Supplementary Materials for

Aeolian activity in foredune notches: Evidence from multiannual wind observations

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Paper DOI: 10.59236/geomorphica.v2i2.67

Table of Contents:

Supplementary Text

Wind speed predictions

Wind speed predictions were needed at sensor locations to fill in gaps in a measured time series of U_{SA} (e.g., Section 3.4) or to estimate U_{SA} when the anemometers were deployed in another notch (e.g., Section 4.2). Here the prediction approach and its accuracy are described.

For each of the 9 sensor locations, a feedforward neural network (FNN; Hsieh (2009)) was trained with a single hidden layer to reproduce the non-linear dependence of the normalised wind speed U_{SA}/U_{ref} on the incident wind direction $\theta_{N,ref}$ (that is, the trends in Fig. 7 using $\theta_{N,ref}$ rather than $\theta_{A,ref}$). With a trained FNN, the wind speed at the corresponding sensor location can be predicted for an observation (U_{ref}, $\theta_{N,ref}$) using $\theta_{N,ref}$ as input and multiplying the predicted U_{SA}/U_{ref} by U_{ref}. The size of the hidden layer was set to 15 nodes in each FNN because this resulted in the smallest FNN that accurately described the general trend at all locations, with the performance of the FNN calculated as the mean square difference (MSD) between the observed and predicted values of the normalised wind speed. Training was performed with the Levenberg-Marquardt algorithm, with 70% of all available observations at each location randomly selected for training, with the data set divided into a training and validation part to avoid the undesirable situation in which the FNN also fits noise in the observations. The total number of observations available at each location is listed in Table S2. These numbers exceed those in the third column of Table S1 because in the FNN training there was obviously no restriction that all three sensors should be operational simultaneously. Each FNN was trained 100 times with a different random seed to ensure that the global minimum in MSD was found. The FNN with the lowest MSD was retained. These MSD values are listed in Table S2 and illustrate that the MSD was generally the highest at SA01 (between 0.047 in N4 and 0.103 in N2) and the lowest (between 0.041 in N4 and 0.058 in N2) at SA03. In essence, these values reflect the degree of scatter in the observed U_{SA}/U_{ref} around the general dependence of this ratio on $\theta_{N,ref}$. Using each FNN retained, the MSD for U_{SA} was also calculated. These MSD values, shown in the last column of Table S2, ranged from approximately 0.5 to 1.0 m/s, with the highest values at each SA03. The landward increase in MSD reflects the wind speed-up during some conditions (Fig. 10), resulting in a greater range in U_{SA} at location 03 compared to 01.

Supplementary Tables

Table S1

Deployment information

Notch	Deployment period	#10-min. blocks sensors 01–03 + IJmuiden	#10-min. blocks binned sensors 01–03 + IJmuiden
N4	22 November 2016 – 29 October 2018	56,274	36,116
N3	9 October 2018 – 9 November 2020	56,096	34,535
N2	24 September 2020 – 13 December 2023	47,132	25,977

Table S2

FNN performance statistics

Notch	Location	#10-min. blocks	MSD U_{SA}/U_{ref}	MSD U_{SA} (m/s)
N2	SA01	108,682	0.103	0.765
	SA02	89,752	0.062	0.849
	SA03	125,081	0.058	0.922
N3	SA01	84,109	0.076	0.614
	SA02	93,576	0.059	0.631
	SA03	91,436	0.046	1.056
N4	SA01	70,189	0.047	0.524
	SA02	79,406	0.037	0.485
	SA03	76,270	0.041	0.599

Reference

Hsieh, W.W. *Machine learning methods in the environmental sciences – Neural networks and kernels*. Cambridge University Press, Cambridge, United Kingdom, 2009. https://doi.org/10.1017/CBO-9780511627217.