DEVELOPING A NEURAL-NETWORK-BASED “BRDF” TOOL FOR THE UAE COASTAL AND INLAND ZONES

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ABSTRACT

The radiation reflected by any observed surface is highly dependent on both sun illumination and satellite observation angles. These two angles are also described, respectively, as incident and reflected angles. The geometry-dependence of surface reflectance is usually corrected by a tailored Bi-directional Reflectance Distribution Function (BRDF). It is the most common tool used to eliminate or to reduce the effects of sun-sensor geometry on the reflected radiation. Generally, BRDFs are derived empirically (or semi-empirically) for a specific land cover by analyzing a large set of observations (training set) made under different illumination and observation angles. This approach involves fitting the model to collected observations and inverting it. A strong BRDF model tailored to specific land cover characteristics of the UAE is especially needed for applications that use data acquired with variable sun-sensor geometry. In this paper, a neural-network-based tool “BRDF” was developed and applied to quantify the effect of sun illumination and SEVIRI-MSG observation angles on measured reflectance for both land (mostly desert) and coastal water pixels in the UAE.

Index Terms— Bidirectional Reflectance Distribution Function (BRDF), METEOSAT Second Generation (MSG), SEVIRI-MSG, Neural Networks, UAE.

1. INTRODUCTION

Mapping and monitoring land covers and land cover changes is the primary objective of most of land remote sensing applications. The main goal of these applications is to identify major surfaces and to map and distinguish changes in their composition, which are generally introduced by anthropogenic and climatic factors. Currently, the use of satellite data for land and water –related applications requires and accurate quantification of the sun-sensor geometry on the measured reflectance [1].

Optical sensors have been used to map different surface zones but with limitation to daylight and clear sky conditions. Additionally, the low precipitation rates in arid environments like that of the UAE coupled with frequent winds create a dusty atmosphere limiting the chance to get clear observation of the earth surface from space. As compared to polar orbiting satellite data, the availability of geostationary satellite data increases the chance to obtain cloud and dust –free views during a given day [2].

Understanding how the observed surface reflects sunlight under different observation and illumination geometries is prerequisite for a large number of remote sensing applications. This requirement represents the primary motivation in BRDF development and calibration. The BRDF is a 4 dimensional function that explain how the light is reflected at dense surface. It depends on wavelength and is used in modern optical engineering to characterize the structural and optical properties of the surface. Satellite BRDF measurements of different surfaces can be used as a primary tool in reducing the effect of sun illumination and SEVIRI-MSG observation angles on measured reflectance over land and water zones [1],[3].

Over the past two decades, many BRDF models were developed for many different applications. In 1993, the European Space Agency developed a BRDF model called

CSAR adapted to Meteosat data. CSAR model is based on a semi-empirical function that describes the bidirectional reflectance of arbitrary natural surfaces [4]. Another model was developed by the same agency in 2000 in order to solve the atmosphere/surface radiation problem on an operational basis and to generate surface albedo, aerosol load, and possibility land cover change products [5]. More recently, neural networks have been used to model the illumination-observation angles dependency in mapping sea ice coverage with Meteosat data [2]. This approach will be adapted for this study.

2. METHEDOLOGY

SEVIRI-MSG visible channels have been widely used in differentiating between different surface reflectances for a given day under ideal observation conditions (cloud free and clear air). The sun illumination and SEVIRI-MSG observation angles depend on acquisition time. Developing and applying a Bidirectional Reflectance Distribution Function (BRDF) model will help to quantify the effect of observation geometry on measured reflectance for both land (mostly desert) and coastal water pixels in the UAE. The approach involves fitting the model to groups of selected water and land pixels. The need for a strong BRDF model is especially important for EIAST research projects based on geostationary data due to the wide range of variation of both illumination and observation angles of this type of platforms compared to polar orbiting platforms. An Artificial Neural network technique was developed to train and validate the BRDF model. The neural network model has been adapted from a similar technique developed for SEVIRI-MSG data as a part of sea-ice mapping and classification tool [6 - 7]. In this approach, a total of 20,000 pixels equally distributed between water and land were selected at different locations and acquisition times. In addition to the fact that all pixels were collected under cloud-free conditions, a special attention has been made to eliminate pixels under hazy and dusty conditions.

For each collected pixel, three reflectance values (R01, R02, and HRV) and three acquisition angles (solar, satellite, and azimuth) were retrieved. Two neural networks (water and land) were trained, calibrated and validated for each of the three visible channels (R01, R02, and HRV). The available data have been subdivided into three equal sets: training, validation, and testing. The approach used in this study is summarized in the flowchart illustrated in Fig.1.

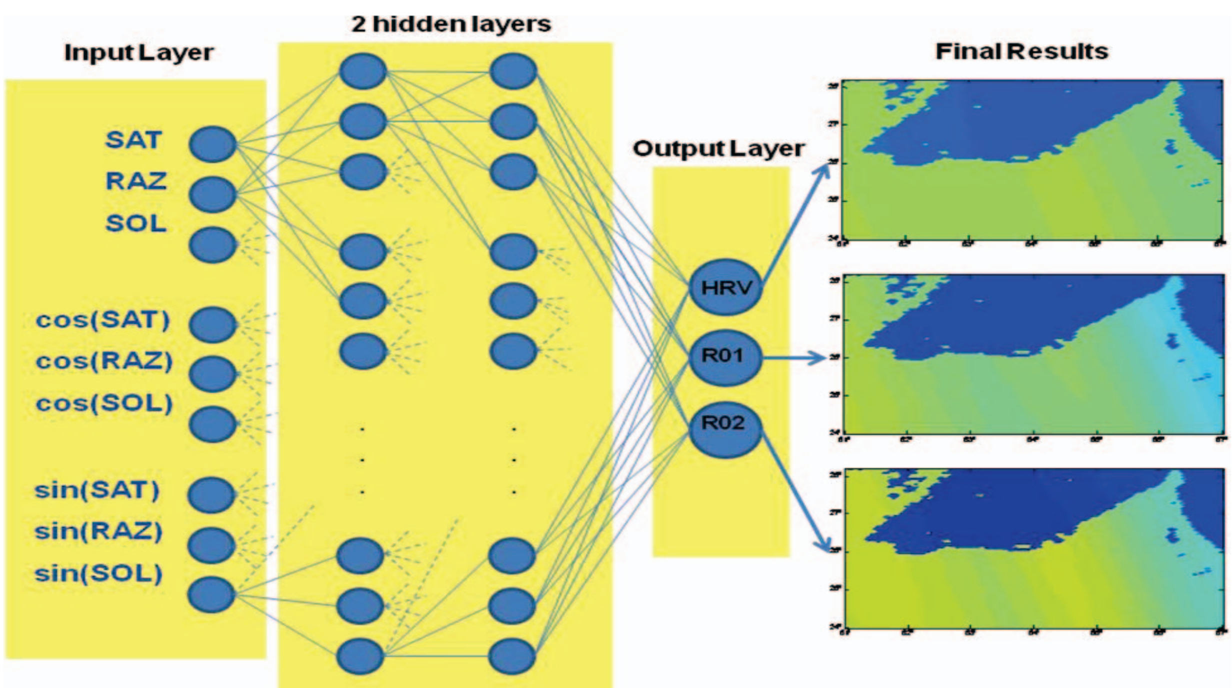

Fig. 1: Methodology flowchart

In this work, the BRDF model describes an existing relationship between three angles i.e. satellite, solar and azimuth angles and observed reflectances. Trigonometric functions such as the sine and cosine of these angles were also tested as additional inputs to the neural network system. Trigonometric transformations are present in most of semi-empirical BRDF functions. As shown in the following equations, a total of nine inputs were presented to nets: three angles, their sine and their cosine.

$$R_{water} = \quad f_W\,[\mathrm{ARZ, SOL, SAT, cos(ARZ), cos(SOL), cos(SAT), sin(ARZ), sin(SOL), sin(SAT)}] \qquad (1)$$

$$R_{land} = \quad f_L\,[\mathrm{ARZ, SOL, SAT, cos(ARZ), cos(SOL), cos(SAT), sin(ARZ), sin(SOL), sin(SAT)}] \qquad (2)$$

SAT is the satellite angle; ARZ is the azimuthal angle and SOL is the solar angle. R_{water} and R_{land} are the observed reflectance manually selected for a set of water and land pixels collected at different solar angles under clear sky conditions.

3. RESULTS AND DISCUSSION

After rigorous calibration and numerous training, six stable neural networks were selected and saved (R01-Water, R02-Water, HRV-Water, R01-Land, R02-Land, and HRV-Land). The accuracy of the six trained nets has been then evaluated against a set of independent data.

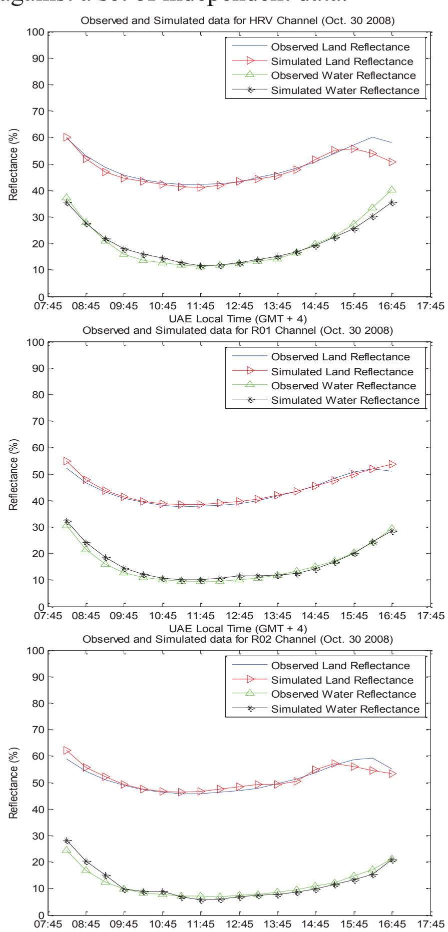

Fig. 2: Time variation of observed and simulated reflectance over one water and one land pixels under clear sky and clean air conditions

The graphs presented in Fig.2 illustrate the hourly variation of observed and simulated reflectance for specific water and specific land pixel in SEVIRI optical channels: HRV (High Resolution Visible: 0.6-0.9 µm), R01 (0.6 µm) and R02 (0.8 µm). The observed reflectance data was provided by MSG, while the simulated reflectances represent the outputs of the six trained nets. These graphs show clearly the high accuracy obtained by the trained nets. The best performance was obtained for the R01 channel. However, a slightly lower accuracy was obtained for HRV and R02 channels. This lower accuracy was observed in land reflectances measured in early morning and in late, which correspond to the time with high solar angles. These results are promising. The obtained root mean square error (RMSE) was 2% for land and 3% for water.

The same trained nets were then simulated for a whole scene to test their spatial consistency. A land/water mask has been used to combine two nets outputs (water and land) for each channel. The images presented in figure 3 show the results of this spatial simulation. The simulated scenes show promising potentials of the developed technique in predicting the effects of both illumination and observation angles on measured reflectances. The simulated results (neural networks outputs) are presented at the left side and the real observed reflectances are presented at the right side.

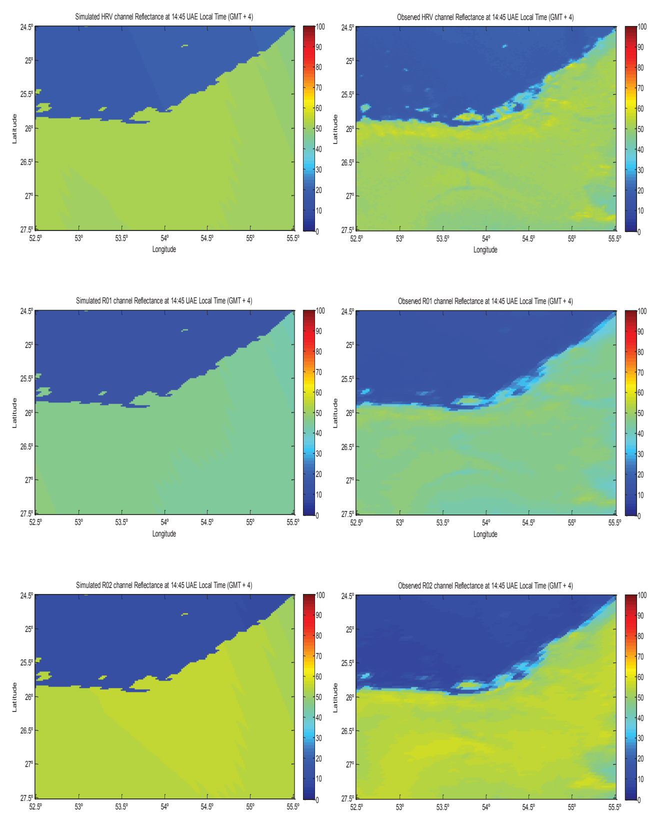

Fig. 3: Comparison between observed and simulated scenes (HRV, R01, R02) under clear sky and clean air conditions (Oct. 30 2008).

The neural-network system has shown a good ability in discriminating between land and costal water zones under cloud free and clear air conditions.

On the other hand, the system can be used to detect changes in atmospheric conditions over both land and water surfaces. Figure 4 illustrates how the system can detect the different events like clouds, fog and presence of dust over both land and water pixels. The observed reflectance can be compared to the simulated one in order to detect any changes in air quality or atmospheric conditions.

The top two graphs presented in figure 4 show the simulated and observed curves for HRV (left) and R01 (right) channels over the same land pixel in cloudy day (December 19 2008). The two graphs in the bottom illustrate the simulated and observed curves for the similar channels over the same water pixel in foggy and partially cloudy day. The early morning fog, occurred on December 17 2008, can be clearly noticed by comparing the observed reflectance to simulated one over the water pixel (two bottom graphs).

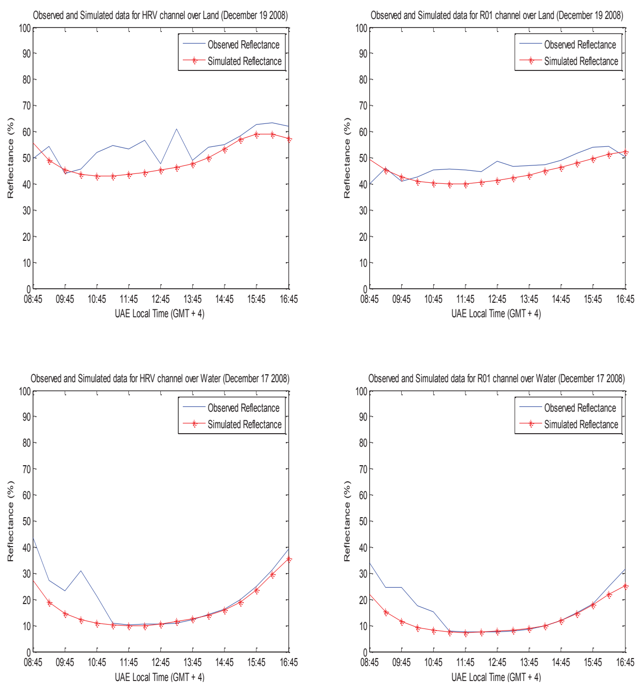

Fig. 4: Time variation of observed and simulated reflectance (HRV and R01) under different atmospheric conditions

4. CONCLUSION

This paper investigated the ability of using neural networks to quantify the effect of sun illumination and SEVIRI-MSG observation angles on measured reflectance for both land and water pixels in the UAE. The obtained results were promising. The developed system has showed a good potential in discriminating between land and water zones, as well as detecting "automatically" different atmospheric conditions such as clouds, fog, sand storms and air dust.

The developed tool will be adapted for other monitoring algorithms in the UAE such as fog detection and mapping, sand and dust storms detection and monitoring…etc. These tools are currently being developed at the Emirates Institution for Advanced Science and Technology (EIAST) in Dubai, UAE.

The next step of this project is to improve the quality of the training sets by using external tools to eliminate pixels with low visibility and high aerosol concentrations. Daily aerosol maps are currently collected and analyzed to identify days with low air quality. Removing such pixels from the training sets will certainly improve the overall performance of the developed tool and make it more sensitive to small variations in air quality and atmospheric conditions.

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