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NON-UNIFORM SPATIAL DOWNSCALING OF CLIMATE VARIABLES

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***Abstract*—The goal of this study is to present a scalable and robust approach to spatial downscaling of climate variables. We explore the ability of artificial neural networks (ANN) to downscale a climate variable to a given location of interest. We illustrate our proposed method in a downscaling application of monthly mean air temperature and precipitations at twelve stations located across the topographically complex province of British Columbia, Canada. Our method generalizes well to different locations and leads to high downscaling accuracy. The performance of the models is measured based on four statistical metrics, including the coefficient of determination, and the root mean square error.**

I. INTRODUCTION

Complete and accurate climate datasets are not readily available in many regions around the world. They are especially lacking in the areas most sensitive to climate change [1], due, in part, to the complex topography of such regions, where it is difficult to install and maintain weather stations. As a result, some of the regions most affected by climate change are unable to obtain detailed climate data needed to understand impacts and develop adaptation plans for future climate change [2].

To address this problem, scientists often rely on *gridded reanalysis products* as a replacement for observational data [3]. These datasets are produced by using the available station observations to constrain a physics-based simulation that then fills in the missing data points to provide a complete, physically realistic gridded data product [4]. However, gridded products for remote areas are typically coarse resolution, and do not capture small-scale climatic characteristics associated with regional topographic features, such as mountain ranges or lakes. For this reason, it is usually necessary to re-process these data sets to a finer scale, in a way that accounts for such features, but does not introduce additional errors and biases. This process is referred to as *downscaling*. This can be done using a high resolution regional dynamical model, but is computationally demanding. *Statistical downscaling* instead relies on statistical or empirical relationships between the large-scale predictor field from the model simulations and the variables of interest, at the location of interest. Statistical downscaling is challenging where there is insufficient historical data to derive robust relationships. Several recent papers review the spatial interpolation methods used for downscaling in meteorology and climatology [5], [6], [7].

We present a novel statistical downscaling method that learns from gridded reanalysis data and local station data. Our method learns a mapping between a low-resolution reanalysis dataset and the climate at specific locations, using an ANN model. It can be used for locations with available historical time-series (task 1) as well as locations where no historical data is available (task 2), a case where existing downscaling methods perform poorly.

II. MODEL DEVELOPMENT

For each task, we investigate the use of an ANN model. The theoretical background for the algorithm is provided in [8]. The predictand of our models is the expected value of a given climate variable at a specific location and time. We have tested the method for two variables: monthly mean temperature and monthly mean precipitation. Our predictors from the reanalysis dataset include monthly means of: cloud forcing net longwave flux; upward and downward solar radiation fluxes; u-wind and v-wind; relative humidity; and sea level pressure.

In the first task, we downscale the gridded reanalysis data to a location for which past observations are available. In this scenario, the historical values recorded at the station were used as the predictand, and the reanalysis data at 16 grid points around the station were used as model predictors, selected such that the location of the station of interest is at the center grid cell of a 4 x 4 sub-grid or square. We refer to these 16 grid points as the station's neighborhood. The studies in [9],

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[4] showed that the sixteen grid points around a station of interest all supply relevant information to the model.

In the second task, the goal was to explore how a gridded dataset can be downscaled to locations where no past observational record is available. The methodology used here is similar to [9], where the focus was on predicting solar energy over a spatial grid by developing a support vector machine model for each individual cell of a gridded dataset. We develop a model for a location of interest, using the information available from that location's neighbourhood. Again, we use the square formed by the nine grid cells (i.e., 16 grid points) as the location's neighborhood. As there is no data for the location of interest, we use other stations within the given neighborhood. For the training set, the input variables are the reanalysis values from the sixteen grid points surrounding these stations along with each stations' coordinates (i.e., latitude, longitude and elevation), and the output variables are the observations recorded at the stations that fall within the neighborhood.

To test the method, we select one station as the location of interest, and exclude its data from the training set. The output variable in our tests corresponds to the observational data recorded at this location, and the input variables are the reanalysis values from the sixteen grid nodes around said location, and the location coordinates. During the training phase, the model has not been fed any value related to the location of interest, and during the testing phase, the model's only input is the information from the reanalysis dataset, and the location's coordinates. Figure 1 illustrates the construction of a test set for a model used to downscale to a location of interest (s1) with three neighbouring stations (s9, s11 and s12) used for training. Following this methodology, the models can be used to downscale to any location (any latitude, longitude, elevation), whether or not it is in the testing set.

III. APPLICATION AND EXPERIMENTS

This section presents the experimental results when applying our method on monthly mean air temperature and precipitation datasets for British Columbia. The station data used as target in our study consists of the observed values of monthly mean air temperatures and precipitation. These were obtained for twelve stations that are part of the Environment and Climate Change Canada network [10]. The reanalysis data used as the models' predictors (inputs) are from the NCEP/NCAR (National Centers for Environmental Prediction/National Center for Atmospheric Research) reanalysis dataset. NCEP/NCAR dataset is a combination of physical

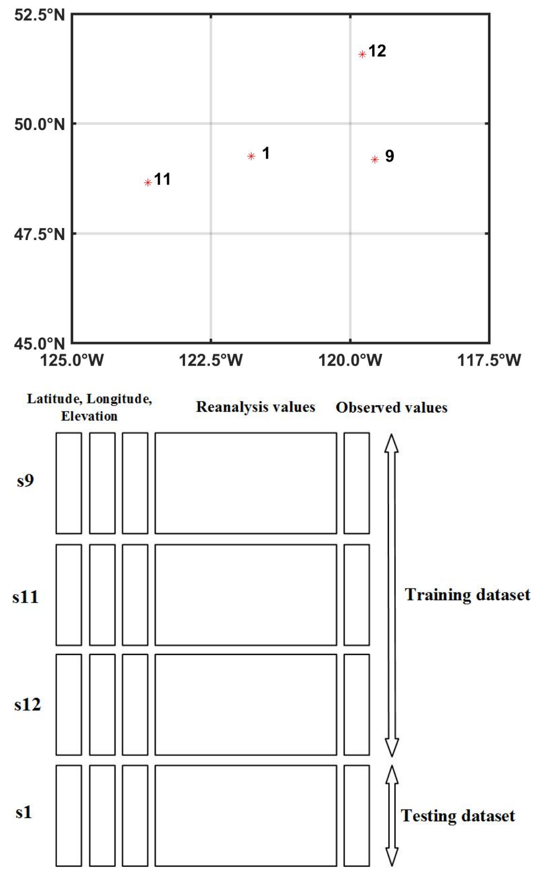

Fig. 1: Development of models' datasets for task 2.

process and model forecast gridded data at the 2.5°x 2.5°spatial resolution. Details regarding this dataset's development can be found in [11]. The data used extended over a 56-year period from 1960 to 2015.

The predictand and predictor data were standardized to fall within a range of [0, 1]. By standardizing the variables and recasting them into dimensionless units, the arbitrary effect of similarity between objects is removed. The data was partitioned into a training and testing set. Parameter tuning was achieved through cross-validation. In all cases, 10% of the available data was used to test the models. In order to compare the developed models' performance, the following measures of goodness of fit were used: the root mean square error ($RMSE$), the mean absolute error (MAE), the mean absolute deviation (MAD) as well as the coefficient of determination (R^2).

A. Results and discussion

The results show that overall, the monthly mean air temperature and precipitations were predicted with high accuracy. In general, the results for the monthly air temperature models are more accurate than the precipitation

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results. In fact, for the monthly air temperature target, the R^2 values, at test time, range between 0.980 and 0.998 for the first task and between 0.987 and 0.997 for the second task. When it comes to the monthly precipitations variable, the R^2 values, at test time, range between 0.616 and 0.893 and between 0.390 and 0.916 for the first and second tasks respectively.

Regarding the first task, downscaling to locations where past observations are available, the results in table I show that the stations where the downscaling accuracy was highest are station 8 for the monthly temperature variable and station 7 for the monthly precipitation target. The worst performance was obtained for station 2 and station 5 for the monthly air temperature and monthly precipitations respectively. The relatively lower R^2 values for both stations 2 and 5 can be explained by their proximity to large bodies of water (i.e., Atlin Lake and Stuart Lake).

When it comes to the second task, where the objective is to downscale to locations with no past observational records, the stations with the highest downscaling accuracy are station 11 for the monthly air temperature and station 4 for the monthly precipitation (see Table II). These results confirm our intuition that one of the key factors impacting the downscaling accuracy is the number of stations in the neighbourhood or square surrounding the station of interest. In fact, station 11 is surrounded by three neighbouring stations (i.e., stations 1, 3 and 4) and station 4 is surrounded by stations 3 and 11. It's also interesting to look at how the performance changes with respect to elevation. Interestingly, the best downscaling accuracy, with respect to each task and climate variable, was obtained for stations 4, 7, 8 and 11 which are located at low elevation at 7, 6, 41 and $18m$ respectively. The worst performance was obtained at stations 2, 5 and 9 located at higher elevations of 674, 686 and $297m$.

Finally, when it comes to the impact of the models' structure on the performance of the machine learning techniques, we noticed that the performance only slightly changes as the number of hidden neurons varied (the results for all the developed models are not shown here due to space constraints). In general, networks with a smaller number of hidden neurons gave poorer performance, and so did networks with a high number of hidden neurons, as they resulted in underfitting and overfitting respectively. Overall, the best performances were obtained when the number of hidden neurons varied between a minimum of 7 and a maximum of 17.

TABLE I: Results of the best models at test time for task 1.

Station	Neurons in layers	Air temperature $RMSE$	Air temperature R^2	Precipitation $RMSE$	Precipitation R^2
s1	(144-17-1)	1.119	0.991	0.576	0.860
s2	(144-7-1)	0.327	0.980	1.299	0.827
s3	(144-17-1)	1.814	0.987	0.538	0.749
s4	(144-17-1)	1.949	0.997	0.199	0.856
s5	(144-17-1)	0.494	0.994	0.673	0.616
s6	(144-7-1)	0.498	0.995	0.625	0.619
s7	(144-17-1)	0.725	0.994	0.335	0.893
s8	(144-17-1)	0.945	0.998	0.160	0.807
s9	(144-7-1)	0.427	0.995	0.647	0.624
s10	(144-7-1)	0.848	0.988	0.896	0.649
s11	(144-7-1)	0.810	0.997	0.299	0.888
s12	(144-7-1)	0.329	0.992	0.750	0.829

TABLE II: Results of the best models at test time for task 2.

Station	Neurons in layers	Air temperature $RMSE$	Air temperature R^2	Precipitation $RMSE$	Precipitation R^2
s1	(144-17-1)	0.444	0.994	1.051	0.888
s2	(144-7-1)	1.093	0.987	0.456	0.581
s3	(144-17-1)	0.371	0.994	1.427	0.877
s4	(144-17-1)	0.328	0.991	1.664	0.916
s5	(144-17-1)	1.018	0.988	0.594	0.490
s6	(144-7-1)	0.707	0.994	0.397	0.752
s7	(144-17-1)	0.318	0.995	0.972	0.831
s8	(144-17-1)	0.290	0.994	1.163	0.775
s9	(144-7-1)	0.737	0.993	0.497	0.390
s10	(144-7-1)	0.629	0.993	0.651	0.701
s11	(144-7-1)	0.286	0.997	1.046	0.869
s12	(144-7-1)	0.649	0.994	0.489	0.637

IV. CONCLUSIONS AND FUTURE WORK

This study presented a new downscaling method for two specific tasks: downscaling at locations where past observations are available to train the models, and downscaling for locations where there is no past record, using neighbouring stations to train the models. We explored the ability of artificial neural networks to downscale monthly mean temperatures and precipitations for selected stations in British Columbia. The results showed that using artificial neural networks to learn from reanalysis gridded data and station observations can lead to accurate downscaling results. In further work, we plan to test the application of these methods for downscaling additional climate variables, including climate extremes as these are important for assessing climate change impacts, and for planning adaptation strategies for future climate change.

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