Modeling monthly and seasonal Michigan snowfall based on machine learning: A multiscale approach

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Abstract:

Snowfall has important significance in water resources management and disaster prevention worldwide. Accurate prediction of both mean and extreme snowfall is challenging because of multiple controlling mechanisms at different spatial and temporal scales. By using a 65 years long in-situ snowfall observation, we evaluated seven different machine learning algorithms for predicting monthly snowfall in the Lower Peninsula of Michigan (LPM). The Bayesian Additive Regression Trees (BART) demonstrates the best fitting ($R^2 = 0.88$) and out-of-sample prediction skills ($R^2 = 0.58$) for the monthly mean snowfall followed by the Random Forest model. The BART also demonstrate strong predictive skills for seasonal and the extreme monthly snowfall. Both machine learning models also demonstrate signals of key physical processes controlling the snowfall including topography, local/regional environmental factors, and teleconnections. Particularly, models with the non-parametric framework can incorporate signals from multiple scales and nonlinear responses from the snowfall to environmental factors and that substantially improved the model prediction skills. The multiscale machine learning approach provides a reliable and computationally efficient alternative approach to predict/forecast weather and climate and has potential to be applied to other extreme weather prediction scenarios.

Keywords: Snowfall, Monthly and Seasonal, Michigan, Machine Learning, Prediction

1. Introduction

Snowfall is an important indicator of winter season severity along with low temperatures, freezing rain, winds, visibility in cold climates (Ford et al., 2021). Snowfall intensity, duration, and amount could have both beneficial and adverse impacts on society and environment (Kenneth E. Kunkel et al., 2002), forest ecosystem (Zhou et al., 2021), plant phenology (Bjorkman et al., 2015), and hydrological processes (Kolka et al., 2010). The Lower Peninsula of Michigan (LPM) in the US Midwest region (Fig. 1) experiences substantial amounts of snowfall during winter seasons and frequent extreme snowstorms due to the lake-effect. It has been demonstrated that snowfall variability in the LPM has increased, although long-term averaged snowfall remains relatively stable since 1970s(Meng & Ma, 2021). Model outputs from the Sixth Coupled Model Intercomparison Project (CMIP6) suggest that snowfall intensity will increase while the amount of snowfall might decrease in middle latitudes of North America under future warming(Quante et al., 2021). Understanding the variability of snowfall will improve its predictability at monthly to seasonal timescales, providing potential benefits for winter road maintenance budget planning, ski industry, insurance company, and human health conditions.

Previous studies have discussed different mechanisms influencing winter snowfall variability in the Great Lakes regions, including both local/regional environmental factors and teleconnections. Local/regional environmental factors influence snowfall developments in the Great Lakes regions through their impacts on atmospheric instability, lift, and moisture exchanges between the Great Lakes and the atmosphere. Similar upward trends in air temperatures (as a proxy of lake surface water temperatures) and snowfall in the Laurentian Great Lakes were also identified (K E Kunkel et al., 2009). It was also found that a strong negative correlation existed between average winter temperatures and lake-effect snowfall in Lake Michigan (Braham & Dungey, 1984).

Our recent studies (Meng et al., 2021; Meng & Ma, 2021) and other previous research (Clark et al., 2016) suggest that both the lake-effect snowfall and the seasonal total snowfall variability have significantly negative correlations with regional average winter temperatures in the LPM. Lake surface water temperatures and ice covers also have significant impacts on lake-effect snowfall from lake-atmosphere interactions. For instance, Baijnath-Rodino et al. (Baijnath-Rodino et al., 2018) suggested that that warm lake surface introduces boundary layer instability and facilitate exchange of moisture and energy, which fuels the lake effect snow. Several regional modeling studies (Notaro et al., 2013; Shi & Xue, 2019) support the same mechanism and describe the roles of lake surface temperatures, ice coverage and wind directions in the development of lake-effect snowfall with more details.

Teleconnections can determine the snowfall in the Great Lakes regions from mechanisms at global or regional scales. For example, the upper-level trough patterns favorable to the lake-effect snow are often associated with a negative phase of Arctic Oscillation (AO) and North Atlantic Oscillation (NAO) and/or a positive phase of Pacific North American Pattern (PNA) (Suriano & Leathers, 2017). Statistical model also shows that inclusion of the PNA, Pacific Decadal PDO, Northern Hemisphere temperature and the NAO/AO improved the prediction skills of snowfall in most stations in the United States (Kluver & Leathers, 2015). El Niño–Southern Oscillation (ENSO) is controlling the snowfall in the Midwest U.S. by modulating the locations of the jet stream (Smith & O'Brien, 2001). Significantly less snowfall has been observed during El Niño (the warm phase of ENSO) years (Clark et al., 2016). Sea surface temperature in the Nino 3.4 region (SST3.4) are also negatively correlated with both seasonal total snowfall and lake-effect snowfall in the LPM (Meng et al., 2021; Meng & Ma, 2021).

Based on the discussions above, most previous studies treat multiple mechanisms influencing the regional snow separately, such as regional mechanisms like the lake-effect snow or large-scale teleconnections such as ENSO. But these multiple atmospheric and environmental factors are at different spatial and temporal scales and may determine snowfall LPM independently or collectively. It is still challenging for the Global Circulation Models (GCMs) or Regional Climate Models (RCMs) to capture all these mechanisms and both are currently computational expensive (Gutowski et al., 2021). Machine learning approaches provide an alternative approach to solve those multiscale challenges in weather and climate prediction. In recent years, machine learning approaches have been more frequently used in parameterization of climate models (O'Gorman & Dwyer, 2018; Schneider et al., 2017) or directly for regional and global climate predictions (Ham et al., 2019). It has been reported that machine learning models are able to give decent prediction skills for general climate variables like temperature and precipitation (Gibson et al., 2021; Robertson et al., 2015). Those machine learning approaches are also demonstrating improved ability to predict hydro-climate extremes, such as drought, extreme rainfall (Wei et al., 2022). However, very few studies have used machine learning approaches to predict snowfall. Non-linear autoregressive networks model was developed to enhance the spatial resolution of snowfall estimate for the black forest using additional topographic information (Sauter et al., 2010). The support vector machine (SVM) and multivariate discriminant analysis (MDA) models both have excellent performance in snow avalanche prediction in the Karaj watershed, northern Iran (Choubin et al., 2019). No machine learning based study is focused on a region like Michigan, which is usually prone to extreme snowfall due to the lake-effect.

In this study, we will evaluate snow prediction models based on multiple machine learning techniques. By doing this work, we will be able to (1) compare different machine learning approaches for their fitting and prediction skills for snowfall in the LPM; (2) discover possible important physical mechanisms that control LPM snowfall; (3) select an optimal model with best predictive performance that can be used for seasonal/monthly forecast or future climate change predictions.

Fig. 1. Locations of all COOP stations with snowfall measurement in LPM.

2. Data and Methods

2.1 Snowfall and independent variables

In this study, we use a monthly snowfall dataset from 8 COOP stations that are temporally homogeneous (K E Kunkel et al., 2009). Only dataset from 1951 to 2015 is used due to constrains of availability in the corresponding teleconnection indices. Only snowfall observations from the peak snowfall season (December, January, and February) are included in our machine learning models.

All independent variables are listed as Table 1. Vapor pressure deficit is the difference between the actual water vapor pressure and saturation vapor pressure. Extreme temperature (maxT & mint) and vapor pressure deficit (vpdmax & vpdmin) at each COOP station were obtained from the nearest grid cell in the Precipitation-Elevation Regression on Independent Slopes Model (PRISM) dataset [53,54] with a 4 km spatial resolution. Extracted from the same data source, both local and regional averaged temperatures (savgT & avgT) are included in our machine learning models. uwind and vwind were obtained from the nearest grid cell in ERA5-land monthly dataset with a 0.25° spatial resolution. The wind direction is calculated from uwind and vwind values.

Table. 1. List of variables used in the modeling process

Acronym	Full name	Description	Unit
maxT	Maximum Temperature	Local, Dynamic	°C
minT	Minimum Temperature	Local, Dynamic	°C
savgT	Station Averaged Temperature	Local, Dynamic	°C
avgT	Regional Averaged Temperature	Regional, Dynamic	°C
rangeT	Range of Temperature	Local, Dynamic	°C
uwind	Meridional Winds	Local, Dynamic	m/s
vwind	Zonal winds	Local, Dynamic	m/s
direction	Direction of the winds	Local, Dynamic	°
vpdmax	Maximum Vapor Pressure Deficit	Local, Dynamic	kPa
vpdmin	Minimum Vapor Pressure Deficit	Local, Dynamic	kPa
tsi	Tropical Southern Atlantic Index	Teleconnections	°C
tni	Tropical Southern Atlantic Index	Teleconnections	°C
np	North Pacific Air Pressure	Teleconnections	mb
sst34	Sea Surface Temperature in Nino3.4	Teleconnections	°C
pna	Pacific North America Index	Teleconnections	NA
nhavgT	Average Temperature of Northern Hemisphere include both land and ocean	Teleconnections	°C
nao	North Atlantic Oscillation	Teleconnections	NA

pdo	Pacific Decadal Oscillation	Teleconnections	NA
ao	Arctic Oscillation	Teleconnections	NA
elev	Elevation	Local, Static	meter
dist2shore	Shortest Distance to Lake Michigan shorelines	Local, Static	Kilometer
lat	Latitude of Station	Local, Static	°
lon	Longitude of Station	Local, Static	°
month	Month of observation	Generic, Dynamic	NA

* All dynamic variables are extracted monthly

The selection of teleconnection indices used in the models is based on previous literature showing their controls in snowfall in the U.S. (Clark et al., 2016; Hartnett et al., 2014; Kluver & Leathers, 2015; Meng et al., 2021; Meng & Ma, 2021; Suriano & Leathers, 2017). All teleconnection indices including tsi, tni, np, sst34, pna, nhavgT, nao, pdo, and ao were obtained from NOAA Physical Sciences Laboratory (PSL, https://psl.noaa.gov/data/climateindices/list/). Latitude, longitude, elevation, and the shortest distance (in km) to Lake Michigan shorelines for each COOP station were also included in our models and they do not change by time in the model (static variables). The *u* and *v* component of the surface wind were collected from ERA5 data (Bell et al., 2021). Wind direction is calculated from the corresponding *u*- and *v*-winds at each grid cell.

2.2 Model Overview

We tested 7 different algorithms that cover major categories of machine learning techniques in this study. The Generalized Linear Model (GLM) are a series of special linear regression models first formulated by Nelder and Wedderburn (1972). They work for the situation when the response variable is reacting nonlinearly with predictors by using a link function (such as logarithm function) to allow variance of each measurement to be a function of its prediction. The Generalized Additive Model (GAM) is a special kind of GLM where the response variable is linearly dependent on smooth functions of some predictor variables (Sasieni, 1992). An exponential distribution is specified for the response variable and the predictor variables is linked with smooth functions such as polynomial, spline or nonparametric functions.

The Bayesian Regularization for Feed-Forward Neural Networks (BRNN) is a two-layer framework of neural network that uses the Nguyen and Widrow Algorithm (Nguyen & Widrow, 1990) to assign initial weight and Gauss-Newton algorithm to perform the optimization. It has been applied to predicting complex quantitative genetic traits (Gianola et al., 2011) and is first applied to climate prediction models in our analysis.

The Supporting Vector Machine (SVM) is a machine learning algorithm that discover an optimal hyper plane that classifies the data points from a multi-dimensional space (Boser et al., 1992). It already has been applied to climate science, such as prediction of extreme rainfall event (Nayak & Ghosh, 2013) and downscaling precipitation from GCMs (Tripathi et al., 2006). Those predictions both show good agreements with observations so here we include the SVM in our model comparison.

The Multivariate Adaptive Regression Splines (MARS) is a non-parametric modeling approach that can model the nonlinearities and interactions in the data without knowing them *a priori* (J. H. Friedman, 1991). This algorithm acts as an expansion of product spline basis functions, where the number of functions and their parameters are automatically determined by the data. The MARS has been successively applied to predict monthly runoff in tropical climate (Reddy et al., 2021) and burn area from wildfire in western boreal North America (Balshi et al., 2009).

The Random Forest (RF) and Bayesian Additive Regression Trees (BART) are both machine learning algorithms based on ensembles of decision trees. The RF constructs multiple decision trees and its mean prediction is given by those trees (Breiman, 2001). This approach is believed to be able to provide more robust predictions and suffer from less overfitting to the training set as compared with single decision tree. The BART algorithm is another "sum-of-trees" based model where each tree starts with constrain as a weak learner, then the fitting and inference are finished by using iterative Bayesian backfitting MCMC algorithm creating samples from a posterior (Chipman et al., 2012). The BART adds the Bayesian prior-posterior framework in the ensemble tree modeling. And its predictive performance is proved better than boosting, the lasso, MARS, neural nets, and the RF with even less computation resources. We will test both RF and BART for our snowfall modeling.

2.3 Model evaluation and selection

We start our modeling by splitting our data randomly into 80% training data and 20% testing data. The classification and regression training (caret) R package (Kuhn, 2008) is used to select the optimal combination of variables for each model in the model training by using the included Recursive Feature Elimination (RFE) function. For example, the RFE use stepwise feature selection for the GLM model and use cross validated recursive variable selection for GAM, SVM, MARS, RF, and BART. There is no variable selection for BRNN. The RFE test all possible combinations of variables into the model, evaluate their cross-validation results (RMSE, R^2, and MAE from 10-folds cross validation), and finally select the model with the best results. We will train those models using the selected variables and compare the model fitting results for all 7 those algorithms.

The next step is to use the 20% testing data to execute the out of sample cross validation to test the models' sensitivity and robustness to new data. We will use the identical models trained from the previous step to make predictions for the snowfall observations in the testing data and make comparisons. The RMSE, MAE, and R^2 will be calculated to gauge different models' out of sample prediction skills. We will choose one or two machine learning algorithms with the best prediction skills for further evaluation, which will be the hold-one-year-out cross validation. The purpose is to test models' sensitivity and stability in predicting seasonal snowfall in LPM. We will iteratively hold out each year's data and train the model only with other 64 years. Each hold-out model will be used to predict monthly snowfall at each station for that hold-out year. Monthly predictions and observations will be both aggregated seasonally (three months) and compared.

One of the major challenges for all machine learning research is model interpretation (Molnar et al., 2020). Model interpretation will help identify important variable/physical process involved in the machine learning model and understand how the dependent variables are interacting with independent variables. We will be able to calculate the variable importance for different machine learn approaches used in this study(Grömping, 2009). For example, the t-statistic for each model parameter is used for GLM. The reduction (addition) to the model performance (such as residual sums of squares) when a predictor is added to (removed from) the model is calculated as the importance of each predictor for models including MARS, RF, and BART. For better comparison purposes, we will calculate the relative variable importance (VI) relative VIs based on a 0–100 scale for model comparison purposes. Finally, the Partial Dependence Plot (PDP) is a useful tool to demonstrate the marginal effect from one or two predictors to the predicted outcome (Jerome H. Friedman, 2001). We will be able tell how snowfall is reacting to one specific predictor (e.g., linearly or non-linearly) in the model. Combining the VI and PDP calculation, we expect to reveal important physical mechanisms that control snowfall in the LPM.

3. Results

3.1 Linear Correlations

Linear correlations between all monthly snowfall and environmental/climatological factors are shown in Table 2. Maximum temperature (maxT) has the highest correlation with the snowfall in the LPM, followed by the regional averaged temperatures (avgT). Both the maxT and avgT have a strong negative correlation with the snowfall. Station's geographical locations also have an impact on the amount of snowfall. More snowfall is associated with stations with shorter distance from the Lake Michigan and locations with higher latitudes tend to have more snowfall. Most of the teleconnections have weak or no statistically significant correlation with the snowfall. Two strongest signals are SST 3.4 and North Atlantic Oscillation.

Table 2. Linear correlations between Michigan snowfall and independent variables

month	lon	lat	elev	dist2shore	ao
-0.1*	-0.004	0.32*	-0.25*	-0.24*	0.03
nhavgT	np	pdo	pna	sst34	nao
-0.01	0.04	-0.07	-0.05	-0.14*	-0.11*
avgT	tni	tsi	savgT	minT	maxT
-0.36*	0.05	0.08	0.06	-0.26*	-0.42*
rangeT	uwind	vwind	direction	vpdmax	vpdmin
-0.09	0.26*	-0.19*	0.18*	-0.11*	-0.03

* Indicates statistically significant correlation at 99% level

3.2 Model fitt

The correlation analysis provides information about snowfall's linear response to individual predictors. In this section, we will evaluate seven different machine learning algorithms to explore their combined effect. We used the Recursive Feature Elimination (RFE) algorithm to test all possible combinations of predictors and chose the optimal combination (statistics shown as SI. 1-5). The number of required variables for the best fitting models varies from 4 to all independent (24) variables. Significant differences exist in the model fitting accuracy among the seven algorithms (Table 2). The R^2 varies from 25% (SVM) to 88% (BART). The BART model also has the lowest mean absolute error (MAE) and Root Mean Square Error (RMSE), followed by the RF model.

The VI rankings also show differences among seven machine learning algorithms (Table 3). Similar to the correlation analysis, maxT is the most important controlling variable in GLM, MARS, SVM, and RF and the third important variable in BART. avgT is another important variable in many machine learning models (ranked second in GLM, SVM, and RF). Elevation is an important static variable along with the latitude, which appears in the top 10 VIs of most models except the SVM. For the BART with the best fitting performance, the top 5 important variables are vpdmax, dist2shore, maxT, rangeT, and elevation.

Table 2. The Model fitting result for the 80% training data

	GLM	GAM	BRNN	SVM	MARS	RF	BART
Number of Predictors	24	19	24	4	10	17	24
R^2	0.4	0.42	0.45	0.25	0.44	0.58	0.88
MAE	18.11	18.03	18.03	19.76	17.58	15.29	8.48
RMSE	23.95	23.52	23.11	26.97	23.01	20.24	11.07

Table 3. Relative variable importance (VI) for different ML algorithms (only up to 10 most important variables are shown).

	GLM		GAM		MARS		SVM		RF		BART	
Rank	Var	VI	Var	VI	Var	VI	Var	VI	Var	VI	Var	VI
1	maxT	100	lat	100	maxT	100	maxT	100	maxT	100	vpdmax	100
2	avgt	69	month	99	elev	76	avgt	78	avgt	70	dist2shore	97
3	minT	55	elev	87	month	54	minT	55	minT	61	maxT	97
4	lat	54	pdo	86	dist2shore	46	lat	54	dist2shore	42	rangeT	90
5	uwind	32	avgt	74	pdo	40			elev	42	elev	89
6	direction	31	minT	64	tsi	32			lat	27	tsi	88
7	elev	27	t1	60	vpdmax	25			vpdmax	25	avgt	85
8	dist2shore	23	rangeT	45	np	22			rangeT	24	np	82
9	vwind	22	tni	39	pna	16			t	23	lat	73
10	t	16	np	34	minT	13			np	22	vwind	72

3.3 Cross Validation

Next, we used those trained models to make out-of-sample predictions using the 20% testing data (Fig. 2). Comparison of model predictions demonstrates that most models are robust and have stable prediction skills for the new data. BART has the best prediction skills, followed by RF, BRNN, GAM, GLM, MARS, and SVM, based on their MAE and RMSE statistics. BART has a $R^2 = 0.58$ with RMSE = 18.4 and MAE = 13.83. The RF Model's prediction skill is slightly lower than BART, with $R^2 = 0.55$ and MAE =14.43. Particularly, the BART model has the best prediction skill for the > 100 cm snowfall. Most other models (GLM, GAM, SVM, MARS, and RF) tend to have systematic underestimate for this range of extreme snowfall. BRNN (Fig. 2c) have both large overestimates and underestimates for the > 100 cm snowfall.

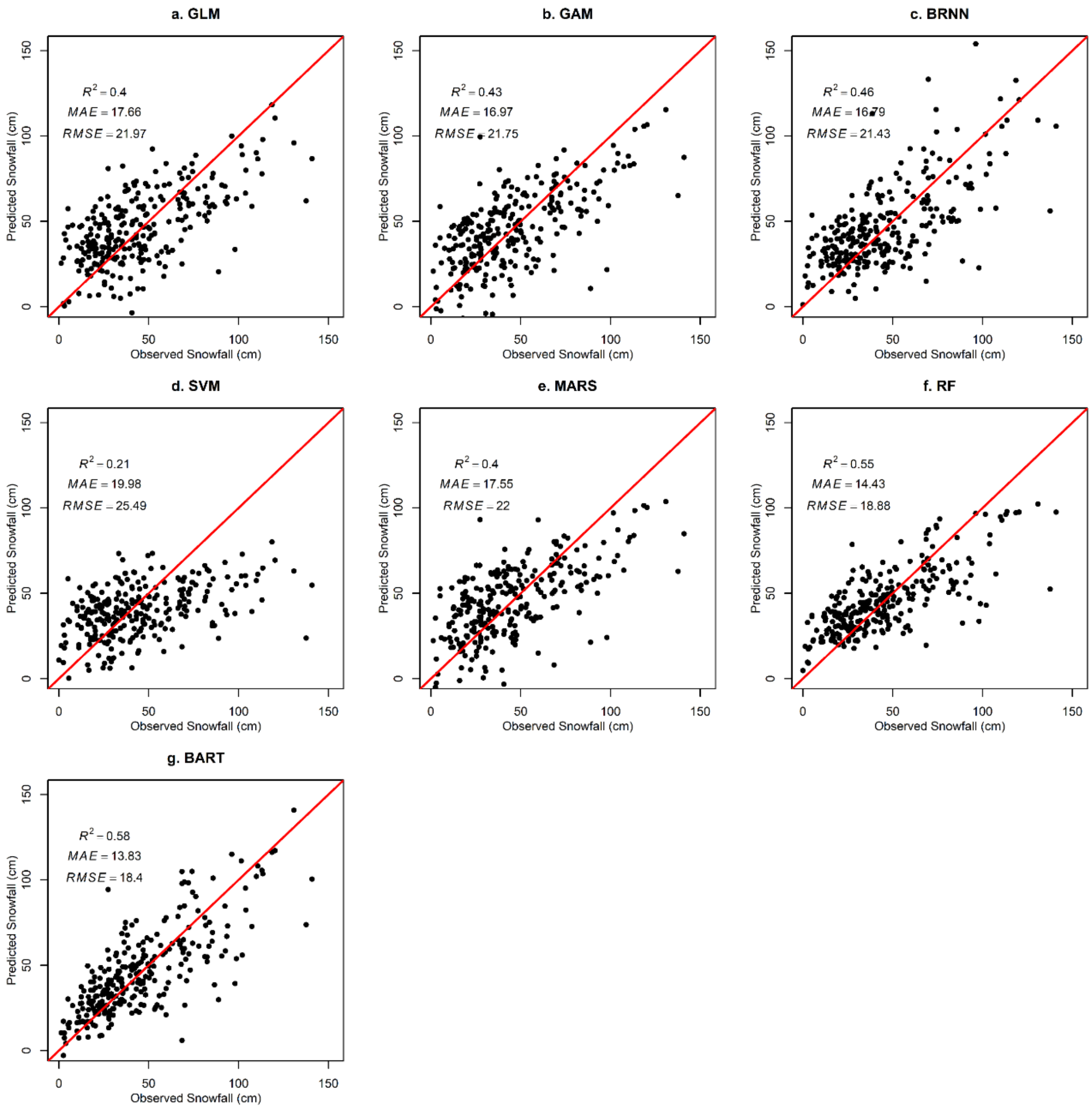

Fig 2. The model prediction skills for different ML algorithms, calculated from the out-of-sample cross validation using the 20% testing data. Prediction and observation (same 20% testing data) are compared with the y=x line (red).

We further evaluated model performances through the leave-one-year-out-cross validation for BART and RF because they have the best performance shown by the fitting and out-of-sample cross-validation tests. Fig. 3 shows that BART model can explain 62% to 92.4% of seasonal snowfall variance (summed as Dec, Jan and Feb) while RF can explain 15% to 38.6% of seasonal snowfall variance in the LPM as indicated by their R^2. When the snowfall predictions are averaged over the 8 stations, there is a significant improvement in model prediction skills and error statistics (Fig. 3i). The BART model demonstrates an exceptional high R^2 value of 99.8% and low values of MAE (1.32 cm) and RMSE (1.96 cm) for the station averaged regional snowfall prediction. The Random Forest model also shows improvement in predicting regional mean snowfall (R^2 = 0.5, MAE = 19.67) as compared with the single station prediction. Besides inter-annual and inter-decadal variability, both RF and BART also capture temporal trends at some locations' time series (Such as East Jordan, Battle Creek, and the Regional Mean)

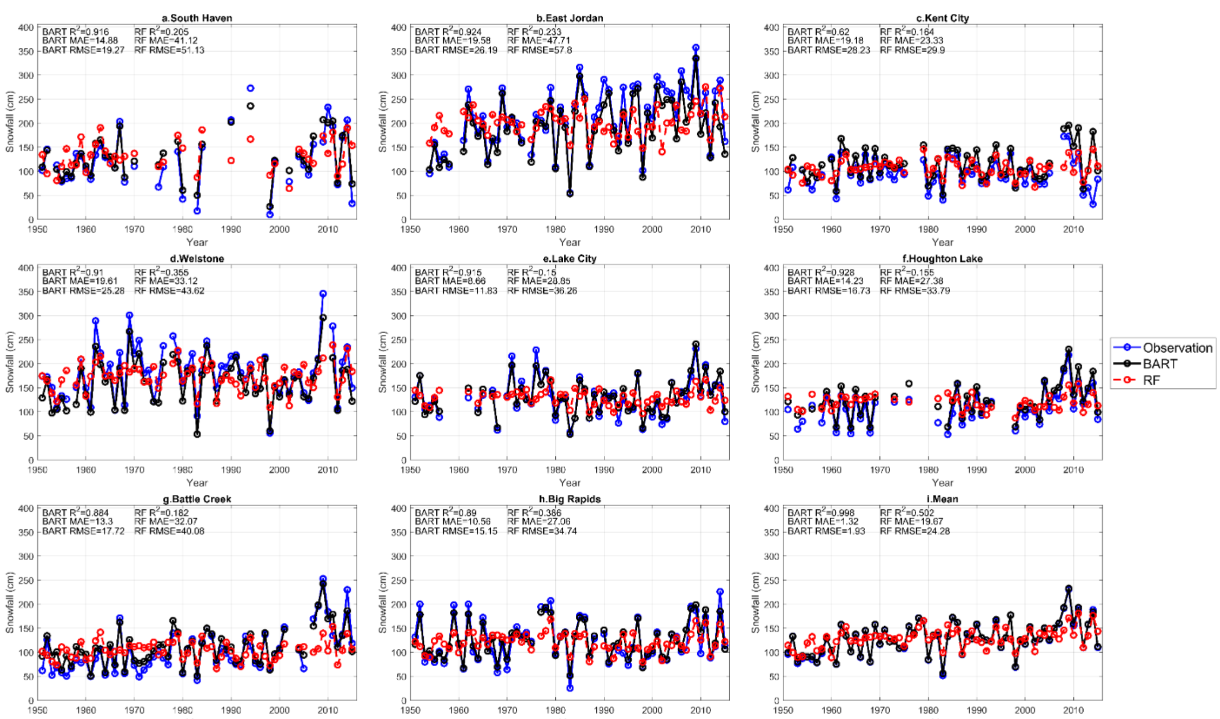

Fig 3. Hold one year out cross validation results for RF and BART models. For each year, both model (RF and BART) are trained only using data exclusively from other 64 years. Each hold-out model is used to predict snowfall monthly snowfal at each station and then they are aggregated into the seasonal snowfall as shown by the time series.

3.4 Variable and Model Interpretations

The partial dependence plots (pdps) can be used to estimate each dependent variable's marginal effect on the predicted outcome of a machine learning model (Jerome H. Friedman, 2001). The pdps for BART (Fig. 4) shows that snowfall generally increases as maxT, minT and avgT decreases. This agrees with the correlation analysis and previous studies (Meng et al., 2021; Meng & Ma, 2021) . The air temperature is likely to influence the rate of accretion of ice and sublimation/deposition of snow as well as the mean size of snow aggregate (Hong et al., 2004). The snowfall reacts to station mean temperature (savgT) in a more complex way. While the snowfall generally decreases when the savgT increases in the BART (Fig 4s), the maximum snowfall happens when the savgT is between 0 and 5 °C. And the RF demonstrate a positive relationship between snowfall and savgT (Fig. 5i). At a much larger scale, higher north hemisphere average temperature (nhavgT) generally agree with higher amount of LPM snowfall in both models (Fig 4o and 5o). This could be related to the breaking down of polar vortex due to the melting of arctic sea ice (Francis & Vavrus, 2012) or the general warm up of water temperature that may intensify the lake-effect snow.

Static variables such as latitudes, dist2shore and elevation also play important roles in both RF and BART. Snowfall is generally higher at locations nearer to the lakeshore (Fig 4i and 5d) and locations with higher elevations (Fig 4h). This also agrees with the correlation analysis and indicates signals from lake-effect snow because the process is directly determined by the approximity to the great lakes and topography. Snowfall increases as the station's latitude increases in both BART (Fig 4e) and RF (Fig 5f). The relationship is also controlled by temperature's influence in snowfall.

More snowfall amounts in the LPM are associated with the cold phase of ENSO (La Niña). Previous studies have discussed how ENSO regulates the Pacific jet stream and therefore influence the storm tracks over the continental U.S.(J. Chen & Kumar, 2002; Trenberth & Guillemot, 1996). During the cold phase (La Niña), positive precipitation anomalies have been observed in Washington, Oregon, and southwestern Canada (J. Chen & Kumar, 2002). Such negative correlation has also been identified by recent studies on winter snowfall in Michigan (Meng et al., 2021; Meng & Ma, 2021). Here both BART (Fig 4q) and RF (Fig 5l) models show ENSO's controls in snowfall amount, while more nonlinearity is demonstrated by BART's relationship.

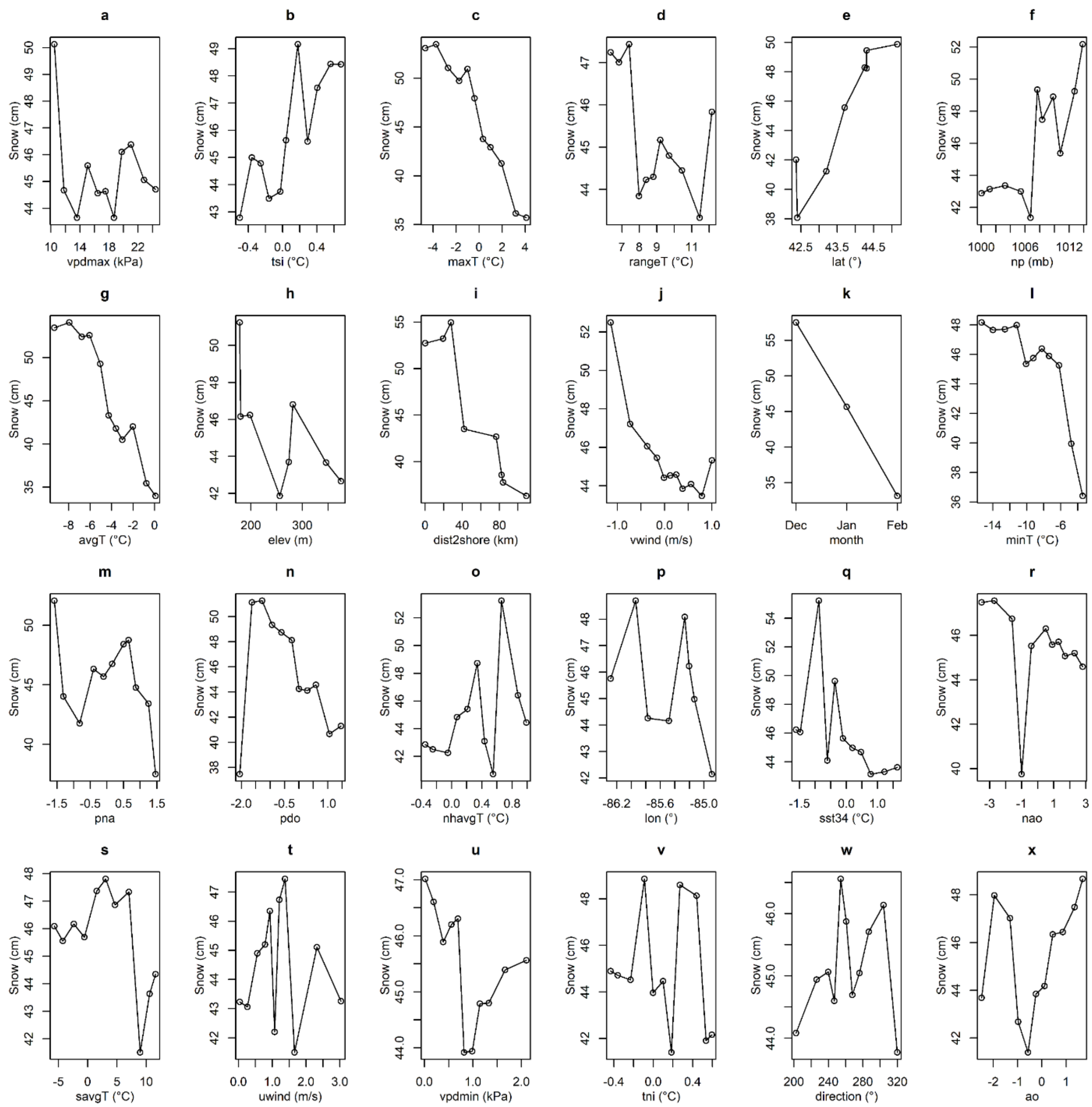

Fig. 4 The partial dependence plot (pdp) for the BART model developed by 80% training data

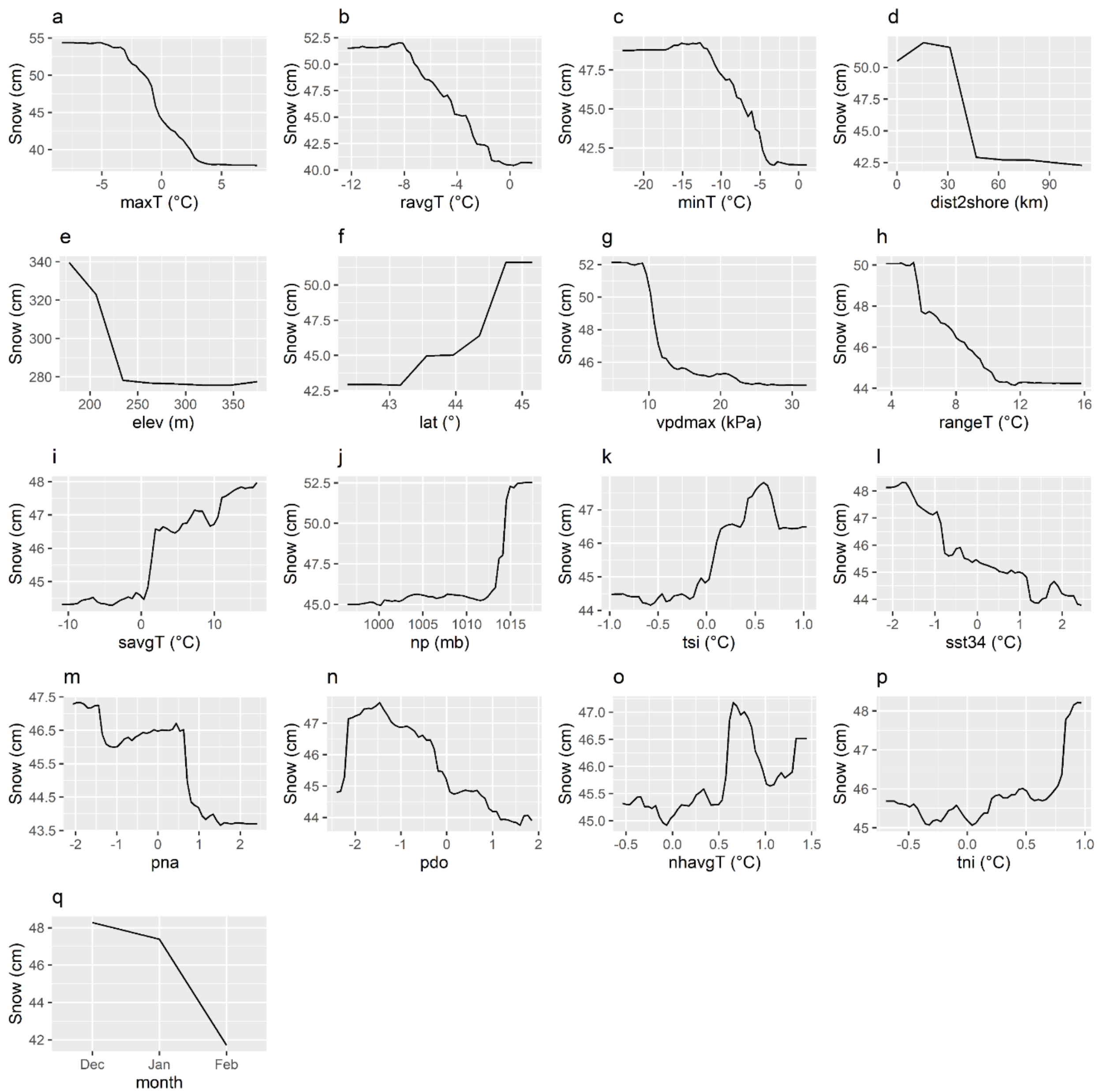

Fig. 5 The partial dependence plot (pdp) for the RF model developed by 80% training data, the pdp shows how the dependent variable changes with each predictor used in the model.

BART's pdps also demonstrate that the maximum vapor pressure (vpdmax) (Fig 4a) has a nonlinear relationship with snowfall. More snowfall is generally corresponding to < 14 kPa vpdmax. The vpd describes the difference between the amount of moisture in the air and the saturated moisture in the air. It is another measurement of relative humidity and has been applied for estimating evapotranspiration (ET) in vegetations (Novick et al., 2016) and predicting the wildfire (Chiodi et al., 2021). In our case low vapor pressure deficit values (< 14 kPa) corresponds to high amount of atmospheric water vapor, which is favorable to the nucleation process in all kinds of precipitation including snowfall. The snowfall remains fluctuated when vpd > 14 kPa and demonstrates two small peaks when the vpdmax is at ~ 14.5 kPa and ~ 21 kPa (Fig. 4a). In the RF model, vpdmax relationship has the same direction but with less nonlinearity (Fig 5g). Interestingly, the BART model shows that higher snowfall is associated with weak vwind from the north (negative anomaly) and the wind direction from 250° to 310° (northwesterly). During the winter, the North American High transports cold air from the north and interacts with the warm air from the south to form synoptic winter storms. The cold air also interacts with the warm lake surface to form lake effect snow in Michigan. Theis processe is also controlled by the ENSO intensity. For example, La Niña winter is associated with displaced Polar jet to the great plains (Smith & O'Brien, 2001) and cooler/wetter winter in the upper Midwest U.S. (Budikova et al., 2022).

Besides the ENSO, several other teleconnection indices also show different inluences on LPM snowfall in BART and RF models. The North Pacific index (np) is calculated as the area-weighted seal level pressure over the North Pacific (Trenberth & Hurrell, 1994). The np is closely related to the tropical and subtropical SST through ocean-atmosphere interactions and it also interacts with the ENSO cycle. We show that snowfall amounts significantly increase when the np is above 1006 millibars. This agrees with Chen and Song (2018) which shows significant negative relationships between np and temperature in central Canada and U.S great lakes. The PDO reflects remote changes of SST in the North Pacific and the sea level pressures over the Aleutian Island (Mantua et al., 1997; Newman et al., 2016), which has teleconnections with winter temperature and precipitation pattern in large portion of Midwest U.S. Both BART and RF pdps demonstrate that the snowfall generally increases when the PDO anomaly is negative. Previous studies also indicates that negative phases of PDO are normally associated with above normal winter precipitation in a large portion of interior U.S. (Mantua et al., 1997; Newman et al., 2016). The PNA is a changing pattern of SST and sea level pressure in the Pacific associated with ENSO but also with atmospheric internal variability and SST anomalies (Li et al., 2019). It has strong influence on precipitation in North American by modifying Polar jet flows and associated storm tracks. Negative PNA phases are usually more favorable to northern displacement of jet over the eastern U.S. It frequently causes intruding of maritime tropical air from the Gulf (Budikova et al., 2022; Leathers et al., 1991) and enhancement in local precipitation in the eastern U.S. The pdps (Fig 4m & Fig 5m) are showing similar patterns, where negative PNA anomalies are generally associated with more LPM snowfall. The BART's PNA pdp has more nonlinearity than the RF with a spike of snowfall increase when the PNA value is between -0.8 and 0.5 (Fig. 4m).

The Tropical Southern Atlantic Index (tsi, Fig 4b) is showing a general positive relationship with the snowfall and this is a new relationship we have discovered from the model. The tsi is closed related to the NAO on interannual to decadal time scales (Marshall et al., 2001). Such relationship might be related to the existing linkage between snowfall and NAO. The NAO and AO signals are closely related and they both control the upper-level winds and the polar vortex in the Northern Hemisphere (Budikova et al., 2022). Positive NAO/AO phases are associated with a stronger polar vortex that locks the cold air in the higher latitude while negative NAO/AO is usually associated with enhanced meandering of polar jet and outbreaks of colder air into the lower latitude (Budikova, 2012). This cold air usually introduces extreme low temperature and snowfall (Ghatak et al., 2010). The NAO/AO only appear in the BART model with minor variable importance. Fig 4r shows that higher snowfall is generally associated with negative NAO but its relationship with AO is more complex (Fig 4x).

3.5 Extreme snowfall

Our results have clearly shown that BART and RF are the two best models for predicting snowfall in the LPM. To evaluate their performance in predicting extreme snowfall events and examine important factors, we selected the upper 30% (> 70th percentile) of the snowfall data to develop two new BART and RF models. Results (Table 4) show that both extreme models have decreases in their fitting skills as compared with those general models trained by the 80% randomly selected sample (Table 3). The R^2 for RF has changed from 0.58 to 0.30 (-48%) while the R^2 for BART has changed from 0.88 to 0.63 (-28%). The RF's RMSE increased from 20.24 to 21.06 (+4%) and MAE increased from 15.29 to 15.93 (+4%), while the BART's RMSE increased from 11.07 to 15.29 (+38%) and MAE increased from 8.48 to 11.53 (+36%). Therefore, the RF has larger relative changes in R^2 while the BART has larger relative changes in RMSE and MAE. Meanwhile, the BART model still performs better than the RF model with higher R^2, lower MAE and RMSE.

Table 4. Fitting statistics for RF and BART models based on the upper 70 percentile of snowfall data (extreme snowfall)

Model	RMSE	R^2	MAE
RF	21.06	0.30	15.93
BART	15.29	0.63	11.53

In terms of VIs, both RF and BART extreme models show slightly differences from the general models (Table 5). It is interesting to note that maxT and vpdmax are the two most important predictors for both extreme models (Table 5). More snowfall is corresponding to lower maxT as well as lower vpdmax (Fig 6), which are similar to their relationships shown by the regular models. Note that fluctuations in snowfall in higher range of vpdmax in Fig 4a disappear in Fig 6b, indicating a more dominate control of higher atmospheric moisture in generating extreme snowfall events. Other temperature variables (rangeT, avgT, minT) are also important in both RF and BART models for the extremes. And they all show negative relationships with the snowfall. The np is the only teleconnection variable that shows in the top 10 VI list for both RF and BART (Table 5). In Fig 6 and SI 6, we also find that the np and other teleconnection variables (ENSO, PDO, NAO, AO, and PNA) follow their relationship with the LPM snowfall in general models (Fig 4&5). The tsi has a positive relationship with snowfall in pdps for both BART (Fig 6d) and RF (SI 6i).

Many previous studies have mentioned that climate extremes prediction is challenging from both Earth System Models and Machine Learning models (Sillmann et al., 2017; Zhu & Aguilera, 2021; Zwiers et al., 2013). Our result shows that the RF and BART models both have slight degradations in their fitting skills for modeling extreme snowfall observations. They still can offer decent amount of explained variance (R^2), relatively small error statistics based on the extreme snowfall observations containing much larger variability and uncertainty. It can be also referred from the above analysis that the BART model overall does a reasonable job in the prediction of overall and extreme snowfall events in the LPM.

Table 5. Relative variable importance (VI) for the 70 percentile models RF and BART

Rank	RF		BART	
1	maxT	100	maxT	100
2	vpdmax	93	vpdmax	98
3	rangeT	85	elev	94
4	avgT	84	tsi	87
5	minT	68	rangeT	86
6	np	67	avgT	83

7	elev	64	lat	80
8	dist2shore	62	dist2shore	76
9	savgT	62	np	75
10	lat	52	vwind	73

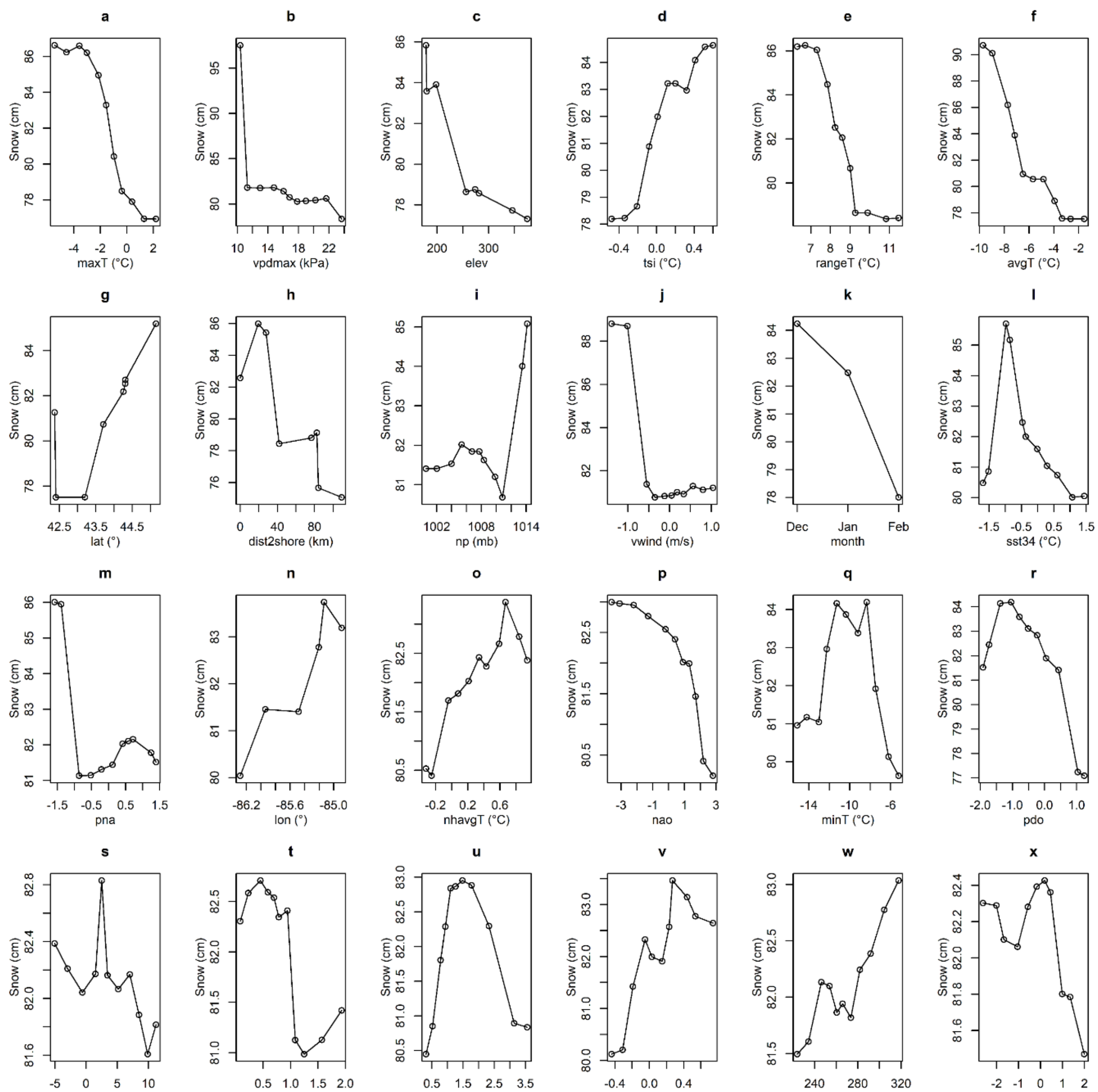

Fig 6. The partial dependence plot (pdp) for the BART model developed by the 70 percentile data

4. Discussion and conclusion

Our analysis suggests that temperatures are one of the most important predictors in machine learning techniques predicting snowfall in the LPM. At each station, maximum and minimum temperatures have a stronger impact on snowfall than the average temperatures. This indicates that snow formation process in this region is more sensitive to extreme temperatures. Similar results were found over the Canadian domain of the Great Lakes basin (Baijnath-Rodino et al., 2018). At the global level, the north hemisphere averaged temperatures demonstrate negative relations with the LPM snow. Physical mechanisms for this relationship such as polar vortex break or increased temperature difference between lake surface and air need further investigations (Agee & Hart, 1990; Meng & Ma, 2021).The moisture availability is another important factor in both BART and RF models and they generally show negative relationships with the snowfall. We need process based Regional Climate Models (RCM) to understand more details about how the changing temperature and water vapor in the atmosphere determine the lake-effect snow through lake-land-atmosphere interactions and other synoptic processes.

Our models also demonstrate that latitude, elevation, and distance to shoreline are important predictors for snowfall. The importance of these variables is possibly associated with regional physical processes that lead to the development of lake-effect snowfall events. Elevation's control in snowfall amounts in the Great Lakes region has been mentioned in previous literatures (Hill, 1971; Niziol, 1987). RCM simulations also suggest that both annual snowfall and frequency (days per year) decreases as the downwind distance from the Great Lakes increases (Notaro et al., 2013). Inclusion of these local static variables has greatly improved the prediction skill of our machine learning models.

Seven teleconnection indices, including NP, SST34, PNA, NAO, PDO, TNI, and AO, were included in our snow prediction models. Machine leaning techniques have no assumption of non-collinearity among independent variables. Therefore, these teleconnections can work together to improve the model prediction skill. Our results demonstrate several important teleconnection indices in the snow prediction models, including SST34, PDO, and NP. These indices have non-linear or linear relationships with snowfall in the LPM. Further investigations are needed to validify the physical process reflected by those relationships shown by the machine learning models. Particularly, we need to improve understanding the partition of snowfall into lake-effect and non-lake effect snowfall in the Great Lakes regions because these two different types of snowfall are produced through different physical mechanisms (Pettersen et al., 2020).

Our comparison of various machine learning models suggests the BART model can predict mean and extreme monthly LPM snowfall with high accuracy. The machine learning approach assimilates dynamic atmospheric/oceanic signals from multiple scales and static environmental variables such as topography and distance to shore. It provides a reliable and computational efficient alternative to current numerical weather/climate predictions (Chantry et al., 2021) as well as a new way to identify possible physical mechanisms. In the future, the machine learning models can be tested for other snow prone regions and used for predicting regional snowfall variability and changes based CMIP climate projections for the future.

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Author Contributions:

L.Z. conceptualized and designed the research. L.M. and L.Z. executed the data analysis and drafted the manuscript. L.M. and L.Z. edited the manuscript.

Competing Interests statement

The authors declare no competing interests.

Data and materials availability:

All data, code, and materials used in the analyses will be available from the authors upon request.

References

Agee, E. M., & Hart, M. L. (1990). Boundary layer and mesoscale structure over Lake Michigan during a wintertime cold air outbreak. *Journal of the Atmospheric Sciences*, *47*(19). https://doi.org/10.1175/1520-0469(1990)047<2293:BLAMSO>2.0.CO;2

Baijnath-Rodino, J. A., Duguay, C. R., & LeDrew, E. (2018). Climatological trends of snowfall over the Laurentian Great Lakes Basin. *International Journal of Climatology*, *38*(10). https://doi.org/10.1002/joc.5546

Balshi, M. S., McGuire, A. D., Duffy, P., Flannigan, M., Walsh, J., & Melillo, J. (2009). Assessing the response of area burned to changing climate in western boreal North America using a Multivariate Adaptive Regression Splines (MARS) approach. *Global Change Biology*, *15*(3). https://doi.org/10.1111/j.1365-2486.2008.01679.x

Bell, B., Hersbach, H., Simmons, A., Berrisford, P., Dahlgren, P., Horányi, A., et al. (2021). The ERA5 global reanalysis: Preliminary extension to 1950. *Quarterly Journal of the Royal Meteorological Society*, *147*(741), 4186–4227. https://doi.org/10.1002/qj.4174

Bjorkman, A. D., Elmendorf, S. C., Beamish, A. L., Vellend, M., & Henry, G. H. R. (2015). Contrasting effects of warming and increased snowfall on Arctic tundra plant phenology over the past two decades. *Global Change Biology*, *21*(12), 4651–4661. https://doi.org/10.1111/gcb.13051

Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). Training algorithm for optimal margin classifiers. In *Proceedings of the Fifth Annual ACM Workshop on Computational Learning Theory*. https://doi.org/10.1145/130385.130401

Braham, R. R., & Dungey, M. J. (1984). Quantitative Estimates of the Effect of Lake-Michigan on Snowfall. *Journal of Climate and Applied Meteorology*, *23*(6), 940–949. https://doi.org/Doi 10.1175/1520-0450(1984)023<0940:Qeoteo>2.0.Co;2

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1). https://doi.org/10.1023/A:1010933404324

Budikova, D. (2012). Northern Hemisphere Climate Variability: Character, Forcing Mechanisms, and Significance of the North Atlantic/Arctic Oscillation. *Geography Compass*. https://doi.org/10.1111/j.1749-8198.2012.00498.x

Budikova, D., Ford, T. W., & Wright, J. D. (2022). Characterizing winter season severity in the Midwest United States, part II: Interannual variability. *International Journal of Climatology*, *42*(6). https://doi.org/10.1002/joc.7429

Chantry, M., Christensen, H., Dueben, P., & Palmer, T. (2021). Opportunities and challenges for machine learning in weather and climate modelling: Hard, medium and soft AI. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2194). https://doi.org/10.1098/rsta.2020.0083

Chen, J., & Kumar, P. (2002). Role of terrestrial hydrologic memory in modulating ENSO impacts in North America. *Journal of Climate*, *15*(24). https://doi.org/10.1175/1520-0442(2003)015<3569:ROTHMI>2.0.CO;2

Chen, S., & Song, L. (2018). Impact of the Winter North Pacific Oscillation on the Surface Air Temperature over Eurasia and North America: Sensitivity to the Index Definition. *Advances in Atmospheric Sciences*, *35*(6). https://doi.org/10.1007/s00376-017-7111-5

Chiodi, A. M., Potter, B. E., & Larkin, N. K. (2021). Multi-Decadal Change in Western US Nighttime Vapor Pressure Deficit. *Geophysical Research Letters*, *48*(15). https://doi.org/10.1029/2021GL092830

Chipman, H. A., George, E. I., & McCulloch, R. E. (2012). BART: Bayesian additive regression trees. *Annals of Applied Statistics*, *6*(1). https://doi.org/10.1214/09-AOAS285

Choubin, B., Borji, M., Mosavi, A., Sajedi-Hosseini, F., Singh, V. P., & Shamshirband, S. (2019). Snow avalanche hazard prediction using machine learning methods. *Journal of Hydrology*, *577*. https://doi.org/10.1016/j.jhydrol.2019.123929

Clark, C. A., Elless, T. J., Lyza, A. W., Ganesh-Babu, B., Koning, D. M., Carne, A. R., et al. (2016). Spatiotemporal snowfall variability in the Lake Michigan Region: How is warming affecting wintertime snowfall? *Journal of Applied Meteorology and Climatology*, *55*(8). https://doi.org/10.1175/JAMC-D-15-0285.1

Ford, T. W., Budikova, D., & Wright, J. D. (2021). Characterizing winter season severity in the Midwest United States, Part I: Climatology and recent trends. *International Journal of Climatology*. https://doi.org/10.1002/joc.7431

Francis, J. A., & Vavrus, S. J. (2012). Evidence linking Arctic amplification to extreme weather in mid-latitudes. *Geophysical Research Letters*, *39*(6). https://doi.org/10.1029/2012GL051000

Friedman, J. H. (1991). Multivariate Adaptive Regression Splines. *The Annals of Statistics*, *19*(1), 1–141.

Friedman, Jerome H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5). https://doi.org/10.1214/aos/1013203451

Ghatak, D., Gong, G., & Frei, A. (2010). North American temperature, snowfall, and snow-Depth response to winter climate modes. *Journal of Climate*, *23*(9). https://doi.org/10.1175/2009JCLI3050.1

Gianola, D., Okut, H., Weigel, K. A., & Rosa, G. J. M. (2011). Predicting complex quantitative traits with Bayesian neural networks: A case study with Jersey cows and wheat. *BMC Genetics*, *12*. https://doi.org/10.1186/1471-2156-12-87

Gibson, P. B., Chapman, W. E., Altinok, A., Delle Monache, L., DeFlorio, M. J., & Waliser, D. E. (2021). Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. *Communications Earth & Environment*, *2*(1). https://doi.org/10.1038/s43247-021-00225-4

Grömping, U. (2009). Variable importance assessment in regression: Linear regression versus random forest. *American Statistician*, *63*(4). https://doi.org/10.1198/tast.2009.08199

Gutowski, W. J., Ullrich, P. A., Hall, A., Leung, L. R., O'Brien, T. A., Patricola, C. M., et al. (2021). The ongoing need for high-resolution regional climate models: Process understanding and stakeholder information. *Bulletin of the American Meteorological Society*, *101*(5). https://doi.org/10.1175/BAMS-D-19-0113.1

Ham, Y. G., Kim, J. H., & Luo, J. J. (2019). Deep learning for multi-year ENSO forecasts. *Nature*, *573*(7775). https://doi.org/10.1038/s41586-019-1559-7

Hartnett, J. J., Collins, J. M., Baxter, M. A., & Chambers, D. P. (2014). Spatiotemporal Snowfall Trends in Central New York. *Journal of Applied Meteorology and Climatology*, *53*(12), 2685–2697. https://doi.org/10.1175/Jamc-D-14-0084.1

Hill, J. D. (1971). *Snow squalls in the lee of Lakes Erie and Ontario.*

Hong, S. Y., Dudhia, J., & Chen, S. H. (2004). A revised approach to ice microphysical processes for the bulk parameterization of clouds and precipitation. *Monthly Weather Review*, *132*(1). https://doi.org/10.1175/1520-0493(2004)132<0103:ARATIM>2.0.CO;2

Kluver, D., & Leathers, D. (2015). Winter snowfall prediction in the United States using multiple discriminant analysis. *International Journal of Climatology*, *35*(8), 2003–2018.

Kolka, R. K., Giardina, C. P., McClure, J. D., Mayer, A., & Jurgensen, M. F. (2010). Partitioning hydrologic contributions to an “old-growth” riparian area in the Huron Mountains of Michigan, USA. *Ecohydrology*, *3*(3). https://doi.org/10.1002/eco.112

Kuhn, M. (2008). Building predictive models in R using the caret package. *Journal of Statistical Software*, *28*(5). https://doi.org/10.18637/jss.v028.i05

Kunkel, K E, Ensor, L., Palecki, M., Easterling, D., Robinson, D., Hubbard, K. G., & Redmond, K. (2009). A new look at lake-effect snowfall trends in the Laurentian Great Lakes using a temporally homogeneous data set. *Journal of Great Lakes Research*, *35*(1), 23–29.

Kunkel, Kenneth E., Westcott, N. E., & Kristovich, D. A. R. (2002). Assessment of potential effects of climate change on heavy lake-effect snowstorms near Lake Erie. *Journal of Great Lakes Research*, *28*(4). https://doi.org/10.1016/S0380-1330(02)70603-5

Leathers, D. J., Yarnal, B., & Palecki, M. A. (1991). The Pacific/North American Teleconnection Pattern and United States Climate. Part I: Regional Temperature and Precipitation Associations. *Journal of Climate*, *4*(5). https://doi.org/10.1175/1520-0442(1991)004<0517:tpatpa>2.0.co;2

Li, X., Hu, Z. Z., Liang, P., & Zhu, J. (2019). Contrastive influence of ENSO and PNA on variability and predictability of north American winter precipitation. *Journal of Climate*, *32*(19). https://doi.org/10.1175/JCLI-D-19-0033.1

Mantua, N. J., Hare, S. R., Zhang, Y., Wallace, J. M., & Francis, R. C. (1997). A Pacific Interdecadal Climate Oscillation with Impacts on Salmon Production. *Bulletin of the American Meteorological Society*, *78*(6). https://doi.org/10.1175/1520-0477(1997)078<1069:APICOW>2.0.CO;2

Marshall, J., Kushnir, Y., Battisti, D., Chang, P., Czaja, A., Dickson, R., et al. (2001). North Atlantic climate variability: Phenomena, impacts and mechanisms. *International Journal of Climatology*, *21*(15). https://doi.org/10.1002/joc.693

Meng, L., & Ma, Y. (2021). On the relationship of lake-effect snowfall and teleconnections in the Lower Peninsula of Michigan, USA. *Journal of Great Lakes Research*, *47*(1). https://doi.org/10.1016/j.jglr.2020.11.013

Meng, L., Ayon, B. D., Koirala, N., & Baker, K. M. (2021). Inter-annual Variability of Snowfall in the Lower Peninsula of Michigan. *Frontiers in Water*, *3*. https://doi.org/10.3389/frwa.2021.746354

Molnar, C., Casalicchio, G., & Bischl, B. (2020). Interpretable Machine Learning – A Brief History, State-of-the-Art and Challenges. In *Communications in Computer and Information Science* (Vol. 1323). https://doi.org/10.1007/978-3-030-65965-3_28

Nayak, M. A., & Ghosh, S. (2013). Prediction of extreme rainfall event using weather pattern recognition and support vector machine classifier. *Theoretical and Applied Climatology*, *114*(3–4). https://doi.org/10.1007/s00704-013-0867-3

Nelder, J. A., & Wedderburn, R. W. M. (1972). Generalized Linear Models. *Journal of the Royal Statistical Society. Series A (General)*, *135*(3), 370–384.

Newman, M., Alexander, M. A., Ault, T. R., Cobb, K. M., Deser, C., di Lorenzo, E., et al. (2016). The Pacific decadal oscillation, revisited. *Journal of Climate*, *29*(12). https://doi.org/10.1175/JCLI-D-15-0508.1

Nguyen, D., & Widrow, B. (1990). Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights. In *IJCNN. International Joint Conference on Neural Networks*. https://doi.org/10.1109/ijcnn.1990.137819

Niziol, T. A. (1987). Operational Forecasting of Lake Effect Snowfall in Western and Central New York. *Weather and Forecasting*, *2*(4). https://doi.org/10.1175/1520-0434(1987)002<0310:ofoles>2.0.co;2

Notaro, M., Zarrin, A., Vavrus, S., & Bennington, V. (2013). Simulation of Heavy Lake-Effect Snowstorms across the Great Lakes Basin by RegCM4: Synoptic Climatology and Variability. *Monthly Weather Review*, *141*(6), 1990–2014.

Novick, K. A., Ficklin, D. L., Stoy, P. C., Williams, C. A., Bohrer, G., Oishi, A. C., et al. (2016). The increasing importance of atmospheric demand for ecosystem water and carbon fluxes. *Nature Climate Change*, *6*(11). https://doi.org/10.1038/nclimate3114

O'Gorman, P. A., & Dwyer, J. G. (2018). Using Machine Learning to Parameterize Moist Convection: Potential for Modeling of Climate, Climate Change, and Extreme Events. *Journal of Advances in Modeling Earth Systems*, *10*(10). https://doi.org/10.1029/2018ms001351

Pettersen, C., Kulie, M. S., Bliven, L. F., Merrelli, A. J., Petersen, W. A., Wagner, T. J., et al. (2020). A Composite Analysis of Snowfall Modes from Four Winter Seasons in Marquette, Michigan. *Journal of Applied Meteorology and Climatology*, 103–124. https://doi.org/10.1175/JAMC-D-19

Quante, L., Willner, S. N., Middelanis, R., & Levermann, A. (2021). Regions of intensification of extreme snowfall under future warming. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-95979-4

Reddy, B. S. N., Pramada, S. K., & Roshni, T. (2021). Monthly surface runoff prediction using artificial intelligence: A study from a tropical climate river basin. *Journal of Earth System Science*, *130*(1). https://doi.org/10.1007/s12040-020-01508-8

Robertson, A. W., Kumar, A., Peña, M., & Vitart, F. (2015). Improving and promoting subseasonal to seasonal prediction. In *Bulletin of the American Meteorological Society* (Vol. 96). https://doi.org/10.1175/BAMS-D-14-00139.1

Sasieni, P. (1992). Generalized additive models. T. J. Hastie and R. J. Tibshirani, Chapman and Hall, London, 1990. No. of Pages: xv + 335. Price: £25. ISBN: 0-412-34390-8. *Statistics in Medicine*, *11*(7). https://doi.org/10.1002/sim.4780110717

Sauter, T., Weitzenkamp, B., & Schneider, C. (2010). Spatio-temporal prediction of snow cover in the Black Forest mountain range using remote sensing and a recurrent neural network. *International Journal of Climatology*, *30*(15). https://doi.org/10.1002/joc.2043

Schneider, T., Lan, S., Stuart, A., & Teixeira, J. (2017). Earth System Modeling 2.0: A Blueprint for Models That Learn From Observations and Targeted High-Resolution Simulations. *Geophysical Research Letters*, *44*(24). https://doi.org/10.1002/2017GL076101

Shi, Q., & Xue, P. (2019). Impact of Lake Surface Temperature Variations on Lake Effect Snow Over the Great Lakes Region. *Journal of Geophysical Research: Atmospheres*, *124*(23). https://doi.org/10.1029/2019JD031261

Sillmann, J., Thorarinsdottir, T., Keenlyside, N., Schaller, N., Alexander, L. v., Hegerl, G., et al. (2017). Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities. *Weather and Climate Extremes*. https://doi.org/10.1016/j.wace.2017.10.003

Smith, S. R., & O'Brien, J. J. (2001). Regional snowfall distributions associated with ENSO: Implications for seasonal forecasting. *Bulletin of the American Meteorological Society*, *82*(6), 1179–1191. https://doi.org/Doi 10.1175/1520-0477(2001)082<1179:Rsdawe>2.3.Co;2

Suriano, Z. J., & Leathers, D. J. (2017). Synoptic climatology of lake-effect snowfall conditions in the eastern Great Lakes region. *International Journal of Climatology*, *37*(12), 4377–4389. https://doi.org/10.1002/joc.5093

Trenberth, K. E., & Guillemot, C. J. (1996). Physical processes involved in the 1988 drought and 1993 floods in north America. *Journal of Climate*, *9*(6). https://doi.org/10.1175/1520-0442(1996)009<1288:PPIITD>2.0.CO;2

Trenberth, K. E., & Hurrell, J. W. (1994). Decadal atmosphere-ocean variations in the Pacific. *Climate Dynamics*, *9*(6). https://doi.org/10.1007/BF00204745

Tripathi, S., Srinivas, V. v., & Nanjundiah, R. S. (2006). Downscaling of precipitation for climate change scenarios: A support vector machine approach. *Journal of Hydrology*, *330*(3–4). https://doi.org/10.1016/j.jhydrol.2006.04.030

Wei, W., Yan, Z., Tong, X., Han, Z., Ma, M., Yu, S., & Xia, J. (2022). Seasonal prediction of summer extreme precipitation over the Yangtze River based on random forest. *Weather and Climate Extremes*, *37*, 100477. https://doi.org/10.1016/j.wace.2022.100477

Zhou, Q., Li, D., Xia, S., Chen, Z., Wang, B., & Wu, J. (2021). Plant–rodent interactions after a heavy snowfall decrease plant regeneration and soil carbon emission in an old-growth forest. *Forest Ecosystems*, *8*(1). https://doi.org/10.1186/s40663-021-00310-2

Zhu, L., & Aguilera, P. (2021). Evaluating Variations in Tropical Cyclone Precipitation in Eastern Mexico Using Machine Learning Techniques. *Journal of Geophysical Research: Atmospheres*, *126*(7). https://doi.org/10.1029/2021JD034604

Zwiers, F. W., Alexander, L. v., Hegerl, G. C., Knutson, T. R., Kossin, J. P., Naveau, P., et al. (2013). Climate Extremes: Challenges in Estimating and Understanding Recent Changes in the Frequency and Intensity of Extreme Climate and Weather Events. In *Climate Science for Serving Society*. https://doi.org/10.1007/978-94-007-6692-1_13