Toward a Climatology of Fog Frequency in the Atacama Desert via Multispectral Satellite Data and Machine Learning Techniques

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ABSTRACT: In many hyperarid ecosystems, such as the Atacama Desert, fog is the most important freshwater source. To study biological and geological processes in such water-limited regions, knowledge about the spatiotemporal distribution and variability of fog presence is necessary. In this study, in situ measurements provided by a network of climate stations equipped, inter alia, with leaf wetness sensors are utilized to create a reference fog dataset that enables the validation of satellite-based fog retrieval methods. Further, a new satellite-based fog-detection approach is introduced that uses brightness temperatures measured by the Moderate Resolution Imaging Spectroradiometer (MODIS) as input for a neural network. Such a machine learning technique can exploit all spectral information of the satellite data and represent potential nonlinear relationships. Relative to a second fog-detection approach based on MODIS cloud-top height retrievals, the neural network reaches a higher detection skill (Heidke skill score of 0.56 as compared with 0.49). A suitable representation of temporal variability on subseasonal time scales is provided with correlations mostly greater than 0.7 between fog occurrence time series derived from the neural network and the reference data for individual climate stations, respectively. Furthermore, a suitable spatial representativity of the neural-network approach to expand the application to the whole region is indicated. Three-year averages of fog frequencies reveal similar spatial patterns for the austral winter season for both approaches. However, differences are found for the summer and potential reasons are discussed.

KEYWORDS: Fog; Satellite observations; Machine learning

1. Introduction

With annual precipitation rates below 2 mm (Houston 2006), fog water supply is the main driver for biological and geological processes for various regions within the Atacama Desert in South America. It constitutes the major freshwater and nutrition source for several plant species within the coastal desert (e.g., Rundel et al. 1997; Muñoz-Schick et al. 2001; Pinto et al. 2006; Koch et al. 2019). This is manifested, for instance, in a strong dependence of the nitrogen isotopic composition of *Tillandsia* populations on fog water supply (Latorre et al. 2011; Jaeschke et al. 2019). Furthermore, water sources, such as fog, impact soil formation (Voigt et al. 2020) and control the amount of soil organic traces (Mörchen et al. 2019) as well as microbial activity (Cáceres et al. 2007; Jones et al. 2018; Knief et al. 2020). Moreover, the collection of fog water is of major social and economic importance in this region (Schemenauer and Cereceda 1994; Osses et al. 2000;

Larraín et al. 2002). However, a regionally resolved fog climatology is not available yet.

Fog is frequently formed at the coast when the maritime stratocumulus intercepts with the steep topography. Near surface fog water supply has been quantified using different types of fog collectors (e.g., Cereceda et al. 2002, 2008; Lobos Roco et al. 2018; Osses et al. 2005; del Río et al. 2018). Based on a 17-yr long time series of monthly resolved measurements of collected fog water at a research site at the coastal cliff (Alto Patache), the seasonal cycle with a maximum for austral winter (July–September) and a minimum between December and April has been revealed (del Río et al. 2018). This research station is almost the only available in situ source for fog that provides a multiyear record.

With the very limited amount of in situ sites, satellite remote sensing has to be utilized to determine the spatial distribution of fog and low cloud frequency. Using spaceborne observations, it has been revealed that the southeast Pacific stratocumulus deck is most persistent and most extended in austral winter resulting in highest fog and low cloud frequencies at the coastal desert and rapidly decreasing frequencies farther inland (Cereceda et al. 2008; Lehnert et al. 2018; del Río et al. 2018). Furthermore, observations from geostationary satellites reveal that these coastal maritime low clouds intercept with the coastal orography most frequently at night and dissipate during the day (Fariás et al. 2005; Fariás 2007; Cereceda et al. 2008). The nocturnal maximum is the result of the stratocumulus deck being advected toward the coast at this time while the circulation reverses during the day (Rutllant et al. 2003).

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Furthermore, entrainment of warm and dry free tropospheric air and warming forced by absorption of solar radiation lead to dissipation of coastal stratocumulus during daytime (Garreaud and Muñoz 2004).

The coastal cliff and mountain range typically prevent inland advection of the stratocumulus. However, individual fog corridors have been identified in case studies using satellite remote sensing techniques and related to fog occurrence in the central depression (Fariás et al. 2001, 2005). Furthermore, favorable conditions for radiation fog have been reported for parts of the central depression (Cereceda et al. 2002; Fariás 2007; Westbeld et al. 2009).

To date, satellite-based studies are temporally and spatially limited and do not distinguish between fog and low clouds. The goal of this study is to utilize spaceborne observations to develop a fog retrieval method for the region of the Atacama Desert. It needs to be suitable to derive a long-term climatology and to study seasonal and interannual variability of fog occurrence.

Conventional satellite-based detection techniques of cloud height regimes rely on simultaneous measurements of radiances at various frequency bands. These radiances are the result of complex radiative transfer mechanisms depending on various factors, such as cloud heights and thickness, cloud droplet size distribution, ice particle properties, distribution of temperature and water vapor content, and surface type. Traditionally, radiative transfer calculations are carried out to develop thresholds for the detected radiances or brightness temperatures that can be applied to distinguish different cloud scenes (e.g., Bendix et al. 2006; Cermak 2012; Gaurav and Jindal 2018; Andersen and Cermak 2018). While it is comparatively easy to distinguish between low and high clouds using infrared wavelengths due to higher differences of the respective cloud-top temperatures, the distinction between low clouds, fog and land surface is more difficult because the temperature at which these features emit thermal radiation is very similar (Güls and Bendix 1996).

A distinction between low clouds and land surfaces is possible because the emissivity of liquid water clouds is significantly lower in the shortwave infrared (e.g., $3.8\ \mu\text{m}$) than in the longwave infrared (e.g., $11\ \mu\text{m}$) (Hunt 1973; Ellrod 1995; Gaurav and Jindal 2018). In particular for smaller droplets, this results in greater brightness temperature differences observed for low-level clouds than for land surfaces (Ellrod 1995). However, a further distinction between low clouds and fog is usually not feasible by only considering these wavelengths.

Instead of a threshold-based detection according to costly radiative transfer simulations for a limited amount of frequency bands, the aim of this study is to explore the entire spectral information available from spaceborne sensors. To capture different, yet presumably distinct, radiative signatures that are characteristic for various fog, cloud or clear-sky scenes, a machine learning technique is applied to recognize the relevant patterns. Machine learning techniques are becoming increasingly popular in remote sensing and earth observation (e.g., Gardner and Dorling 1998; Lary et al. 2016) and have also been used to detect fog in previous studies (e.g., Egli et al. 2018).

Present-day spaceborne sensors, such as the Advanced Baseline Imager (ABI) on the Geostationary Operational Environmental Satellite (GOES) or the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the polar orbiting satellites *Terra* and *Aqua*, provide high spectral resolution. Here, we utilize MODIS data products because they provide the longest data record (*Terra*: 2000–present, *Aqua*: 2002–present) with a horizontal resolution of 1 km at nadir.

As fog occurrence typically peaks at night, we focus on the detection of nocturnal fog. This way, all thermal infrared channels can be considered without additional complexity from the solar component that affects the middle infrared channels during daytime.

For the evaluation of novel fog and low cloud detection methods, previous studies have considered ground-based observations of cloud heights and visibility typically available from METAR and synoptic (SYNOP) reports (e.g., Cermak and Bendix 2008; Egli et al. 2018) or net radiation (Andersen and Cermak 2018). As there are only very few climate stations available within the Atacama Desert, an effort has been made by the Collaborative Research Center (CRC 1211) “Earth—Evolution at the dry limit” (sfb1211.uni-koeln.de; Dunai et al. 2020) to fill this observational gap by installing a network of climate stations that started in 2017 (Hoffmeister 2017; Schween et al. 2020). In addition to standard meteorological instrumentation, these stations include a leaf wetness sensor that can distinguish fog and dry conditions. This study takes advantage of these novel in situ measurements to train and examine a neural-network approach to detect fog. To identify the benefit of the neural-network retrieval method, an alternative fog-detection method is created based on simple thresholds applied to a satellite-based cloud-top height product.

The paper is structured as follows. In section 2, utilized satellite data products and climate station measurements are described. In section 3, the ground-based reference dataset and the fog retrieval methods are introduced. In a twofold evaluation (section 4), event-based statistics according to a contingency table analysis are presented first followed by an investigation of the spatiotemporal representativeness of the detection methods. The proposed fog retrieval methods are then utilized to derive a nationwide distribution of fog occurrence frequency averaged for a 3-yr period. The study is summarized and concluded in section 5.

2. Data

a. MODIS

MODIS is an imaging sensor capturing data in 36 spectral bands at wavelengths ranging from visible ($0.4\ \mu\text{m}$) to infrared ($14.4\ \mu\text{m}$). The spatial resolution at nadir is generally 1 km. Additionally, a few channels in the visible range provide data at 500 and 250 m. The instrument is installed on both the *Terra* and the *Aqua* platform. Both satellites are in sun-synchronous orbits at a height of about 705 km and a swath width of approximately 2330 km. For the Atacama Desert, local times of the respective nocturnal overpasses considered herein vary between 2230 and 0010 Chile standard

time (CLT) (*Terra*) and 0110 and 0245 CLT (*Aqua*) as a result of orbit characteristics.

We utilize the spectral radiances provided by the level-1B 1-km Calibrated Radiances Product (MOD021KM, MYD021KM; [MODIS Characterization Support Team 2017a,b](#)). Additionally, we include the cloud-top height provided by the level-2 Cloud Product (MOD06, MYD06; [Platnick et al. 2017a,b](#)) [section 2a(2)] to derive an alternative fog retrieval. For geolocation of the acquired fields, longitude, latitude, and elevation are taken from the Geolocation Fields Product (MOD03, MYD03; [MODIS Characterization Support Team 2017c,d](#)). For all products, the collection 6.1 data are acquired for this study. Data are acquired for a 3-yr period (2017–19) covering the Atacama Desert region within 18°–26°S and 71°–69°W.

1) MODIS BRIGHTNESS TEMPERATURES

As only nighttime satellite overpasses are considered, only the thermal emissive bands, which include wavelengths between 3.75 and 14.24 μm (MODIS bands 20–25 and 27–36), are processed further. Further information, such as central wavelengths and atmospheric features that are targeted by each band can be found, for example, in [Xiong et al. \(2008\)](#). Furthermore, band 36 (14.2 μm) is omitted because in about 13% of all cases with collocated and coincidental station measurements, no valid retrieval is provided for this particular band. According to Planck's law, spectral radiances are converted to brightness temperatures, which are then applied as explanatory variables to predict fog using the neural network (section 3c).

2) MODIS CLOUD PRODUCT

According to [Menzel et al. \(2008\)](#) and [Baum et al. \(2012\)](#), the cloud-top height provided by the MODIS Cloud Product is derived for pixels that are cloudy according to the MODIS cloud mask via the CO₂-slicing technique ([Chahine 1974](#); [Smith and Platt 1978](#)) using four spectral bands near the CO₂ absorption region at 15 μm . The initially determined cloud pressure is converted to height using atmospheric profiles derived from the National Centers for Environmental Prediction Global Data Assimilation System (GDAS; [Derber et al. 1991](#)). Furthermore, the CO₂-slicing technique utilizes clear-sky radiances that are determined via radiative transfer calculations using GDAS temperature, moisture, and ozone profiles.

If the calculated difference between observed and clear-sky radiance is within the instrument noise level, which is typically the case for clouds below 3 km, the CO₂-slicing technique is not applied. In such cases, the brightness temperature of the cloud is determined using the infrared window band at 11 μm . The cloud pressure and height are then inferred via brightness temperature profiles calculated from GDAS temperature, water vapor, and ozone profiles. In the presence of low-level temperature inversions, the height of the matching temperature above the inversion is chosen introducing a positive bias into the MODIS cloud-top height. Starting with MODIS collection 6, this problem is mitigated for retrievals over ocean ([Baum et al. 2012](#)). However, over land temperature inversions remain problematic. Furthermore, thick high clouds obscure the satellite's view of lower levels. While such situations are

typically not supportive of nocturnal radiation fog formation, some advective fog events may be missed. Additionally, the retrieval relies on the MODIS cloud mask, which may not indicate a cloudy situation in case of very thin or patchy low clouds.

b. Climate stations

The climate stations installed by the CRC 1211 are deployed in a southern (around 25°S; stations 31, 32, 33, and 34), central (around 21.4°S; stations 11, 12, 13, 14, and 15), and northern (20°S; stations 20, 21, 22, 23, 24, and 25) latitudinal transect, making up a total of 15 stations ([Fig. 1](#)). The station network is assumed to represent the spatial variability of occurring fog morphology and surface emissivity suitably well due to its spread across the Atacama Desert covering latitudes between 20° and 25°S and topographic heights between 770 and 2630 m ranging between the coastal cliff and the slopes of the Andes. However, it cannot be ruled out that individual locations are not well represented by the stations. The installation was carried out between April 2017 and March 2018 and continuous measurements are provided since. Metadata, such as considered time intervals, coordinates, and elevation, are listed in [Table 1](#) for each station.

Among other sensors, each station is equipped with a leaf wetness sensor, which mimics the characteristics of a leaf and provides a voltage output ([Campbell Scientific 2018](#)). Values above $U = 284 \text{ mV}$ indicate that the sensor is wet according to the manufacturer. This threshold was validated for each station at the time of their installation ([Schween et al. 2020](#)). In the presence of fog, impacting water droplets wet the sensor's surface reducing the electrical resistance. At the end of a fog event, evaporation and drainage remove the water from the surface.

Furthermore, we include other measured variables to estimate fog conditions: relative humidity rh , air temperature at 2-m height ϑ_{2m} , surface temperature ϑ_{srf} measured by an IR thermometer, upwelling and downwelling longwave radiation P_{up} and P_{down} . The longwave radiation sensors are only installed at so-called master stations of each transect (stations 13, 23, and 33) that are deployed about 20 km from the coast at heights between 1150 and 1700 m above sea level ([Table 1](#)). Measurements are taken every 10 s, and averages are stored every 10 min.

Stations in close proximity to the Pacific Ocean (stations 11, 21, and 31) had to be omitted from the analysis because they show an increase of fog frequency within 2 weeks after deployment and every cleaning, which is inconsistent with measurements of relative humidity. This is probably due to salt deposition as they are exposed to sea spray ([Schween et al. 2020](#)). Furthermore, the leaf wetness sensor of station 12 faces technical issues since December 2018 so that measurements from this station are only considered until this break point.

3. Fog-detection methods

a. Ground-based reference

The goal is to derive a binary classification, fog or dry, from the station measurements that can be applied to develop

FIG. 1. Topographic map of the study region. Color shading indicates the elevation above sea level according to the Shuttle Rader Topography Mission (SRTM; Farr et al. 2007). Black vertical lines mark major cities (Arica, Iquique, and Antofagasta) located at the coast. The climate stations are indicated by black and white pie charts along with their respective station identifiers. The pie charts indicate annual fog occurrence frequency (the fog portion is in black) determined from the stations as listed in Table 1. For coastal stations 11, 21, and 31, these data are not available.

satellite-based retrieval methods. Using the leaf wetness sensor alone would be problematic at the beginning and end of fog episodes, as the sensor is expected to require some time to adjust to the change of the ambient conditions. Therefore, collocated and coincident measurements of U , rh , the temperature difference $\Delta\vartheta = \vartheta_{2m} - \vartheta_{srf}$, and the longwave radiation budget $\Delta P = P_{up} - P_{down}$ are taken into account as well. For each climate station s and each measurement time t_n , these variables are bundled in a state vector $\mathbf{v}_s = \mathbf{v}_s(t_n)$. To consider the response time of the leaf wetness sensor, two time differences are added to the state vector: (i) if the sensor is wet, the time from t_n until it is dry, denoted as $\Delta t_{wet2dry}$, and (ii) if the sensor is dry, the time from t_n until it is wet, denoted as $\Delta t_{dry2wet}$. A priori, the response time of the leaf wetness sensor is not known. Furthermore, it varies most likely depending on the

TABLE 1. Climate station metadata. Listed are station identifier, longitude (lon), latitude (lat), altitude (alt), fog occurrence frequency (fof), and start and end times of the considered measurements (respectively t_{start} and t_{end}). The fof is given for the year between April 2018 and March 2019 for all stations except station 12 (December 2017–November 2018) including only measurements that coincided with a nocturnal overpass by MODIS. Locations of the climate stations are indicated in Fig. 1.

Station	Lon (°)	Lat (°)	Alt (m)	Fof	t_{start}	t_{end}
12	−69.96	−21.42	771	0.25	3 Apr 2017	30 Nov 2018
13	−69.84	−21.40	1152	0.13	3 Apr 2017	31 Dec 2019
14	−69.54	−21.36	795	0.29	25 Sep 2017	31 Dec 2019
15	−69.07	−21.11	2408	0.02	26 Sep 2017	31 Dec 2019
20	−70.16	−20.83	776	0.69	7 Mar 2018	10 Dec 2019
22	−70.10	−19.61	1179	0.11	10 Mar 2018	9 Oct 2019
23	−69.94	−20.07	1280	0.11	10 Mar 2018	31 Dec 2019
24	−69.65	−19.76	1392	0.02	11 Mar 2018	9 Oct 2019
25	−69.39	−19.53	2628	0.04	10 Mar 2018	31 Dec 2019
32	−70.40	−25.10	1026	0.24	24 Mar 2018	31 Dec 2019
33	−70.28	−25.09	1700	0.00	24 Mar 2018	31 Dec 2019
34	−69.65	−25.09	2535	0.00	14 Mar 2018	23 Jul 2019

TABLE 2. Setup parameters of the self-organizing maps.

Parameter	Configuration	Remarks
Grid	32×32	Result is not sensitive to grid size; small grids $\rightarrow$ higher variability of assigned state vectors; large grids $\rightarrow$ more nodes without assigned state vectors
Topology	Hexagonal	
Neighborhood radius	Linearly decreasing from $\frac{2}{3}$ of all unit distances to 0 between first and last iteration	Nodes are updated within this radius for every presented observation
Learning rate	Decreasing from 0.05 to 0.01 between first and last iteration	Maps converge after 60 iterations

meteorological conditions. To determine a robust classification of the fog state, we investigate which configurations of $\mathbf{v}_s$ usually occur during fog or dry episodes, respectively. In case of fog, we expect that U and rh are high, ϑ_{2m} is close to or below ϑ_{srf} , and ΔP is low.

Under certain conditions, these expectations may not be fulfilled. In particular at the beginning or end of a fog episode, U might not be consistent with the other quantities because the leaf wetness sensor is expected to react slower than the other sensors to changing conditions. To identify these transition episodes, we apply a self-organizing map (SOM) using the state vector $\mathbf{v}_s$ as input. Following the principle introduced by Kohonen (2001), SOMs enable to investigate which individual configurations of $\mathbf{v}_s$ typically cluster together. Here, the Kohonen package for R (Wehrens and Buydens 2007; Wehrens and Kruisselbrink 2018) is applied to create SOMs from the climate station data.

We filtered the data from the climate stations for times between 2200 and 0400 CLT to comply with fog detection at nighttime. Prior to the training, the input data were scaled so that the input values for each quantity are centered (reduced by the respective means) and divided by the standard deviation of the centered values. An overview on various parameters that are utilized to create the SOMs is provided in Table 2.

Once the SOMs are trained, that is, for each grid cell a representative codebook state vector has been derived, all state vectors from the observations can be assigned to a certain grid cell for which the Euclidean distance to the codebook vector is minimized. For each grid cell, the mean of all assigned observations can be calculated for each quantity. Then, each quantity can be visualized separately on the two dimensional grid. By comparing corresponding grid cells, it is easy to see visually which values typically occur concurrently. An example is shown for master station 13 (Fig. 2). SOMs for the other stations are available in the online supplemental material.

As expected, high values of U are usually accompanied by higher rh and lower values for $\Delta\vartheta$ and ΔP . However, there are some cases for which the leaf wetness sensor is indicating fog, even though $\Delta P \gg 0$ reveals a strong energy loss at the surface indicating clear conditions (e.g., hexagons with a white minus sign in Fig. 2). For this region within the SOM grid, $\Delta t_{wet2dry}$ is low, indicating that such configurations occur at the end of a fog episode. We assume that fog ended and that the sensor is in the drying phase but still wet. According to the spread of $\Delta t_{wet2dry}$ for this region on the SOM, this drying period lasts between a few minutes up to 3 h.

In a similar way, grid cells of the SOM can be identified that represent the following situation: While the leaf is dry, a high

rh , a low $\Delta\vartheta$, and a low ΔP indicate foglike conditions. For some of these cases, the time until the leaf wetness sensor switches to wet is less than 2.5 h (hexagons with white plus sign in Fig. 2). Therefore, we assume that fog is already present but that the sensor is not wet yet.

By visual inspections of all the resulting SOMs, a fog definition is derived that consists of an initial classification according to U followed by additional tests taking the other variables into account. A flowchart summarizes the process (Fig. 3). If $U > 284$ mV, the initial classification is set to fog, otherwise, it is set to dry. If fog was determined and $\Delta t_{wet2dry} < 185$ min, the initial classification is revoked and set to dry if at least one of the following conditions is fulfilled: $rh < 80\%$, $\Delta\vartheta > 1$ K, or $\Delta P > 50$ W m $^{-2}$. An initial dry classification is revoked and set to fog in case all conditions $rh \geq 84\%$, $\Delta\vartheta \leq 0$ K, $\Delta P \leq 40$ W m $^{-2}$, and $\Delta t_{dry2wet} < 155$ min are fulfilled simultaneously.

This fog definition is applied equally to measurements from all considered climate stations. For 278 events, an initial fog classification is revoked, which corresponds to 12.7% of all initial fog events. This number is only partly compensated by 187 events that have been switched to fog after initial dry classification. This indicates that on average the drying of the sensor takes more time than the wetting.

For regular stations that do not provide the longwave radiation budget, the condition for ΔP is omitted. Furthermore, the condition for rh is omitted for climate station 20 for the period between September 2018 and February 2019 because no valid humidity data are provided for this period. For station 14, the SOM analysis reveals a puzzling picture. When the leaf wetness sensor indicates fog, $\Delta\vartheta$ is mostly high, unlike what is seen for all other stations. Here, the air temperature is predominantly about 2–4 K higher than the surface temperature, which is atypical for fog events and rarely observed at the other stations. Since the surface temperature is determined with an infrared thermometer with an assumed surface emissivity of 0.94 for all stations, the different temperature signature could be due to a local surface emissivity anomaly as the location is in close proximity to the Salar de Llamara, a salt flat in the central depression. Such an anomaly would also affect the radiative signature for the thermal emissive MODIS bands. Another explanation could be dew, which would wet the sensor but does not prevent cooling of the surface.

Following the presented fog definition, a ground-based reference dataset is ready to be applied to derive and validate satellite-based fog retrieval methods. MODIS data and station

FIG. 2. SOM for climate station 13. Shown is the average for each grid cell for (a) leaf wetness sensor voltage, (b) relative humidity, (c) temperature difference between air and surface ($\Delta\theta = \theta_{2m} - \theta_{surf}$), (d) longwave radiation budget ($\Delta P = P_{up} - P_{down}$), (e) time until a wet leaf wetness sensor switches to dry, and (f) time until a dry leaf wetness sensor switches to wet. Initially, grid cells are set to fog if the leaf wetness sensor is wet on average (white frames). Otherwise, grid cells are set to dry. The initial classification is changed from fog to dry (white minus sign) or from dry to fog (white plus sign) according to additional tests (see the text and Fig. 3, below). SOMs for other climate stations are available in the online supplemental material.

data are assigned to each other by taking the nearest MODIS pixel and the station measurements that are closest in time. About 13 800 valid MODIS and station measurement pairs are available within the considered time period including 11 stations.

b. Classification assessment measures

This study faces a binary classification problem (fog or dry conditions). Comparing the satellite-based fog detection introduced in the following sections with the reference dataset can be done using a confusion matrix (2×2 contingency table for binary classification) (e.g., Cermak and Bendix

2011; Egli et al. 2017; Andersen and Cermak 2018) that yields the number of true positives (correct fog prediction), true negatives (correct dry prediction), false positives (incorrect fog prediction or false alarm), and false negatives (missed fog event). These numbers are used to derive further evaluation measures such as the probability of detection (POD), also known as true positive rate (TPR), which gives the fraction of all ground truth fog events that are correctly detected; the accuracy (ACC), which gives the fraction of all observations with correct classification; the false-alarm ratio (FAR), which gives the fraction of all fog predictions that are false alarms; the critical success index (CSI), which gives the portion of fog hits

FIG. 3. Flowchart of binary fog state classification (fog or dry) as based on climate station measurements. After an initial classification according to the leaf wetness sensor voltage U , additional tests are applied for relative humidity rh , temperature difference $\Delta\theta$, radiation budget ΔP , and the time until U crosses the threshold of 284 mV $\Delta t_{\text{wet2dry}}$ and $\Delta t_{\text{dry2wet}}$. Note that for the OR conjunction the whole box is “TRUE” if at least one of the listed conditions is fulfilled, whereas the AND conjunction requires all individual conditions to be fulfilled for the whole box to be “TRUE.” Depending on the additional tests, the initial classification can be revoked or confirmed.

out of all false classifications and fog hits combined; and the bias score (BS), which gives the bias of the classification with an overestimation of fog for $BS > 1$ and an underestimation for $BS < 1$. Furthermore, the Heidke skill score (HSS; Heidke 1926; Hyvärinen 2014) is applied as a measure for prediction skill. The HSS gives the fractional improvement relative to a random classification. A perfect forecast would result in $HSS = 1$, a random forecast would result in $HSS = 0$.

Definitions of these measures are provided in the appendix. Further insights into classification assessment methods are given by Fawcett (2006) or Tharwat (2018), for example.

c. Neural network

To exploit the available spectral information and represent the interactions of various factors and processes involved in the radiative transfer, we employ a neural network to detect fog. In general, neural networks map output variables to input variables by propagating the input (signal) through a net of nodes (e.g., LeCun et al. 2015; Goodfellow et al. 2016). Next to the input layer with the input nodes, several hidden layers with various numbers of nodes and an output layer can be set up. At each node, an activation function is applied to modify the incoming signal (e.g., Ding et al. 2018). Along each path between two nodes a weight factor is applied to the signal. These weights are modified during the training process in a way to minimize a defined loss function. The loss function provides a measure of error by comparing the final output of the network and the target values. This error is propagated backward through the net and each weight is updated according to the

gradient of the loss function weighted by the learning rate. Furthermore, regularization options such as a drop out of randomly selected connection between nodes are available to prevent the network from specializing for the training dataset (overfitting).

Different software packages are available to build neural networks. In this study, the Keras software package, a deep learning application programming interface (Chollet et al. 2015) written in Python, is utilized via the Keras package for R (Chollet et al. 2017) with the TensorFlow (Abadi et al. 2015) machine learning platform selected as backend. Brightness temperatures from 15 unique emissive MODIS bands (section 2a1) and the corresponding fog state (fog or dry) from the ground-based reference dataset (section 3a) are used as input and target variables, respectively. The neural-network architecture consists of an input layer with 15 nodes, one for each selected MODIS channel, several hidden layers with varying numbers of nodes and an output layer with one node (cf. Fig. 4). Hyperparameters that have been chosen to maximize the accuracy according to some initial testing are listed in Table 3.

The neural network is trained in two different modes. For the first mode, all observations from all considered stations are randomly split into a training (75%) and a test sample (ALL mode). For the second mode, observations from all considered stations except one are used for the training, and the station left out is used for evaluation [leave-one-out (LOO) mode]. An additional 20% of the training data are set aside by the network itself so that the loss and accuracy of the model can be calculated for training and validation data separately during the training process (Figs. 5b,c). This allows evaluation whether the model has converged during the training process.

The output of the neural network is not a binary classification immediately. Instead, the sigmoid activation function of the output node returns a value x_{out} in the range $0 \leq x_{\text{out}} \leq 1$, which can be seen as a probability of fog occurrence. To obtain a binary classification, a threshold for fog prediction has to be applied at which the output is divided into dry (below threshold) and fog (above threshold). Once the binary classification is determined according to the chosen fog prediction threshold, the TPR and the false positive rate (FPR, also known as the false-alarm rate) can be calculated along with other skill scores (for definitions, see the appendix). By varying the fog prediction threshold, TPR and FPR vary accordingly. In a TPR-versus-FPR diagram, also known as receiver operating characteristic (ROC) curve, the model performance can be visualized. Ideally, a low FPR coincides with a high TPR. However, in reality, a higher TPR usually is accomplished at the cost of a higher FPR.

To determine the optimal number of hidden layers and respective numbers of nodes, multiple neural networks were trained applying several setups. To evaluate the performance of each model, the area under the ROC curve (AUC) is determined (Fig. 5a) that serves as a measure of separability of the two classes (fog, dry) by the trained neural network. A perfect separation would result in an AUC of 1, whereas no separation skill would result in an AUC of 0.5. After testing models with varying number of layers and nodes (Fig. 5a), a

FIG. 4. Schematic illustration of the setup of the neural network. Normalized MODIS brightness temperatures (BTs) are inserted into the network via the input layer (left two orange circles), which consists of 15 nodes (neurons, with only two shown). At each node of a hidden layer (blue circles), the output $y_{m,n}$ from each node n of the previous layer m is used as input $x_{m,n}$. By applying the respective weights $w_{m,n}$ and biases $b_{m,n}$ to each input and summation over all these terms, the output for a hidden-layer node is created. After the rectified linear unit (ReLU) is applied as activation function, it serves as input for the nodes of the next layer. For the output of the final hidden layer, the sigmoid activation function is applied so that the final output (orange circle on the right) of the network is a value ranging between 0 and 1. To regularize the network (avoid overfitting), 10% of the connections are randomly dropped after each hidden layer (dotted lines). For illustration purpose, the schematic only shows two hidden layers with 4 and 3 nodes, respectively. The setup of the actual chosen model consists of four hidden layers, with 128, 64, 32 and 8 nodes, respectively.

model is chosen with four hidden layers consisting of 128, 64, 32, and 8 nodes, respectively.

For this model, the evolution of the loss and the accuracy indicate that the model is sufficiently trained with marginal overfitting (Figs. 5b,c). Its capability to separate between the two classes is manifested in the two separate peaks revealed by the distributions of the output of the trained neural network for fog and dry conditions according to the ground-based reference, respectively (Fig. 5d).

While not shown explicitly, we also investigated the suitability of additional input data such as 1) the 10 m wind from reanalysis, 2) climatologies of the brightness temperatures for each channel, or 3) percentiles of brightness temperatures within a certain time window around each measurement. While these variables can improve the predictive skill of the model and increase the resulting correlations with the ground-based reference at an individual station, these improvements do not hold anymore when the training is carried out in LOO mode. A similar behavior is found when the station identification number is provided to the network. This indicates that any additional variable used in the training process that has unique signature at each station will result in an overfitted model. Therefore, such a model would not be suitable to apply region wide. Moreover, incorporating further neighboring MODIS pixels in addition to the nearest neighbor (3×3 pixels around the station) did not improve the detection skill.

Furthermore, including station 14 in the training process resulted in an overall lower performance of the network. As a result of the SOM analysis (section 3a), abnormal $\Delta\vartheta = \vartheta_{2m} - \vartheta_{srf} > 0$ accompany a wet leaf wetness sensor.

This could be due to frequent dew events in the absence of fog or a deviating surface emissivity corrupting the retrieval of ϑ_{srf} . Either of these scenarios would affect the radiative signature associated with fog or dry events for this location. Ultimately, including any doubtful or anomalous fog signatures in the training process could confuse the neural network and explain the overall lower performance. Therefore, we decided to omit station 14 from the analysis.

d. MODIS cloud-top height

The MODIS cloud product provides the cloud-top height (CTH) above sea level. For a conversion to heights above ground level (AGL), elevations of the climate stations are

TABLE 3. Parameters and schemes implemented in the neural network used for this study.

Feature	Value
Activation function hidden layer	Rectified linear unit (ReLU)
Activation function output layer	Sigmoid
Dropout rate	10%
Iterations (epochs)	100
Batch size	1000
Weight update scheme	Adam optimization algorithm (Kingma and Ba 2014)
Learning rate	0.001
Loss function	Binary cross entropy

FIG. 5. (a) ROC curve of the neural-network fog prediction calculated from the test dataset (not used for training). Different curves (colors) represent different architectures (numbers of layers and nodes) that are indicated by the legend along with the respective AUC. True positive rate and false positive rate have been additionally determined for the MODIS CTH approach to detect fog (blue circle). (b) Evolution of the loss, which represents the deviation between reference and neural-network-predicted values after each training iteration (epoch) calculated using the binary cross entropy function. It is shown for the training data (red) and test data (blue) separately. (c) Evolution of the accuracy of the neural network over the number of training iterations (epochs) for training data (red) and validation data (blue). To determine the accuracy (portion of correct classification; see the [appendix](#) for definitions), the binary classification is made by rounding the network output at 0.5, which results in 0 (dry conditions) or 1 (fog conditions). (d) Histogram of the neural-network output for fog (blue) and dry (red) conditions according to the ground-based reference classification. The y axis represents the number of counts for each bin normalized by the total number of observations for each condition, respectively. The dashed vertical line denotes the determined binary classification threshold (fog prediction threshold of 0.27; [Fig. 8](#), below).

subtracted from the corresponding MODIS CTHs. In case of very low cloud-top heights and complex topography with the station being higher than the satellite-based CTH, this can result in negative CTHs AGL.

The MODIS cloud-top heights that are collocated with the climate stations reveal a bimodal distribution ([Fig. 6a](#)). While fog situations yield a pronounced peak between 2 and 4 km and a less pronounced peak around 11 km (high clouds; cirrus), for dry situations low and high cloud peaks are less distinct. This indicates that fog occurrence is less likely alongside high cloud presence. However, fog events with simultaneous presence of an optically thick enough high cloud are missed because the view is obscured so that the CTH of a possible lower cloud cannot be provided. Furthermore, the low cloud peak is shifted to lower cloud-top heights for dry situations, indicating that the lowest observed clouds are typically not associated with fog occurrence. An explanation could be that nocturnal fog typically coincides with a ground inversion. This would lead to ambiguous cloud-top height retrievals for which the MODIS CTH retrieval algorithm chooses the highest possible option [[Menzel et al. 2008](#); [Baum et al. 2012](#), cf. [section 2a\(2\)](#)].

The distributions for fog situations peak similarly around 3 km for individual stations, which highlights the homogeneity in cloud properties across the study region. An exception is station 33 for which the peak is seen around 1 km. However, only few cloudy scenes ([Fig. 6b](#)) and almost no fog events ([Table 1](#)) were detected for this station.

To determine a CTH range that gives the best prediction of fog occurrence a combination of a lower and an upper threshold height is estimated that maximizes the HSS. The best model is obtained if cloud-top heights between 2000 and 3750 m are declared fog. This approach yields about 87% correct classifications (accuracy) with a probability of detection of 55% and a false-alarm ratio of 43%. More parameters are listed in [Table 4](#). MODIS CTH below the lower threshold, seem to indicate the absence of a ground inversion and thereby unlikely fog conditions. Therefore, the predictive skill of this approach appears to stem from the detection of a possible ground inversion that serves as a proxy of fog presence.

4. Evaluation

For the evaluation of the fog-detection approaches, two different aspects are assessed. First, the event-based algorithm

FIG. 6. Distribution of MODIS CTH AGL for the nocturnal overpasses over the considered climate stations. (a) Normalized density of CTH distinguished by concurrent fog (blue shadings) or dry (red shadings) conditions at collocated climate stations. Densities are shown considering all stations together (thick lines) and for the individual stations (thin lines). (b) Counts of events for each MODIS CTH bin and each station under fog conditions according to the collocated station measurement. MODIS CTH is originally given above sea level. CTH AGL is obtained by subtracting the elevations of the respective climate stations. In the case of complex topography, this method can lead to negative CTHs AGL.

performance is evaluated via a contingency table analysis (section 4b), which is preceded by an investigation of the neural-network sensitivity to the training process (section 4a). Second, the temporal and spatial representativeness of the fog-detection methods based on the neural network and the MODIS CTH are discussed (section 4c). Third, each method is applied to derive a 3-yr climatology (section 4d).

a. Neural-network model sensitivity

During the training of the neural network, random selection processes influence the values of the final model weights leading to different realizations even with exactly the same training data sample. To quantify the introduced variability, a 10-member ensemble is created that results in an ensemble mean of 0.876 for the AUC with a standard deviation of 0.002 (Fig. 7a). This indicates that the improvement, that is, higher AUC, with increasing depths and widths of the models is mostly beyond two standard deviations (Fig. 5), which, in turn, indicates statistical significance since they are all trained with the very same training data sample. A slight decrease in the AUC is observed when a fifth layer is added ($AUC = 0.875$).

Furthermore, the sensitivity to the training data sample is investigated. In a similar fashion, another 10-member ensemble is created by providing each member with a new randomly drawn training data sample. The additional variation of the training data sample results in a higher standard deviation of the AUC (0.007) for this ensemble (Fig. 7b) relative to the ensemble

with a fixed training data sample. For a binary classification obtained by simply rounding the model output, that is, a fog prediction threshold of 0.5, a mean HSS of 0.525 ± 0.023 is derived. The uncertainties for further statistical measures are given

TABLE 4. Statistical evaluation measures based on a 2×2 contingency table for an event-based comparison of binary classification (fog or dry) by the fog-detection methods and the ground-based stations. Measures are listed for fog detection via MODIS CTH and via NNet including only the test samples that were not used to train the network and including all considered observations, i.e., both training and test samples. The prediction threshold (pred thresh) refers to the threshold to discriminate the output of the neural network between fog and dry conditions. The given threshold maximizes the Heidke skill score (HSS) and results in a bias score (BS) closest to unity. Further measures are the true positive rate (TPR), which is also known as probability of detection, false positive rate (FPR), accuracy (ACC), false alarm ratio (FAR), and critical success index (CSI). Definitions of these measures are given in the appendix.

Model	Pred thresh	TPR	FPR	ACC	FAR	CSI	BS	HSS
MODIS CTH		0.55	0.07	0.87	0.43	0.39	0.96	0.49
NNet (test sample)	0.27	0.63	0.07	0.89	0.37	0.46	1.01	0.56
NNet (all obs)	0.27	0.63	0.07	0.89	0.37	0.46	0.99	0.56

FIG. 7. ROC curves for the neural network: (a) 10-member ensemble trained with fixed training data sample and (b) 10-member ensemble trained with randomly drawn training data sample. Ensemble mean and standard deviation are given for the AUC and the following statistical measures (definitions are listed in the [appendix](#)): Heidke skill score (HSS), bias score (BS), critical success index (CSI), false-alarm ratio (FAR), percent correct (PC), and probability of detection (POD).

in Fig. 7b. The standard deviations of these measures derived here are useful to assess whether any of the different fog-detection methods result in significantly different statistical measures.

b. Event-based algorithm performance

A functional relationship exists between statistical measures, such as the HSS, and the fog prediction threshold (Fig. 8). Based on all observations, a maximum HSS of 0.56 is retrieved for the neural network with a fog prediction threshold of 0.27 (Table 4), which indicates a much better detection skill relative to a determination by chance ($HSS \approx 0$). The same fog prediction threshold also results in the best bias score, which almost reaches unity ($BS = 0.99$). This means that the model estimates the total number of fog events essentially correct. Based on the independent test data sample, the HSS is maximized for the same fog prediction threshold (0.27). Except for the bias score, all considered statistical measures are basically identical to the results based on all observations (Table 4). This further supports that the neural network is valid beyond the training dataset at least for the locations of the climate stations included in the study.

Application of the MODIS CTH to detect fog results in a lower HSS (0.49). While almost the same number of fog events are predicted by the MODIS CTH approach ($BS = 0.96$) as by the neural network, the true positive rate is lower and the false-alarm ratio is higher (Table 4). This proves that exploiting the spectral information of the MODIS emissive bands via a neural network outperforms a fog-detection algorithm based on the MODIS CTH.

c. Spatiotemporal representativeness

To assess spatial and temporal consistency of the proposed fog-detection algorithms, time series of fog occurrence frequency are derived for the locations of the climate stations. To derive the time series, the binary classifications from the

station measurements and from the MODIS CTH detection approach (CTH inside or outside the designated height range) are converted to numeric values (1 for fog conditions and 0 for dry conditions). A binary classification from the neural network is achieved by applying the derived threshold of 0.27. While the output of the neural network could also be viewed as a fog probability, it appears more appropriate to convert the output to binary prior to calculating the time series because the neural network's ability to distinguish between the two classes appears asymmetric (Fig. 5d). Although for dry situations the output is very close to 0, the output peaks around 0.7 for fog situations. The bias score close to unity (0.99) reached for the derived threshold (Fig. 8e, Table 4) further supports this choice.

To allow a fair comparison, the time series comprise only coincidental observations from MODIS and the climate stations. For every day, the mean fog state is calculated for each fog retrieval approach. Then, centered moving averages of various interval lengths are applied to each of these daily resolved time series.

To assess the temporal consistency, time series from the neural network trained in ALL mode are compared with the ground-based reference. Station 13 is used as an example (Fig. 9a). On a synoptic scale (7-day moving average), many fog peaks are well in agreement, with an overall Pearson correlation coefficient of $r = 0.74$. Extending the time interval of the moving average to a subseasonal scale (60 days) brings out seasonal variations that are represented well by the neural network ($r = 0.89$). Higher frequencies during late winter and early spring and lower frequencies during late summer and early fall are revealed by both the neural network and the ground-based fog retrievals. This cycle is also captured by the MODIS CTH approach (Fig. 10a) but with a slightly lower correlation to the ground-based reference ($r = 0.77$). Such pronounced seasonal cycles are consistent with reports from previous studies about the coastal desert (e.g., Farías et al. 2005; del Río et al. 2018). Time series for other stations are provided in the online supplemental material.

FIG. 8. Statistical measures calculated for the neural-network fog prediction in dependence on the fog prediction threshold that is applied to the network output to obtain a binary classification (fog or dry). The fog prediction threshold that maximizes the HSS is highlighted as a vertical orange dashed line in all panels. The point P of the intersection with the curve is annotated in each panel (see also Table 4). The thick black line denotes the statistics calculated using all observations. The shaded area denotes the area between the 5th and 95th percentile of a distribution derived via a bootstrap resampling of all observations with 1000 iterations.

Extending the analysis to all stations, correlations between time series derived from the neural network and the ground-based reference dataset are studied in dependence on the moving average interval lengths (Fig. 9b). For increasing interval lengths, the correlation typically increases, which indicates a better fog frequency representation for longer time scales. Overall high correlations, in particular on subseasonal scales, prove the suitability of the neural network to represent seasonal and interannual variability of fog frequency. The same results hold true for the MODIS CTH approach (Fig. 10b) but with overall lower correlation.

The root-mean-square error (RMSE; Fig. 9d) decreases with increasing interval length for the moving average. It is highest for the stations that have the highest fog occurrence frequency (stations 12, 20, and 32). Therefore, their RMSE in relation to the mean fog occurrence frequency is comparably low (35%, 27%, and 30%, respectively). For the other stations, the absolute RMSE is about or below 0.04 for moving average intervals greater than 60 days. For six stations, the relative RMSE is below 40%.

Next, the spatial consistency of the neural network is investigated by withholding one station during the training of the network and evaluating the time series for that station (LOO training mode). Relative to the neural network trained with all stations, the correlation remains almost the same for five

stations (within ± 0.03 for stations 12, 13, 20, 22, and 24; Fig. 11) and differs only slightly for another two stations (within ± 0.07 for stations 15 and 23).

To give an example of how the network learns from other stations, a detailed look is taken at the easternmost stations of the northern and center transect (station 25 and 15). They share similar site specific characteristics such as altitude (~ 2500 m; Table 1) and fog frequency seasonality (summer peak; Figs. S14 and S15 in the online supplemental material). Therefore, the related fog signature can be expected to be similar for these two stations but rather distinct from the signatures of stations closer the coast within their respective transects that are characterized by lower altitudes and opposite seasonality. For station 25, the correlation drops from 0.89 to 0.51 when it is left out from the training. The lower yet still apparent detection skill stems from the other stations including the very few fog events recorded at station 15 (overall fog frequency of 0.01). On the other hand, the correlation for station 15 remains high (increase from 0.81 to 0.88) when it is left out from the training. The network is capable of identifying the summertime fog peaks at this station regardless of its inclusion in the training (supplemental Fig. S14), which indicates that the slightly higher fog frequency at station 25 (0.02) helps to provide the neural network with sufficient examples from which to learn.

FIG. 9. (a) Fog frequency time series derived from the neural network (blue) and the station measurements (red) for a 7-day (dark) and a 60-day (light) centered moving average at the location of station 13. Corresponding Pearson correlation coefficients r_7 and r_{60} for the respective moving-average intervals are indicated in the top right of the panel. (b),(c) Pearson correlation coefficient and (d),(e) RMSE in dependence on interval length of the moving average for each climate station. Two different training modes are distinguished: training on all stations [ALL mode in (b) and (d)] and leaving one station out from training and deriving the statistics for this station [LOO mode in (c) and (e)]. Dashed lines indicate stations with very low fog occurrence frequency ($f \leq 2\%$). Black dashed vertical lines highlight the moving-average intervals for which the exemplary time series in (a) is shown. The time series in (a) is based on the ALL training mode. Time series for all stations based on the LOO training mode are given in the online supplemental material.

For station 32, the correlation drops from 0.85 to 0.62 when it is left out from the training of the neural network. While for the other transects, more fog events from nearby stations can introduce the local fog structure, this is not the case for station 32. The nearby stations 33 and 34 of the southern transect do not provide a sufficient number of fog events that could introduce local fog signatures to the neural network. For stations 33 and 34, the correlation coefficients cannot be meaningful due to fog frequencies of almost 0 and very low variances.

Overall similar correlations resulting for respective stations for the two training modes (ALL and LOO; Fig. 11) show that the neural network is not specializing for the training data.

Instead, the approach has potential to be generalized region wide including locations for which no observations are provided to train the model. This is further supported by the absolute RMSE, which shows differences below 3% for most stations when the two training modes are compared (Figs. 9d,e and 11).

It is assumed that the overall variability of fog morphology and surface emissivity across the study region is represented in the training data. The validity of the assumption could be tested by leaving out an entire transect from the training and using the corresponding stations for testing. This would allow to assess the homogeneity of the fog signature across the study

FIG. 10. (a) Comparison of fog frequency time series derived from the fog detection based on the MODIS CTH (dark blue), the neural network in both ALL training mode (lighter blue) and LOO training mode (lightest blue), and the climate station measurements (red) at the location of station 13. The time series is smoothed by a 60-day centered moving average. Pearson correlation coefficient r and bias B between the time series of the proposed detection algorithms and the reference time series (station) are indicated in the legend, respectively. (b) Pearson correlation coefficient and (c) RMSE between time series derived from the detection via MODIS CTH and from the station measurements in dependence on the interval length of the moving average for each station. Dashed lines indicate stations with very low fog occurrence frequency ($f \leq 2\%$). Black dashed vertical lines highlight the moving-average intervals for which the exemplary time series in (a) is shown (60 day). Time series for other stations are provided in the online supplemental material.

area in more detail. However, a sufficient amount of reference data is needed for each transect for such an analysis. This will be possible in the near future when more data have been gathered.

To further assess the spatial representativeness, the biases that result for different stations are investigated. For the LOO training mode of the neural network, these biases are mostly positive and below 10% of fog frequency when a 60-day moving average is applied (Fig. 11c). This means the neural network overestimates the fog presence relative to the reference dataset. Exceptions are station 20 for which a negative (dry) fog frequency bias of -0.12 is determined and station 32 for which a stronger bias of 0.33 is determined. The strong bias increase from ALL (-0.1) to LOO mode for station 32 indicates that the fog signature at the southern transect differs from the other transects. Moreover, the network needs to include station 32 to learn this signature as the remaining stations of the southern transect (stations 33 and 34) do not provide sufficient fog events (Table 1).

Enhanced wet biases for the LOO training mode are also found for most other stations with increases below 0.12 relative to the ALL training mode (Fig. 11c). For station 13, for example, the fog frequency lies systematically higher throughout the considered period if the neural network has not seen any

observations from this station (Fig. 10a), in particular for winter and spring season (e.g., August–December 2017). A possible reason for this overestimation, which appears similarly for the MODIS CTH approach, could be that very low clouds are classified as fog even though a portion of them might not touch the ground. Once the network is introduced to observations specifically from this station (ALL training mode), such cloud scenes can be distinguished as indicated by a better agreement with the ground-based reference. This illustrates how the neural network is learning from the observations. While the observations from other locations generally suffice to detect fog with great temporal representativeness ($r = 0.92$), it can learn more scene specific details once it is presented with local observations leading to further improvement with an overall bias reduction from 0.08 to 0.03 .

The MODIS cloud-top height allows the derivation of high cloud (here above 5000 m) frequency time series. Since high clouds can obscure the scene below, an introduction of a bias could be expected from their presence. For stations of the northern and center transects, a typical high cloud season is observed for the summer months (December–March; supplemental Figs. S13–S15). However, the fog frequency time series derived from the neural network do not reveal a particular break point associated with enhanced high cloud presence

FIG. 11. Boxplots of (a) fog occurrence frequency as well as statistical metrics such as (b) Pearson correlation coefficient, (c) bias, and (d) RMSE derived from the comparison of fog frequency time series based on the neural network trained in ALL and LOO mode and the MODIS CTH classifications for each station (colored circles). Thick horizontal lines within the boxes denote the median, the boxes indicate the 25th and 75th percentile, and the upper and lower whisker give the maximum and minimum, respectively, but not farther than $1.5 \times$ the interquartile range (IQR) away from the box.

(e.g., Fig. 10a). While the high cloud frequency reveals a clear seasonality except for the southern transect, no consistent seasonal cycle appears for the bias of the neural network or the MODIS CTH approach (Fig. 12). For instance, the bias at station 13 decreases from 0.035 to -0.025 between winter and summer season, respectively, whereas for nearby station 12 an increase from -0.055 to 0.04 can be observed. The absence of a seasonal bias consistent across the stations for the northern and center transect further indicates that high clouds do not affect the performance of the neural network. However, only one or two high-clouds seasons are included within the utilized time periods of the stations.

d. Climatology

To exploit the indicated potential of the neural network to represent fog within the entire region, a 3-yr climatology (2017–19) is derived. For comparison, a climatology is also derived based on fog detection via MODIS CTH.

For austral winter (July–September), the neural network and the MODIS CTH approach both reveal very high fog occurrence frequencies for the coastal regions and low values for most inland regions ($<5\%$) (Figs. 13a,b). The coastal maximum stays mainly below 50% (MODIS CTH), whereas it exceeds 70% for the neural network. Overall, this sharp west–east gradient is expected because the near coast maritime stratocumulus is most persistent yielding the highest cloud cover during austral winter (Farías et al. 2005; Cereceda et al. 2008; Muñoz et al. 2016; Lehnert et al. 2018).

Furthermore, due to the lower cloud heights during winter (Muñoz et al. 2016; Böhm et al. 2019), the stratocumulus is more prone to intersect with the coastal cliff and mountain range, which prevents farther inland advection. Inland penetration is visible for both fog retrieval approaches at corridors

where the coastal cliff is intercepted by canyons or generally lower, for example, at the northern end around the Peruvian border. Such fog corridors have been identified and related to fog occurrence in the central depression (Farías et al. 2001, 2005). Individual areas within the central depression stand out with enhanced fog frequencies up to 50% for the MODIS CTH approach and even higher frequencies for the neural network,

FIG. 12. Boxplots of seasonal biases with respect to the derived ground-based reference fog frequency for the neural-network approach in ALL training mode (NNet) and the CTH approach (CTH) for austral winter (JAS) and summer (JFM). Thick horizontal lines within the boxes denote the median, the boxes indicate the 25th and 75th percentile, and the upper and lower whisker give the maximum and minimum, respectively, but not farther than $1.5 \times$ IQR away from the box. Results are provided for each station by colored circles. Diamonds denote respective mean values.

FIG. 13. Seasonal climatology of fog occurrence frequency f for (a)–(c) austral winter (JAS) and (d)–(f) summer (JFM) based on the neural network [NNet in (a) and (d)], MODIS CTH [in (b) and (e)], and ERA5 low cloud cover [ERA5 in (c) and (f)]. Utilized climate stations are indicated according to the respective overall bias by circles (positive bias) and triangles (negative bias). Respective fill color denotes the bias difference ΔB between absolute values of NNet bias and CTH bias. Negative ΔB represent a smaller absolute bias for NNet (red shades). Salt flats (salars) according to C. Albers (2020, personal communication) are outlined in red.

in particular between 20° and 21.5°S where no validation data are available.

Across the study region, the neural network estimates slightly higher fog occurrence frequencies relative to the MODIS CTH approach, which is consistent with the higher bias shown for the LOO training mode (Fig. 11c). However, higher fog frequencies are expected at the coast as daily mean low stratus frequencies exceeding 50% for August 2001 based on retrievals from GOES have been reported (Fariás et al. 2005; Cereceda et al. 2008). For the nocturnal MODIS overpasses, even higher frequencies are expected considering the diurnal cycle. Therefore, the coastal frequencies based on the neural network seem more plausible. The dry bias found for station 20 (Fig. 11c), which is the closest station to the coast, indicates that the coastal frequencies might still be underestimated even for the neural network. For all stations except station 12 and station 22, the absolute value of the bias is smaller for the neural network relative to the MODIS CTH approach (Figs. 13a,b). However, the overall patterns are mostly in agreement among the presented approaches and appear plausible.

Consistent with the previous discussion, both approaches agree that fog occurrence is reduced at the coast (Figs. 13d,e) for austral summer (January–March). A distinctly enhanced coastal fog frequency is only apparent south of 24°S for both approaches. Besides these agreements, the patterns derived from the neural network and the MODIS CTH differ overall. The neural network reveals a north–south gradient with values up to 15% in the north and below 5% in the south. North of 21°S, this gradient is overlaid by a less pronounced west–east

gradient with fog frequencies mainly within 5%–10% toward the coast and within 10%–15% toward the Andes. On the contrary, the MODIS CTH approach results in an opposite west–east gradient with values up to 35% in the coastal cordillera decreasing to values below 5% toward the Andes.

For the neural network, the summer pattern resembles a potential high cloud frequency pattern that could be expected from the summer maximum of high clouds for the northern Atacama Desert (cf. Fig. 10a and online supplemental Figs. S13–S16). Summer time high cloud presence can be expected given the typical summer circulation with upper-level moist easterlies for this region (Garreaud et al. 2003). However, the absence of a particular seasonal bias does not support this explanation. In fact, the opposite seasonality when compared with the coastal desert observed for stations 15 and 25 (supplemental Figs. S14 and S15), which are located at the eastern ends of the northern and center transects, is consistent with the higher summer frequencies in the northeast, which are found for the neural-network-based climatology (Fig. 13d). In particular for the northern transect, the increase from west (station 22; supplemental Fig. S14) to east (station 25; supplemental Fig. S15) for the summer season is only noticeable for the neural-network approach. An opposite gradient results for the MODIS CTH approach. Therefore, the climatology based on the neural network appears more plausible.

As for the winter season, both approaches show enhanced fog occurrence frequencies for some parts of the central depression for the summer season. However, for the neural network, this is hardly pronounced. On the contrary, the MODIS CTH approach reveals values exceeding 50% for these regions.

Cereceda et al. (2008) report that the region between 20° and 22°S is mostly cloud free (fog frequency equal to 0) inland with only few patches falling in the next higher category for mean low stratus frequency (0%–5%) based on GOES retrievals for January 2002. Since their estimate represents a diurnal average and fog frequency peaks at night, a conversion of our frequency estimates would have to be carried out. By assuming representativity for a 4-h window between 2200 and 0200 LT (roughly the satellite overpass times for *Terra* and *Aqua*) and a fog frequency of about 30%, which is even exceeded for some patches, the diurnal mean fog frequency could be estimated to about 5% ($0.3 \times 4/24 \approx 0.05$). Considering that the most parts of the region appeared cloud free, the overall lower fog frequencies determined by the neural network seem more plausible. However, the comparison with Cereceda et al. (2008) is difficult because they use observations from different hours of the day, analyze a different time period (15 years prior to our period), use GOES estimates featuring a coarser resolution, and do not distinguish between low clouds and fog to name some of the differences.

To further investigate which representation of the summer climatology is more realistic, we compare the seasonal bias difference between the neural network and the MODIS CTH approach. Within the region of enhanced fog frequency for the CTH approach extending from the coastal desert north of 20.5°S into the central depression between 20° and 22°S lie two stations (station 22, and station 23). For both stations, the bias is a lot smaller for the neural network (Figs. 13d,e). While this further indicates the superiority of the of neural network, the low number of stations within this particular region hampers a solid validation.

Further structural differences can be found for the summer climatology. The MODIS CTH approach shows a much higher spatial variability on a scale of a few kilometers relative to the neural network, which is consistent with a higher spread of the station specific biases (Fig. 12). Furthermore, the MODIS CTH approach shows lower fog frequencies along some coastal canyons relative to the surroundings in particular north of 21°S for the summer climatology (Fig. 13). For the neural network, these local structures are not visible. While it seems more plausible that these canyons allow more frequent inland penetration as it is observed for both approaches for the winter season, we cannot validate this any further at this point.

5. Conclusions

This study introduces a new satellite-based fog retrieval approach for the Atacama Desert region that utilizes a neural network to process MODIS brightness temperatures. An attempt is made to derive a regionwide climatology of fog frequency. The development of this approach benefits from a new network of climate stations deployed at various locations throughout the Atacama. Based on a leaf wetness sensor and some additional constraints, a ground-based reference fog dataset is derived that is utilized to train and validate the retrieval method. An uncertainty assessment for the reference data is difficult. For future validation of the ground-based fog retrievals, an additional installation of visibility sensors would

be beneficial. Furthermore, the ground-based reference data are utilized to develop an alternative fog retrieval method, which is based on simple height thresholds applied to MODIS CTHs, for comparison.

A contingency table analysis based on binary classification of individual events results in an overall accuracy of 0.89, a POD of 0.63, a FAR of 0.37, and a HSS of 0.56 for the neural network when an optimal fog prediction threshold of 0.27 is applied to convert the probabilistic neural-network output into a binary classification. Another satellite-based algorithm for fog and low cloud detection has recently been developed by Andersen and Cermak (2018) for the Namib region, a similar subtropical west coast desert environment. The authors report an accuracy of 0.97 and a HSS of 0.89. However, their approach does not make a distinction between fog and low clouds, which is attempted here. For Europe, a pure fog-detection approach is presented by Egli et al. (2018) who report a HSS of 0.58 for a satellite-based fog-detection method that is validated against visibility provided by METAR and SYNOP reports. However, due to the completely different reference datasets and different environmental conditions for their study region, a comparison to our study is difficult.

To further assess the suitability of the neural-network approach to derive a climatology and to study the variability of fog frequency on different time scales, time series are considered for each climate station. On a subseasonal scale (60-day moving average), Pearson correlation coefficients between the time series based on the neural network and the climate stations range between 0.75 and 0.90 for stations with overall fog frequencies greater than 2%, indicating a suitable representation of the temporal variability of the fog frequency. Slightly lower correlations are determined for the MODIS CTH approach.

To investigate whether the neural network is representative for locations aside from the climate stations that are included in the training process, a second training mode is introduced. By leaving out one station from the training and then using it to evaluate the performance (LOO mode), we simulate the situation that is faced once the network is applied to regions that do not host climate stations and hence cannot be trained for. The correlations for the individual climate stations remain similar or drop only slightly for most stations when compared with the neural network trained with samples from all stations. Therefore, we conclude that the performance of the network does not depend greatly on the stations used in the training, which means the network can be generalized and applied regionwide across the Atacama Desert.

The derived 3-yr climatologies based on the MODIS CTH and the neural network reveal very similar patterns for the austral winter [July–September (JAS)] with slightly higher fog frequencies derived for the neural network. Fog is mainly present at coastal regions and penetrates farther inland through fog corridors, which is consistent with reports from literature. Both methods reveal fog hot spots within the central depression, which might be an indication of radiation fog that forms at night when the near surface layer cools. The required moisture could be advected from the Pacific with the westerly winds that

develop typically during the day and reverse later at night (Schween et al. 2020).

The climatology reveals a more puzzling picture for the summer season [January–March (JFM)]. For the neural network, a north–south gradient is revealed inland with higher fog frequencies in the north overlaid by a weakly pronounced west–east gradient with increasing fog frequencies toward the Andes. This is consistent with the seasonality for the easternmost stations, which show highest fog frequencies for the summer season unlike the stations closer to the coast. Given, that the MODIS CTH-based summer climatology reveals the opposite west–east gradient with higher frequencies within the coastal desert, the neural network appears more plausible for this season. Moreover, both methods reveal enhanced fog frequencies for some regions within the central depression. However, while this is hardly pronounced for the neural network, the MODIS CTH approach results in fog frequencies even exceeding 50% for some of these regions. Such high frequencies are inconsistent with very low frequencies of low clouds or even clear-sky conditions derived from GOES observations for January 2002 (Cereceda et al. 2008). Moreover, for the two stations lying within this region, the observed absolute bias is about 5% less for the neural network further indicating its superiority over the MODIS CTH approach.

An interesting issue could be identified for a station located close to the Salar de Llamara (station 14). Unusual infrared temperatures measurements, reported by this station, might indicate a distinct surface emissivity anomaly. If such anomalies are a common feature among regional salt flats, the radiative signature manifested in the MODIS brightness temperatures may differ for these regions. Within the Atacama Desert, multiple salt flat regions have been identified (C. Albers 2020, personal communication; marked in Fig. 13). Therefore, it would be beneficial to have more ground-based measurements for model training and validation in particular for the salt flat regions.

As we have generated the first satellite-based regionwide climatology for the Atacama, there are only reanalysis data available for comparison. Reanalyses provide atmospheric quantities with high spatial and temporal coverage. Here, we include the low cloud cover derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation reanalysis ERA5 (Hersbach et al. 2020) to illustrate the capabilities of contemporary reanalyses. With a horizontal resolution of 31 km, which is comparably high for a reanalysis, it does not provide a realistic representation of the orography in particular of the coastal cliff and cordillera. Therefore, the advection of the stratocumulus deck is not represented correctly. Small corridors that are visible for the other fog-detection approaches are not resolved (Figs. 13c,f). This demonstrates that observations with much higher spatial resolution, such as the satellite observations that are utilized in this study, are required in order to study regionwide fog frequencies.

Aside from the salt flats that pose uncertain terrain due to the lack of in situ reference data, the neural-network fog-detection approach reveals suitable skill to represent spatial and temporal variability of fog frequency on a subseasonal and to some degree on a synoptic scale for the Atacama

Desert. In future studies, it can be applied to derive a long-term climatology including the entire MODIS data record, which dates back to the year 2000 (*Terra*) and 2002 (*Aqua*). This would enable to derive seasonal cycles, study interannual variability and the potential relationship to large-scale climate variations such as El Niño–Southern Oscillation (ENSO), and investigate local trends of fog frequency. Particular care for additional validation should be taken in applications for the central depression. Even though the superiority of the neural network relative to the MODIS CTH approach has been elucidated, higher uncertainty remains for this region including local salt flats. Furthermore, applying the method presented here to *GOES-16* measurements, which are available at temporal resolution of 15 min, would enable to study the whole diurnal cycle and thus be complementary to the MODIS-based study.

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Data availability statement. Measurement data from the climate stations are available at the Collaborative Research Center 1211 Database (<https://www.crc1211db.uni-koeln.de/wd/index.php>). MODIS Geolocation Fields Product, level-1B Calibrated Radiances Product, and level-2 Cloud Product were downloaded from the NASA Level-1 and Atmosphere Archive and Distribution System Distributed Active Archive Center (LAADS DAAC; <https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/>). ERA5 data were downloaded from the Copernicus Climate Data Store via web API.

APPENDIX

Definitions of Statistical Measures

TPR, POD, FPR, ACC, FAR, CSI, BS, and HSS are defined as follows:

$$\text{TPR} = \text{POD} = \frac{a}{a + c}, \quad (\text{A1})$$

$$\text{FPR} = \frac{b}{b + d}, \quad (\text{A2})$$

$$\text{ACC} = \frac{a + d}{a + b + c + d}, \quad (\text{A3})$$

$$\text{FAR} = \frac{b}{a + b}, \quad (\text{A4})$$

$$\text{CSI} = \frac{a}{a + b + c}, \quad (\text{A5})$$

$$\text{BS} = \frac{a + b}{a + c}, \quad \text{and} \quad (\text{A6})$$

$$\text{HSS} = \frac{2(ad - bc)}{(a + c)(c + d) + (a + b)(b + d)}. \quad (\text{A7})$$

Here, a is the number of true positives (fog hits), b is the number of false positives (false alarms), c is the number of false negatives (missed fog), and d is the number of correct negatives (correct dry).

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