Development of Day Fog Detection Algorithm Based on the Optical and Textural Characteristics Using Himawari-8 Data

Ji-Hye Han1) · Myoung-Seok Suh2)† · So-Hyeong Kim3)

Abstract: In this study, a hybrid-type of day fog detection algorithm (DFDA) was developed based on the optical and textural characteristics of fog top, using the Himawari-8/Advanced Himawari Imager data. Supplementary data, such as temperatures of numerical weather prediction model and sea surface temperatures of operational sea surface temperature and sea ice analysis, were used for fog detection. And 10 minutes data from visibility meter from the Korea Meteorological Administration were used for a quantitative verification of the fog detection results. Normalized albedo of fog top was utilized to distinguish between fog and other objects such as clouds, land, and oceans. The normalized local standard deviation of the fog surface and temperature difference between fog top and air temperature were also assessed to separate the fog from low cloud. Initial threshold values (ITVs) for the fog detection elements were selected using hat-shaped threshold values through frequency distribution analysis of fog cases. And the ITVs were optimized through the iteration method in terms of maximization of POD and minimization of FAR. The visual inspection and a quantitative verification using a visibility meter showed that the DFDA successfully detected a wide range of fog. The quantitative verification in both training and verification cases, the average POD (FAR) was 0.75 (0.41) and 0.74 (0.46), respectively. However, sophistication of the threshold values of the detection elements, as well as utilization of other channel data are necessary as the fog detection levels vary for different fog cases (POD: 0.65–0.87, FAR: 0.30–0.53).

Key Words: Fog, Fog detection algorithm, Himawari-8/AHI, visibility

1. Introduction

A phenomenon where very small water droplets or ice pellets suspend in the atmosphere, rendering the horizontal visibility lower than 1 km (KMA, 2017), is known as a fog. Microphysically, it is defined as the occurrence of 0.05–0.2 g of water vapor per unit kg of the atmosphere (Lee and Ahn, 2013) while
geographically, it is defined as a low cloud over the land surface, at the slope of the surrounding topography, or within a stabilized boundary layer covering a valley or a basin (Bendix, 2002). Such fog can be divided into three types: a cooling fog due to cooling of the atmosphere, an evaporation fog due to supply of water vapor, and a mixed fog due to a blending of two air masses of different temperatures. There are different kinds of cooling fog: a ground fog that occurs due to radiational cooling, an advection fog that occurs due to advection of cold or a warm air parcel, and an upslope fog that occurs due to uplift-cooling of air parcels along the terrain (Jhun et al., 1998; Lee and Ahn, 2013; Lutgens and Tarbuck, 2016).

Unlike clouds, fogs occur near the Earth’s surface, aggravating visual range, significantly impacting public transportation, airlines, and shipping (Jhun et al., 1998; Bendix, 2002; Song and Yum, 2013; Yi et al., 2015; Shim and Lee, 2017). Moreover, fogs often cause problems by accumulating pollutants in the boundary layer when they occur within a stable atmosphere, influencing the radiation balance as well (Bendix, 2002; Yi et al., 2015).

Early studies on fog primarily used ground observation data to statistically analyze characteristics such as spatial distribution, occurrence rate and dissipation time (Jhun et al., 1998; Heo and Ha, 2004; Lee and Ahn, 2013; Song and Yum, 2013; Shim and Lee, 2017; Lee and Suh, 2018). Within the Korean Peninsula, the occurrence frequency of fog is at its highest during the summer and decreases in the fall, followed by spring, and winter (Lee and Ahn, 2013). In all seasons, the occurrence frequency is the highest around dawn (03:00-06:00 KST) and usually dissipates by 09:00-12:00 KST (Jhun et al., 1998; Heo and Ha, 2004; Lee and Ahn, 2013; Lee and Suh, 2018). Jeon et al. (1998) analyzed the relationship between fog and air pollutant concentration to demonstrate that fog occurrence largely varies regionally and is more sensitive to atmospheric conditions than pollutant concentrations. Furthermore, as a result of analyzing the relationship between fog occurrence and synoptic systems over the Korean Peninsula, Heo and Ha (2004) concluded that fog occurrence is high when fronts are passing and under low atmospheric pressure conditions, and additionally that the fog duration was found to be affected more by regional conditions than the synoptic environment. Also, it has been discovered that fog occurrences are influenced by atmospheric elements such as wind, humidity, and precipitation (Jhun et al., 1998; Lee and Ahn, 2013; Song and Yum, 2013).

Recently there has been a lot of researches on fog characteristic analysis and its detection using numerical weather prediction (NWP) models or satellite data, to overcome the limitations faced by using spatially discontinuous ground observation data (Gultepe et al., 2006; Gultepe and Milbrandt, 2007; Gultepe et al., 2007; Muller et al., 2007; Van der Velde et al., 2010; Shi et al., 2012). There are various studies in fog researches that use NWP models, such as those that investigate fog characteristics (Van der Velde et al., 2010) using the Weather Research and Forecasting (WRF) model or a High-Resolution Limited-Area Model (HIRLAM), along with those that investigate fog properties (Gultepe et al., 2006; Gultepe and Milbrandt, 2007) such as liquid water content (LWC), droplet number concentration, and others that detect fog (Muller et al., 2007; Shi et al., 2012) using a combination of 1D and 3D models. However, there is a great limitation to fog detection or prediction using NWP model data due to constraints on the predictability of current NWP models, especially regarding the simulation accuracy of precipitation and clouds (Gultepe and Milbrandt, 2007; Gultepe et al., 2007; Van der Velde et al., 2010; Song and Yum, 2013). Moreover, the greatest obstacle to fog detection/prediction research, which must properly consider local and regional characteristics of their environments, is the limited resolution of the NWP models to a few tens of kilometers (Song and Yum, 2013).
Fog detection research has been actively conducted using an increasing amount of meteorological satellite data. Reflectivity of visible channels is primarily used for day fog detection, as the reflectivity of fog is lower than or similar to that of clouds but higher than that of land or ocean (Yoo et al., 2005; Walther and Heidinger, 2012; Wen et al., 2014; Lee, 2016). However, it is difficult to distinguish between low clouds and fog, because although the reflectivity of fog is lower than that of thick upper-middle level clouds, it is similar to those of low clouds. Therefore, methods using the textural characteristics of fog are also being utilized for fog detection. For example, taking advantage of the fact that the fog top and the ground surface have similar temperatures (as fogs do not have large thicknesses), and using the low variability of textural characteristics of the fog top compared to clouds (Park and Kim, 2012; Lee and Ahn, 2013; Shin et al., 2013; Wen et al., 2014; Yi et al., 2015; Jeon et al., 2016; Lee, 2016).

Although many fog detection methods have been developed using polar orbiting and geostationary satellite data, fog detection still remains a difficult task. The polar orbiting satellite data can be used to detect fogs on a regional scale because they have many high-resolution channels, but it can’t provide information about the fog in real-time since the satellites only pass over the same region twice a day. Alternatively, geostationary orbit satellites have an advantage wherein they can continuously provide information about fogs, although their fog detection capability is limited by their low resolution and fewer channels. However, since Japan’s recent launch of the Himawari-8 satellite, it has become possible to utilize high resolution data in a spatiotemporal sense compared to data from previous geostationary satellites. The Advanced Himawari Imager (AHI) loaded on the Himawari-8 not only conducts global observations every 10 min, but also possesses a Band 3 visible channel, which has a spatial resolution of 500 m, which is 4 times higher the resolution of the Communication, Ocean, and Meteorological Satellite/Meteorological Imager (COMS/MI) (Bessho et al., 2016; Choi and Ho, 2015). The Himawari-8 has the most number of channels (Wen et al., 2014) amongst all geostationary satellites, and generally uses a narrow bandwidth spectrum for each channel. Use of the advanced spatiotemporal data provided by the Himawari-8/AHI is expected to increase the level of fog detection compared to previous geostationary satellite data, and fog detection is anticipated to possible given the increased spatial resolution.

Therefore, in this study, a day fog detection algorithm is developed using AHI data from the Himawari-8 satellite, which possesses channels similar to those of the Advanced Meteorological Imager (AMI) of the GEO-KOMPSAT-2A (GK-2A) satellite, expected to launch from South Korea in 2018 (Kim and Jang, 2018). Section 2 describes and demonstrates the data and detection methods in detail and Section 3 highlights the results and validates the fog detection results using the method developed. Discussion and summary are presented in Section 4.

2. Data and Method

1) Data

In this study, the AHI data from the Himawari-8 satellite for nine fog cases over the Korean peninsula were used for fog detection. Additionally, 2 m air temperature (Ta) data from the Local Data Assimilation and Prediction System (LDAPS), provided by the Korea Meteorological Administration (KMA), and sea surface temperature (SST) data from the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA), provided by the British Met Office, were used as supplementary data, along with data from visibility meter provided by the KMA which was used to verify the fog detection results (KMA, 2016a; KMA, 2016b; NASA, 2016).
The Himawari-8 is a currently operating geostationary orbit satellite launched in October 2014 with the highest resolution imager (AHI) (Bessho et al., 2016). The global observation cycle of Himawari-8/AHI is 10 minutes and it employs 16 channels with 12 infrared channels having a 2 km resolution, 1 visible channel with a 500 m resolution, and the remaining visible channels having a 1 km resolution (Table 1) (Bessho et al., 2016). In this study, data of the Band 3 (0.64 μm) visible channel and the Band 14 (11.2 μm) infrared channel of the Himawari-8 satellite provided by the National Meteorological Satellite Center (NMSC/KMA) were used for day fog detection.

In addition, the 2 m Ta from the LDAPS and SST data from the OSTIA were used to distinguish between low clouds and fog, which is the greatest obstacle in the fog detection process (Shin et al., 2013). The spatial resolution and temporal frequency of the LDAPS are 1.5 km and 1 h, respectively (NASA, 2016). The OSTIA SST data is generated by combining field observation data and numerous satellite data to improve the global scale NWP, and is produced daily for a global ocean at a 1/20° (approximately 6 km) resolution (Stark et al., 2007; Shin et al., 2013; NASA, 2016).

Visibility meter data provided by the KMA were used to quantitatively validate the fog detection algorithm developed in this study (Lee, 2016; Kim et al., 2018). The observation frequency of the visibility meter is 1 min, but is provided for 10 min intervals from approximately 235 observatories in South Korea (Fig. 1). As the quantitative verification of fog detection results using visibility meters is limited to the land area of South Korea, we are plan to use other satellite data such as Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) to verify sea fog.

In order to analyze the optical and textural characteristics and set threshold values, cases of strong fog were chosen using visible channel of the Himawari-8 and the visibility meter. Mainly land fog cases were selected so their existence can be verified by the visibility meters. After selecting six fog cases, three (10/20/2015, 10/21/2015, 11/3/2015) were used as training cases to set the threshold values and the other three were (11/4/2015, 12/1/2015, 12/22/2015) used as verification cases to assess the fog detection level. In order to assess the detection level for the non-fog cases, the three non-fog cases with high clouds, low clouds,

### Table 1. Specifications of Himawari-8/AHI

<table>
<thead>
<tr>
<th>Band number</th>
<th>Center wavelength (μm)</th>
<th>Spatial resolution (km)</th>
<th>Usage (O)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (VIS) blue</td>
<td>0.46</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2 (VIS) green</td>
<td>0.51</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3 (VIS) red</td>
<td>0.64</td>
<td>0.5</td>
<td>O</td>
</tr>
<tr>
<td>4 (VIS)</td>
<td>0.86</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5 (NIR)</td>
<td>1.6</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>6 (NIR)</td>
<td>2.3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>7 (IR)</td>
<td>3.9</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>8 (WV)</td>
<td>6.2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>9 (WV)</td>
<td>7.0</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>10 (WV)</td>
<td>7.3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>11 (IR)</td>
<td>8.6</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>12 (IR)</td>
<td>9.6</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>13 (IR)</td>
<td>10.4</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>14 (IR)</td>
<td>11.2</td>
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<td>O</td>
</tr>
<tr>
<td>15 (IR)</td>
<td>12.3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>16 (IR)</td>
<td>13.3</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

The meteorological observation stations measuring visibility over the Korean peninsula.
and cloudless weather were also selected (Fig. 2) and have been assessed. All analysis was done around 09:00-11:00 KST, considering the dissipation time of fog, such that all pixels in detection domain fall into the daytime.

2) Methodology

In this study, a fog detection algorithm that uses the optical and textual characteristics of day fog has been developed. The optical and textual characteristics of fog used for its detection are: (1) greater reflectivity than that of a land/ocean surface and similar to that of clouds on visible channels (Yoo et al., 2005; Walther and Heidinger, 2012; Wen et al., 2014; Lee, 2016; Suh et al., 2017), (2) temperature of fog top is similar to that of land/ocean surface, since fog is not as elevated as middle or high clouds (Park and Kim, 2012; Lee and Ahn, 2013; Shin et al., 2013; Yi et al., 2015; Kim et al.,

Fig. 2. Himawari-8 visible images for the selected cases. Panels (a), (b), (c), (d), (e) and (f) are fog cases at 00:00UTC (09:00 KST) on October 20, October 21, November 03, November 04, December 01, and December 22, 2015. Panel (g) is a cirrus case at 00:00UTC on March 10, 2016. Panels (h) and (i) are clear sky cases at 00:10UTC on May 17, 2016, and low cloud case at 00:00UTC on July 17, 2016, respectively.
and (3) low spatial variability of the fog top compared to clouds, since fog generally occurs when the atmosphere is stable (usually when inversion layers occur) (Park and Kim, 2012; Wen et al., 2014; Jeon et al., 2016; Lee, 2016; Suh et al., 2017). Assessment elements that correspond to each characteristic are the normalized albedo (NAlbedo) which is the normalized reflectivity using the optical characteristics of fog, difference between fog top temperature and air temperature (ΔFTA) or difference between fog top temperature and SST (ΔFTs) that show temperature differences in the fog top and land/ocean surface, and the normalized local standard deviation (NLSD) using the spatial variability of the fog surface.

In the case of geostationary orbit satellites that continuously observe identical regions for 24 h, the effects of the solar zenith angle (SZA) must be adjusted as the solar radiance varies for different observation times. Therefore, this study uses a normalized albedo as shown in Eq. (1) (Behrangi et al., 2009).

\[
\text{NAlbedo} = \frac{\text{Albedo}}{\cos(SZA)}
\]  

(1)

ΔFTA and ΔFTs, used as supplementary detection elements to distinguish the low clouds, were calculated using Eqs. (2) and (3), respectively.

\[
\Delta\text{FTA} = T_a - \text{BT(Brightness Temperature) of 11 μm}
\]  

(2)

\[
\Delta\text{FTs} = \text{SST} - 3.79 \text{K} - \text{BT(Brightness Temperature) of 11 μm}
\]  

(3)

For this, satellite data (brightness temperature of 11 μm) and colocation of Ta and SST are needed as the resolution and frequency of satellite and supplementary data differ. Spatially, grid values that are closest to the satellite pixels, at a reference of 11 μm, are used for collocation. Temporally, the LDAPS data at 1 h intervals was used as a reference at corresponding times, and OSTIA data, that is produced once a day, was used at the reference time 00:00 UTC. Because of this, deviations occur between the brightness temperature of 11 μm and the SST data even in cloudless pixels (Shin et al., 2013). Therefore, SST was adjusted appropriately to match the brightness temperature of 11 μm, using the distribution of SST and brightness temperature at 11 μm in cloud free pixels, after using the Himawari-8 cloud mask data to distinguish cloudless pixels (Fig. 3). As a result of analyzing the distribution of SST and brightness temperature of 11 μm on 10/20/2015, as seen in Fig. 3, the SST was found to be approximately 3.79 K higher than the brightness temperature of 11 μm. Also, since there are large differences between the two temperatures, depending on regions, it must be considered when deciding the threshold values.

NLSD (or NLSD_VIS), used as the second supplementary detection element, is the value of the LSD (Local Standard Deviation) of NAlbedo divided by the average. The LSD represents the standard deviation of 3 × 3 pixels, and LSD divided by the average of 3 × 3 pixels gives the NLSD, as shown in Eq. (4) (Lee, 2016).

\[
\text{NLSD} = \frac{\text{LSD (3 × 3 Pixels)}}{\text{Mean (3 × 3 Pixels)}}
\]  

(4)

Fig. 4 is a flow chart of the fog detection algorithm, largely divided into offline and online processes, each having 2 and 6 steps respectively. In the offline process,
the initial threshold values were selected based on the optical and textual characteristics of the fog using the training cases, and these threshold values were optimized using statistical methods. Initial threshold values were set through the frequency analysis of the test elements for fog, clouds, land, and oceans, which were visually selected from the satellite image. The characteristics of threshold values are explained in detail in Section 3.2, and ranged threshold values were set instead of a single value, considering the variability of fog properties. The initial threshold range values were optimized by using a point at which the Threat Score (TS) was the greatest among the various statistical verification indexes (Behrangi et al., 2009).

During the online process, the fog detection algorithm was designed for a real-time implementation based on the threshold range values obtained during the offline process. First, the AHI data and supplementary data (LDAPS Ta, OSTIA SST, Land/Sea Mask) needed for the fog detection were read, and fog detection elements such as the NAlbedo, NLSD_VIS, and ΔFTa were calculated. Following this, the SZA values were used to determine and divide the data into day and night, and fog is detected using the preprocessed assessment elements. A detailed process for the fog detection is shown in Fig. 5.

When the NAlbedo is applied to the satellite pixels, it can distinguish the pixels into “probably fog” pixels and “probably clear” pixels. “Probably fog” pixels may include clouds and land/ocean which could cause a ‘false alarm’. Also, “probably clear” pixels may include fog, causing ‘missing’. Assessment elements such as NLSD_VIS and ΔFTa were used to minimize false alarms. Here, to collocate 500 m resolution, ΔFTa/ΔFTs

![Flow chart for the fog detection of daytime using Himawari/AHI and auxiliary data.](image-url)
with other detection element values corresponding to 2 km resolution were directly copied to 500 m resolution. The undetected fog was re-detected in the post-processing step conducted after the initial fog detection. Here, the results of the fog detection are presented as a probability (0-100%) representing the likelihood of fog, taking into consideration the uncertainty of fog detection (Suh et al., 2017; Kim et al., 2018). Moreover, in the case of land fog, the post-processing method suggested by Lee (2016) was employed, since such fog often occurs locally and that its edges are hard to detect, assuming that fog is spatially continuous. In this method, a weight is assigned to the number of pixels having a probability of fog that is greater than 50% that are near a 3 × 3 pixels grid centered about pixels having a less than 50% probability of fog, and adding them to the result of the fog detection process (Fig. 6).

After the post-processing, the visibility meter (land observation data) was used for verification by quantitatively assessing the level of fog detection (Lee, 2016). Here, the visibility meter is assumed to be nearly error-free, as the readings are more objective and consistent than observations made with the naked eye, although they are not perfect (NOAA, 2017). Moreover, while the spatial resolution of the satellite...
data is 500 m, spatial representation of the visibility meter differs depending on the environment of the observation points. Therefore, in order to match the spatial resolutions of the two datasets, satellite pixels that are closest to the visibility meter were searched and verified based on the data from the visibility meter. Since this study presents the existence of fogs as a probability, pixels having over a 50% probability of fog are defined and verified as fog pixels.

Quantitative assessment of fog detection based on the contingency in Table 2, produced statistical verification indices as follows (Wilks, 2011).

\[
POD = \frac{A}{A + C} \quad (5) \\
FAR = \frac{B}{A + B} \quad (6) \\
KSS = POD - FAR \quad (7) \\
TS = \frac{A}{A + B + C} \quad (8) \\
Bias = \frac{(A + B)}{(A + C)} \quad (9)
\]

The probability of detection (POD), also called the ‘hit rate’, represents a higher detection level as it approaches 1. The false alarm ratio (FAR) represents the ratio detected as fog, which is not actually fog; the smaller the number, the lower the false detection. The Hanssen-Kuiper skill score (KSS) is a value generated when the FAR is subtracted from the POD, and is equal to 1 when the fog detection level is error-free. The TS, also called the critical success index (CSI), assesses accuracy by also considering ‘false alarms’ while the POD only considers cases of the ‘missing’. Therefore, it is a more accurate assessment tool than the POD and signifies a higher detection level as it approaches 1. Moreover, bias is a measurement that identifies over-detection (bias > 1) or under-detection (bias < 1).

### 3. Results

#### 1) Optical and textural properties

In order to analyze the optical properties of fog, the 10/20/2015 case was selected, during which a strong fog had occurred over the west coast and the mid-western hinterlands of the Korean Peninsula. The spatial distribution and frequency distribution of fog assessment elements are presented in Figs. 7 and 8. Clouds, land, ocean, sea fog, and land fog were selected through visual analysis of the visible image as shown in Fig. 8(b). In Fig. 7(b), the NAlbedo values are higher in clouds and fog than over ocean and land. Also, in the frequency distribution, land fog and sea fog are distinctly distinguished with the ocean and land when the overlap between land fog and land is excluded (Fig. 8(a)). The large range of NAlbedo shows that land can be included in the domain of land fog at the boundary because fog occurs locally, especially on land. Moreover, the NAlbedo characteristics differ between land fog and sea fog because the reflectivity at 0.66 μm is affected by the optical properties of fog such as size, number of droplets, density, and thickness (Gultepe and Milbrandt, 2007). It is also suggested that it would be difficult to distinguish between fog and cloud solely based on this value because large parts of the NAlbedo for fog and cloud overlap.

Spatial distribution of the fog that occurred in the west midlands of South Korea and sea fog across the west coast has been confirmed by NLSD_VIS as well (Fig. 7(c)). Also, the NSLD_VIS value is low, under 0.02, near the central region of the fog and in the oceans, but it is as high as 0.1 at the boundary of the fog and in the clouds. Since both sea and land fogs,
unlike other objects, show the highest frequencies (near 0.02) as seen in the frequency distribution of Fig. 8(c), it is suggested that the NLSD_VIS can be used for fog detection. However, in the cloud domain, there is a limit to distinguishing between low clouds and fog using this element solely, since the frequency distribution of the NLSD_VIS in the cloud domain is shown to be similar to that of fog.

The ΔFTA, which represents the temperature difference in land fog, is usually distributed at -2 – 3 K, but the ΔFTs which represents a temperature difference in sea fog is concentrated around 7 – 9 K. Moreover, the distributions of the ΔFTA and ΔFTs values are seen to differ greatly (Fig. 7(d)). Those which are found in clouds across northern China, and those between the Jeju Island and southern China, show large values over 10 K. The ΔFTA is usually concentrated around -5 – 0 K over land and the ΔFTs is usually concentrated around -1 – 1 K over the ocean. From their spatial and frequency distributions, the temperature differences between land surface and fog top can be used as supplementary data to distinguish between land surface, clouds, and fog. However, since the characteristics of surface temperature data used for ΔFTA and ΔFTs differ, not only there are discontinuities along the coast, but there are also large differences between land fog and sea fog (Fig. 7(d)). These are mainly caused by the accuracies of the Ta and SST that are used in the temperature difference calculation process.

Fig. 7. Spatial distribution of optical and textural properties for the selected fog case at 00:00 UTC (09:00 LST) on October 20, 2015. (a) VIS image of Himawari-8, (b) NAlbedo, (c) NLSD_VIS, and (d) ΔFTA or ΔFTs.
2) Determination of initial and optimized threshold values

Threshold values were set within respective ranges instead of providing a single threshold value, since the frequency distribution of each assessment element was shown to have a hat shape as shown in Figs. 8 and 9. Initially, the fog probability is set at 100% by choosing a section that shows a high frequency distribution of fog which can be distinguished from other targets. Also, for a case in which fog and other targets overlap in the frequency distribution, the probability of fog is set between 0-100% so that threshold value could be set.
in a form similar to the frequency distribution of the fog. In Fig. 9, a confident range of fog is seen from the Left Threshold (LT) to the Right Threshold (RT), and a possible range for fog to occur has a probability between 0-100% with slopes from LT to the Left Limit (LL) and RT to the Right Limit (RL). Using such a method, the three cases where a typical strong fog occurred (10/22/2015, 10/21/2015, and 11/03/2015) were used to set the initial threshold values presented in Table 3.

<table>
<thead>
<tr>
<th>Test elements</th>
<th>Initial thresholds</th>
<th>Optimized thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAlbedo (%)</td>
<td>15, 25, 30, 60</td>
<td>18, 28, 50, 60</td>
</tr>
<tr>
<td>NLSD_VIS</td>
<td>0.00, 0.00, 0.02, 0.06</td>
<td>0.00, 0.00, 0.01, 0.28</td>
</tr>
<tr>
<td>ΔFTa (K)</td>
<td>-5.0, 0.0, 2.0, 5.0</td>
<td>-4.8, -2.8, 2.8, 4.8</td>
</tr>
</tbody>
</table>

Table 3. Initial and optimized threshold values of the test elements used for fog detection

Fig. 10. Optimization of the threshold values based on the maximum TS value using iteration methods. Points on the lines are the best value of each statistical element. (a), (b), (c) and (d) are results of NAlbedo test, ΔFTa test with NAlbedo test, NLSD_VIS test with NAlbedo and combined test of ΔFTa and NLSD_VIS with NAlbedo test, respectively.
Initial threshold values were set subjectively, therefore, each threshold value should be optimized for the accurate and stable detection of fog for the various fog cases. All the threshold values were optimized through the iteration method by minute changes in the threshold values, final threshold values were selected when the TS is maximum (Table 3 and Fig. 10). In this optimization process, the threshold values of NAlbedo were primarily optimized because it is a key element for the day fog detection (Fig. 5). Fig. 10 shows the statistical results of fog detection for the combined applications of evaluation elements through the iteration method for the training cases. Fig. 10(b) and 10(c) are results of the threshold optimizing experiment using ΔFTa and NLSD_VIS with respect to the ‘probably fog’ pixels among the NAlbedo assessment results. Fig. 10(d) is the result of assigning the “or” condition to ΔFTa and NLSD_VIS when the NLSD_VIS threshold value experiments were added to the selected ΔFTa threshold values. In this study, the pixels with over 50% fog probability in the NAlbedo test are defined as probably fog pixels. As shown in Fig. 10b, inclusion of ΔFTa test clearly improved the fog detection level, increasing and decreasing of POD and FAR, respectively. However, inclusion of NLSD_VIS test (Fig. 10(c)), the fog detection level shows a no significant change in terms of POD, FAR and KSS. Such results suggest that NLSD_VIS can be used as a supplementary element for sea fog that occurs over a wider area (Fig. 7(c)) but it has limitations for detecting local land fog (Fig. 11). Therefore, only the NAlbedo and ΔFTa were used for land fog detection in this study.

3) Fog detection results

(1) Fog cases

VIS images from the Himawari-8 satellite and visibility data are presented together in order to qualitatively assess the detection level of the fog detection algorithm (Fig. 12). The cases presented here are those that were used for threshold optimization to accurately identify the fog regions, i.e., only values that had over 50% probability of fog are indicated. When the fog detection results is visually compared to visible images and visibility meter data, it is observed that the algorithm detects most of the large-scale land fog that had occurred across the mid-western Korean Peninsula. It also accurately detects most of the fog in cases between 10/20/2015 and 11/3/2015, where the fog had occurred generally around the mid-western Korean Peninsula. Moreover, a large-scale low cloud (Fig. 12(e)) that had occurred in the Shandong Peninsula and a low cloud (Fig. 12(d)) that sporadically occurred on the southern coast were not detected as a fog. However, in the 10/21/2015 case when a large-scale fog had
occurred across the western region of the Korean Peninsula, it was observed that the fog was under-detected in the western region while being over-detected in the southeastern region. Additionally, sea fog was not appropriately detected from the northern Shandong Peninsula to the Korean Peninsula (Fig. 12(d)) and a large-scale land fog that had occurred in the western region of North Korea was under-detected (Fig. 12(c)).

Fig. 13 presents the fog detection results for the three verification cases, as in Fig. 12. Similar to the training cases, the verification cases also well detected most of the fog that occurred regionally in the Korean Peninsula. Furthermore, various types of large-scale clouds that had occurred near the Korean Peninsula, such as on the west coast and over the East Sea, were not detected as fog. However, in all three cases, errors occur particularly on the edges of the low clouds, and specifically for the 12/22/2015 case, the errors often occur in the large-scale clouds over the west coast. Also, the algorithm was unable to appropriately detect the center of strong fog that had occurred in the

Fig. 12. Sample images of fog detection results at 00:00UTC on October 20 and 21, 2015, and November 03, 2015. Upper ((a), (b), (c)), middle ((d), (e), and (f)), and lower ((d), (e), and (f)) panels indicate the VIS images of Himawari-8/AHI, fog detection results, and visibility measured by ground stations for the three training cases respectively.
midlands of South Korea on 12/22/2015, and apart from the case studies, the algorithm also under-detected fogs that had occurred in the southwestern region of South Korea. Using a qualitatively analysis, many ‘false alarms’ and ‘missing’ were observed in all three training and verification cases respectively.

Verification was conducted using visibility meter data to quantitatively assess the detection level of the fog detection algorithm. The verification results are presented by separating them from the training cases to assess the detection levels of the optimized threshold values (Table 4). For the 10/20/2015 case, although the algorithm showed high POD, KSS, and TS values, it also showed a high level of bias, which made it the case with the highest over-detection rate among the three training cases. The POD and FAR were the lowest on the 11/3/2015 among the three training cases, and the KSS and TS were the lowest on the 10/21/2015. Fog was under-detected with a bias less than 1 on 11/3/2015. Although most of the assessment elements showed high variabilities depending on the training cases, the TS representing the levels of fog detection was observed to be relatively stable at 0.46–0.53. The level of fog detection in the three verification cases was
found to be 0.74, 0.46, 0.28 for the POD, FAR, and KSS respectively, which are relatively lower values than those from the training cases. However, since the differences are not very large, they show a level of detection similar to the training cases. Yet, like in the training cases, the results of fog detection for the verification cases also show variation among cases. Therefore, it is suggested that adjustment of the

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Fig. 14. Same as Fig. 12 except for 00:00 UTC on March 10, May 17, and July 17, 2016.
threshold values and incorporation of other channels are also necessary to increase the reliability of fog detection results.

(2) Non-Fog cases

The fog detection algorithm in this study requires higher level of detection even in cases without fogs, since it aims at site operation. Fig. 14 represents cases where fog did not occur in South Korea: (a) is a case in which a high-level cloud developed over the southern region, (b) is a case where most of the Korean Peninsula is clear, and (c) is a case in which a low-middle level cloud developed across most of the Korean Peninsula. As seen in Fig. 14(d) and 14(e), these are detected as completely fog-free for the high-level cloud and clear sky cases. However, errors are seen sporadically over the central region and eastern coast of the Korean Peninsula with low-level clouds over the west coast. It is seen in Fig. 14(h) that even with a clear sky the visibility was within the 1 km. Although it is not seen in the image, it was observed from analyzing the visibility data (obtained at 10 min intervals) that the visibility rapidly changed from 1 km-10 km within 10 min. Although the large-scale low-middle level clouds across the Korean Peninsula were not detected as a fog (Fig. 14(f)), errors occurred partially over the west coast and East Sea region of the Korean Peninsula.

4. Conclusions

In this study, we developed a hybrid type of day fog detection algorithm using Himawari-8/AHI data and supplementary data. The result of the fog detection algorithm was presented as a probability of fog occurrence (0-100%). Nine cases of imagery data from Himawari-8/AHI were used to develop and validate the hybrid type of fog detection algorithm. The SST data from OSTIA and Ta data from the NWP model were also used as supplementary data in order to increase the level of fog detection. Additionally, verification of the fog detection was conducted using ground observed visibility data provided by the KMA.

In this algorithm, three sets of detection elements are used based on the optical and textural characteristics of fog surface for the detection of day fog; NAlbedo test, ΔFTa (ΔFTs) test and NLSD_VIS test. The threshold and weight values for each test element were determined empirically using the histogram analysis of frequency distribution for the test elements and optimized to a maximum TS by minutely adjusting the threshold values via an iterative technique using the three training cases. Unlike the previous studies, the threshold and weight values of test elements were set using a hat-shaped distribution based on the frequency distribution of each fog detection element, instead of a single threshold value.

In this study, the fog detection algorithm was verified using six fog cases and three fog-free cases (clear sky, higher-level clouds, and low clouds). Among the six fog cases, three cases were used for threshold optimization of each test element, and the other three cases were verification.

The visual comparison of fog detection results with ground visibility data showed that a large-scale land fog that had occurred across the mid-western region of South Korea was well-detected. However, ‘missing’ occurred in parts of sea fog that had occurred across the Shandong Peninsula to the midlands of South Korea, and in land fog that had occurred in South Korea. Additionally, ‘false alarms’ were found sporadically in clouds occurring near the Korean Peninsula. In the case of clear sky and higher-level clouds, the algorithm appropriately detected the absence of fog over the entire South Korean region, with the exception of a few ‘false alarms’. In the cases of lower-level clouds occurring at large scales across the Korean Peninsula, the algorithm properly detects no inland fog over the Korean Peninsula. However, there were a few ‘false alarms’ over the west and east coasts of the Korean Peninsula.
The quantitative verification of the fog detection level for the training and verification cases using visibility meter data showed that averaged POD of 0.75 and 0.74, averaged FAR of 0.41 and 0.46, and averaged TS of 0.49 and 0.45 respectively, which are relatively stable values. And the averaged biases showed that each training and verification cases had values of 1.27 and 1.36, with tendencies to over-detect, and in some cases, under-detect as well.

Also, there was a large difference in the level of fog detection depending on the fog cases, with POD ranging from 0.65–0.87 and the FAR ranging from 0.30–0.53. For this algorithm to be used in site operation, reducing false detections and increasing the stability of fog detection irrespective of the training and verification cases are of foremost necessity. Another reason for the high FAR may be the low accuracy of Ta and SST used as supplementary data. The infrared channel would have been affected since data with a resolution of 2 km was simply downgraded to 500 m to fit that of the visible channels (500 m). Therefore, in order to reduce the FAR, it is necessary to develop a qualified interpolation method for IR channels, increase Ta and SST accuracy, or develop calibration techniques. Moreover, it is necessary to optimize the threshold and weighted values using many more cases for the development of a more stable fog detection algorithm.

Acknowledgements

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Development of Day Fog Detection Algorithm Based on the Optical and Textural Characteristics Using Himawari-8 Data


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