Spatiotemporal variability of fog and dew occurrence in the Atacama Desert – a view from a network of weather stations

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1. Introduction

In hyperarid regions, such as the Atacama Desert (precip. < 2mm/yr)[1], fog and dew provide essential water supply to sustain unique ecosystems[2,3], and drive geomorphological processes[4,5]. While the importance of fog has been documented, the role of dew has rarely been assessed[6]. However, it has been hypothesized that dew is crucial for survival of certain species[7]. Here we determine fog and dew occurrences from a network of weather stations deployed in the Atacama Desert (Fig. 5) by the Collaborative Research Center "Earth – Evolution at the Dry Limit" (sfb1211.uni-koeln.de) of the German Science Foundation (DFG SFB1211. It is hypothesized that dew occurs more frequently than fog and that it can complement fog water supply.

2. Data Usage

From weather stations (Fig. 5):
- leaf wetness sensor (wet/dry)
- 2m and surface temperature
- 2m relative humidity
- incoming shortwave radiation
- incoming longwave radiation (only stations 13, 23, 33)

from ECMWF's reanalysis ERA5[8]:
- integrated water vapor (IWV)

ID	Period	ID	Period
12	2017-04-02 – 2024-12-30	24	2018-03-10 – 2021-03-26
13	**2017-04-02 – 2024-11-14**	25	2018-03-09 – 2024-12-30
14	2017-09-24 – 2024-12-30	32	2018-03-23 – 2024-12-30
15	2017-09-25 – 2024-12-23	**33**	**2018-03-23 – 2024-04-20**
20	2018-03-06 – 2023-03-15	34	2018-03-13 – 2020-12-02
22	2018-03-09 – 2024-12-30	40	2023-03-19 – 2024-12-30
23	**2018-03-09 – 2024-12-30**	41	2022-11-03 – 2024-12-30
		42	2023-03-19 – 2024-12-30

Table 1: *Station ID (Fig. 5) and corresponding time period considered here. Further data gaps occur for some stations. Master stations used for MLP training appear in bold.*

Derived quantities:
- Dry sky factor (DSF): $X_{\mathrm{DSF}} = \frac{Q_{\mathrm{lw,in}}}{Q_{\mathrm{lw,t,J}}}$
- Clear Sky Index (CSI): $X_{\mathrm{CSI}} = \frac{Q_{\mathrm{sw}}}{Q_{\mathrm{sw,t,J}}}$

With incoming long- and shortwave rad. Q_{lw} and Q_{sw}. References $Q_{\mathrm{lw,t,J}}$ and $Q_{\mathrm{sw,t,J}}$ as 20[th] percentile of Q_{lw} or Q_{sw} for a specific time of day for a specific Julian Day of the year (±5 days).

Objectives & challenges:
- fog/dew distinction using DSF
- model DSF at stations w/o pyrgeometer
- variables to distinguish low/high DSF: $T_{\mathrm{air}} - T_{\mathrm{srf}}$ (night), CSI (day, Fig. xx)
- non-linear model for DSF retrieval

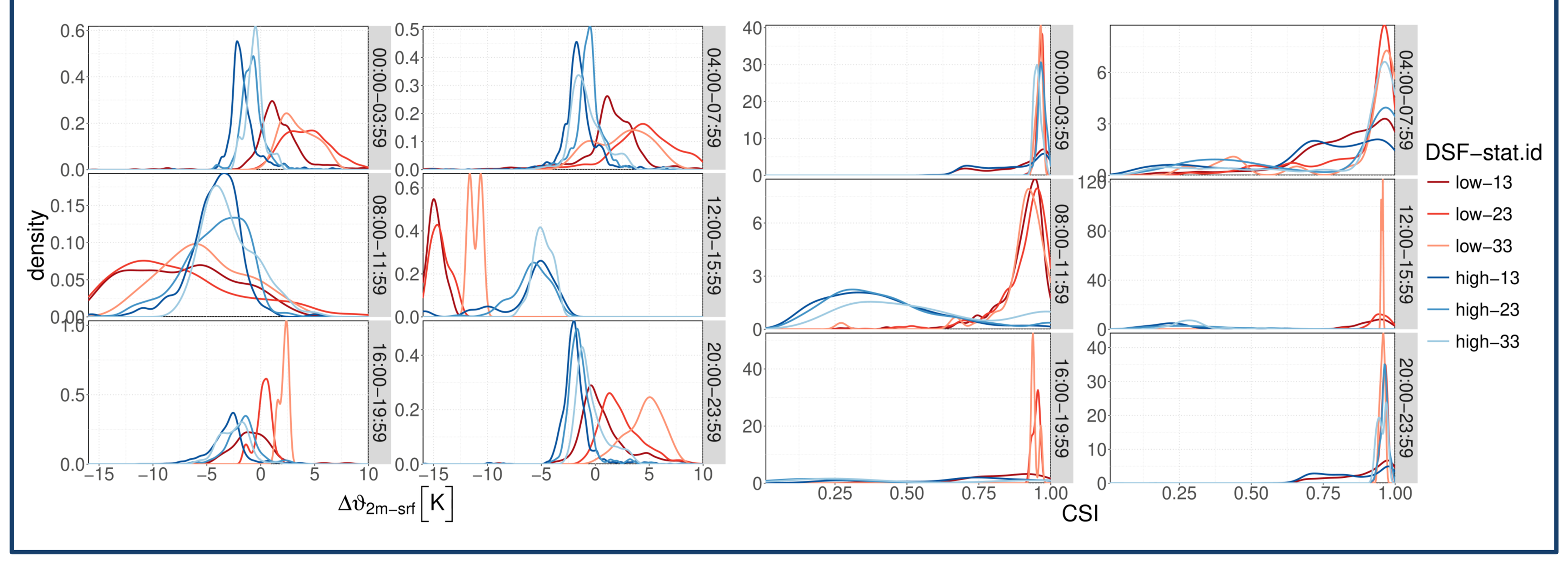

Fig. 1: *Distribution of temperature difference between 2m and surface (left) and CSI (right) for the 3 master stations used for training the model to predict DSF.*

3. DSF estimation via multi-layer perceptron (MLP)

Input: Julian Day; time of Day; solar zenith angle; rel. hum.; $T_{\mathrm{air}} - T_{\mathrm{srf}}$; CSI; IWV anomaly
Output: DSF
Architecture:
- 8 hidden layer:
- 1024-512-256-128-64-32-16-8 neurons per layer
- batch normalization in between

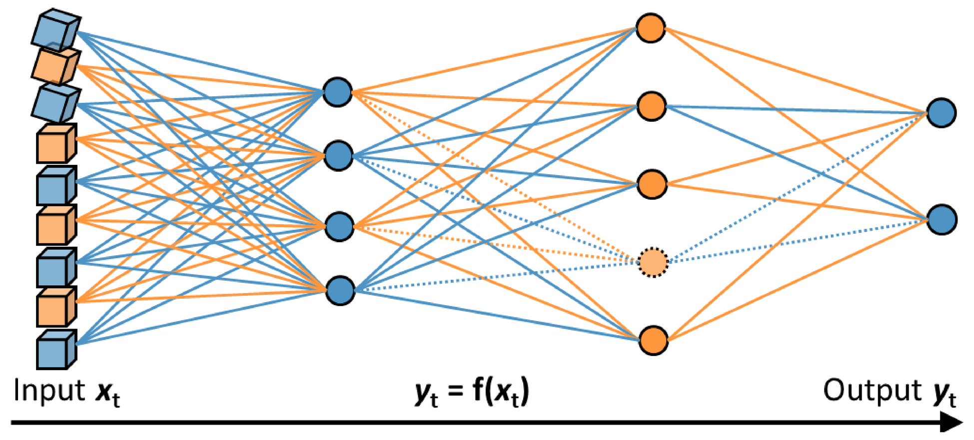

Fig. 2: *Schematic example of utilized MLP which maps the input (i.e. quantities derived from weather stations to the output (i.e.DSF).*

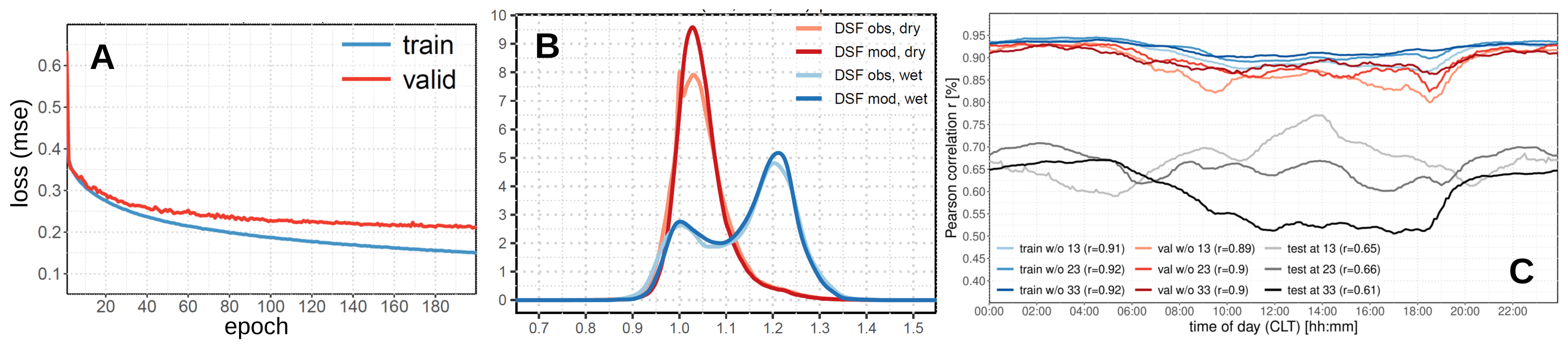

Fig. 3: *MLP training evaluation.* ***A:*** *mean squared error (mse) loss vs. training epoch.* ***B:*** *density of observed and modeled DSF for dry (red) and wet (blue) situations.* ***C:*** *Correlation for different times of day when only 2 stations are used for training and validation while the left out station is used for testing.*

dataset	r	bias	rmse
training	0.92	0.001	0.026
test	0.88	0.001	0.032
validation	0.88	0.002	0.032

Table 2: *Pearson correlation coeff., bias and RMSE for a random data split including all master stations.*

- overall suitable prediction skill & spatial generalization despite some overfitting
- likely higher generalizability for final model trained on all master stations
- suitable threshold for low/high DSF distinction at 1.1 (Fig. 3B)

4. Classification scheme

	DSF low	DSF high
LWS dry	dry	subs. class fog → fog onset subs. class dry → dry (cloudy)
LWS wet	prev. class fog → fog residual prev. class dry → dew	fog

Table 3: *Confusion matrix for scene classification according to leaf wetness (LWS) and dry sky factor (DSF). For a wet LWS and low DSF, fog residual wetness and dew are distinguished by considering the previous class. For a dry LWS and high DSF, fog onset and cloudy (i.e. dry) are distinguished by considering the subsequent class.*

Fig. 4: *Example camera images from station 13 for identified dry, fog, fog residual, and dew situations (left to right).*

References:

[1]Reyers et al., 2020, doi.org/10.1175/MWR-D-20-0038.1; [2]Koch et al., 2019, doi.org/10.1007/s00606-019-01623-0; [3]Sun et al., 2023, doi.org/10.1111/gcb.17068; [4]Voigt et al., 2020, doi.org/10.1016/j.gloplacha.2019.1030; [5]Dunai et al., 2020, doi.org/10.1016/j.gloplacha.2020.103275; [6]Lobos-Roco et al., 2024, doi.org/10.1016/j.jaridenv.2024.105125; [7]Garcia et al., 2021, doi.org/10.1007/s00606-021-01775-y; [8]Hersbach et al., 2020, doi.org/10.1002/qj.3803

5. Fog and dew frequencies

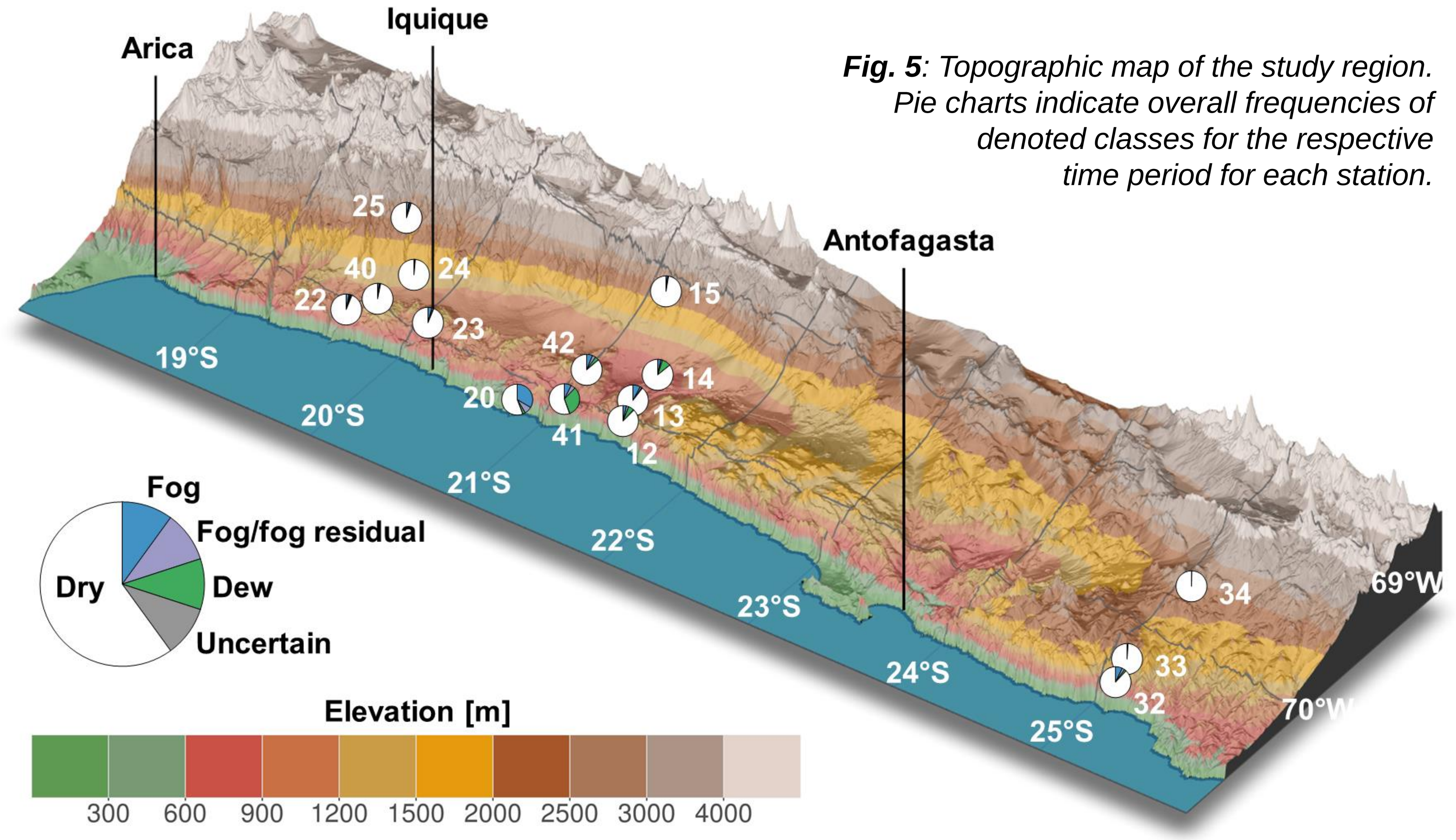

Fig. 5: *Topographic map of the study region. Pie charts indicate overall frequencies of denoted classes for the respective time period for each station.*

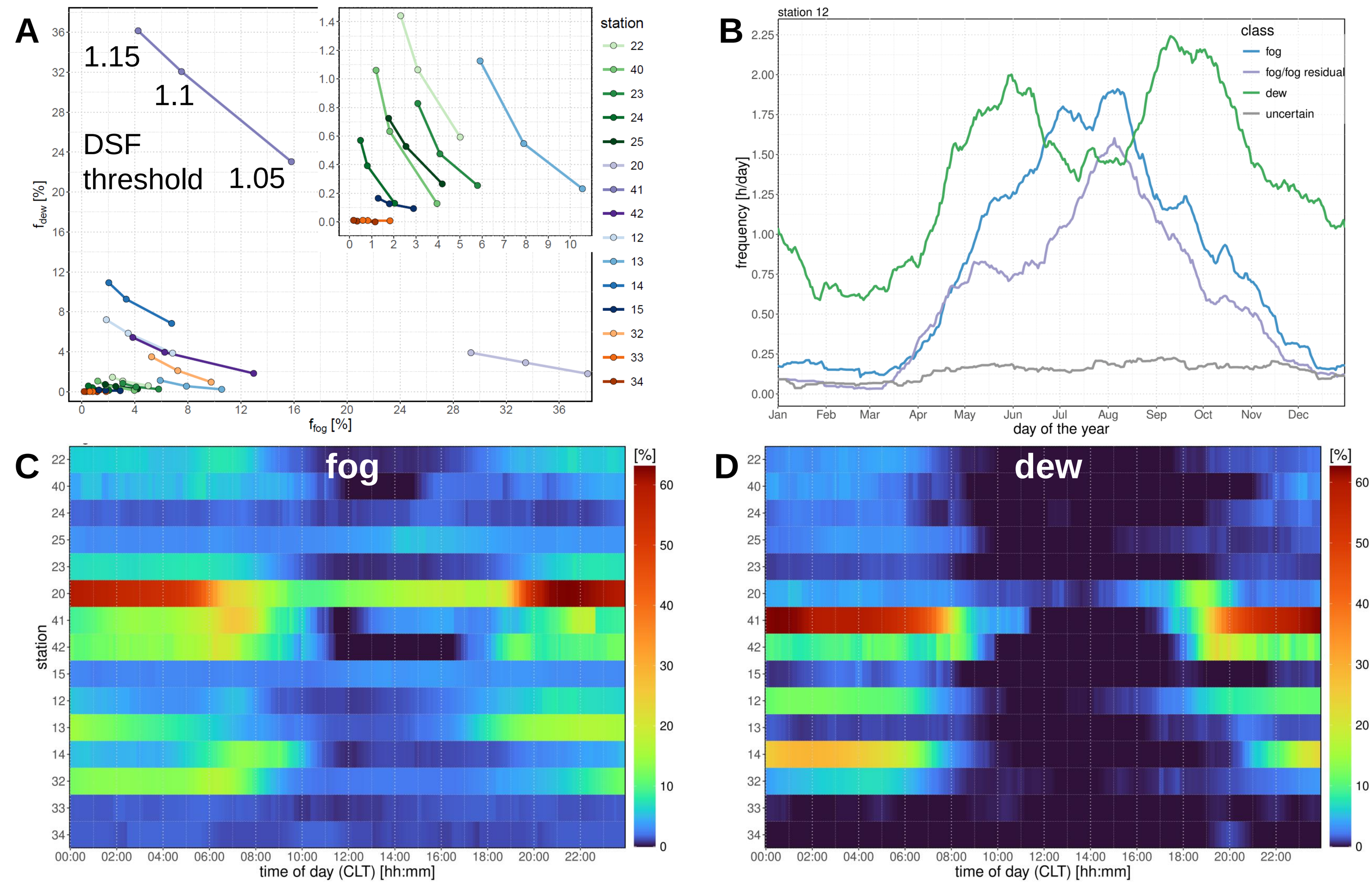

Fig. 6: ***A:*** *predicted dew vs. fog frequency for different DSF thresholds.* ***B:*** *seasonal cycle (centered mov. avg. of 60 days) of predicted classes for station 12.* ***C:*** *diurnal cycle of fog frequency (color) for each station.* ***D:*** *as C for dew.*

6. Conclusions and Outlook

- suitable classification scheme based on modeled DSF and leaf wetness
- for some regions, dew freq. exceeds fog freq. (e.g. stations 12, 14, 41; Fig. 6A)
- dew can extend the wet season (Fig. 6B)
- uncertainties due to missing data
- classification is sensitive to DSF threshold

Future steps
- compare temporal class evolution with soil moisture
- assess variability of class persistence and evolution in light of meteorological context
- utilize classification data set as ground truth for satellite-based fog and dew retrieval