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Application of Artificial Intelligence Models for Aeolian Dust Prediction at Different Temporal Scales: A Case with Limited Climatic Data

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Abstract: Accurately predicting ambient dust plays a crucial role in air quality management and hazard mitigation. This study explores the accuracy of Artificial Intelligence (AI) models: adaptive-network-based fuzzy inference system (ANFIS) and multi-layered perceptron artificial neural network (mlp-NN) over the southwestern United States (SWUS) based on the observed dust data from IMPROVE stations. The ambient fine dust (PM2.5) and coarse dust (PM10) concentrations at monthly and seasonal timescale from 1990-2020 are modeled using average daily maximum wind speed (W), average precipitation (P), and average air temperature (T) available from North American Regional Reanalysis (NARR). The model's performance is measured using correlation (r), root mean square error (RMSE), and percentage bias (% BISA). ANFIS model generally performs better than mlp-NN model in predicting regional dustiness over the SWUS region with r of 0.77 and 0.83 for monthly and seasonal fine dust respectively. AI models perform better in predicting regional dustiness at a seasonal timescale than the monthly timescale for both fine dust and coarse dust. AI models better predict fine dust than coarse dust at both monthly and seasonal timescales. Compared to precipitation, the near-surface average temperature is the more important predictor of the regional dustiness at both monthly and seasonal timescale. However, compared to the monthly timescale, air temperature is less more important predictor than precipitation at the seasonal timescale for PM2.5 and vice versa for PM10. The findings of this study demonstrate that the AI models have a good potential to predict monthly and seasonal fine and coarse dust at acceptable accuracy based on basic climatic data.

Keywords: Artificial Intelligence; ANFIS; MLP-NN; aeolian dust

1. Introduction

Aeolian dust storms degrade visibility and cause several health problems including traffic accidents, degradation in industrial machinery, cardiovascular diseases, and lung cancers (Domínguez-Rodríguez et al. 2021; Achakulwisut et al. 2019; Al-Hemoud et al. 2019; Bhattachan et al. 2019). Fine dust (soil dust with particle matter <= 2.5 μm) contributes about 20 – 50 % of total fine particulate matter (PM2.5) in the western United States (WUS) (Hand et al. 2017). Dust particles also play an important role in the global climate system and regional and local climate and environment primarily by absorbing and scattering both solar and terrestrial radiation (Evans et al. 2020, 2019; Saidou et al. 2020; Mallet et al. 2009). For example, aeolian dust on snow increases the snow albedo and accelerates snowmelt in the Colorado River (Painter et al. 2018), and alters the North American monsoon by heating the lower troposphere (Zhao et al. 2012).

The dust emission, transport, and deposition are influenced by complex land-atmospheric interactions, mainly high wind speed, land erodibility and bareness, and humidity, among other influencing factors (Csavina et al 2014). Studies show that ambient dustiness over dust-prone regions heavily depends on the regional drought (Javadian et al. 2019; Achakulwisut et al. 2018; Nabavi et al. 2016). Nabavi et al. (2016) demonstrated that 2007 – 2008 Winter and Spring (October to May) dust in Western Asia were associated with severe precipitation deficit. Intermodal spread in CMIP6 simulated dust emission is explained by the differences in the models' drought sensitivity to dust emission (Aryal and Evans 2021). Therefore, understanding the predictability of regional dustiness based on the regional hydroclimate is an interesting research topic.

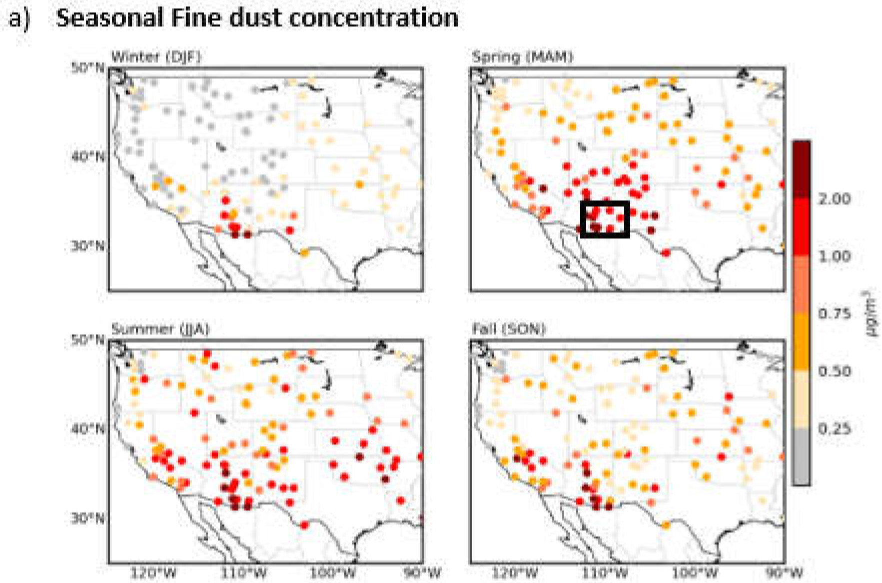
Few previous studies have analyzed the predictability of western US dust. For example, Bing Pu used the linear regression technique to predict the Spring season's high concentration coarse dust event frequency based on wind speed, precipitation, and surface bareness. Aryal (2022) showed that machine learning models better predict fine dust than coarse dust at a monthly timescale. Temperature strongly depends on the monthly timescale while precipitation is important to explain the long-term variability of ambient dust (Aryal 2022; Namdari et al. 2018). Earth system models heavily underestimate coarse dust (Kok et al. 2018). However, much less effort has been made to compare the predictability of fine and coarse dust at different temporal scales based on climatic data.

The specific objectives of this work are 1) To predict the aeolian dust using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and multi-layered perceptron Artificial Neural Networks (mlp-ANN) models and 2) To compare the models' performance for fine dust (particle diameter ≤ 2.5 μm; PM2.5) and coarse dust (particle diameter 2.5–10 μm; PM10) at monthly and seasonal timescales.

2. Materials and Methods

2.1. Study Area and Data

The southwestern US is a major dust source in the USA (Ginoux et al. 2012). The Chihuahuan Desert, the Colorado River, and the High Plains are well-known dust sources in the region. The Interagency Monitoring of Protected Visual Environments (IMPROVE) network provides the observed near-surface dust concentration over the region (DeBell et al. 2006; available online: https://views.cira.colostate.edu/fed/Express/ImproveData.aspx (accessed on 10 April 2022)). The location of the observation stations over the study region is shown in Figure 1. The 24-hour dust concentration was measured every Saturday and Wednesday before 2001 and after that observations are done every third day. The total precipitation (P), average 2 m air temperature (T), and monthly average daily maximum 10 m wind speed (W) were taken from the North American Regional Reanalysis (NARR) at 0.3 deg resolution(Mesinger et al. 2006 available online: https://psl.noaa.gov/data/gridded/data.narr.monolevel.html (accessed on 10 April 2022)), at 0.3 × 0.3 resolution. The analysis is done on a regional scale (Figure 1). Data from1988 to 2010 are used as training data and those from 2011 to 2020 as test data. The model performance results are shown for the test data.



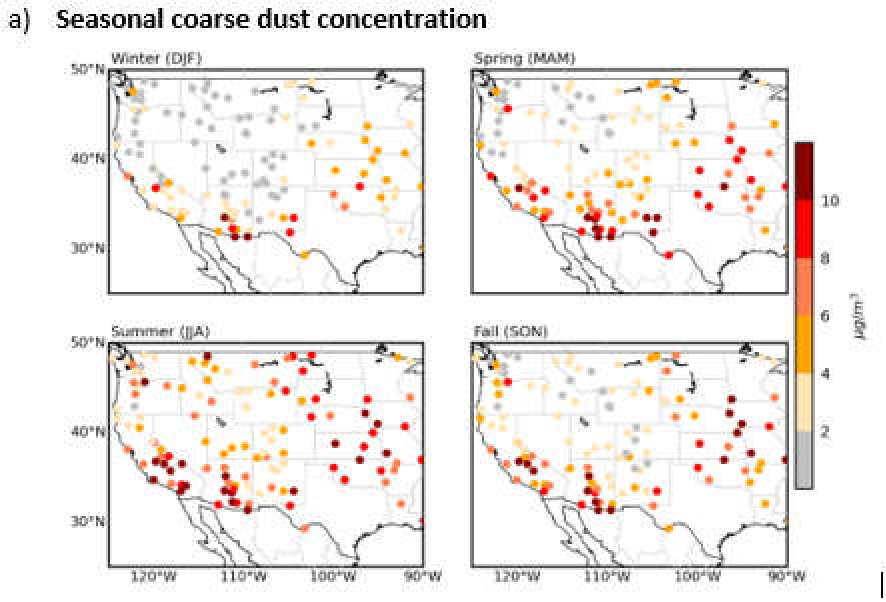


Figure 1. Location of the IMPROVE stations across the US. The Black box in the top right corner indicates the study region of this study.

2.2. *Artificial Intelligence (AI) Models*

The performance of two widely used AI models: adaptive-network-based fuzzy inference system (ANFIS) and multi-layered perceptron artificial neural network (mlp-NN) are examined. All computations are done in R (R Core Team 2013).

2.2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS model, proposed by Jiang (1993), combines fuzzy logic and neural network. The layered structure (Figure 2) in the ANFIS model adds fuzzy logic to the artificial neural networks.

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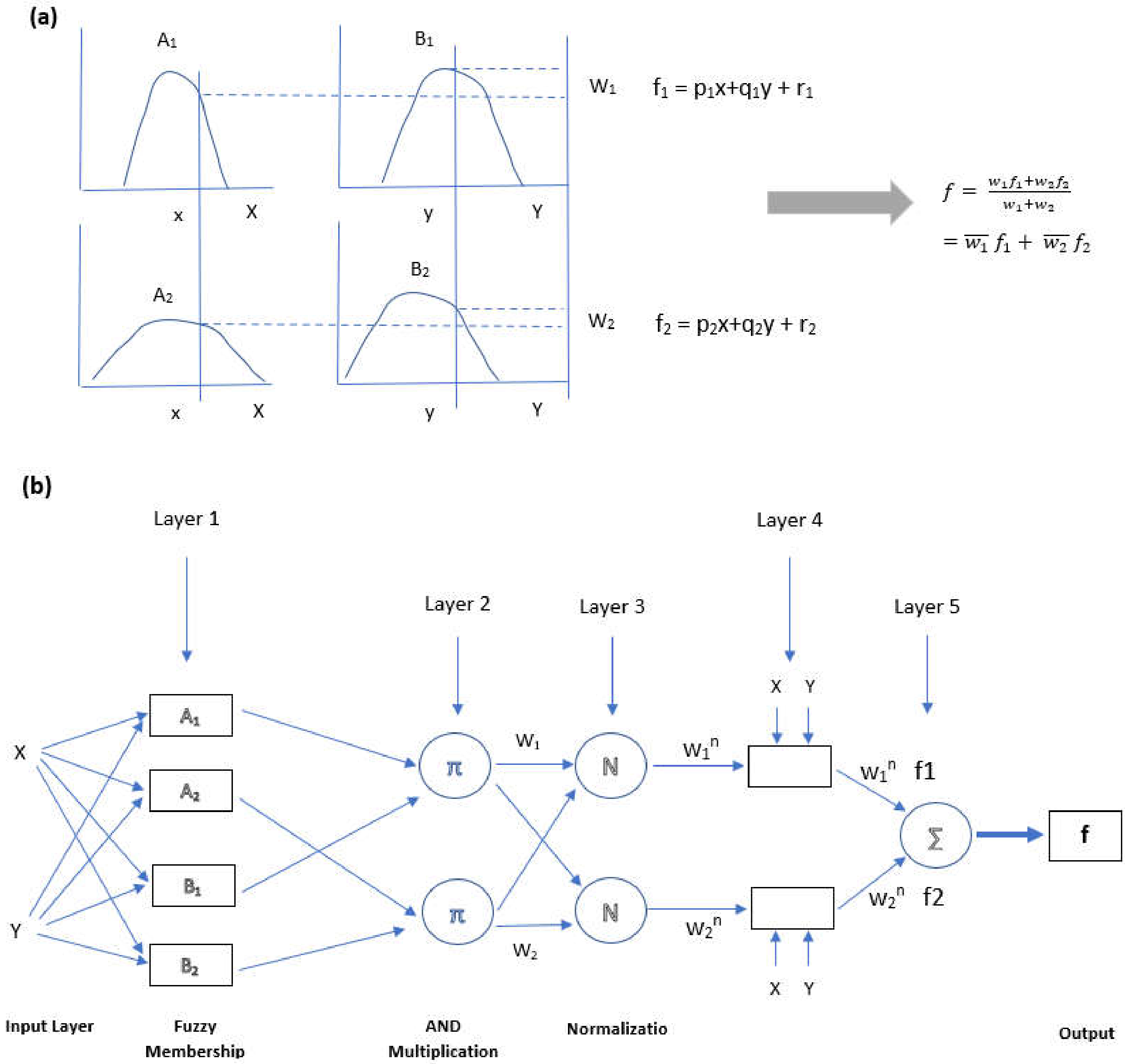

Figure 2. (a) Fuzzy inference system and (b) equivalent ANFIS architecture.

The fuzzy interference system uses the hybrid learning algorithm to identify the system parameters and teach the model (Rehman and Mohandes 2008). For two inputs (x,y) and output (f), the fuzzy if-then rules from Takagi and Sugeno (1983) are as follows

1. $if\ x\ is\ A_1 and\ y\ is\ B_1, then\ f_1 = a_1x + b_1y + r_1$

2. $if\ x\ is\ A_2 and\ y\ is\ B_2, then\ f_2 = a_2x + b_2y + r_2$

The five-layer architecture of ANFIS (Nayak et al. 2004; Tabari et al. 2012; Karandish and Šimůnek 2016), shown in figure 2, is as follows:

Layer 1: This is the input layer. In this fuzzy layer, each node in the layer is the degree of membership function $\left(MFs,\ \mu_{Ai}(x)\right)$ from the input. The output of the first layer is the membership values of each input for specific MFs. The shape of the MFs can be any appropriate functions that are continuous and piecewise differentiable such as Gaussian, generalized bell-shaped, trapezoidal-shaped and triangular-shaped functions (Talpur et al. 2017). In this study the Gaussian MF is used that is defined as:

$$G(x, c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}$$

Layer 2: This layer multiplies the input values from the incoming signal. The AND fuzzy operator is applied to get the weight (firing strength). For example, for the first node,

$$w_i = \mu_{Ai}(x) * \mu_{Bi}(x), i = 1,2$$

where,

w_i is the firing strength of the ith rule

$\mu_{Ai}(x)$ is the degree of membership function fuzzy sets A_i

$\mu_{Bi}(x)$ is the degree of membership function fuzzy sets B_i

Layer 3: The circle nodes in this layer normalize the firing strength. The normalized weight is the ratio of the firing strength of ith rule to the sum of all firing strength

$$\overline{w_1} = \frac{w_1}{\sum_{i=1}^{n} w_i}, \quad i = 1,2, \ldots, n$$

where n is the number of nodes in each layer.

Layer 4: This is a de-fuzzy layer and each node is called an adaptive node. In this layer terms are the results of operation on input signals:

$Z_i = \overline{w_1}\, f_1 = \overline{w_1}\,(p_1 x + q_1 y + r_1)$

where, $p_1, q_1, and\ r_1$ are the consequent parameters

Layer 5: The overall output calculated in this output layer as the summation of all incoming signals from previous layers

$$Overall\ output = \sum_{i=1}^{n} \overline{w}_i\, f_i$$

2.2.2. Multilayer perceptron neural network (MLP-NN)

The mlp-ANN is the most widely used feed-forward neural network. The basic structure of the mlp-NN with two hidden layers is shown in Figure 3. A detailed explanation of MLP-NN is given in Schalkoff (1997) and Hanoon et al. (2021).

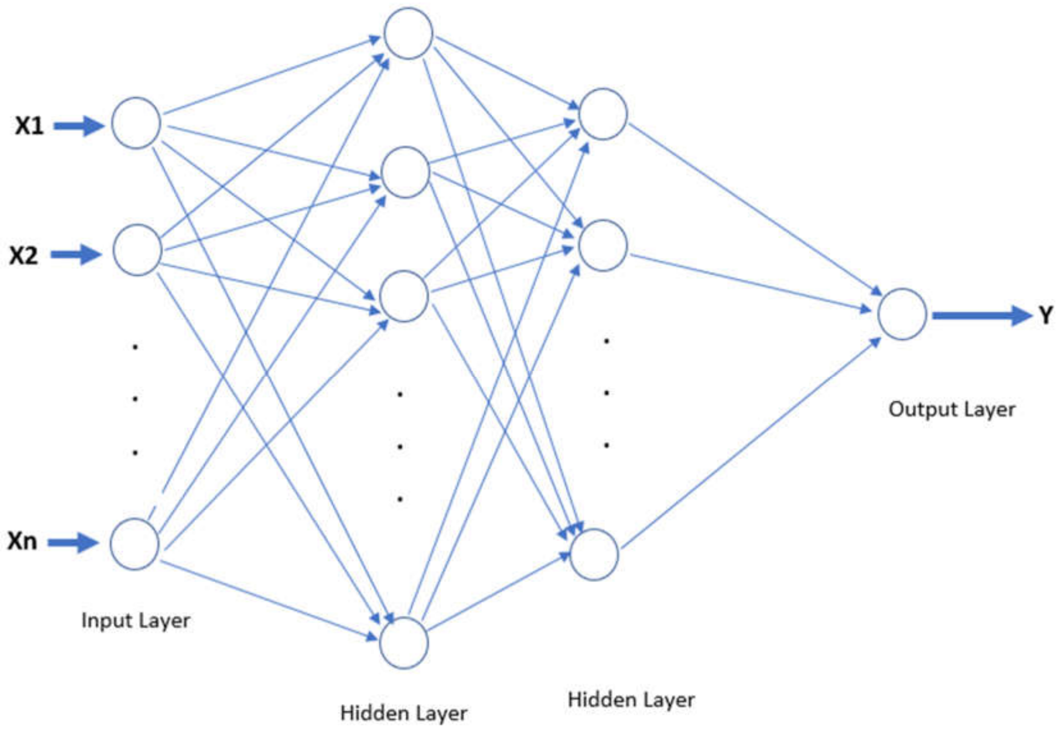

Figure 3. mlp-NN architecture with two hidden layers.

The neurons in the input layer work as a buffer for the distribution of input signals to the hidden layers. Any hidden neuron j sum up the signals from the input layers x_i based on the strength of connection wj_i. Then the output yj of any neuron j is calculated as the function of sums up as follows:

$$yj = F\left(\sum wj_i * x_i\right)$$

where, function F can be radial bias function (RBF), hyperbolic tangent, a sigmoidal or simple threshold function. The backpropagation and gradient descent is the most common training algorithms in Multilayer perceptron. The change in connection weights between neurons i and j are:

$$\Delta wj_i = \eta \delta j x_i$$

where, η is known as the learning rate and δ depends on whether j is input or hidden neuron.

For hidden neurons:

$$\delta j = \left(\frac{\partial f}{\partial netj}\right) \sum wqj * \delta_q$$

A variation of a desired and factual output of neurons in hidden layers j which are replaced via weighted sums of δq term previously achieved for neuron q connecting to the output of j.

For output neuron:

$$\delta j = \left(\frac{\partial f}{\partial netj}\right) (yj^t - y_j)$$

$netj$ is an overall weighted total of signals in the input layer. yj^t is the goal output for neurons j

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2.3. Uncertainty analysis.

The prediction uncertainty of the AI models was quantified using the d-factor as in Mohsenzadeh et al. (2020).

$$d - factor = \frac{d\bar{x}}{\sigma x}$$

where, σ is the standard deviation and $d\bar{x}$ is the average distance between the upper and lower bands

$$d\bar{x} = \frac{1}{n}\sum_{1}^{n} XU - XL$$

3. Results and discussions

The performance of ANFIS and mlp-NN models in predicting fine dust and coarse dust at monthly and seasonal timescales are shown in Figures 4 -7 and Table 1 - 2. The results from this case study show that the ANFIS model performs better than the mlp-NN model to predict aeolian dust at both monthly and seasonal timescales. The correlation (r), root mean square error (RMSE), and percentage bias (% Bias) for monthly fine dust prediction (ANFIS model) is 0.7, 0.45 μg/m3 and 40.64 % respectively. The models' performance is generally better to predict seasonal dust than monthly dust. At seasonal timescale r, RMSE, and % BIAS (ANFIS model, fine dust) are 0.83, 0.31 μg/m3, and 28.30 % respectively. Hanoon et al. (2021) also showed that AI models better predict the temperature and relative humidity at (longer) monthly timescale than (shorter) daily timescale. This might be attributed to the nonstationary spurious internal variability of the climate system that is difficult to capture by the models (Shi et al. 2018). The results demonstrate that AI models based on the climatic data only predict Southwestern US dust with similar skill as the models using land surface conditions. Long-term climatic data are more readily available than long-term land surface conditions data.

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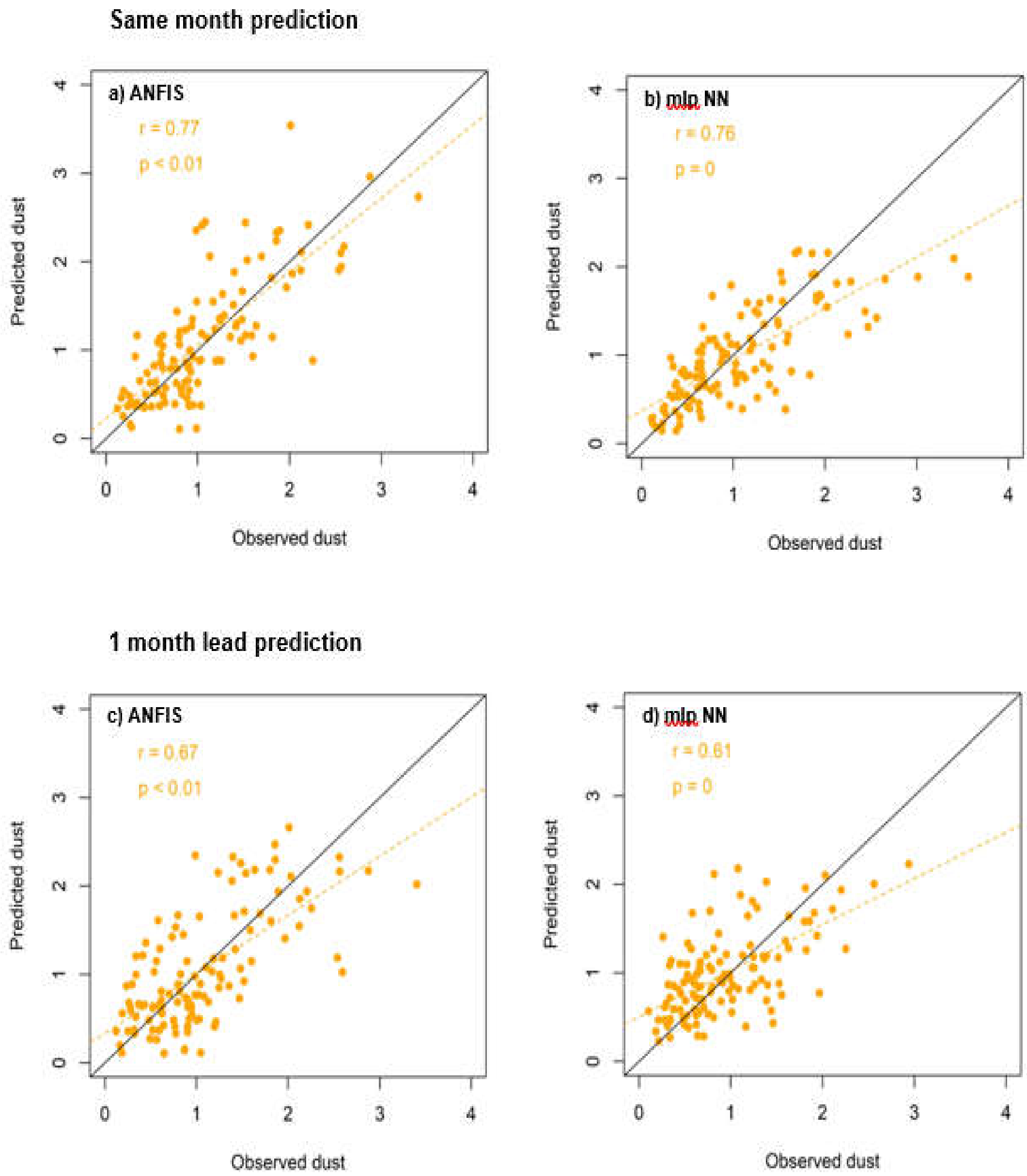

Figure 4. AI models for fine dust (PM2.5, µg/m3) at a monthly timescale.

As shown in Figures 4 – 7 and Tables 1-2, same month/or season predict skills are better than one month/or season lead prediction skills. This highlights that ambient dustiness over the region depends more on the same month/or season climate than the previous month/or season climate. Pu et al. (2019) also noted that spring Season dust in the western US depends more on the Spring climatic and surface condition than the Winter climate and land conditions.

Comparing Figures 1-2 with Figures 3-4, the correlation for fine dust is better than the correlation for coarse dust at both monthly and seasonal timescales (Aryal 2022). The IMPROVE stations are located on federal lands and national parks at some distance from the dust source (DeBell et al. 2006). The coarse dust has a short transport distance and air retention time. Therefore, observation stations are more likely to miss coarse dust than fine dust. Therefore, the regional climate has difficulty explaining coarse dust variability.

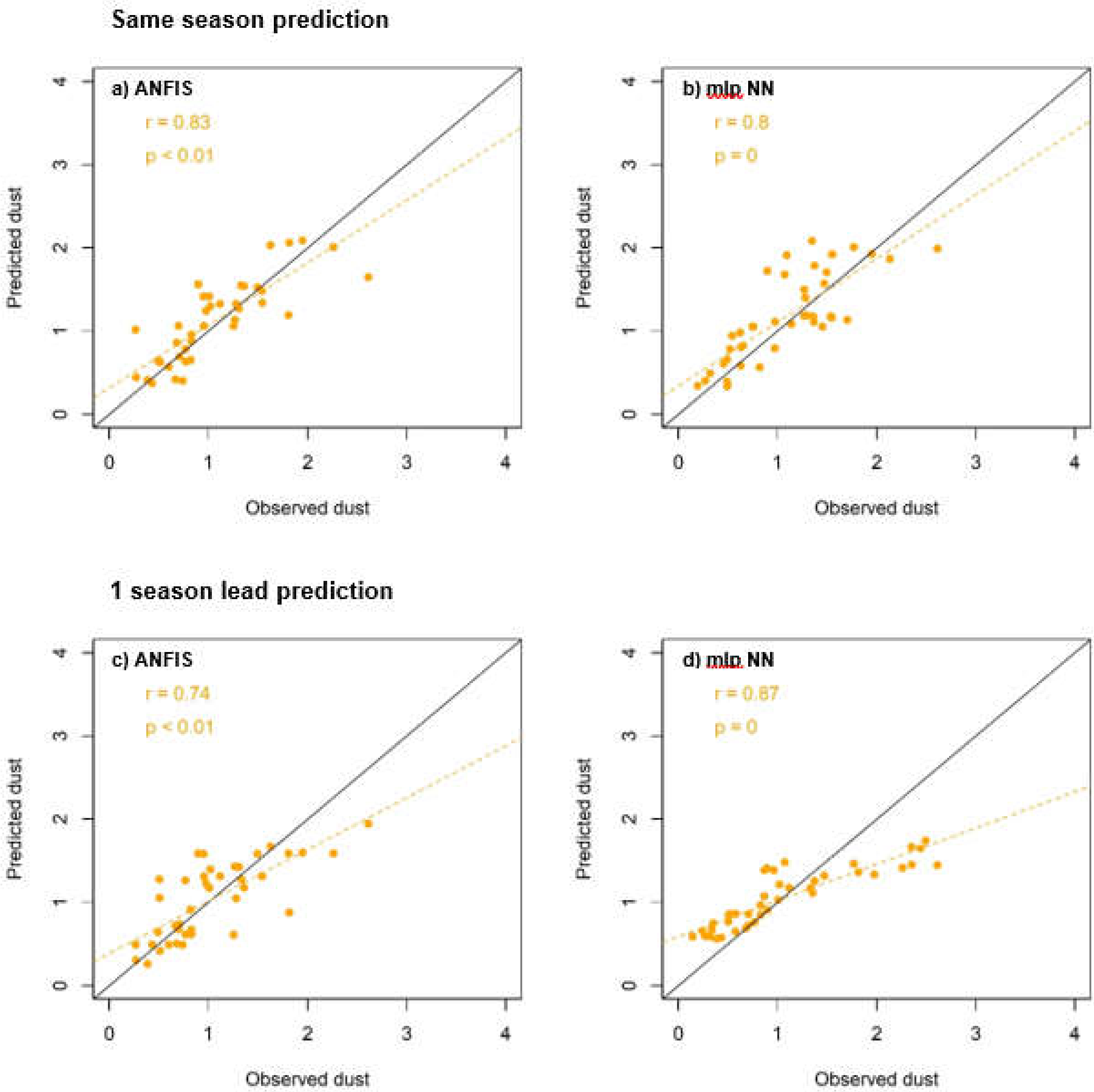

Figure 5. AI models for fine soil (PM2.5, μg/m3) at the seasonal timescale.

However, if we look at the % BIAS (comparing Tables 1 and 2) the results on the accuracy of predicting fine dust and coarse dust are not consistent. This highlights that different statistical indices should be examined to confirm the effectiveness of the examined models (Hanoon et al. 2021).

The relative importance of precipitation and temperature to predict dust over the region is further examined. A previous study showed that temperature is a more important predictor followed by precipitation to predict monthly dust over the SWUS region (Aryal 2022). This study compares the relative importance of temperature and precipitation predicting dust at monthly and seasonal timescales. Table 3 shows the results from the ANFIS model. % BIAS is lower for the prediction based on T and W than the model based on P and W for predicting fine dust and coarse dust at

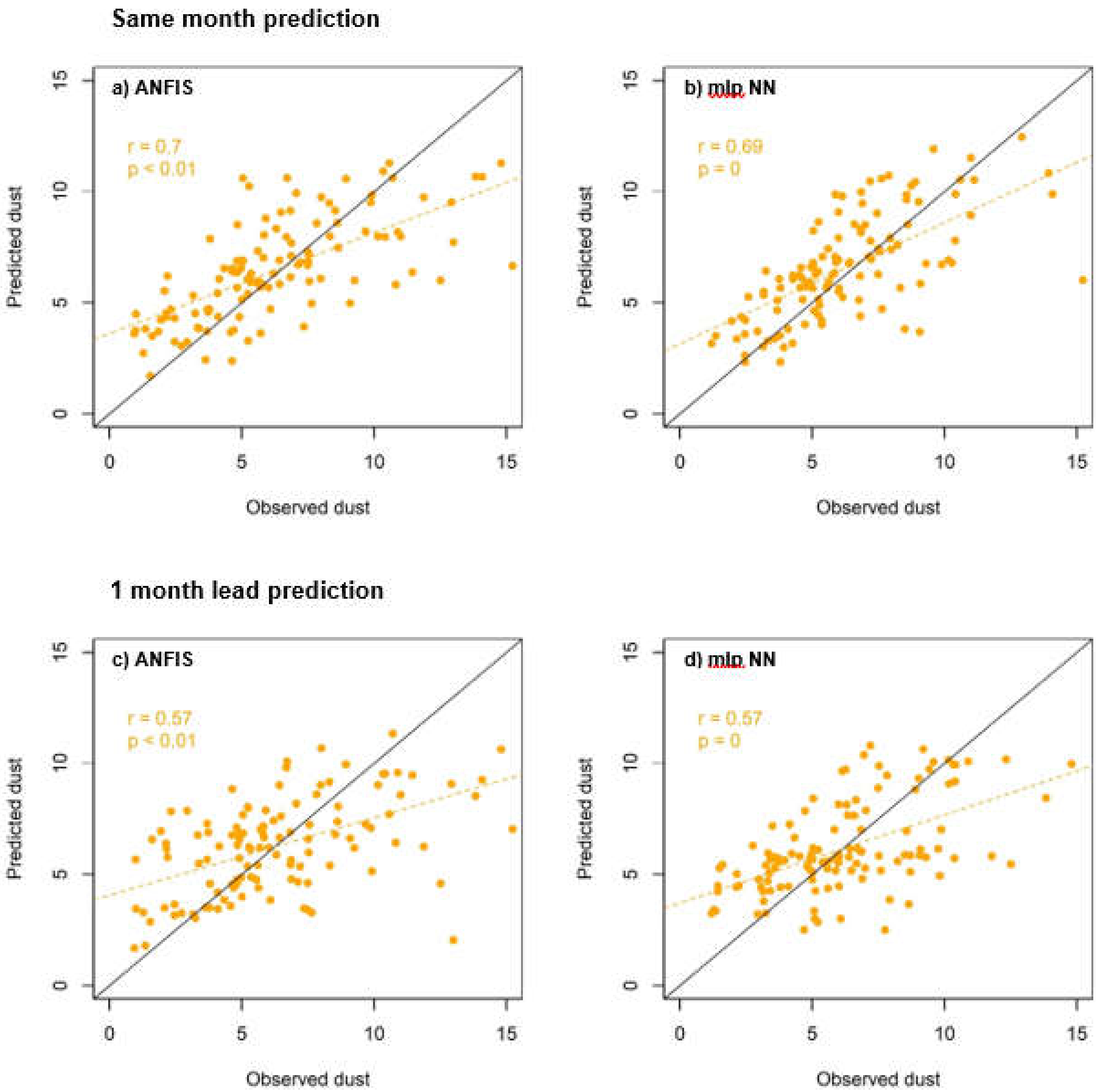

Figure 6. AI models for coarse dust (PM10, μg/m3) at a monthly timescale.

Both monthly and seasonal dust implying the relative importance of temperature in predicting dust over the SWUS. This is consistent with the previous study, Aryal (2022), on a monthly timescale. On the shorter timescale (i.e., monthly to seasonal timescale) dust emission quickly responds to the warming due to the soil moisture variability in the surface soil layer. On the other hand, the impacts of precipitation on dust emissions are strongly detected on a longer timescale (i.e., annual to decadal) due to changes in vegetation cover (Namdari et al. 2018). Comparing the relative importance of precipitation and temperature, the difference between the relative importance of temperature and precipitation is larger at the monthly timescale for fine dust prediction (Table 3a difference in % BIAS; -23.4 Vs -14.85). For the coarse dust prediction, the difference between the relative importance of temperature and precipitation is larger at seasonal timescale (Table 3b difference in % BIAS; -8.35 Vs -22.59).

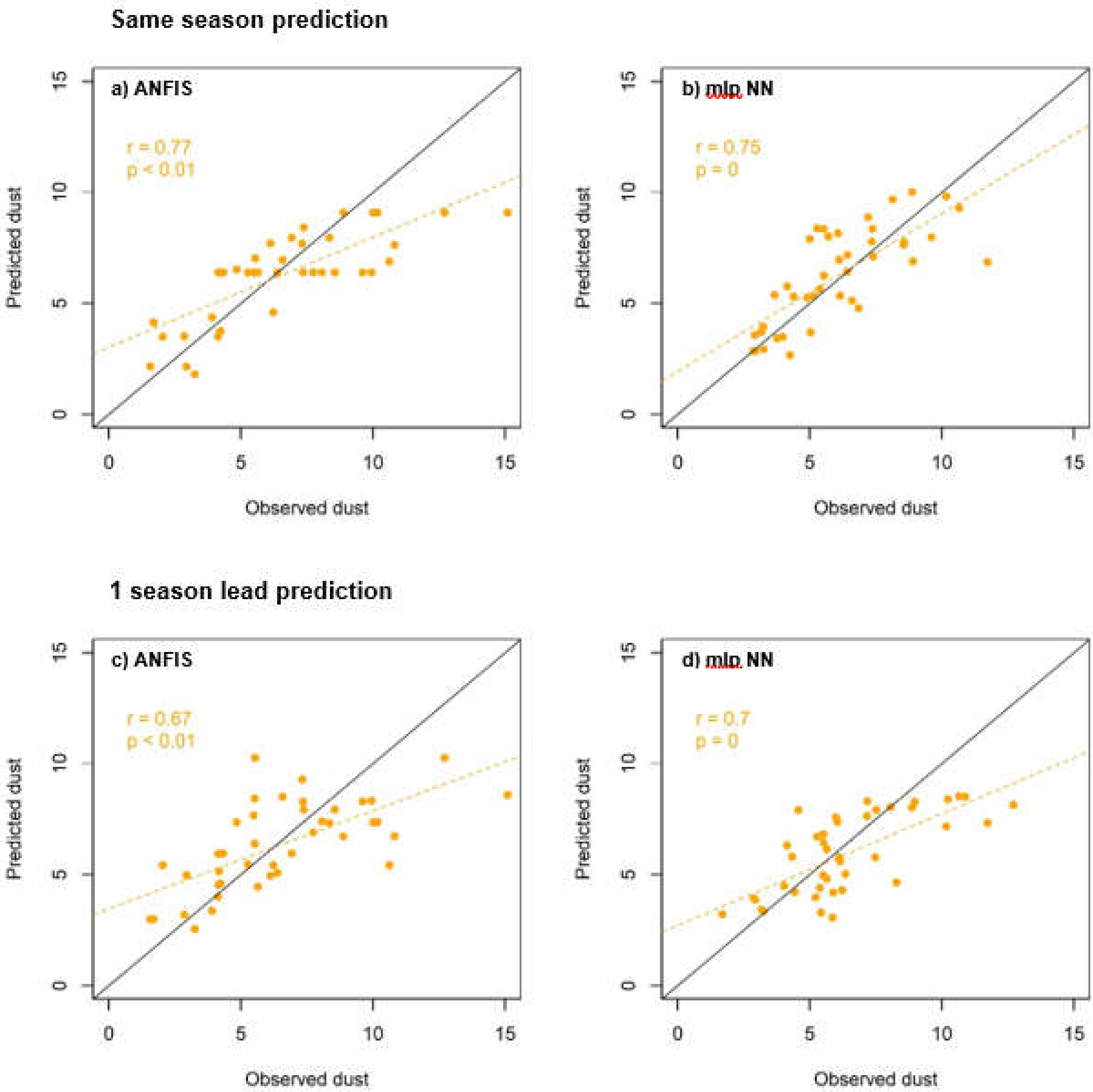

Figure 7. AI models for coarse dust (PM10 µg/m3) at seasonal timescale.

Table 1. Performance of ANFIS model to predict fine dust (PM2.5) during testing phase (2010-2020).

Inputs	Output	RMSE (µg/m3)	% BIAS	Change in % BIAS	
P(m),T(m),W(m)	Dm	**0.455**	**40.640**		
P(m),W(m)	Dm	0.561	78.90	-38.26	
T(m),W(m)	Dm	0.448	55.50	-14.86	-23.40
P(s), T(s), W(s)	Ds	0.308	28.304		
P(s),W(s)	Ds	0.401	44.45	-16.14	
T(s),W(s)	Ds	0.310	29.60	-1.30	-14.85

Table 2. Performance of ANFIS model to predict coarse dust (PM10) during testing phase (2010-2020).

Inputs	Output	RMSE (μg/m3)	% BIAS	Change in % BIAS	
P(m),T(m),W(m)	**Dm**	**2.57**	**42.08**		
P(m),W(m)	Dm	2.62	50.57	-8.49	
T(m),W(m)	Dm	2.59	42.22	-0.14	-8.35
P(s), T(s), W(s)	Ds	1.96	27.82		
P(s),W(s)	Ds	2.95	50.73	-22.92	
T(s),W(s)	Ds	1.98	28.14	-0.32	-22.59

The results from the uncertainty analysis are given in Table 3. The d-factor of both fine and coarse dustiness is low implying the reasonable accuracy of the model for predicting regional dustiness.

Table 3. d-factor for ANFIS mode

	d-factor
PM2.5	
Monthly	0.002
Seasonal	0.00035
PM10	
Monthly	0.1
Seasonal	0.067

4. Conclusions

In this study, the performance of artificial intelligence (AI) models: adaptive-network-based fuzzy inference system (ANFIS) and multi-layered perceptron neural network (mlp-NN) are investigated to predict aeolian dust over the southwestern US. The ambient dust data was taken from the Interagency Monitoring of Protected Visual Environments (IMPROVE) network while the regional meteorology data (precipitation, temperature, wind speed) were retrieved from North American Regional Reanalysis (NARR). The models' performances for fine dust and coarse dust at monthly and seasonal timescales are compared.

- AI models better predict regional dustiness at seasonal timescale than monthly timescale.
- ANFIS model works better than mlp-NN model in predicting regional dustiness at both monthly and seasonal timescales.
- The ambient dustiness over the region is better predicted by the same month (or season) climatic condition than using the precious month (or season) climatic condition.
- Compared to precipitation, the temperature is the more important predictor of the regional dustiness at both monthly and seasonal timescales. However, compared to the seasonal timescale, the difference between the relative importance of temperature and precipitation is larger at the monthly timescale for fine dust prediction and vice versa for coarse dust.

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