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Fractional snow cover mapping from MODIS data using wavelet-artificial intelligence hybrid models

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SUMMARY

This study was carried out to evaluate the wavelet-artificial intelligence hybrid models to produce fractional snow cover maps. At first, cloud cover was removed from MODIS data and cloud free images were produced. SVM-based binary classified ETM+ imagery were then used as reference maps in order to obtain train and test data for sub-pixel classification models. ANN and ANFIS-based modeling were performed using raw data (without wavelet-based preprocessing). In the next step, several mother wavelets and levels were used in order to decompose the original data to obtain wavelet coefficients. Then, the decomposed data were used for further modeling processes. ANN, ANFIS, wavelet-ANN and wavelet-ANFIS models were compared to evaluate the effect of wavelet transformation on the ability of artificial intelligence models. It was demonstrated that wavelet transformation as a preprocessing approach can significantly enhance the performance of ANN and ANFIS models. This study indicated an overall accuracy of 92.45% for wavelet-ANFIS model, 86.13% for wavelet-ANN, 72.23% for ANFIS model and 66.78% for ANN model. In fact, hybrid wavelet-artificial intelligence models can extract the characteristics of the original signals (i.e. model inputs) accurately through decomposing the non-stationary and complex signals into several stationary and simpler signals. The positive effect of fuzzification as well as wavelet transformation in the wavelet-ANFIS model was also confirmed.

1. Introduction

Precipitation is an important source of water supply over the world. In Iran, considerable part of precipitation occurs in winter except in the northern part i.e. Caspian plain which majority of precipitation occurs in autumn (Mofidi et al., 2008). Away from the Caspian plain area, most precipitation falls on regions with the highest elevation. Over the mountainous area, it is generally in the form of snow, which forms an important component of the winter ecosystem. Therefore, snowmelt is considered as a critical component of water supply in Iran (Ghobadian, 1990) and it is important to know how much water is stored in a basin in the form of snow. Moreover, due to the reported global warming (IPCC, 2007) and climate change (Kousari et al., 2011, 2013), monitoring snow cover changes in Iran can be of great importance.

Remote sensing is a very powerful tool used in snow cover mapping. However, there are some challenges in this case. One of the most important obstacles is the tradeoff between the temporal and spatial resolution of satellite imageries. On the one hand, when the spatial resolution is high, images are not available for all dates (for example, for ETM+, the temporal resolution is 16 days). This is very important in monitoring the changes in snow cover and calculating the runoff from snow melting. On the other hand, when the temporal resolution is considerable, the main limitation is associated with the spatial resolution; therefore, the precision of snow cover maps produced using these imageries may not be very reliable. Thus, a good idea to cope with this problem can be soft classification or sub-pixel classification of low or moderate resolution images (Foody and Cox, 1994).

Furthermore, one of the most frequently used satellite imageries in snow cover mapping is the Moderate Resolution Imaging Spectro-radiometer (MODIS) (Barton et al., 2000; Hall et al., 2002; Hall and Riggs, 2007; Liang et al., 2008). It is a passive imaging spectro-radiometer, with 36 spectral bands (Barnes et al., 1998). It has two bands with a nominal spatial resolution of 250 m at nadir, five bands with 500 m, and the remaining bands with 1 km spatial resolution. The MODIS binary snow mapping algorithm established by Hall et al. (1995) uses two indices namely the Normalized Difference Snow Index (NDSI) and the Normalized Difference Vegetation Index (NDVI) as well as the thresholds of MODIS bands 2 and 4. Soft classifiers try to disclose existing mixtures and define for each pixel the area fractions covered by the different cover types. Although the exact location of the class fractions within each coarse resolution

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pixel remains unknown, the true class distribution may be well estimated (Verbeiren et al., 2007). Several studies have been performed using MODIS data and sub-pixel classification method. Raleigh et al. (2013) used the MODIS data to produce snow cover maps in the sub-alpine meadows and forests of the Sierra Nevada. They indicated the limitations and challenges of snow cover mapping in forested area. Dobreva and Klein (2011) and Salminen et al. (2013) also used MODIS data in order to fractional snow cover mapping and produced approximately accurate maps using ANN models and reflectance model-based methodology, respectively. Generally, the sub-pixel classification is most often performed using the linear mixture model or neural networks or both (Swinnen et al., 2001; Kavzoglu and Mather, 2003; Lobell and Asner, 2004; Shabanov et al., 2005; Lee and Lathrop, 2006; Painter et al., 2009). There are several deficiencies associated with linear mixture models (Borel and Gerstl, 1994). Therefore, several robust non-linear methods e.g. artificial intelligence (AI) approaches are developed to cope with these deficiencies.

Artificial neural network (ANN) is a machine learning technique which can gain knowledge of relationships between specified input and output variables. Neural networks constitute an information processing model that stores empirical knowledge through a learning process and subsequently makes the stored knowledge available for future use (Haykin, 1999). The other powerful approach to model non-linear systems is the combination of fuzzy logic and neural networks called neuro-fuzzy. In neuro-fuzzy approach, the ability of fuzzy-ruled based systems in managing uncertain and noisy data and the learning capability of neural networks are combined to form enhanced predictors. A particular form of neuro-fuzzy systems is ANFIS, which has demonstrated significant results in modeling non-linear functions (Jang et al., 1997). However, as the number and the complexity of data sets for training of ANN or ANFIS increases, these models alone may not be efficiently used (Hadad et al., 2011). Therefore, performing preprocessing approaches on the original data can improve the performance of artificial intelligence techniques such as ANN and ANFIS. One of the most important and useful data preprocessing approaches is the wavelet analysis which can be combined with artificial intelligence methods (Anctil and Tape, 2004; Cannas et al., 2006; Kisi, 2008; Adamowski, 2008; Adamowski and Sun, 2010; Adamowski and Fung Chan, 2011; Nourani et al., 2011; Kisi and Cimen, 2011; Kisi and Shiri, 2012; Moosavi et al., 2013). Wavelet analysis is a multiresolution analysis in time (or position) and frequency domain and is an important derivative of the Fourier transform. A wavelet offers multiresolution decomposition to separate components of a function for improving the analysis (Akansu and Haddad, 1992). Several studies in addition to those mentioned above, have been performed on the combination of wavelet transformation with AI methods in several fields. The combination of wavelet transformation with ANN models was first performed by Aussem et al. (1998) for financial time series forecasting. Zhang et al. (2001) used wavelet-AI to predict programmed-temperature retention values of naphthas. Wang and Ding (2003) applied a wavelet-ANN hybrid model to forecast shallow groundwater level and daily discharge. Mellit et al. (2006) illustrated wavelet-ANN architecture with an impulse infinite response filter for modeling and prediction of the daily total solar radiation. Avci (2007) developed an expert system based on wavelet-AI for texture classification. Partal and Cigizoglu (2008) and Kisi (2008) used the hybrid wavelet-ANN model for forecasting daily suspended sediment and monthly river flow, respectively. Dong et al. (2008) used fuzzy wavelet-ANN and rough sets for predicting fault diagnosis accuracy of power transformers. Kisi (2011) introduced a Wavelet regression model for neural networks for river stage forecasting. However, to the best of our knowledge, no research has been published that explores coupling wavelet analysis with ANFIS and ANN for fractional snow cover mapping until now. The main objective of this research is to evaluate the hybrid wavelet-AI models in fractional snow cover mapping and compare these methods with ANFIS and ANN models.

2. Materials and methods

2.1. Study area

The study area is located in the Central Alborz Mountains at the northern part of Iran, between 49°05′ to 53°58′E. longitudes and 35°05′ to 37°06′N. latitudes. This area covers almost 40,000 km^2 (Fig. 1). The region constitutes two distinct northern and southern slopes. The Alborz mountain range forms a barrier between the south Caspian and the Qazvin-Tehran plateau. It consists of sedimentary series dating from Upper Devonian to Oligocene, prevalently Jurassic limestone over a granite core. Eocene volcanic and volcanic lastic rocks form the major geological formations of the southern parts of the Alborz Mountains. However, in the northern parts, Middle Jurassic to Upper Cretaceous lime stone formations become more important and form some very high rock cliffs along the East–West directed thrust fault zones (Stocklin, 1974). The maximum, minimum and mean elevations in the study area are 5600 m, 48 m and 1870 m, respectively. In most portions of the Alborz Mountains, precipitation is directly connected to altitude. The annual mean temperature is 10.5 °C, the maximum of annual mean temperatures is 14.8 °C and the minimum is 3.3 °C (Naderi et al., 2012). The precipitation reaches to more than 1000 mm annually in the lowlands of the Gilan region and is even more abundant at higher elevations. Even though it decreases toward the east, it still suffices to nourish a humid forest for the whole length of the chain on the Caspian side, where the soils are mostly of the brown-forest type. In the higher elevations the precipitation is generally in the form of snow. The natural vegetation of this slope grows in distinct zones: the Hyrcanian forest on the lowest levels; a beech forest in the middle zone; and oak forest in higher elevations. Its higher elevations, in the Alburz Range forest steppe eco-region, are arid with few trees, but its northern slopes, in the Caspian Hyrcanian mixed forests eco-region are lush and forested (Stocklin, 1974). Fig. 2 shows the flow chart of the study.

2.2. Remote sensing data preprocessing

In order to produce sub-pixel snow cover maps using MODIS data, clouds should be initially removed from images. In the next step, cloud-free imageries could be imported to the soft classification process. The elimination of clouds consists of two steps including the detection of clouds and the replacement of cloud pixels with cloud-free ones. Cloud and snow are easily confused with each other in the classification of a remote sensing imagery, because of their similar spectral responses in some spectral ranges (Ackerman et al., 1998). Although the reflectance of cloud and snow are both high in visible and short wave near-infrared, in the long wave near-infrared the reflectance of cloud is high and the reflectance of snow is very low (Sirguey et al., 2009). This property was used to distinguish cloud from snow cover. In the visible and near-infrared spectral ranges, the spectral response of cloud differs significantly from the spectral response of other ground objects except for snow; therefore, cloud is in consequence unproblematic to separate from other ground objects. The normalized difference cloud index (NDCI), introduced by Li et al. (2005) was also used to detect cloud pixels in MODIS data.

$$\mathrm{NDCI} = \frac{b_1 - b_6}{b_1 + b_6} \tag{1}$$

where b_1 and b_6 are the first and sixth bands of MODIS data, respectively. The NDCI values of cloud are greater than zero. In the