DETECTION OF RAINY CLOUDS BASED ON THEIR SPECTRAL AND TEXTURAL FEATURES ON METEOSAT MULTISPECTRAL INFRARED DATA

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Abstract

The present study aims at investigating the possibility of developing precipitating cloud detection schemes using the enhanced thermal infrared spectral resolution of the Meteosat Second Generation - Spinning Enhanced Visible and Infrared Imager (MSG-SEVIRI). Two different classification methodologies were proposed that use the cloud top brightness temperature (BT) $T_{10.8}$ and brightness temperature differences (BTDs) along with textural parameters derived from the thermal infrared MSG channels to delineate rain from no rain clouds. The first is an algorithm based on the probability of rain (POR) for each pixel of the thermal infrared MSG satellite data and the second is an Artificial Neural Network (ANN) model. Both schemes were trained using as rain information spatially and temporally matched gauge data from 88 stations in Greece, for 20 rainy days covering the period from April 2008 to February 2009. Both schemes were evaluated against an independent sample of rain gauge data for four rainy days. It was found that the introduction of textural parameters tends to improve discrimination between rain and no rain clouds only for the POR scheme in the training dataset while for the validation dataset both POR and ANN models based on both spectral and textural parameters provide worst results. The ANN algorithm based only on spectral parameters shows the best performance among all the rain area delineation models for both the training and validation dataset. During the training phase, POR model based on spectral parameters exhibited the lowest performance among the rain areas delineation techniques. When evaluating against the independent dataset, the POR model produces scores significantly better than the two algorithms based on both spectral and textural parameters. All rain detection algorithms overestimate the rain occurrences detected by the rain stations network.

INTRODUCTION

Rainfall retrieval algorithms applied to single channel satellite infrared data are based on the cloud top temperatures and have limited application in the mid-latitudes, due to the difficulty of distinguishing precipitating and non-precipitating clouds. The problem of rain clouds detection affects the rainfall estimation algorithms that tend to overestimate precipitation. In order to overcome the single channel infrared-based method’s difficulty to detect non-precipitating cold thick cirrus clouds from deep convective ones, multispectral rainfall detection methods have been developed with the combination of different channels from the geostationary satellite images that provide wide spatial coverage and high temporal resolution. Thies et al. (2008a) proposed a new approach based on the probability of rain for delineation of rain area in the mid-latitudes using night-time multispectral satellite data. The same technique was applied by Thies et al. (2008b) to develop an algorithm for daytime scenes using geostationary Meteosat Second Generation data. Feidas and Giannakos (2010) developed an algorithm based on the probability of rain (POR) for each pixel using MSG multispectral satellite data for the study area of Greece. The high spectral resolution of the Spinning Enhanced Visible and Infrared Imager (SEVIRI) on board the Meteosat Second Generation (MSG) satellites, with eleven 3-km-resolution channels and one 1-km-resolution visible channel, offers the possibility of an improved detection of the rain cloud areas.
Several studies have shown that the performance of the rain detection algorithm is improved when textural cloud parameters derived from MSG satellite data are used for the discrimination of precipitating cloud areas by the spatial distribution characteristics of brightness temperature levels from MSG satellite images. The spectral properties of clouds often change temporally and spatially between adjacent cloud pixels but their textural properties are often spatially distinct and tend to be less sensitive to the effects of atmospheric attenuation or detector noise. The objective of this study is to investigate the contribution of the SEVIRI high spectral resolution to the delineation between raining and non-raining clouds over Greece in order to improve rainfall estimation from geostationary infrared data. Two kinds of techniques are used to develop rain area discrimination models. The first model is an empirical algorithm which is based on the estimation of the probability of rainfall (POR) on a pixel basis for the satellite infrared dataset and the second is a statistical approach (Artificial Neural Network, ANN) capable of developing a technique for rain cloud areas delineation that uses spectral and textural parameters from the SEVIRI dataset. Models’ training and validation are carried out by comparing spectral and textural cloud parameters with rain gauge observations.

DATA AND METHODOLOGY

Data

In this study the rain areas detection schemes were trained and validated using spatio-temporally matched 15min observation datasets of seven SEVIRI thermal infrared channels and rain gauge data for the area of Greece (Figure 1). In order to develop the two rain area delineation models SEVIRI datasets were used that include seven channels in the thermal infrared with center wavelengths at 6.2, 7.3, 8.7, 9.7, 10.8, 12.1 and 13.4 µm. They are acquired at 15 min time intervals with a spatial resolution of 3 x 3 km² at sub-satellite point, reaching 4 x 5 km² at the area of study. Rain gauge data from 88 stations of the National Observatory of Athens Hellenic (Greek) for 16 rainy days covering the period from April 2008 to February 2009 were used as rainfall information to train the models. Models are validated against four independent rainy days, provided by the National Observatory of Athens during November 2008 and January 2009, that were not used for training the rain area delineation algorithms.

![Figure 1: Geographical domain of the area of study. Locations of rain gauge network used to train models are also shown.](image)

Spectral cloud parameters

The rain delineation methodologies make use of the relationship between cloud spectral characteristics and physical parameters such as cloud water path (related to the particle size and the cloud thickness) and cloud phase to detect potentially precipitating cloud areas. The basic assumption is that clouds with a
large enough cloud water path together with ice particles in the upper parts have a high probability of producing precipitation (Thies et al. 2008a). The two rain area classification schemes were developed using the original BTDs from the SEVIRI infrared channels. The following spectral parameters were used as cloud information from the SEVIRI thermal infrared satellite data:

Brightness temperature $T_{10.8}$ is an indication of the vertical extent of the cloud because in general brightness temperature of the system depends on the cloud top height. The split window $T_{10.8} - T_{12.1}$ is a good indicator of the cloud optical thickness and is very effective in discriminating optically thick cumuliform clouds from optically thin cirrus clouds. Optically thick cumulus type cloud shows the smaller BTD due to their black-body characteristics, while optically thin cirrus cloud shows the larger BTD due to the differential absorption characteristics of ice crystals between the two channels.

The BTD $T_{8.7} - T_{10.8}$ can be utilized to gain information about the cloud phase (Thies et al. 2008a). The imaginary (absorption) component of the index of refraction, which is a direct indicator of absorption/emission strength, differs for ice and water at these two wavelengths. More specifically, the difference in water particle absorption is small between the two wavelengths, but very large for ice particles. Radiative transfer simulations show that for ice clouds, $T_{8.7} - T_{10.8}$ tends to be positive in sign, whereas for low-level water clouds, $T_{8.7} - T_{10.8}$ tends to be small negative.

Test $T_{6.2} - T_{10.8}$ is effective in distinguishing between high-level and low-level/mid-level clouds. The 6.2 $\mu$m channel is dominated by atmospheric water vapor absorption. Low-level clouds produce temperatures at the 6.2 $\mu$m channel lower than their actual cloud top temperatures due to the absorption from water vapor above them. In contrast, their cloud top temperatures at the 10.8 $\mu$m window channel are representative of actual cloud top temperature, because the atmosphere is transparent to this wavelength. For low-level clouds $T_{6.2} - T_{10.8}$ tends to be very negative while positive differences may occur for convective clouds.

The BTD $T_{6.2} - T_{7.3}$ can be used to give information about the cloud height and about the early detection of convective activity. The two water vapor channels are dominated by atmospheric water vapor absorption. Low clouds tend to give large negative temperature differences $T_{6.2} - T_{7.3}$ and without high clouds show large negative temperature differences. Positive differences may occur for very high clouds that can reach the stratosphere.

Test $T_{13.4} - T_{10.8}$ provides estimation of cloud top height and detection of cumulus cloud growth development, in MSG images. The 13.4 $\mu$m channel is the CO$_2$ absorption band. Low-level clouds produce large negative values since the temperatures at 13.4 $\mu$m are reduced significantly due to the absorption from CO$_2$ above them. The 10.8 $\mu$m channel is not affected by water vapor absorption and yields larger values than 13.4 $\mu$m channel. $T_{13.4} - T_{10.8}$ difference exhibits small negative values because growing cumulus clouds state are above most of the CO$_2$ layer and ice crystal absorption is similar for both wavelengths that detect equivalent temperatures.

The BTD $T_{8.7} - T_{12.1}$ can provide information about clouds’ optical thickness. The $T_{8.7} - T_{12.1}$ difference takes positive values at high cloud optical thickness due to the scattering processes and the dependence on particle size which are stronger in the 8.7 $\mu$m channel relative to the 12.1 $\mu$m channel. Therefore the difference exhibits high values for large cloud particle size and large optical thickness. For low cloud optical thickness the BTD $T_{8.7} - T_{12.1}$ gives negative values because water vapor absorption in the 8.7 $\mu$m channel is higher than in 12.1 $\mu$m channel and 8.7 $\mu$m channel yields brightness temperature values colder than these at 12.1 $\mu$m channel.

Test $T_{9.7} - T_{13.4}$ is an indicator of cloud top height. For high clouds over 12 km the brightness temperature at 9.7 $\mu$m showed significantly larger values than brightness temperature at 13.4 $\mu$m due to the warming by stratospheric ozone. The heating effect is responsible for the presence of positive brightness temperature difference values at high level clouds. The two channels at 9.7 $\mu$m and 13.4 $\mu$m are dominated by O$_3$ and CO$_2$ absorption accordingly. Low level clouds exhibit temperatures at the 9.7 $\mu$m channel lower than their actual cloud top temperatures due to the O$_3$ absorption from above them. Also the 13.4 $\mu$m channel yields brightness temperature values lower than the cloud top temperatures at the 10.8 $\mu$m window channel which are representative of actual cloud top temperature. Kwon (2010) using cloud top heights from
CloudSat observations, showed that for low level clouds the $T_{9.7} - T_{13.4}$ produces negative difference values because 9.7 μm channel temperatures are colder than temperatures from 13.4 μm channel.

**Textural cloud parameters**

The use of textural parameters as complementary source of data along with spectral parameters is investigated for the possibility to improve rain and no rain clouds classification models. Several recent works have shown that cloud classification algorithms are significantly improved when textural measures are taken into account. Ameur et al. (2004) used textural and spectral parameters from Meteosat satellite images in the visible and infrared to develop a cloud classification model over North Africa during the month of December 1994.

In this study two different methods were applied to calculate texture measures from MSG satellite data in the thermal infrared: 1) Brightness Temperature Level Co-occurrence Matrix (BTLCM) and 2) Brightness Temperature Level Difference Vector (BTLDV). The BTLCM method is a two-dimensional histogram of brightness temperature levels for a pair of pixels and calculates co-occurrence matrix which approximates the brightness temperature level joint probability distribution of MSG satellite images. A brightness temperature level co-occurrence matrix contains information about the location of pixels having similar brightness temperature level values. The following texture measures are computed from the co-occurrence matrix to quantify textural variation (Haralick, 1973) and capture the spatial dependence of brightness temperature level values from the MSG satellite images: 1) Homogeneity 2) Contrast 3) Dissimilarity 4) Mean 5) Standard Deviation 6) Entropy 7) Angular Second Moment 8) Correlation. The BTLDV method is also calculated from the co-occurrence matrix but is based on absolute differences between pairs of brightness temperature levels. From the histogram of brightness temperature level differences can be computed the following measures: 1) BTLDV Angular Second Moment 2) BTLDV Entropy 3) BTLDV Mean 4) BTLDV Contrast and 5) BTLDV Inverse Difference.

**DATA PREPROCESSING**

The two rain area delineation models were trained using rain gauge data obtained for 16 rainy days from April 2008 to February 2009. Rain accumulations were recorded at 10-min time intervals and down to the rain amount of 0.1 mm. A rainy day is defined as a day on which any rainfall is recorded at a more than 5 stations out of the 88 stations used in this study. The SEVIRI datasets were spatially and temporally collocated with rain gauge observations during the period of interest. Each 10-min rain gauge amount was first converted to rain rate and then the temporal match between the two datasets was carried out with the satellite data over the corresponding 15-min scan time. Then a spatial match of each station to a pixel position in the satellite images was performed by taking into account parallax error. Parallax error refers to a horizontal displacement of cloud location in the image when the satellite views the earth at an oblique angle. The parallax dislocation can be corrected by shifting the location of the ground station in the image by a distance that depends on the satellite view angle and the cloud-top height. In this study, the cloud-top height was obtained by comparing cloud-top temperatures at the 10.8 μm channel with the temperature profiles of the analyses of the European Center for Medium-Range Weather Forecasts (ECMWF).

For each rainy day and each station, we computed all the spectral and textural cloud parameters at the satellite temporal resolution (15 min). Furthermore the value of a spectral and textural cloud parameter obtained over a station is flagged as “rain” when a detectable rain (above 0.1 mm) is present in a time frame of one hour, centered at the time of the satellite observation. This time frame was chosen because it includes a large variety of typical mid-latitude precipitation processes. Finally, the range of values of each spectral and textural cloud parameter was divided into two parts based on the categorical dichotomous statement of “rain/no-rain” events detection.

From the 13 texture measures that were computed from the co-occurrence matrix a calculation and comparison of the correlation coefficient was performed among all texture measures. Texture measures that exhibit high correlations were rejected and finally four texture parameters were used in the rain area delineation algorithms: 1) Homogeneity 2) Contrast 3) Angular Second Moment and 4) BTLDV Entropy.
Models’ development methodology

Two different methods were used to develop rain area detection models. The first is an algorithm based on the probability of rain for each pixel of the satellite data and the second is an Artificial Neural Network algorithm that combines cloud textural and spectral parameters in order to delineate rain and no rain clouds.

Probability of rain technique

An empirical algorithm for the detection of rain areas was created (POR1) that uses eight spectral variables $T_{10.8}$, $T_{10.8}$, $T_{12}$, $T_{6.2}$, $T_{7.3}$, $T_{6.2}$, $T_{10.8}$, $T_{8.7}$, $T_{10.8}$, $T_{8.7}$, $T_{12.1}$, $T_{9.7}$, $T_{13.4}$ and calculates the probability of rainfall (POR) on a pixel basis. Two eight-dimensional contingency matrices are constructed based on raining and no-raining pixels. These two arrays of multivariate frequency distribution in the eight-dimensional $(T_{10.8}, T_{10.8}, T_{12}, T_{6.2}, T_{7.3}, T_{6.2}, T_{10.8}, T_{8.7}, T_{10.8})$ space are then combined to yield a probability of rain distribution.

By using multispectral matrices of all the twelve spectral and textural cloud parameters, an empirical algorithm for the detection of rain areas was performed based on the probability of rainfall (POR2) on a pixel basis (Thies et al. 2008a, 2008b). This parameter is calculated as a function of the value combinations of the eight spectral variables $T_{10.8}$, $T_{10.8}$, $T_{12}$, $T_{6.2}$, $T_{7.3}$, $T_{6.2}$, $T_{10.8}$, $T_{8.7}$, $T_{10.8}$, $T_{8.7}$, $T_{12.1}$, $T_{9.7}$, $T_{13.4}$ and $T_{13.4}$, $T_{10.8}$ and four texture measures Homogeneity, Contrast, Angular Second Moment, and BTLDV Entropy that represent the percentage value of pixels with a certain combination of the twelve spectral cloud parameters that have been identified as raining by the gauge data. Two twelve-dimensional contingency matrices were created based on raining and no-raining pixels. These two arrays of multivariate frequency distribution in the twelve-dimensional $(T_{10.8}, T_{10.8}, T_{12}, T_{6.2}, T_{7.3}, T_{6.2}, T_{10.8}, T_{8.7}, T_{10.8}, T_{8.7}, T_{12.1}, T_{9.7}, T_{13.4}, T_{13.4})$ space are then combined to yield a probability of rain distribution as a function of the twelve cloud parameters. More precisely, the probability of rainfall for the two PoR models is calculated as a function of the different variables $x_1$, $x_2$, ..., $x_i$ using the following equation:

$$\text{POR}(x_1, x_2, ..., x_i) = \frac{N_{\text{rain}}(x_1, x_2, ..., x_i)}{N_{\text{rain}}(x_1, x_2, ..., x_i) + N_{\text{no-rain}}(x_1, x_2, ..., x_i)}$$

where $i = 8$ for PoR1 and $i = 12$ for PoR2 model, $x_1$, $x_2$, ..., $x_i$ denote the spectral and textural variables and $N_{\text{rain}}$ and $N_{\text{no-rain}}$ are the number of raining and non-raining pixels, respectively, in each distinct interval in the $(x_1, x_2, ..., x_i)$ space. Then an i-dimensional contingency matrix is constructed based on the PoR values. PoR of each pixel in the satellite data can be looked up in the i-dimensional matrix of PoR($x_1, x_2, ..., x_i$) for the i corresponding variables so that each pixel is assigned a “rain” or “no-rain” flag if PoR is exceeding a lower threshold.

Neural Network Algorithm

A rain detection scheme based on Artificial Neural Networks (ANN) was developed that makes use of the high spectral resolution of the SEVIRI satellite data. The nonparametric ANN approach approximates the best nonlinear function between spectral and textural features derived from MSG satellite data and rain information from rain gauge data to classify rain and no rain clouds. In this study a multilayer perceptron (MLP) is selected from other statistical methods for the following reasons: 1) The MLP algorithm does not require any a priori knowledge of the statistical distribution of the data 2) The MLP can model non linear functions and can be trained to perform accurate generalization when inserting new unknown data 3) Capability of the algorithm to perform classification with data that have high spatial variability. Firstly an ANN MLP scheme (MLP1) was created using only the eight spectral cloud parameters that were calculated from MSG thermal infrared satellite images. The MLP1 optimal classification scheme consists of 8 input neurons (number of spectral cloud parameters derived from SEVIRI data), 10 neurons in the hidden layer and 2 output neurons in the output layer that represent the two classes for rain and no rain cloud pixels. Furthermore an ANN MLP algorithm (MLP2) (Figure 2) was created with three layers (input, hidden, and output) that consist of 12 input neurons (number of spectral and textural cloud parameters...
derived from MSG satellite images), 15 neurons in the hidden layer and 2 output neurons in the output layer that represent the two classes for rain and no rain cloud pixels.

Figure 2: Structure of Multilayer Perceptron rain area delineation algorithm (MLP2) that combines twelve spectral and textural cloud parameters from SEVIRI satellite images

RESULTS

Models' training

The threshold value of the POR algorithm appropriate for the detection of rain clouds is selected from the statistical measures POD (Probability of Detection), FAR (False Alarm Ratio), POFD (Probability of False Detection), BIAS, CSI (Critical Success Index), ETS (Equitable Threat Score) and HK (Hanssen and Kuipers score) that have been applied to find thresholds that would provide optimal model performance in rain area detection as well as to validate models against an independent rain gauge dataset.

Initially the two ANN rain delineation algorithms were trained using spectral cloud parameters (MLP1) and spectral with textural parameters (MLP2) that were computed from SEVIRI dataset for 12 rainy days during the period from April 2008 to February 2009. During the training phase for each neural network algorithm, different number of neurons for the hidden layer and iterations for the adjustment of the weights were applied to find the optimal rain and no rain classification model that minimizes the network’s error. The verification scores calculated for the POR and MLP schemes during the period from April 2008 to February 2009 are displayed in Table 1.

<table>
<thead>
<tr>
<th>MODELS</th>
<th>POD</th>
<th>FAR</th>
<th>POFD</th>
<th>BIAS</th>
<th>CSI</th>
<th>ETS</th>
<th>HK</th>
</tr>
</thead>
<tbody>
<tr>
<td>POR1</td>
<td>64.2</td>
<td>50.5</td>
<td>48.1</td>
<td>1.2</td>
<td>0.388</td>
<td>0.163</td>
<td>0.2</td>
</tr>
<tr>
<td>POR2</td>
<td>67.9</td>
<td>48.3</td>
<td>42.3</td>
<td>1.5</td>
<td>0.423</td>
<td>0.197</td>
<td>0.256</td>
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<tr>
<td>MLP1</td>
<td>74.7</td>
<td>31.4</td>
<td>33.5</td>
<td>1.82</td>
<td>0.56</td>
<td>0.213</td>
<td>0.412</td>
</tr>
<tr>
<td>MLP2</td>
<td>74.3</td>
<td>31.5</td>
<td>35.7</td>
<td>1.85</td>
<td>0.528</td>
<td>0.243</td>
<td>0.386</td>
</tr>
</tbody>
</table>

Table 1: Verification scores computed from MLP1 and MLP2 algorithms during the training phase from April 2008 to February 2009

From the inspection of table 1 the MLP1 model stands out as having the best overall performance (POD = 74.7%, FAR = 31.4%, POFD = 33.5%) among the four rain area delineation models during the training phase, followed at a short distance by MLP2, while the worst scores are obtained for POR1. It seems that the addition of the textural parameters into a model improves the discrimination between rain and no rain clouds only for the MLP2 model.
Models’ validation

To evaluate the models’ performance the rain delineation models were applied on the MSG satellite images obtained during four rainy days between November 2008 and January 2009. The precipitation events chosen for the evaluation study are independent from the above mentioned precipitation events used to train the models. The results of the verification analysis are presented in Table 2.

<table>
<thead>
<tr>
<th>MODELS</th>
<th>POD</th>
<th>FAR</th>
<th>POFD</th>
<th>BIAS</th>
<th>CSI</th>
<th>ETS</th>
<th>HK</th>
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<tbody>
<tr>
<td>POR1</td>
<td>81.5</td>
<td>39.4</td>
<td>44.9</td>
<td>1.89</td>
<td>0.464</td>
<td>0.25</td>
<td>0.366</td>
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<tr>
<td>POR2</td>
<td>83.6</td>
<td>44.7</td>
<td>48.2</td>
<td>1.96</td>
<td>0.417</td>
<td>0.215</td>
<td>0.354</td>
</tr>
<tr>
<td>MLP1</td>
<td>76.5</td>
<td>29.9</td>
<td>34.8</td>
<td>1.72</td>
<td>0.583</td>
<td>0.326</td>
<td>0.417</td>
</tr>
<tr>
<td>MLP2</td>
<td>73.6</td>
<td>35.3</td>
<td>36.4</td>
<td>1.93</td>
<td>0.517</td>
<td>0.227</td>
<td>0.372</td>
</tr>
</tbody>
</table>

Table 2: Verification scores computed for the four models during the evaluation phase from April 2008 to February 2009.

The intercomparison of the four rain detection algorithms during the evaluation phase (Table 2) unveiled a pattern slightly different to that shown when using the dependent sample dataset. The MLP1 algorithm still performs best among the four algorithms but the ranking of the other three algorithms according to their relative performance is different to that of the dependent sample. The MLP2 model shows the second best performance followed by the two POR models (POR1 and POR2). The incorporation of textural parameters into MLP2 and POR2 models give worst results compared with the MLP1 and POR1 models which are based only on spectral parameters. More precisely, the best skilled MLP1 algorithm for the validation dataset correctly identifies the 76.5% (POD) of the rain occurrences whereas it misclassifies as rain cases the 29.9% (FAR) of the estimates and the 34.8% (POFD) of the observed no rain events. The MLP1 overestimates the rain occurrences detected by the rain stations network, as indicated by the bias of 1.72. The POR2 algorithm during the evaluation phase exhibits the worst scores with the exception of POD (83.6%). POR2 yields the highest FAR (44.7%) and POFD (48.2%) values and bias (1.96).

Figure 3: (a) SEVIRI brightness temperature at the 10.8 μm channel and detected rain area by (b) POR1, (c) POR2, (d) MLP1 and (e) MLP2 satellite models, for 12 December, 2008 at 09:00 UTC.

In order to gain a visual impression of the spatial distribution of the rain-expected cloud areas the rain information by gauges is compared with the four rain delineation algorithms: 1) POR1, 2) POR2, 3) MLP1 and 4) MLP2.

The classified rain area derived by the four detection schemes for a scene at 09:00 UTC, 12 December, 2008, is shown in Figure 3b to 3e. The rain-expected cloud area derived by the POR1 and MLP1 schemes, which are based on spectral parameters, does not exhibit any important difference but the
detected rain area from the two models is larger than the actual rain area defined by the rain gauge network. Both models provide a good estimate of the rain expected area over the thick cloudiness with cold cloud tops in the Aegean Sea as well as over the low-level clouds located over the mainland. POR2 and MLP2 algorithms which are based on both spectral and textural parameters provide significant smaller estimated rain cloud area than POR1 and MLP1 algorithms. The rain-expected cloud area by the POR2 algorithm is significantly smaller than that by the MLP2 algorithm, but both POR2 and MLP2 models assign rain only to the edges of main cloud band located over the Aegean due to the contribution of textural parameters. As a result these models based on both spectral and textural parameters offer the worst rain area detection compared with models based only on spectral parameters.

CONCLUSION

The potential of using the high infrared spectral resolution of MSG SEVIRI to discriminate between precipitating and non-precipitating clouds over Greece was investigated. Two different methods were developed that use spectral (POR1, MLP1) along with textural parameters (POR2, MLP2) derived from the thermal infrared MSG channels to classify rain from no rain clouds pixels. The training and validation of the rain area detection models based on spectral parameters showed that the use of MSG SEVIRI channels in the thermal infrared gives encouraging results for the detection of rainy clouds in the mid-latitudes. The additional use of textural cloud parameters in a model did not induced any improvement in the discrimination between rain and no rain clouds. The rain detection algorithms based on spectral parameters generally produce better verification scores than the algorithms based on both spectral and textural parameters and provide improved rain area delineation results. Finally, all schemes clearly overestimate the rain occurrences detected by the rain stations for both the training and validation dataset.

ACKNOWLEDGEMENTS

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