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WEB2TISAT: AUTOMATED SATELLITE IMAGES DOWNLOADING AND PROCESSING FOR ENVIRONMENTAL AND HYDROLOGICAL USE

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Assessment of land use and land cover change is a necessary technical tool to solve a series of current environmental issues in a specific region. Issues such as climate change impact on agriculture and water resources. A lot of projects have been carried out to find solutions to some of these environmental problems. To contribute to these efforts, we propose in this paper a web application, which we have called "Web2TISat", to automate the process of downloading and processing satellite images. The "Web2TISat" has been implemented with the statistical language R using Shiny. This application is particularly intended for non-programmer scientists and practitioners.

INTRODUCTION

At different spatial and temporal scales, remote sensing provides essential information on land use, land cover and land change (Siamak et al., 2016; Mushore et al., 2017; Stratoulias et al., 2017; Sheffield et al., 2018). This information allows a better understanding of land use impacts on climatic and environmental systems. Over the past decades, a policy of free and unrestricted access to data has been adopted by various space agencies and satellite product suppliers (Stratoulias et al., 2017). Therefore, the wide variety of data sets available ; which vary in spatial, spectral, radiometric and temporal resolutions; has opened up many avenues for research in various fields such as resource planning and management (Sheffield et al., 2018), climate change assessment (Kassogué et al., 2017), urban growth impact (Mushore et al., 2017) and agricultural monitoring (Weiss et al., 2020).

Up till now, various methods have been developed and applied for processing and classifying images. However, only few of these methods are fully automated and integrate optical and radar data. In addition, they are not based on free and open source software. Lack of process automation can be a daunting task for the user, especially when it comes to mapping large areas.

Multi-spectral image processing is generally divided into three stages: preprocessing, processing, and post-processing. Each of these steps has its own set of common tools and techniques (Siamak et al., 2016). In preprocessing case, radiometric and geometric corrections are required to minimize atmospheric conditions effects (Li et al., 2014, Toure et al., 2019). In the literature, various indices were developed to determine crop development state, soil surface temperature and/or soil moisture like NDVI (Penuelas et al., 1997), NDWI (Gao, 1996), NDBI (Zha et al., 2003). Image classification is a process in which each pixel or area of an image is classified according to certain rules into a category based on its spectral characteristics, and spatial structural characteristics (Siamak et al., 2016). This process consists of two phases, namely feature extraction and classifiers learning. When extracting characteristics, the functionalities are designed manually according to prior human knowledge in order to obtain regions of interest. Li et al. (2014) conducted a study on the state of the art of classification methods. More advanced methods (or classifiers) have been used for land cover mapping (k-nearest neighbors (kNN) (Samaniego et al., 2008), random forest (RF) (Gislason et al., 2006), neural networks (Civco, 1993) and support vector machines (SVM) (Huang et al., 2002)). Previous research implies that the selection of the best classifiers depends primarily on the specific study area, data and land cover classification system (Lu and Weng 2007; Li et al., 2014).

With the Big Data age, the efficient and autonomous use of exploitable data becomes a requirement. For this, voluminous data analysis is not manually feasible and therefore requires the use of automatic and semi-automatic tools. In this regard, we are using the R programming language (R Core Team, 2019) to develop a web application to automate the process of downloading, processing, classifying and visualizing satellite images. This article therefore aims to present the main functionalities of this web application and to demonstrate its potential. Some examples of this application will be put forward to illustrate our approach.

WEB2TISAT APPLICATION PRESENTATION

Development and implementation

Principle

The Web2TISat application principle is to enable the user to download and process datasets, classify images, compare classification performance, create interactive graphs and export underlying datasets

without having any special programming knowledge. In addition, this application will save scientists and practitioners a lot of precious time for.

Approach

We developed a Web2TISat application through Shiny (Chang et al., 2019), ShinydashboardPlus (Granjon, 2019) and ShinyWidgets (Perrier et al., 2019) packages. The combination of these packages allows the development of an interactive and user-friendly web page with input and output widgets based on the statistical language R (R Core Team, 2019). Shiny is designed to enable interactive applications to be deployed quickly and easily. Shiny uses a responsiveness concept that automatically updates the output objects when a user changes the input objects. ShinydashboardPlus makes it easy to generate applications in the form of dashboards via a Bootstrap extension: AdminLTE. ShinyWidgets integrates JavaScripts and CSS libraries into Shiny and provides better control of user interaction buttons.

Typically, any Shiny application consists of two components that communicate with each other (Beeley, 2013): (1) ('ui. R') which is a user interface script describing the structure and functionality of the web application; and (2) ('server '.R') which is a database script detailing all data preparation, calculation, statistical processing and analysis instructions. These instructions in Web2TISat consist of downloading datasets, preprocessing, classification, analysis and visualization of satellite images and results.

Section Descriptions

Web2TISat homepage is shown in Figure 1.

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Figure 1. Overview of Web2TISat application

The seven sections are as follows:

Downloading images: The user can download geographic input data sets by selecting a satellite type, a time period and a study area. However, users must register before being able to start listing or downloading images. To do this, once a satellite type is chosen, a tab is displayed containing a username and password. The user has to fill it in according to the image download platform (Copernicus or Usgs). When clicking on "List images" button, a table is displayed with all necessary

information about the images the user wants to be downloaded. Downloads are automatically saved either in a directory named "Download" by default or in a user-defined working directory.

Pretreatment: This section aims to simplify image processing process in a single graphical user interface. The user is faced with two alternatives. The first alternative allows all the preprocessing phases to be carried out simultaneously. In this case, the user must specify the atmospheric correction method, the projection system, the resampling method (bilinear or nearest neighbor), the resolution, the image format (GTiff or VRT) as well as the area file in *shp* format. The second alternative is to carry out each pre-treatment phase separately from the other. First, the user has to choose a directory for importing and exporting images. Second, he/she specifies the preprocessing phase and the precondition. Among the available preprocessing phases, we can mention: image decompression, atmospheric correction, re-projection, mosaicking, resampling, study area reduction, band dissociation and band stacking.

Post-processing: This section is composed of four sub-tabs. 1) the Visual Interpretation allows the user to display the bands in black and gray as well as in a color composite mode such as false color and agriculture. 2) Pan-sharpening aims to apply Brovey's method (Chavez et al., 1991) to improve the spatial resolution of multi-spectral images. Other methods will be added. 3) Indices calculation: the user can calculate one or more vegetation, soil, water and urban indices such as NDVI (Penuelas et al., 1997), NDBI (Zha et al., 2003). 4) Values extraction: first, the user imports raster and shapefile. Then, he chooses raster type to import (DEM, soil type, land cover, index) and extraction method (simple or bilinear). Once extraction is completed, a table is displayed containing different raster classes, statistical parameters (min, max, mean and standard deviation), a number of pixels, an area in meters and in hectares and the name of the polygon.

Image classification: The user imports the image to be classified as well as the file containing the regions of interest. It should be specified that the user must create his/her regions of interest outside this application; for example, through Qgis (QGIS Team, 2017). He/she then chooses a classification method from the drop-down list (supervised or unsupervised classification). The user also mentions the resampling method and the number of iterations. After starting classification, an estimate of classification time by the chosen method is displayed as well as a table of Train/Test Split data (division in the train and in test). In addition, in Classification Report sub-tab, a report is displayed containing error matrix tables, global and class statistics for each classification model. If the user selects "all" as the supervised classification method, two types of graphs are displayed in Model Comparison sub-tab. The first graph compares the values of 'overall precision' and 'kappa' (Foody, 1992) for each classification method.

Raster visualization: In this section, users can generate graphs by importing relevant raster and shape file, then choosing a category of this raster. These categories include: physical parameters of terrain (DEM, land cover and soil type), water types resulting from 2CAFDYM model (Kassogué et al., 2017) (evaporated water, surface water and groundwater), vegetation indices. The exported graphs can be saved in three formats (pdf, png and jpeg).

Data Analysis: The user selects a file in csv or excel format in file explorer. If the chosen file is of csv type, he defines file parameters, namely separator type (comma, tab, space), quote type (simple, double, none) and presence/absence of column names (header). When the file is of Excel type, it defines sheet name to be analyzed. This tab contains sub-tabs such as time profile, calculation of areas per class, detection of land use variation and availability and global balance.

Contact us: This section contains information about the developer.

APPLICATION EXAMPLE

Illustrations are presented in this section to show Web2TISat application functionality, calculations and graphics it can provide. The illustration area concerns irrigated perimeter of Loukkos located in North of Morocco. It is characterized by a Mediterranean climate with an average annual temperature of 18.61 °C and annual rainfall of 74,631.51 mm.

The optical image preprocessing interface is shown in Figures 2 and 3. Figure 2 indicates criteria to be chosen for simultaneous pre-processing, and Figure 3 shows criteria for various phases separately.

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Figure 2. Overview of optical image preprocessing (simultaneous phases)

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Figure 3. Overview of optical image preprocessing phases (one by one)

In general, urban false-colour composites are created by combining the shortwave infrared (SWIR1 & 2) and red bands, respectively. For example, urban areas appear in dark purple, vegetation in green and water in dark blue, as shown in Figure 4.

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Figure 4. Result of urban false color composition of a Landsat 8 image (31-07-2018) for Loukkos perimeter-Maroc

Figure 5 shows the result of Landsat 8 image (07-31-2018) before and after Pansharping processing. We can see that the image becomes sharper using Brovey method (Chavez et al., 1991).

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Figure 5. Image processing result before and after Pan-sharping

To illustrate the use of Web2TISat, we have classified a Sentinel 2 image from 30-08-2018 which was obtained from the Scihub Copernicus platform (through our image download section). Figure 6 illustrates regions of interest distribution and classification criteria. The regions of interest were created manually through Qgis software (QGIS Team, 2017) based on our knowledge of the terrain and photos taken in the field. This phase could be automated if we had a history on spectral signature of the training data set. As classification criteria, we chose the supervised classification using four classifiers kNN, NNET, RF and SVM with the "Cross Validation" resampling method and 10 as the number of iterations.

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Figure 6. Visualisation of study area location, regions of interest and classification criteria

Classification Report sub-tab and results of model(s) are shown in Figure 7. This sub-tab facilitates the display of results after simulation end (classification). The results in this figure show that, for "random forest" method, kappa index is 0.98 and overall accuracy is 99%. According to Girard, M-C. and Girard, C-M. (2010), a classification is considered acceptable when the overall precision value exceeds 75% (Girard and Girard, 2010), our results indicate a better precision of "random forests" classification.

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Figure 7. Result of the classification report (confusion matrices, Kappa coefficient and overall precision)

The comparison between the four classifiers is shown in Figure 8. The first graph shows the comparison of the classification methods according to Kappa values and overall accuracy. The results show that the higher values of Kappa and overall precision are obtained by RF classifier followed by KNN then SVM and finally NNET.

The second graph presents F-Score values (Rijsbergen, 1979) by category and by classifier. In order to judge whether a category is identified by a given method, we define a grid based on the F-Score

values: <40%: Category very weakly detected. 40%-55%: Category weakly detected. 55%-70%: Category moderately detected. 70%-85%: Category well detected. >85%: Category very well detected. The results obtained show that all categories were very well detected by the RF and KNN classifier. However, the water category was poorly detected by SVM classifier and was not detected by NNET classifier.



Figure 8. Result of classification method performance graphs

The land use map produced for hydrological year (1984-1985) is shown in Figure 9. In this map, we were able to identify six categories, namely water, buildings and infrastructure, vegetation, agricultural land, forests and bare land. From this figure, we notice that the study area was covered with vegetation and bare soil. While the forest came in third place and was concentrated mostly in the west of the area. Water, buildings and infrastructure categories did not cover large areas.



Figure 9. Result of visualization an image classified by random forest classifier

In the same area, Figure 10 shows an example of the time profile of a rice parcel with an area of 19.53 hectares. The values generated in the graph were extracted from a time series of Sentinel 1 images (74 images) and NDVI and NDWI for the period 01 September 2017 to 31 August 2018. Results such as those shown in Figure 10 could be taken as a starting point for a more detailed assessment of the time path of each crop type. This may improve our understanding of the role of agriculture in climate change.



Figure 10. Result of time profile for rice-type parcel P16_2. Period (2017-2018)

CONCLUSION AND PERSPECTIVES

In recent years, information extraction from Earth's surface has been facilitated by the existence of several software packages implementing methods for processing, classifying and visualizing satellite images. However, these methods remain inaccessible to many scientists and practitioners who do not have adequate programming skills to use the required software effectively. In this paper, we have proposed Web2TISat (Automated satellite image downloading and processing) application with its main functionalities. The application has been created with the statistical language R using Shiny. It is particularly intended for non-programmer scientists and practitioners. Furthermore, it is not intended to replace existing software solutions or to compete with operational decision support systems. Future work could also focus on adding a tab for radar image pre-processing and improving the other tabs.

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