Assessment of predictability in Downscaling GEFS Precipitation Forecasts

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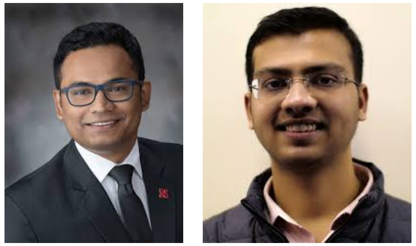


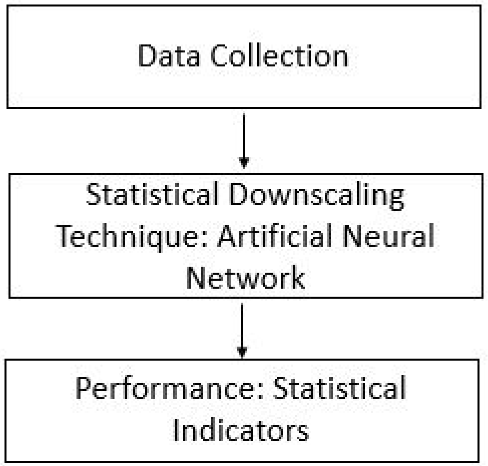
PRESENTED AT:

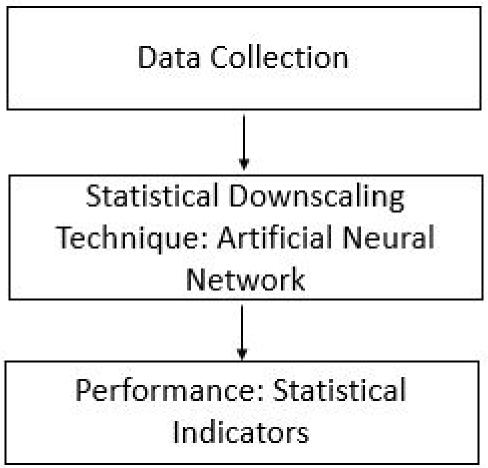
AGU FALL MEETING
Online Everywhere | 1–17 December 2020

OVERVIEW

- Assessment of performance of ensembles of precipitation forecast obtained from Global Ensemble Forecast System (Reforecast Version -2) and assessing statistical downscaling technique to improve forecasting system.

figure: framework



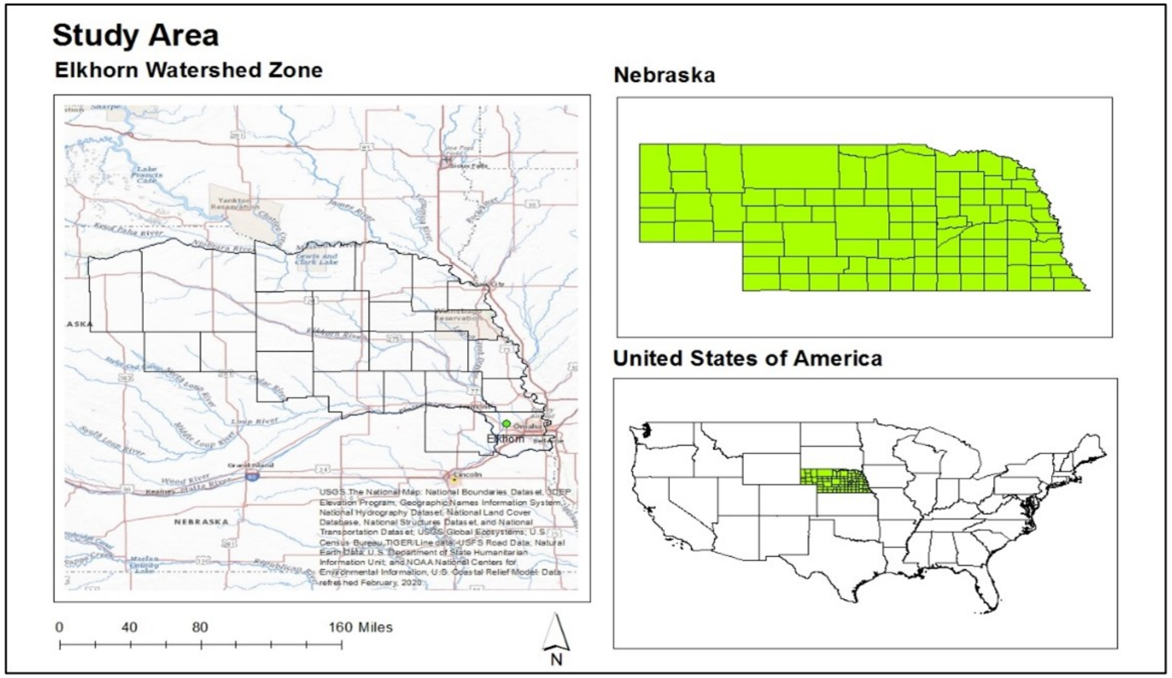


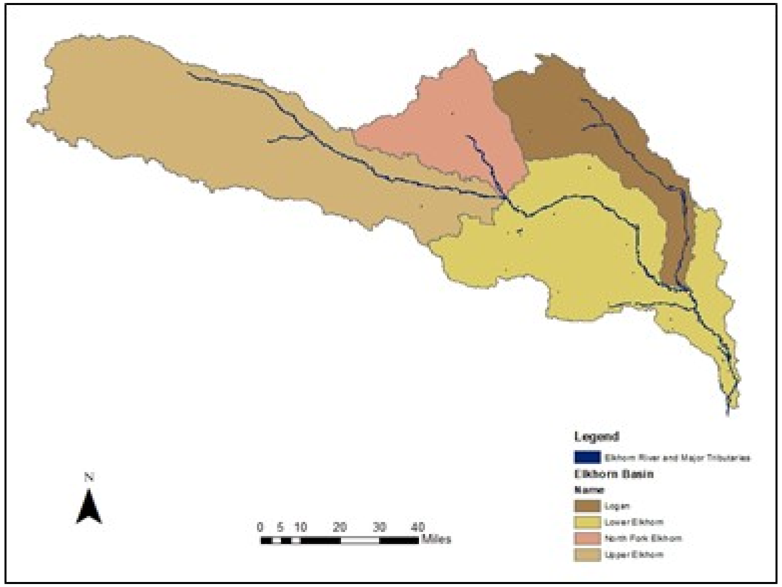
3. STUDY AREA & 4. DATA COLLECTION

3. Study Area:

- Catchment: Elkhorn river basin
- Sub-catchments: Upper Elkhorn, North Fork Elkhorn, Logan, and Lower Elkhorn.
- Location: Northeast and north-central Nebraska
- Area of catchment: 17,871 km^2
- Length of Elkhorn river: 466.71 km

Figure: Elkhorn River Basin



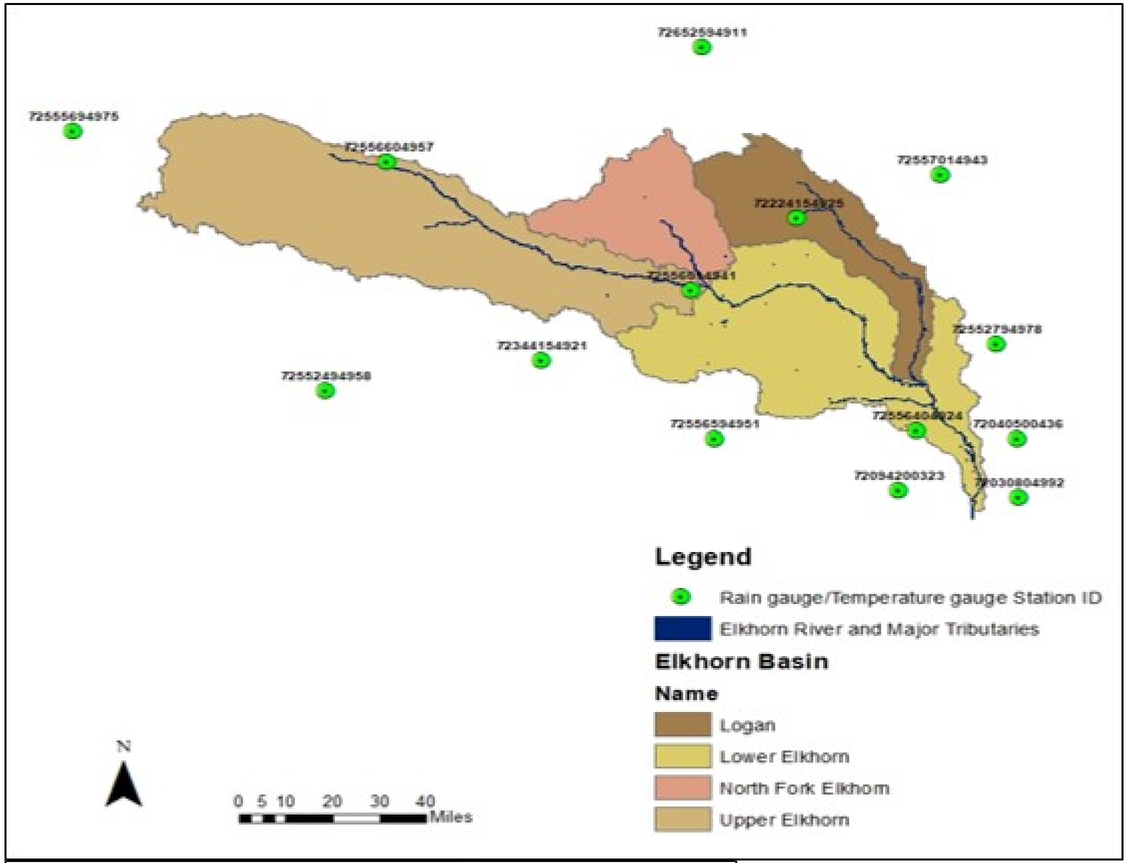


4. Data Collection:

1. Climatological Data:

- For Land-Based Station: National Water Information System: USGS Water Resources (NWIS, 2020)

Figure: Meteorological stations in Elkhorn river basin



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72040500436
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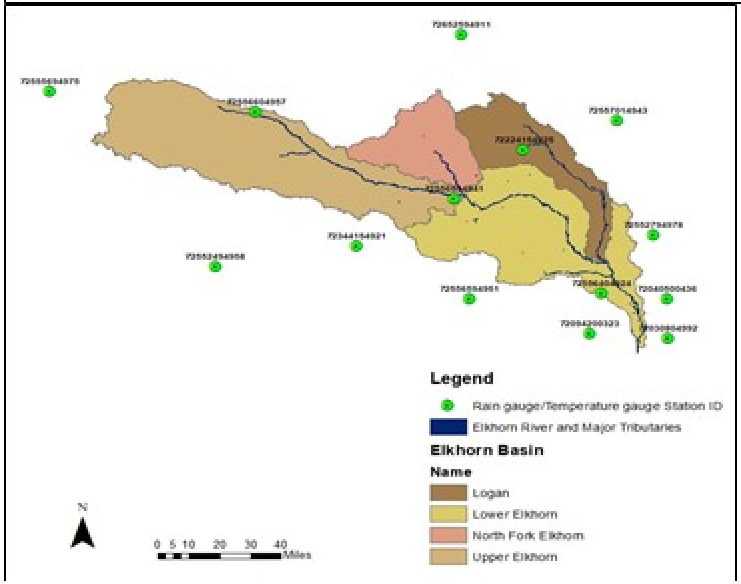
72030804992
Legend
Rain gauge/Temperature gauge Station ID
Elkhorn River and Major Tributaries
Elkhorn Basin
Name
Logan
Lower Elkhorn
North Fork Elkhorn
Upper Elkhorn
N
0 5 10 20 30 40
Miles



Legend
Rain gauge/Temperature gauge Station ID
Elkhorn River and Major Tributaries
Elkhorn Basin
Name
Logan
Lower Elkhorn
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Upper Elkhorn
N
0 5 10 20 30 40
Miles

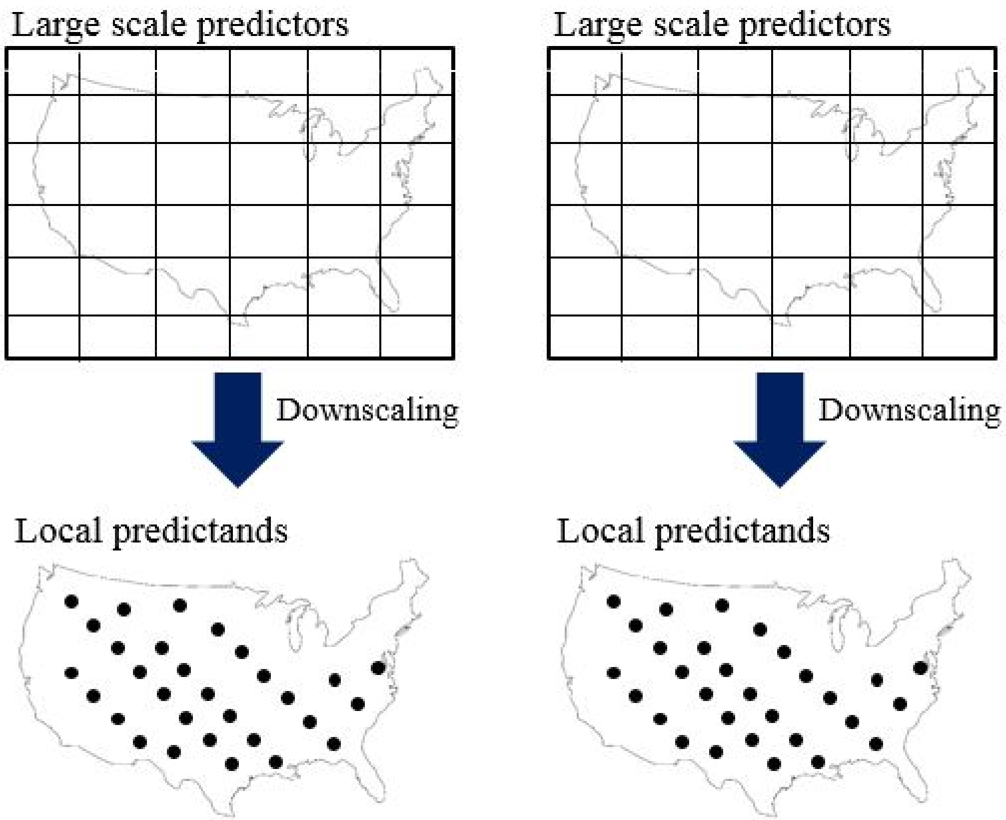
- For Ensemble Data: Earth System Research Laboratories (ESRL): Global Ensemble Forecast System (GEFS-Reforecast-V2) (GEFS,2020)

5. METHODOLOGY

Statistical Downscaling:

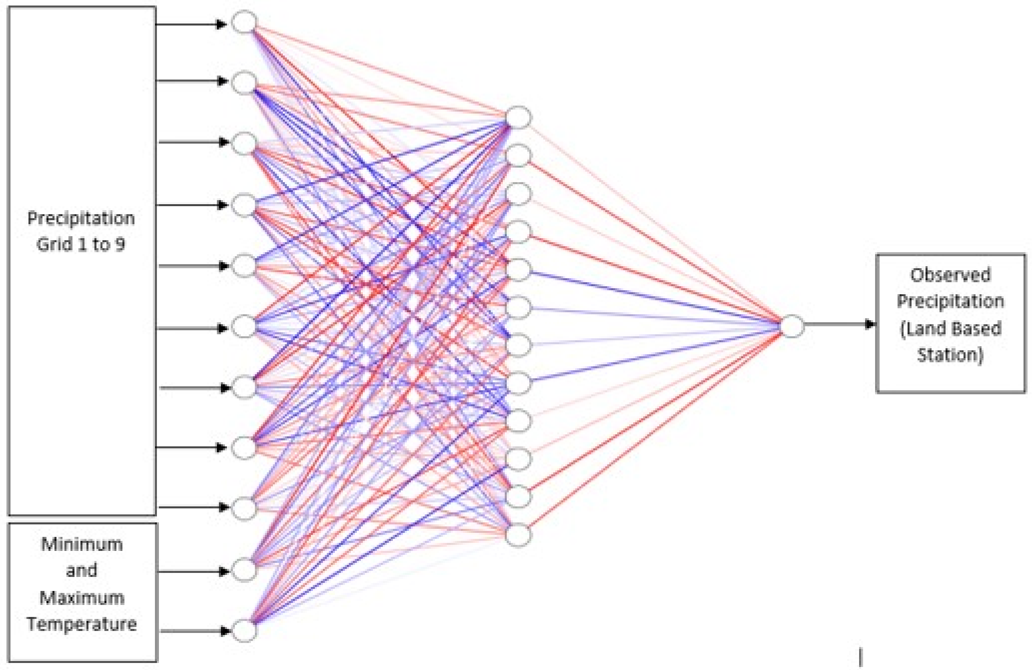
- Establishing linear/non-linear relationships between predictor and predictand

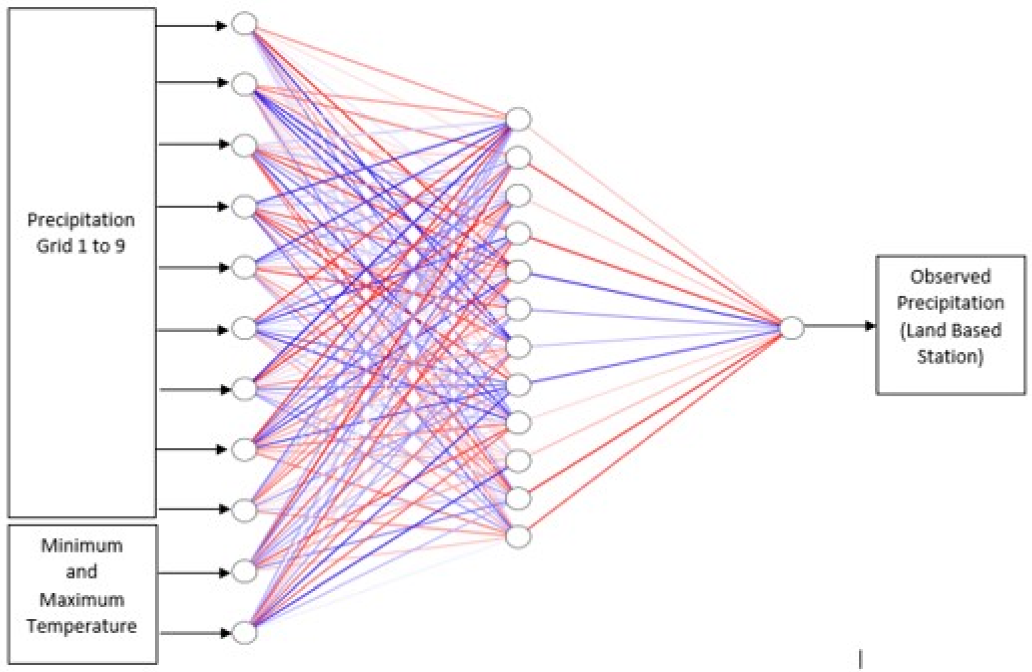
Figure: Statistical Downscaling Technique:



Artificial Neural Network:

Figure: Neural Network diagram


Precipitation
Grid 1 to 9
Minimum
and
Maximum
Temperature
Observed
Precipitation
(Land Based
Station)


Precipitation
Grid 1 to 9
Minimum
and
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Observed
Precipitation
(Land Based
Station)

- Feed-forward backpropagation neural network trained with Levenberg-Marquardt algorithm.
- Input variables: 9 precipitation grid, minimum and maximum temperature using 11 ensembles of GEFS.
- Output variable: observed precipitation from land-based station.
- The sigmoid transfer function was used between the input and hidden layers, whereas the linear transfer function was used between the hidden and output layers.
- Number of iterations: 500; number of neurons: 11; number of hidden layer: 1
- The available data was divided into calibration (2009 to 2016) and validation (2017 to 2019). In the calibration data set, the training was carried out with 70%, validation with 15%, and testing with 15% of the data.

6. RESULTS AND DISCUSSION

Result 1:

figure: Station 1: Correlation coefficient between land-based precipitation target variable and GEFS precipitation and temperature input variables for all leads (Day 0 to 15)

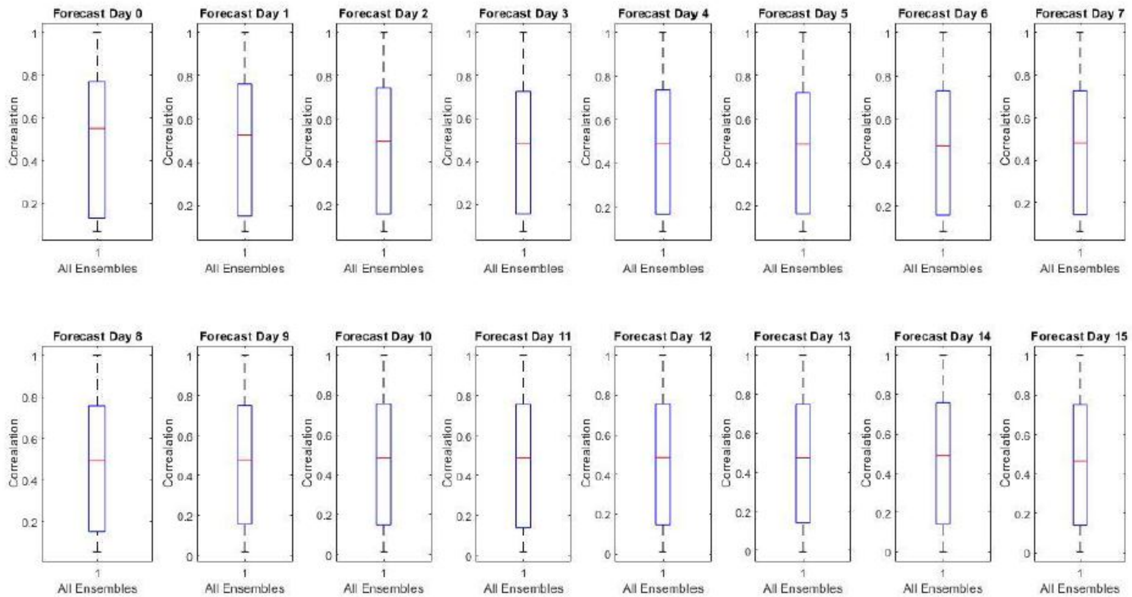


Table: range of correlation matrix for all ensembles, forecast, and stations

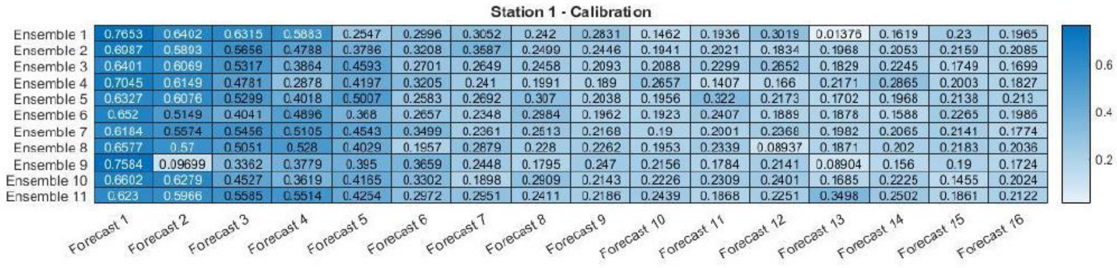
Forecast		Day 0	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15
Station 1	Min	0.0702	0.0822	0.078	0.0747	0.0884	0.0813	0.0851	0.0669	0.0542	0.0161	0.0116	0.0172	0.0088	-0.0097	-5.47E-04	0.0041
	Max	0.8864	0.8855	0.8739	0.9049	0.9028	0.8992	0.8374	0.8711	0.8931	0.8466	0.8682	0.8825	0.8762	0.8653	0.8926	0.841
Station 2	Min	0.1173	0.1439	0.1417	0.134	0.1356	0.1051	0.0649	0.0631	0.0361	0.0188	0.011	0.0017	-0.0038	0.0046	0.0185	0.0123
	Max	0.8876	0.9034	0.8811	0.9034	0.8705	0.911	0.852	0.8746	0.9035	0.8882	0.9082	0.9067	0.8944	0.9175	0.9118	0.8875
Station 3	Min	0.1064	0.0991	0.0776	0.0618	0.0412	0.0325	0.0189	0.0114	-0.0088	-0.0039	-0.0048	-0.0057	-0.0106	0.002	-0.0183	-0.018
	Max	0.901	0.8789	0.8949	0.8834	0.894	0.8828	0.8761	0.8758	0.9252	0.9294	0.893	0.9163	0.8971	0.917	0.9136	0.9141
Station 4	Min	0.1418	0.1584	0.1567	0.1373	0.1532	0.1303	0.0692	0.0605	0.0355	0.0174	0.0097	0.0059	0.009	0.0099	0.0018	0.0078
	Max	0.8896	0.9052	0.8899	0.8849	0.9009	0.8622	0.8425	0.8798	0.893	0.8977	0.8797	0.8844	0.8773	0.9166	0.8833	0.8949
Station 5	Min	0.1325	0.1555	0.1463	0.1408	0.1259	0.1231	0.0769	0.0899	0.0329	0.0161	0.0085	7.23E-04	0.0013	0.009	-0.0058	-0.0022
	Max	0.8701	0.8605	0.8252	0.8856	0.8776	0.8889	0.8713	0.8897	0.8979	0.906	0.891	0.8818	0.8728	0.8921	0.8897	0.8678
Station 6	Min	0.1325	0.1555	0.1463	0.1408	0.1297	0.12	0.0752	0.0886	0.0338	0.0169	0.0168	5.57E-05	2.07E-05	-0.0046	0.0011	0.0098
	Max	0.8701	0.8605	0.8252	0.8856	0.8776	0.8889	0.8713	0.8897	0.8979	0.906	0.891	0.8818	0.8728	0.8921	0.8897	0.8678
Station 7	Min	0.1331	0.1522	0.154	0.1476	0.1413	0.1225	0.0928	0.0676	0.0406	0.0247	0.0206	0.0192	-9.86E-05	-0.0046	0.0061	0.0043
	Max	0.8918	0.8743	0.8541	0.8943	0.8733	0.8829	0.8665	0.8898	0.9059	0.9119	0.8899	0.9179	0.9051	0.9144	0.9033	0.8937
Station 8	Min	0.1467	0.1777	0.1648	0.1608	0.1498	0.144	0.0791	0.0963	0.0458	0.0258	0.0116	0.0103	0.0091	0.0024	-0.0144	0.0053
	Max	0.8758	0.8508	0.8996	0.8802	0.8778	0.8907	0.8711	0.87	0.9169	0.9101	0.9101	0.9074	0.9268	0.9068	0.9211	0.8821
Station 9	Min	0.1467	0.1793	0.1648	0.1223	0.1362	0.101	0.0689	0.065	0.0405	0.0326	0.0106	0.0112	0.0064	0.0052	-0.0016	-1.63E-04
	Max	0.8758	0.8508	0.8996	0.8802	0.8778	0.8907	0.8711	0.87	0.9169	0.9101	0.9101	0.9074	0.9268	0.9068	0.9211	0.8821
Station 10	Min	0.0965	0.1097	0.1118	0.1072	0.1151	0.0928	0.0932	0.053	0.0332	0.0367	0.0255	0.0109	0.0073	0.0057	0.0012	0.0025
	Max	0.8741	0.8702	0.8612	0.8719	0.864	0.91	0.8843	0.8468	0.9046	0.8807	0.9222	0.9055	0.8729	0.8971	0.903	0.8899
Station 11	Min	0.1331	0.1656	0.1541	0.1476	0.1413	0.0975	0.0603	0.0492	0.0288	0.0281	0.0071	0.0031	-0.0054	0.007	-0.0176	0.0056
	Max	0.8918	0.8743	0.8541	0.8943	0.8733	0.8829	0.8665	0.8898	0.9059	0.9119	0.8899	0.9179	0.9051	0.9144	0.9033	0.8937

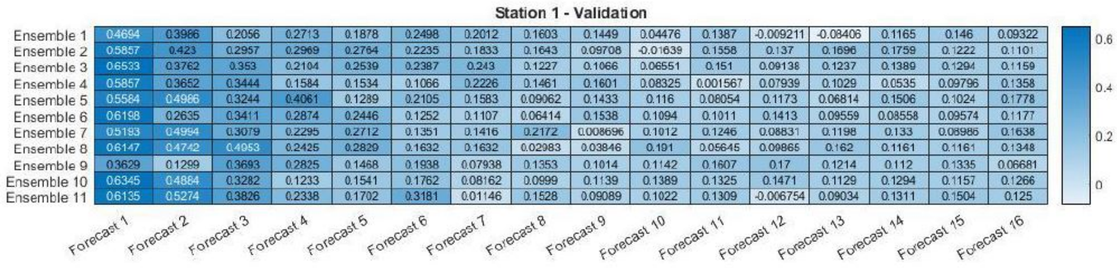
Discussion:

- Input variable from GEFS correlated with land-based station.
- Analysis suggest correlation are within the mean range of [0.4, 0.6].
- The range of minima and maxima varies highly for each day forecast.
- The analysis also suggests that input variables derived from the low-resolution grid (Day +8 to +15) is poorly correlated in comparison with a high-resolution grid (Day 0 to +7).

Result 2:

figure: Station 1: Performance of calibrated and validated results of the trained neural network





Discussion:

- Approximately for any given day 0 to +3 showed higher regression coefficient but the performance dropped with increase in forecast time.
- If there was an extreme precipitation event or if the correlation between the variables and the observed precipitation was not good, that would also negatively impact the model performance.
- Interpretation of the result could be highly advantageous in order to assign the confidence interval for a forecast.

1. OBJECTIVE & 2. RESEARCH QUESTION

1. Objective:

Statistical downscaling of the GEFS forecasts using Artificial Neural Networks.

2. Research question:

How does the predictability of the ensemble precipitation forecasts change along with the lead time within the context of statistical downscaling?

7. CONCLUSION

- Statistical downscaling technique using artificial neural network showed good performance for first few days forecast.
- Further analysis of optimum network architecture can be a good alternative.
- Results of the correlation plot could be used to study how predictability varies along with the forecast lead time. More in-depth analysis is needed to understand the efficacy of different bias correction schemes.
- An assessment with all 32 variables in GEFS would be interesting.

DISCLOSURES

Station ID	Station Number	Station	Start Date	Latitude (m)	Longitude (m)	Elevation (m)
72555694975	1	AINSWORTH MUNICIPAL ARPT	1/1/06	42.58	-100.00	787.60
72344154921	2	ALBION MUNICIPAL AIRPORT	1/1/06	41.73	-98.05	548.34
72040500436	3	BLAIR MUNICIPAL AIRPORT	1/1/09	41.41	-96.11	395.94
72652594911	4	CHAN GURNEY MUNICIPAL ARPT	1/1/06	42.88	-97.36	357.23
72556594951	5	COLUMBUS MUNICIPAL AIRPORT	1/1/06	41.43	-97.35	441.05
72556404924	6	FREMONT MUNICIPAL AIRPORT	1/1/06	41.45	-96.52	366.67
72556014941	7	KARL STEFAN MEMORIAL AIRPORT	1/1/73	41.99	-97.44	472.74
72557014943	8	SIOUX GATEWAY/COL BUD DAY FIELD AP	1/10/42	42.39	-96.38	333.76
72552794978	9	TEKAMAH MUNICIPAL AIRPORT	1/1/06	41.76	-96.18	313.33
72556604957	10	THE O'NEILL MUNI-JOHN L BAKER FIELD AIRPORT	1/1/06	42.47	-98.69	619.05
72224154925	11	WAYNE MUNICIPAL AIRPORT	1/1/06	42.24	-96.98	434.04

AUTHOR INFORMATION

Smit Doshi

Smit worked in the Roy research group from March 2020 to August 2020. He received the prestigious Erasmus Mundus Scholarship for his master's degree. His master’s thesis work was carried out here at UNL on the topic of probabilistic flood inundation mapping in the Elkhorn River basin, Nebraska. He attended two European Universities for his master's coursework, Universitat Politècnica de Catalunya in Spain and Newcastle University in the UK. Smit has a bachelor's degree in Civil Engineering from the Maharaja Sayajirao University of Baroda, India, where he was a gold medalist. His research interests include flood modeling and risk assessment, hydrology, hydraulics, irrigation engineering, machine learning, and stormwater management.

Tirthankar Roy (Advisor)

Tirthankar Roy joined the Department of Civil and Environmental Engineering at the University of Nebraska-Lincoln (UNL) in the fall of 2019. Prior to joining UNL, he was a Postdoc in the Department of Civil and Environmental Engineering at Princeton University (2017-2019). He holds a Ph.D. in Hydrology from the University of Arizona (2017), an M.Tech. in Civil Engineering from the Indian Institute of Technology Kanpur (2012), and a B.Tech. in Agricultural Engineering from Bidhan Chandra Krishi Viswavidyalaya, which is a state agricultural university in West Bengal, India. During his M.Tech., he received the DAAD Scholarship to work on his thesis at Technische Universität Dresden, Germany. He serves on the Early Career Committee of the International Association of Hydrological Sciences and the Hydrological Uncertainty Technical committee of the American Geophysical Union. His research interests include satellite remote sensing applications in hydrology, hydrologic extremes, catchment hydrology, land-atmospheric interactions, statistics and machine learning, water and the society, and water resources management.

ABSTRACT

The NOAA Physical Sciences Laboratory produces the Global Ensemble Forecasting System (GEFS) which comprises 11 ensemble members (1 control and 10 perturbation runs) for over a 36-year period (December 1984 to present), with forecasts initialized every day for the next 16 days (first 8-day forecasts obtained from a high-resolution grid and the next 8-day forecasts from a low-resolution grid). The system provides 36 variables related to a wide range of hydrometeorological processes. In this study, we assess the predictability of precipitation within the context of statistical downscaling using a minimum set of predictor variables (precipitation and temperature). We use feedforward backpropagation neural networks with a suite of training algorithms to determine which variables (features) are of most relevance at different forecast lead times. The outcome of this study will significantly benefit short-term flood forecasting using GEFS data.

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