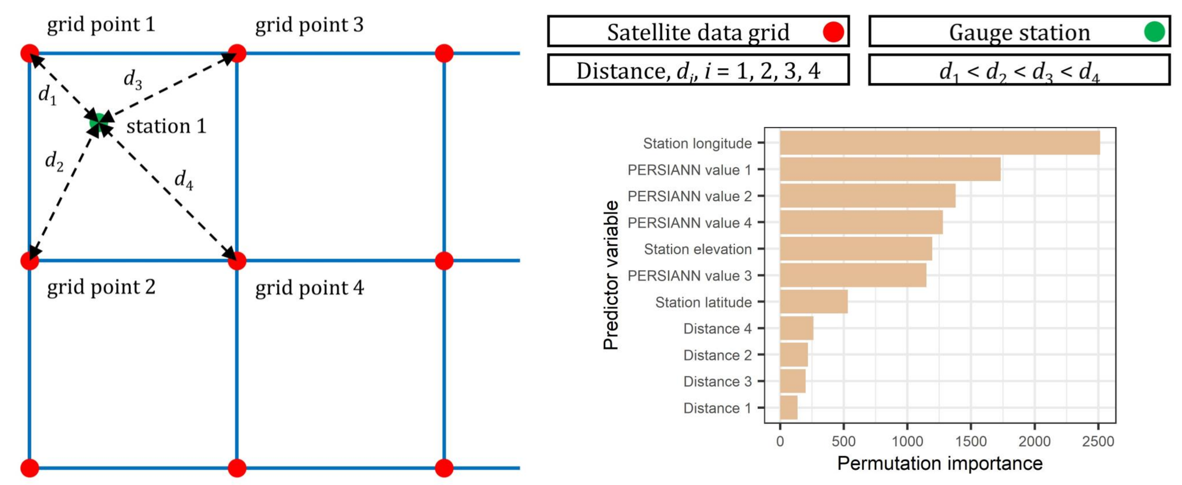
1 421 stations with data in the period 2001–2015



PERSIANN grid with data in the period 2001–2015



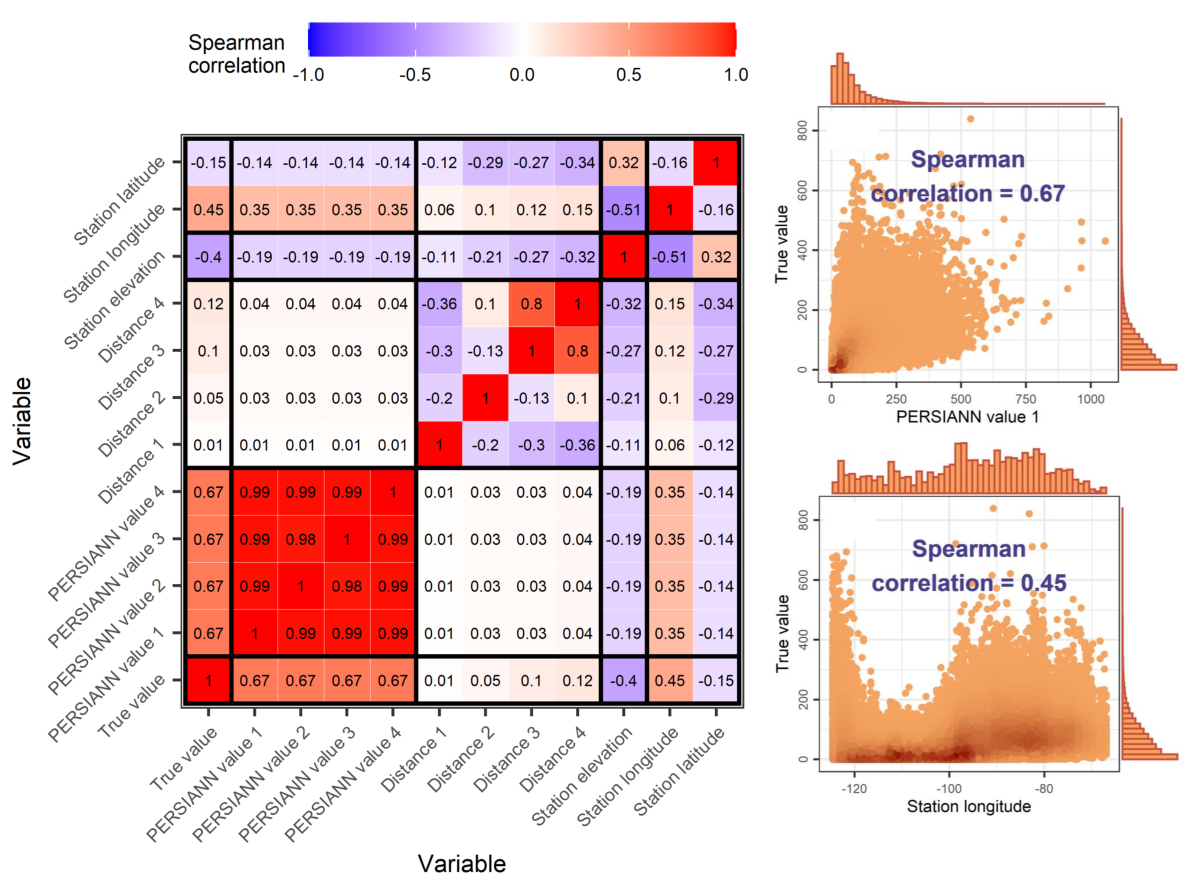
4. Regression setting and importance of predictors



- Grid points are the geographical locations with satellite data.
- Stations are the geographical locations with ground-based measurements.
- Distances 1−4 are the distances d_i, i = 1, 2, 3, 4.
- PERSIANN values 1−4 are the total monthly precipitation values at the grid points 1−4, respectively.

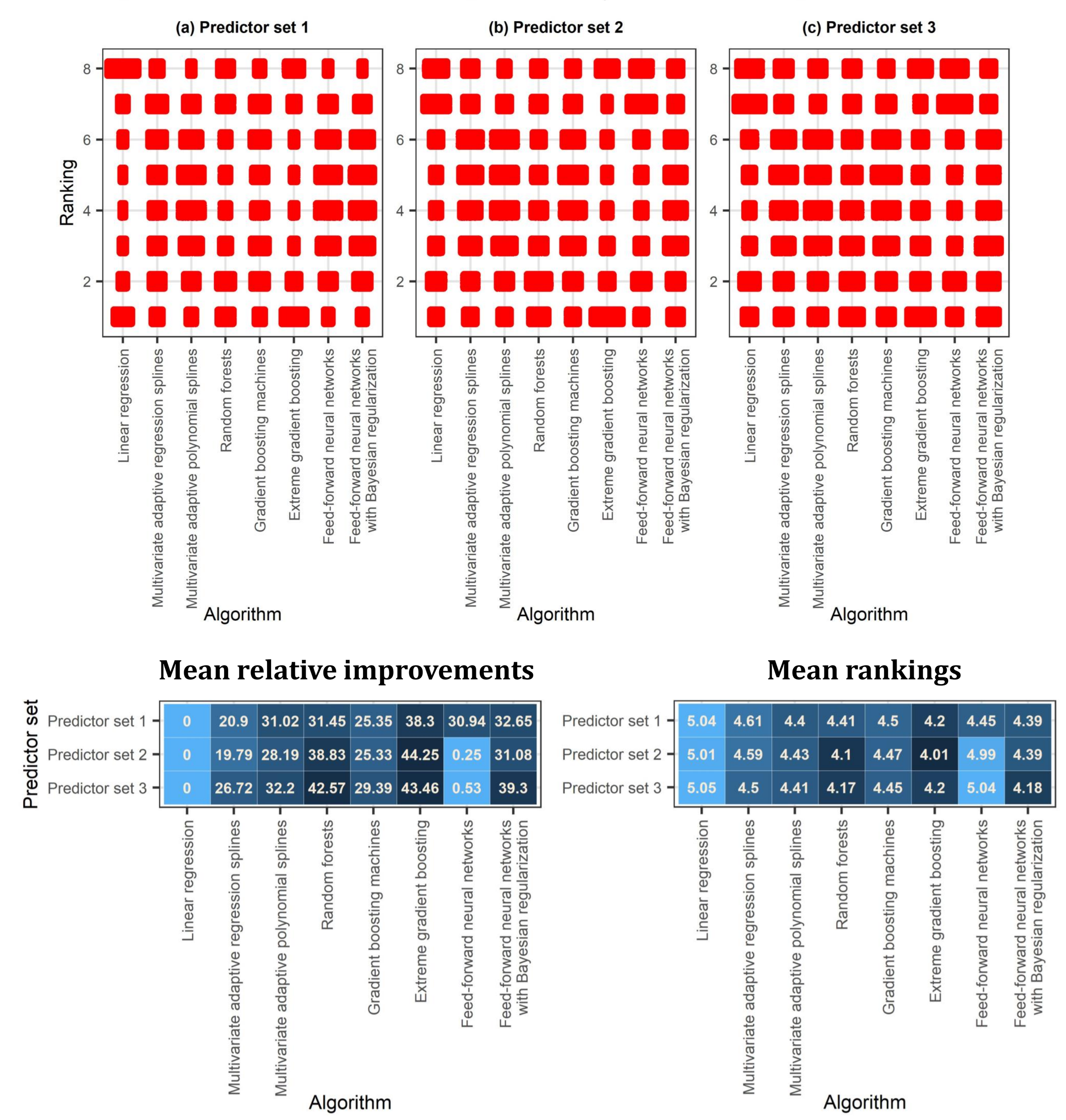
Predictor variable	Predictor set 1	Predictor set 2	Predictor set 3
PERSIANN value 1	✓	✓	✓
PERSIANN value 2	✓	✓	✓
PERSIANN value 3	✓	✓	✓
PERSIANN value 4	✓	✓	✓
Distance 1	×	✓	✓
Distance 2	×	✓	✓
Distance 3	×	✓	✓
Distance 4	×	✓	✓
Station elevation	✓	✓	✓
Station longitude	×	×	✓
Station latitude	×	×	✓

5. Relationships between variables

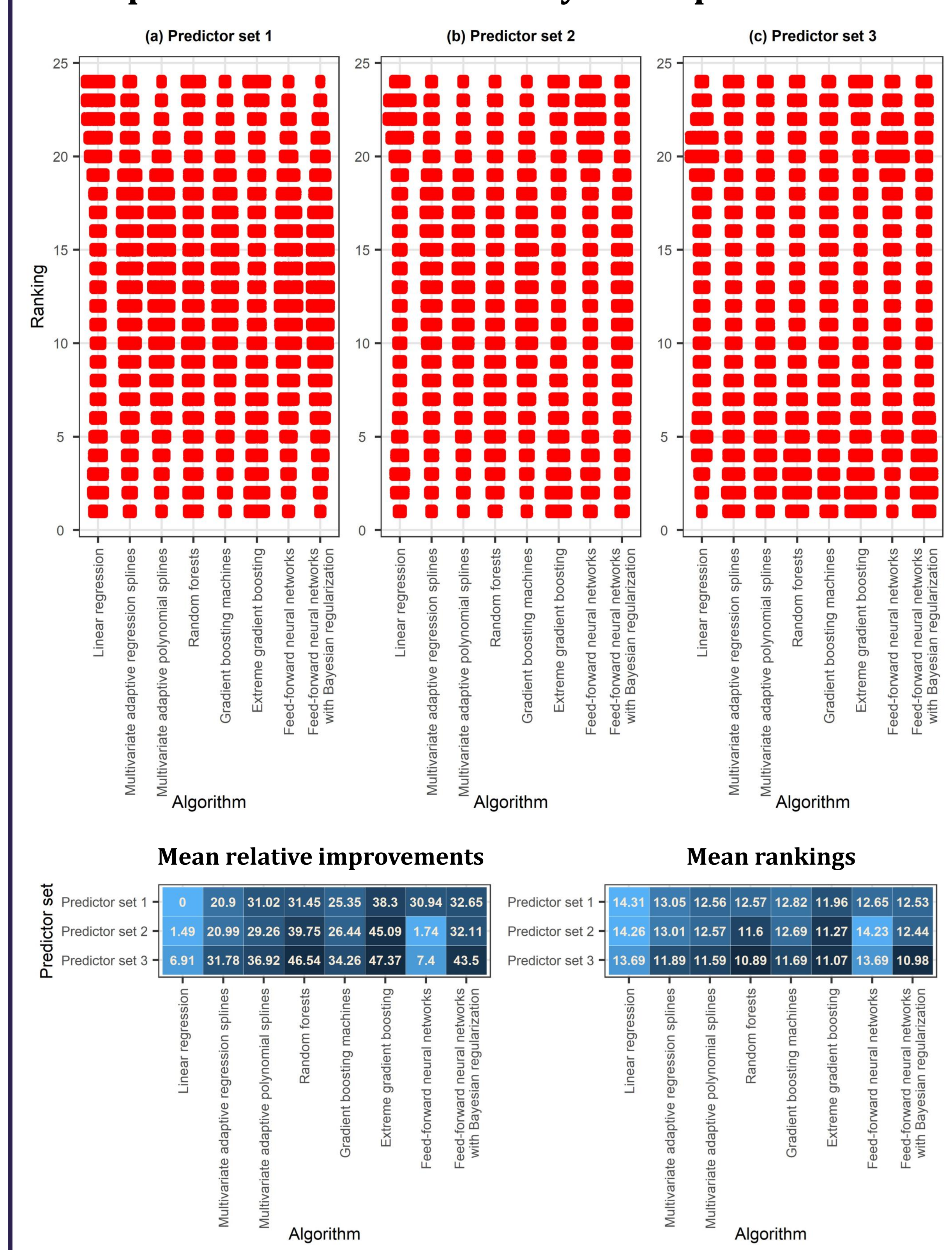


6. Comparison of algorithms

Computations made separately for each predictor set



Computations made collectively for all predictor sets



7. Summary of findings

- Extreme gradient boosting (XGBoost) and random forests are the most accurate algorithms.
- The former algorithm was found to be more accurate than the latter to a small extent based on the majority of the scores.
- The remaining algorithms can be ordered from the best- to the worst-performing as follows:
  - feed-forward neural networks with Bayesian regularization;
  - multivariate adaptive polynomial splines (poly-MARS);
  - gradient boosting machines (gbm);
  - multivariate adaptive regression splines (MARS);
  - feed-forward neural networks; and
  - linear regression.

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