Atmospheric Correction for Inland Waters Using Artificial Neural Networks

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Abstract: The retrieval of water remote-sensing reflectance is an important and fundamental step for water quality monitoring using satellite remote sensing techniques. The atmospheric effects are generally significant and complex, which make atmospheric corrections (ACs) difficult to accurately derive the remote-sensing reflectance. The radiative transfer model is considered a promising method in atmospheric correction. Nevertheless, the approach requires calculating a set of parameters using complicated models and formulas, including aerosol model, atmospheric conditions, and sensor geometric information. This leads to time-consuming and sometimes produces negative water remote sensing reflectance. With a revisit cycle of 16-day, free available, and a high resolution of 30 meters, Landsat 8 OLI imagery is widely utilized for water quality monitoring in inland waters. However, the sensor receives surface reflectance and atmospheric effects, including scattering caused by Rayleigh and aerosol and absorption caused by gas and aerosol. This study proposed an atmospheric correction method based on artificial neural networks for inland waters to retrieve the water remote sensing reflectance (Rrs) using Landsat 8 OLI imagery. The input data required for the neural network model consists of a training dataset and a testing dataset. The number of data for training is 262580 samples, and 71 samples for testing. The training dataset includes eight TOA spectral reflectance (from band 1 to band 9 except the Panchromatic band), three geometric angles data, that is, sensor zenith angle (VZA), sun zenith angle (SZA), and relative azimuth angle (RAA), and aerosol data (AOT). The iCOR Rrses are used as the labels of the training dataset. The *in-situ* Rrs data which was measured in the field campaigns in Vietnam in different lakes and on different Landsat 8 acquisition days using spectra radiometer are separated into two groups: one for training the neural network model and the remaining data is for testing the model. The top of atmospheric (TOA) reflectance can be converted from digital number (DNs) using metadata file attached in Landsat 8 collection 1 Level 1 product, while the geometric angles are provided in Landsat 8 collection 2 Level 1 product, and the aerosol data (AOT) is attached in Landsat 8 level 2 product. The iCOR Rrs is the Rrs data retrieved by using image correction method (iCOR), which is assessed as one of the best radiative transfer models for atmospheric correction for inland water bodies. Our proposed model includes three 3-dimensional convolution layers to extract the TOA spectral feature, five fully connected layers to predict the Rrs, and one output layer. Besides, the model also contains one target layer where the iCOR Rrs and *in-situ* Rrs working as label data. The output Rrs is in five bands in the visible and near-infrared region.

The Keras Tuner function was used for model tuning to obtain the optimal hyperparameters, including the number of hidden layers, the number of neurons for each layer, the dropout rate for each layer, the learning rate, and the best epoch. The proposed AC model was then retrained with the optimal hyperparameters. The retrieved Rrs results were then validated with *in-situ* measurements and compared with existing atmospheric correction methods (including dark object subtraction (DOS), quick atmospheric correction (QUAC), atmospheric correction for OLI lite (ACOLITE), fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH), Landsat 8 surface reflectance code (LaSRC), and Image correction for atmospheric effects (iCOR). The testing data were classified into four trophic classes (including oligotrophic, mesotrophic, eutrophic, and hypereutrophic). The testing results show that the retrieved Rrs values closely match with *in-situ* measurements in all five bands in the visible and near-infared region. The result also reveals that the proposed AC model can avoid producing negative remote-sensing reflectance. Comparing to the six AC methods, the proposed AC model shows the best performance in all trophic levels; while the iCOR processor is more appropriate for eutrophic water, the ACOLITE and LaSRC can be used, but they often failed in the NIR region. In all trophic levels, the DOS and QUAC methods seem unsuitable for atmospheric correction in inland lakes because they produce uncertainties by only removing the haze effect in the atmosphere. The proposed AC model was further tested on lake Laguna, Philippines, and lake Barra Bonita, Brazil, located in the tropical region, bringing reliable results. The proposed method can address the negative remote sensing reflectance issue existing in some traditional atmospheric correction methods. This method is efficient and easy to use when the network is well trained. Therefore, the proposed AC model has the potential for further remote sensing applications in water quality monitoring. However, the proposed model could not estimate Rrs reasonably in hypereutrophic water in algae bloom conditions. Thus, the proposed model is recommended for atmospheric correction in water bodies that have the Chl-a concentration in the range (1.6, 395) mg/m^3 or Secchi disk depth (SD) in the range (0.2, 5.1) meter.

Keywords: Atmospheric correction, inland waters, artificial neural networks, Landsat 8 OLI imagery