

DEVELOPMENT AND VALIDATION OF A BRDF MODEL FOR ICE MAPPING FOR THE FUTURE GOES-R ADVANCED BASELINE IMAGER (ABI) USING ARTIFICIAL NEURAL NETWORK

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Abstract— Information on ice cover extent over seas is crucial for ship navigation. Ice cover can also show interannual fluctuations and reflects climate variations. Ability of satellites to provide global observations at high temporal frequency has made them the primary tool for the ice cover monitoring. This study is a part of GOES-R Cryosphere application group effort to develop new, and improve existing, applications for the future GOES-R Advanced Baseline Imager (ABI). In this paper, a new approach was developed to minimize the effect of both observation and illumination angles on the ice mapping accuracy. A Bidirectional Reflectance Distribution Function (BRDF) was developed to simulate the reflectance of ice and water over the Caspian Sea. The ultimate objective of this research is to develop a daily ice concentration map. The estimation of the reflectance of water and ice is a step toward the achievement of this goal. The Northern region of the Caspian Sea has been selected for algorithm development and calibration. Artificial Neural Networks (ANN) have been used to simulate reflectance values for both water and ice from solar, azimuth and satellite angles. Data collected by SEVIRI instrument onboard of Meteosat Second Generation (MSG) satellite have been used as a prototype. The approach used in the algorithm development includes daily cloud-clear image compositing. The simulated reflectances were compared to observed values and have shown a satisfactory agreement. This implies that the BRDF model coupled with ANN technique can be used to simulate reflectance values.

1. INTRODUCTION

This study is a part of the future GOES-R mission. The ultimate objective of this research is to explore the potentials of the future GOES-R ABI in mapping sea ice and to develop an automated ice-mapping algorithm,

which would make maximum use of ABI's improved observing capabilities.

The future GOES-R instrument will be a 12 channel Advanced Baseline Imager (ABI). Enhanced observing capabilities of the ABI may allow for improved retrievals of atmosphere, land surface and ocean properties and in particular, improved retrievals of the ice cover. Enhancements in the ice identification and mapping are expected primarily owing to additional spectral channels centered in the near-infrared, short-wave infrared and split-window infrared bands. A higher rate of observations and better navigation may also be beneficial and may contribute to the improvement of ice monitoring with ABI. Better image registration may also allow for tracking ice movement. In order to generate these advanced products proper satellite data processing and interpretation techniques and algorithms should be developed (Hillger 2006).

Over the last decade, NOAA/NESDIS prepared and maintained daily ice maps of the Northern Hemisphere. These maps are generated from a multitude of spaceborne sensors on-board of geostationary and polar orbiting satellites. This include: the Geostationary Operational Environmental Satellite (GOES), the European Meteorological Satellite (METEOSAT), the Japanese Geostationary Meteorological Satellite (GMS), and DMSP passive microwave data from SSM/I (Ramsay 1998, 2000).

Microwave data were primary used for ice mapping and monitoring because of their cloud penetration capability and the fact that they do not depend on daylight. Traditionally, SSM/I observations were used [1-2], but recently AMSR-E data have also been used. The algorithms developed in NASA are particularly useful. Traditionally, SSM/I observations were used [1-2], but recently AMSR-E data have also been used. The algorithms developed in NASA are particularly useful.

Satellite observations in the visible and infrared spectral bands have also been used for ice mapping (Kwok et al. 1995). A widely used approach to the atmospheric correction of satellite observations over

water consists in the use of physically-based models which explicitly account for the Rayleigh and aerosol scattering as well as water vapor, ozone and other atmospheric gases absorption. Application of this approach to ice cover identification and mapping from geostationary satellites may not be effective. First, accurate information on aerosol characteristics and large scale distribution is not generally available. Second, the existing atmospheric correction models can provide reliable results only for solar or satellite zenith angle below about 60 deg. The latter limitation is serious since low-solar elevation conditions are typical for observations over ice covered areas. Besides that, areas affected by seasonal and perennial ice are located above 45-50 deg N and hence corresponding view angles for geostationary satellites at zenith angles exceed 50 deg.

Therefore, in this study we have used an empirical approach to the atmospheric and angular correction. In this approach in order to characterize bidirectional properties of the top of the atmosphere reflectance we have used a linear combination of functions depending on observation geometry angles (solar-satellite relative azimuth along with solar and satellite zenith angles). This simplified approach cannot adequately represent bidirectional effects for all possible geometries. However, observation geometries involved in ice identification and mapping from geostationary satellites are limited to high solar zenith and satellite zenith angles, generally over 50 deg. Thus for this particular application, the use of an empirical approach may be appropriate.

This study is a first attempt to apply a Bidirectional Reflectance Distribution Function (BRDF) model for ice cover mapping. Moreover, an Artificial Neural network technique has been also utilized for model calibration and application. Artificial neural networks have been widely utilized in remote sensing applications (Benediktsson et al. 1990; Paola; Schowengerdt 1995). Multi-layer perceptron trained by backpropagation algorithm is the most common neural network used for image classification. This type of neural network has been successfully applied to image processing and has shown a great potential in the classification of different types of remotely sensed data. In contrary to traditional techniques such as regression analysis, neural network uses its complex configuration to find the best nonlinear function between the input and the output data without any constraint of linearity or prespecified non-linearity (Ghedira et al. 2007; Ghedira et al. 2005).

2. METHODOLOGY

Data collected by SEVIRI instrument onboard of Meteosat Second Generation (MSG) satellite have been used as a prototype. Four channels were utilized: HRV (High resolution Visible: 0.6-0.9 μm), R01 (0.6 μm), R02 (0.8 μm) and R03 (1.6 μm).

The northern region of the Caspian Sea has been selected for algorithm development and validation. The surface area of the Caspian Sea is about 371,000 square kilometers (figure 1). Ice conditions dominate during the winter in the northern region of the Caspian Sea. it is crucial to monitor ice extent and conditions

since the Caspian Sea is an oil rich region (Kouraev 2004).

Similar to snow, the reflectance of thick ice cover is very high in the visible and drops substantially in the shortwave- and middle-infrared. This specific spectral signature provides the physical basis for ice identification from space. It will be primarily used in the new ice detection algorithm for GOES-R ABI. Clouds present the major factor hampering ice identification and mapping. As compared to polar orbiting satellite data, availability of frequent observations from geostationary satellites increases the chance to obtain a cloud clear view during a day and thus helps to reduce cloud gaps in the ice map.

The proposed approach is based on combination of a BRDF model and an ANN technique. The output of this combination is a simulated value of reflectance. Reflectances of ice and water were estimated in this study. These reflectances are supposed to be generated by pure ice and water pixels, respectively. However, two necessary steps were performed before simulating ice and water reflectances as it is shown in flowchart of figure 2.

Firstly, a sample of pixels of the Caspian Sea was manually selected. This sample was used for neural network training and model validation. Additional details about the neural network structure will be provided in the following sections. The selected pixels were completely covered by ice or water. Several clear-sky MODIS images have also been used to improve the identification of fully covered ice pixels. A sample of more than 12,000 pixels was selected for both water and ice.

Secondly, an automated approach for cloud detection was performed using a simple threshold method. The channel R03 (1.6 μm) was used to automatically detect cloudy pixels.

In this work, the BRDF model describes an existing relationship between three angles i.e. satellite, solar and azimuthal angles and observed reflectance. Trigonometric functions such as the sine and cosine of these angles were also utilized in the BRDF model formula. The total number of inputs which are the three angles, their sine and cosine is 9 (equation 1).

$$R_{obs} = f(ARZ; SOL; SAT; \cos(ARZ); \cos(SOL); \cos(SAT); \sin(ARZ); \sin(SOL); \sin(SAT)) \quad (1)$$

where: SAT is the satellite angle; ARZ is the azimuthal angle and SOL is the solar angle and R_{obs} is the observed reflectance.

The main assumption of this work is that simulated reflectances do not depend on the ice or water features i.e. roughness, thickness or quality. So, we are assuming that these characteristics remain constant during a day and that observed reflectances are exclusively affected by the three angles variations: Azimuthal, Solar, Satellite.

The ANN has been used, on the other hand, to model the relationship between angles as inputs and reflectances as outputs.

In a multi-layer neural network, the nodes are organized into layers where each node transforms the inputs received from other nodes. The input layer serves as an entry for the vector of data presented to the network (Azimuthal, Solar, Satellite and their sines and cosines). The output layer serves to produce the neural network decision (simulated reflectance) for the pixel presented at the input layer. All layers between the input and output layers are referred to hidden layers. The best neural network architecture can only be determined experimentally for each particular problem.

The number of hidden nodes should be large enough to ensure a sufficient number of degrees of freedom for the network function and simultaneously small enough to keep sufficient the generalization ability to the network. Several tests were conducted to determine the optimal number of hidden nodes. After several tests, a configuration of one hidden layer with 20 hidden nodes was selected.



Figure 1 The Caspian Sea (http://en.wikipedia.org/wiki/Caspian_Sea)

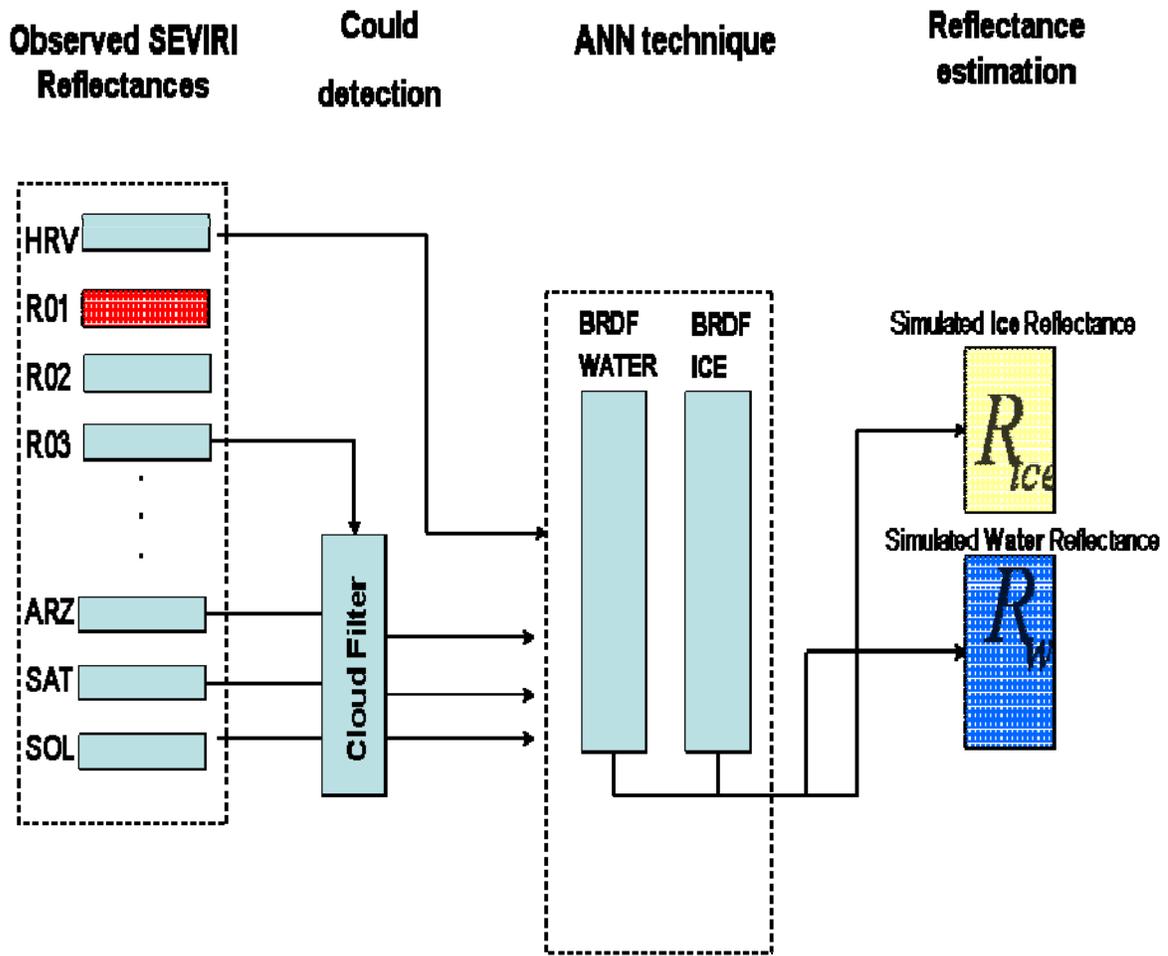


Figure 2 Flowchart of ice and water reflectance estimation

3. RESULTS

The cloud discrimination potentials of the near-infrared channel can be also seen in **Figure 3**. This figure shows the reflectance of the four optical channels at 11:45 am local time. These data were collected on January 23rd 2007.

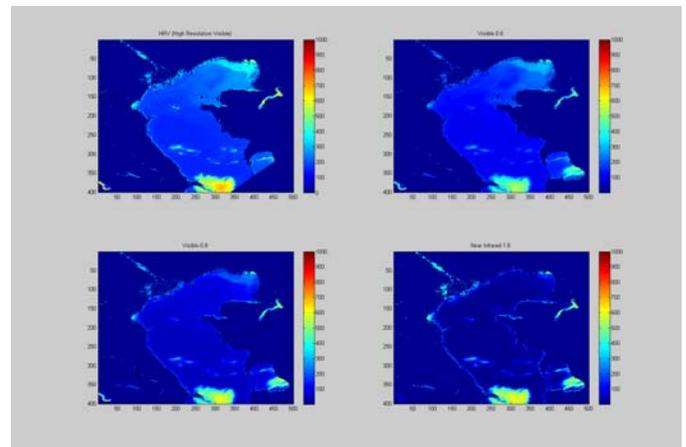


Figure 3 Reflectance of four optical channels (Ghedira et al. 2007)

As it was discussed above, simulations were carried out, according to the flowchart of Figure 2. Cloudy pixels were detected and eliminated. Then, the neural network was trained. The primary goal of this training step is the estimation of the weights connecting the nine

input-layer nodes (angles + trigonometric transformations) to the 20 hidden nodes, and then the ones connecting hidden nodes with the output layer containing the observed reflectance. Two separate neural networks with same structure have been trained to simulate ice and water reflectances.

Figures 4 and 5 show the simulated reflectances for ice and water respectively. Firstly, these results illustrate a satisfactory agreement between simulated and observed reflectances. The root mean squared errors (RMSE) for both ice and water, summarized in table 1, are non significant. However, RMSE values were systematically higher when ice reflectances are simulated. This can be explained by the fact that ice reflectance are highly affected by ice features such as roughness, thickness and presence of fractional ice. RMSE obtained with simulated water reflectances can be generated by the variation of water reflectance due to the atmospheric effect as well as to water properties such as high concentration in sediments, presence of river deltaic deposits and presence of fractional ice. In future work, the simulated reflectances will be used to retrieve these features.

Overall, the simulated performances are acceptable and very encouraging. This implies that a combination of BRDF model and ANN allows simulating ice and water reflectances.

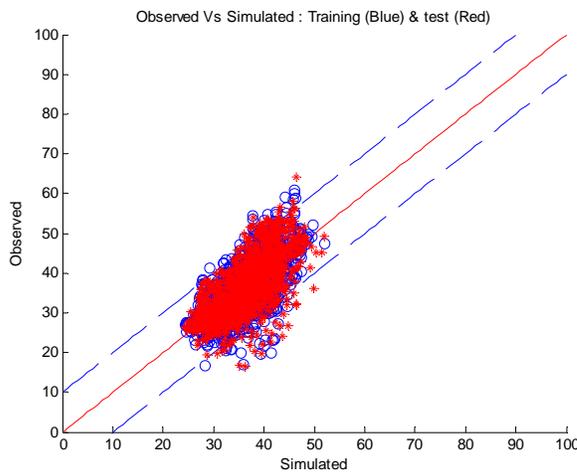


Figure 4 Observed and simulated ice reflectances

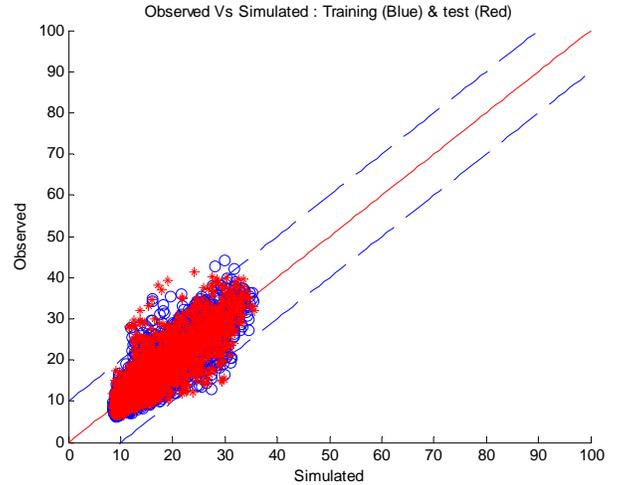


Figure 5 Observed and simulated water reflectances

Table 1 Simulation performances and RMSE values

	RMSE	
	ICE	Water
Training	5.09%	3.38%
Validation	5.35%	3.63%
Testing	5.22%	3.51%

4. CONCLUSION

In this research, the SEVIRI instrument onboard Meteosat Second Generation (MSG) satellite was used as a prototype for the future GOES-R ABI. The rate of observations from SEVIRI (one image per 15 minutes) is the same as for GOES-R ABI.

A neural-network-based model has been used to simulate water and ice reflectances over the Caspian Sea. Pixels geometry defined by the three solar, azimuthal and satellite angles were the primary input to the model. Trigonometric functions such as sine and cosine have also been considered. A fine tuning exercise allowed us to select an optimal structure of the used neural network.

The developed ice detection and mapping algorithm have been applied to MSG SEVIRI data and have been tested over the Caspian Sea. The algorithm has been assessed using observed reflectance values. The obtained acceptable results have shown that a neural-network-based BRDF model has an interesting potential for ice mapping and monitoring from geostationary platforms. The simulated reflectances of water and ice

will be used in future works for ice features determinations.

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