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A SUB-PIXEL VISUALIZATION METHOD TO DISPLAY FUZZY PHENOMENA USING RGB COLOR COMPOSITE (CASE STUDY: MANGROVES FOREST)

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Abstract. Natural phenomena boundaries and complexity of features in an urban area due to the low spatial resolution, lead to more pixels of satellite images included in reflectance of multiple land-cover/object components. The sub-pixel information extracting model outputs are fractional cover maps of interested class (end-member), with membership values between zero and one. These maps represented gradient change in only one fuzzy phenomenon boundaries such as vegetation cover. However, in multiple fuzzy class area or complex fuzzy phenomena such as mangrove forests, in the northwest of the Qeshm Island, Hormozgan, Iran, displaying several fractional covers may cause confusion and misunderstanding for the end-user. In this study, an additive color composite and spectral mixture analysis method is utilized for multiple fractional cover representation. The proposed method is implemented on images acquired from Operational Land Imager (OLI) sensor in the Landsat 8 satellite to extract three fractional covers (water, vegetation, and soil). An RGB color composite was used for each type and percentage of fractional cover for given pixel to display fractional cover separately. Based on such RGB color composite represented both quantitative and qualitative information, we used the RGB color solid cube as map legend for better understanding and map interpretation. The result of this study showed that suggested sub-pixel visualization method, gives new vision to the end-user understanding of fuzzy phenomena.

Keywords: sub-pixel visualization, fuzzy Phenomena, RGB color composite, mangroves forest.

Introduction

Satellite imagery is considered as one of the major spatial data sources to extract information for users. However, since the available satellite images are unclassified, it has always been one of the expert's challenges in this field. Band combination, different types of image enhancement (e.g., band rationing, indices, filters and principal component analysis) and image fusion are existing methods developed for satellite images representation enhancement for better understanding and extract information easily. In some cases, the satellite images (e.g. Landsat (30×30 m)) has an average spatial resolution and the ground surface coverage (urban areas, fuzzy boundaries) has high complexity, therefore the sensor recorded response for each pixel is weighted combination of pure spectrum for any material in the instantaneous field of view (IFOV) of pixel.

There are different methods for sub-pixel extraction in mixed pixels. Some common methods are as follows: Spectral mixed analysis (SMA) (Adams et al., 1995), Normalized spectral mixed analysis (NSMA) (Wu, 2004) and Multiple-end member spectral mixture analysis (MESMA) (Roberts et al., 1998). However, the obtained fractional cover representation from these methods to provide visual information for users is still a challenge for the scientists.

1. Background and related works

1.1. Fuzzy boundaries

The boundary of geographical phenomena is in crisp and fuzzy forms. The crisp boundaries can be prepared with an arbitrary precision depending on the data acquisition techniques. Fuzzy boundaries, unlike the crisp boundaries, are not accurate lines, but they are as a transition zone. Crisp boundaries are mostly used for displaying human-made phenomena such as building boundary; whereas, the fuzzy boundaries are mostly based on the natural phenomena. Geographical information (including remote sensing data) always faced with imprecision and two phenomena boundaries cannot be determined clearly, which is considered as fuzzy boundaries.

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In classical classification logic, a pixel can only be assigned to particular coverage. In this technique, all phenomena (even phenomena are not measured) are only assigned to one class, while being aware that each pixel can have more than a single value and may include different phenomena (mixed pixels). In applying of the data with uncertainty, the fuzzy sets are suitable instruments. In fuzzy classification, "pixel membership" is defined with different membership value in one class (Jensen, 2005). Ambiguity and uncertainty are considered equivalent to being fuzzy. Being fuzzy is a type of imprecision in descriptive classes which cannot have defined boundaries due to different reasons. These imprecisely defined classes are called fuzzy sets (Burrough & Frank, 1996).

1.2. Fuzzy boundary visualization

Visualization is a computer-aided process to depict information on the screen. Geographical data representation, a specific type of visualization on digital maps, is classified in two classes: certain and uncertain map visualization (Barré, 2013). Most of the developed visualization techniques are based on a precise hypothesis from information, and there is no ambiguous information in the image, which has a certain result. Uncertainty is difficult to perceive in traditional maps; as they are not expressed in a clear method (Zhang, 2008). As a result, the object nature specifies the type of visualization method.

A fuzzy spatial object in GIS is often considered for spatial, non-spatial (attribute) and temporal elements. Multiple-membership maps (sub-pixel) display more details and can provide better vision for GIS modeling than polygon maps. Membership maps are applicable for generating colorful maps (Hengl et al., 2002). However, a major challenge for planners to correctly determine some features when continuous features represented by a crisp boundary (Zhang, 2008). The accuracy and uncertainty of fuzzy maps cannot be directly quantified with indices developed for crisp boundary categorizations (Zlinszky & Kania, 2016). Hengl et al. (Hengl, 2003; Hengl et al., 2002, 2004) proposed a technique for map visualization with multiple-membership value (mixed pixels) and presented uncertainty situations with spatial predictions of continuous and crisp variables. They utilized models based on the Hue-Saturation-Intensity (HSI) color model and calculations using the color mixture (CM) concept. In this research, K-means clustering technique is used for six landform parameters in the study area. The legend unit called Fuzzy- metric circular color legend, and two-dimensional legend is suggested to display the maps. Zhang (2008) presented techniques for visualization of the fuzzy objects using various combination of graphics and dynamic visualization variable. The results indicate that spatial planners can be more aware of the fuzzy objects and uncertainty positions by animated representation. In 2013, Barré proposed techniques for visualization of uncertainty positions (a case study of coastal boundaries) in his dissertation. Techniques such as gradients, transparency, and random points are suggested for these positions. Zlinszky and Kania (2016) proposed new techniques for improving the visualization of fuzzy classification maps based on random forest techniques. He applied the alternative method called Hue-preserving rendering, which avoids generating new colors.

Sub-pixel mapping which is mostly referred as mapping with high resolution is a technic for estimation of the spatial distribution of land cover classes in sub-pixel scale (Atkinson, 1997). Soft classification can assign maps, which display different classes of land cover in a mixed pixel. Sub-pixel mapping can be considered as a post-processing of soft classification (Foody, 2002). The key issue with sub-pixel mapping is how to explain the spatial and temporal dependency of land cover classes (Atkinson, 2009). The output of sub-pixel information extraction models is fractional cover maps of interested class (end-member), with membership values between zero (meaning lack of a particular cover in a pixel) and one (meaning there is a pure pixel of a particular coverage). The obtained fractional cover can be displayed separately in continuous or combinational maps (Powell et al., 2007). Gong et al. (2015) used a two-dimensional color ramp (red, white and cyan) to display two fractional covers (land and marine vegetation) simultaneously on a map. Based on this color scale, the pure red related to the dense marine vegetation while the pure cyan related to the dense land vegetation. A composite of the red and cyan tones indicates different vegetation density with different mixed variations. Reschke and Hüttich (2014) used pixels with membership value of 50% and higher to display four continuous covers of land (marshland, mudflats, rivers/channels and water bodies) in wetland regions in a map.

2. Study area and data

The study area is mangrove forests in the northwest of the Qeshm island, Hormozgan, Iran (Figure 1). Mangrove forests play an important role in coastal areas, biogeochemical cycle and economic activity such as aquaculture and fishing (Thu & Populus, 2007). Mangroves islands are the unique vegetation of tropical and subtropical intertidal lands with ecological significance (Peng et al., 2009). Mangrove systems in the North West of Qeshm Island exclusively composed of mangrove growing in the intertidal zone above the 3–6 meters tree height. Mangrove floor completely flooded only during the spring tide (Shahraki et al., 2016). The tides occur twice a day with an intertidal range of 1 to 3 meters at low tide and 3 to 4 meters in spring tide (Reynolds, 2002). According to the features listed, mangrove is an appropriate area to show fuzzy boundaries and phenomena. Figure 1 shows the position of the study area, mangrove photos and infrared color composite of Landsat 8 imagery. Landsat imagery (obtained on June 8, 2016, from 160 passes and 41 rows) were used to sub-pixel feature extraction in mangrove forests.

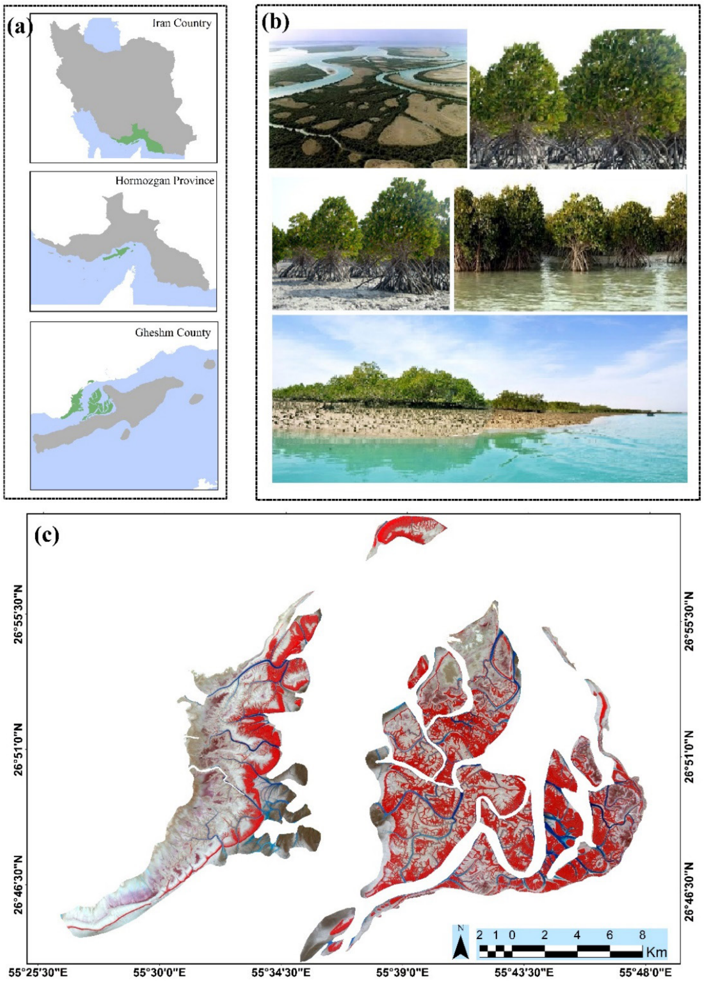

Figure 1. a – Location of the study area; b – in situ photos of mangrove forests; c – infrared color composite image from Landsat 8

3. Approach and methods

3.1. Spectral Mixture Analysis (SMA)

Before any professional processing, a series of pre-processing such as geometric, radiometric and atmospheric correction should be applied on satellite images. After preprocessing, SMA methods including two steps. First, select the appropriate endmember and then implement the SMA.

3.1.1. Endmember selection

The most important step in applying SMA is the selection of appropriate endmembers. There are two types of endmembers; "reference endmember" which is collected in a laboratory or field setting using an imaging spectrometer; and "image endmembers" which is derived from the image itself or other images. There are several ways to select endmembers of the image. Most common method for endmember selection is to extract spectra of pixels from homogeneous areas of known materials using high-resolution images (Myint & Okin, 2009), select endmember using two-dimensional plots (Small, 2005) and using pixel purity index (PPI) (Franke et al., 2009). Typically, a principal component (PC) transformation is utilized to facilitate the selection of image endmembers in multi-spectral satellite data such as Landsat series (Wu, 2004). Here, we used PC analysis on landsat8 images for select endmembers. After the transformation, spectral scatterplots (feature spaces) are generated, and the vertices of these plots are typically chosen as endmembers after verification with reference data.

3.1.2. Implementation of the SMA method

Almost every pixel of satellite images (especially in low and middle-resolution images), the signal recorded by a sensor includes reflectance from multiple land-cover components. The digital number (DN) for each pixel is the weighted sum of the pure spectra of each cover in the pixel's IFOV. SMA method calculates the proportion of each endmember in given mixed pixel; in general, these are assumed to be correlated with the area covered by each material present. The output of SMA is a set of images representing the fractional cover of each endmember, with DN values typically scaled between zero and 1 (i.e., zero representing "not present" and 1 representing 100%

cover). For a given pixel, SMA can be described as follows (Adams et al., 1986; Roberts et al., 1990):

$$DN_i = \sum_{j=1}^{K} F_j \cdot DN_{i,j} + e_i,$$

where DN_i is the measured value of a pixel in band i in DNs recorded by the sensor or in units of radiance or reflectance, F_j is the fraction of endmember j present in the pixel's IFOV, DN_{ij} is the value of the endmember j in band i, and e_i is the residual or the difference between observed and modeled DNs for bandi. There are N bands in the dataset and K endmembers in the mixture model.

In addition, the mixing equation is subject to the following constraint:

$$\sum_{j=1}^{K} F_j = 1,$$

i.e., the fraction of endmembers for each pixel must sum to 1 (or 100% cover). Per-pixel RMS error is effectively the mean residual across all bands, given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} e_i^2}{N}}.$$

3.2. Display of sub-pixel using RGB color model

Digital remote sensor data are usually displayed using a Red-Green-Blue (RGB) color coordinate system, which is based on additive color theory and three primary colors (Jensen, 2005; Westland & Cheung, 2012). In RGB color model each color appears as spectral components of red, green and blue. The RGB color model is an additive color model in which red, green and blue light are added together in various ways to reproduce a broad array of colors. If a mixed pixel is containing three classes (A, B and C), and create an RGB color composite image using the fractional cover of each class, the percentage of each class in RGB color composite is calculated from following equations and illustrated as a chart shown in Figure 2.

$$Class\,A = \frac{R}{R+G+B} \cdot 100;$$

$$Class\,B = \frac{G}{R+G+B} \cdot 100;$$

$$Class\,C = \frac{B}{R+G+B} \cdot 100.$$

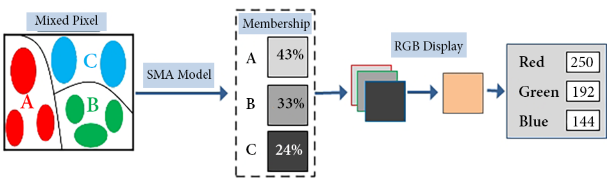

Figure 2. Graphical chart of transformation fractional images to RGB color component

4. Results and discussion

Regarding the existing coverage of the mangrove forests (water, vegetation cover, soil), three end-members were selected for the extraction of sub-pixels. Figure 3 shows the reflection of three pure end-members with the reflection of mixed pixels. The percentage of each land cover in pixels is determined based on how similar the reflection of other pixels is to the reflection of the end-members' pixels, which are entered to the SMA model by the user.

For example, if the reflection of pixel X is linearly 60 percent similar to the reflection of pure soil, 30 percent similar to the reflection of pure vegetation cover, and 10 percent similar to the reflection of pure water, then SMA model considers these percentages as a proportion of each coverage in that pixel.

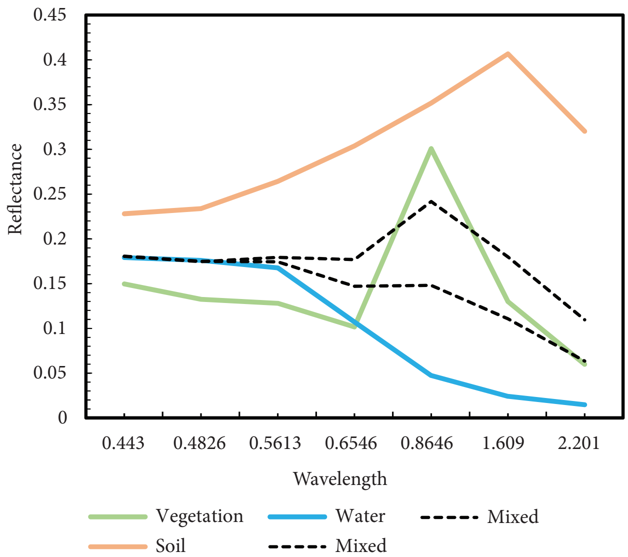

Figure 3. Spectral signatures of the three selected endmembers with reflection of mixed pixels

The output of SMA model is the images of fraction cover, equal to the number of presented input end-members. Fraction images of a special coverage are a continuous value between zero (meaning the absence of special coverage on one pixel) and one, which means a pure pixel of special coverage.

In this study, three end-members, as representative of land covers present in the region were introduced to the model; and output is three images of fraction image with an image that shows the RMSE level of the model. Figure 4 shows fraction vegetation cover (FVC), fraction soil cover (FSC), and fraction water cover (FWC) along with RMSE. To improve the readability and clarity, each pixel of the image in a pure coverage was shown as a percentage of that coverage.

5. Fuzzy display of mangrove forests

The boundaries of fuzzy phenomena cannot be clearly displayed because the border of any phenomenon is in the form of the transition area. One of the most common

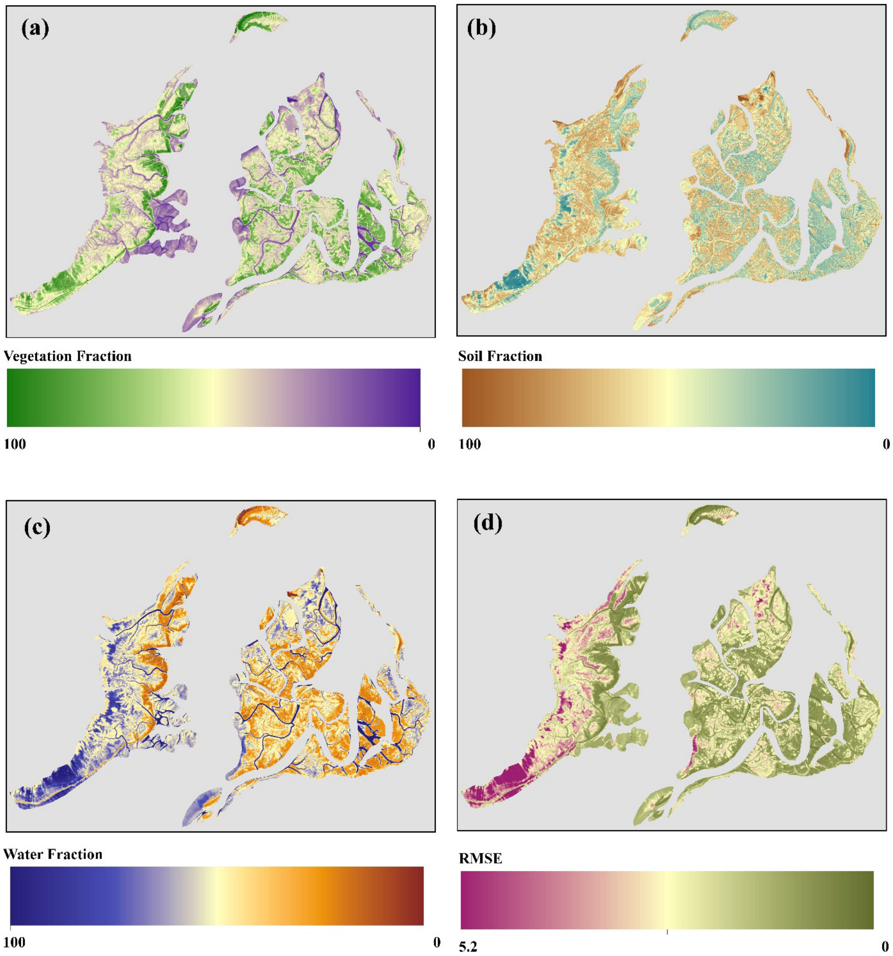

Figure 4. The images of output fraction cover of SMA model: a – fraction vegetation cover; b – fraction Soil; c – fraction Water; d – RMSE level of the model

methods of displaying fuzzy borders is display with membership grade, in which each pixel is given a grade between 1 and 0. That means when we move from a special cover toward the borders, the membership grade of pixels to that cover reduces and tends to zero, while in a pixel with pure cover, membership grade equals one.

Figure 5 shows the fraction vegetation cover in the areas of mangrove forests and is displayed with a color range from green (100% membership grade) to purple (0% membership grade) which is a method to display continuous areas. In continuous areas, the values are variable, and each pixel has one value. Value changes are gradual. In this figure, transition areas are displayed continuously, and the changes are gradual from areas with high membership grade (100%) to low membership grades (zero).

Fraction cover images can also be displayed with discrete areas. In this respect, continuous areas are divided into a series of categories using different methods, and in each category, the values are equal and displayed with one color.

Figure 6 shows membership of pixels to fraction vegetation cover in discrete areas of mangrove forests at a class distance of 10 percent. According to this figure, membership grade of 80 to 100% in some areas is not seen, and the width of transition areas is different in every category.

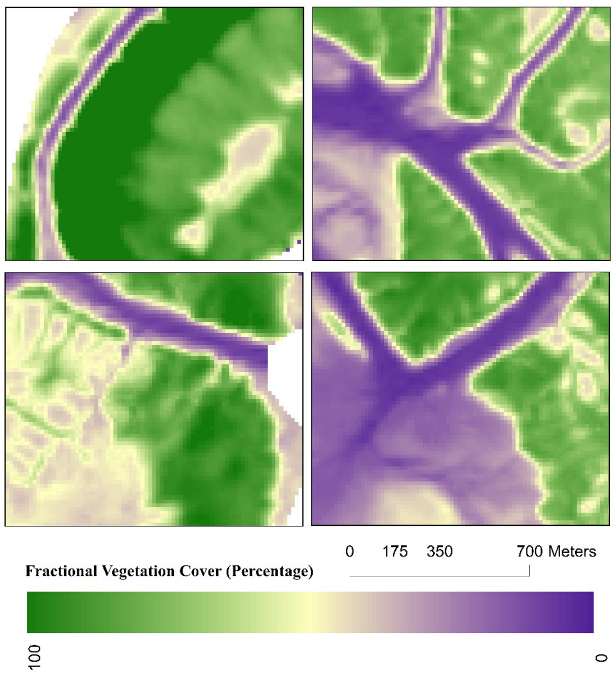

Figure. 5. Display of continuous fraction vegetation cover

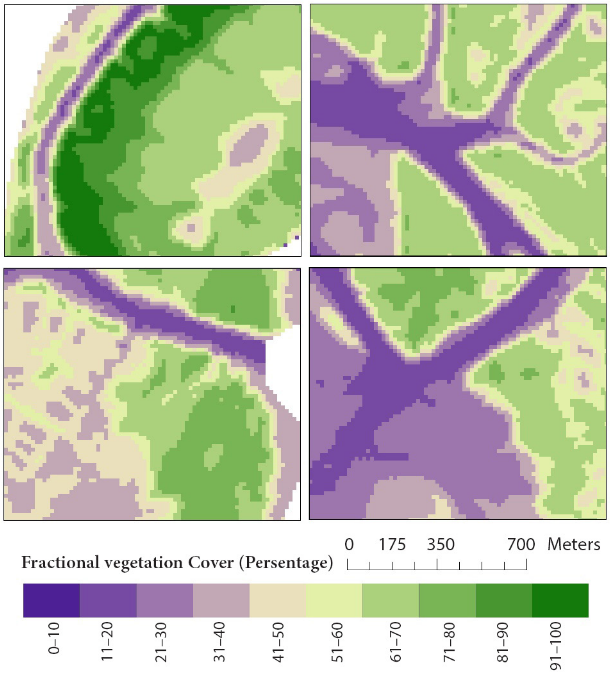

Figure 6. Display of discrete fraction vegetation cover

Fuzzy borders' displays with methods shown in Figures 5 and 6 can be used to display a fuzzy phenomenon using a raster-based method. But if we want to display more of a fuzzy phenomenon, or fuzzy areas altogether, another solution will be needed. One of these solutions is using the theory of additive colors mixing. In this theory, all colors are created by combining the three primary colors of red, green and blue. Therefore, two or three raster layers of fraction cover images can be displayed simultaneously on the map using this theory. Colors appeared in the final map represent a certain percentage of each cover in a particular pixel (relations 4 to 6).

Figure 7 displays color combinations of two or three covers in the area on the same scale of Figures 5 and 6. Here, color images were created by assigning fraction cover images with grayscale to one of the colors red, green and blue in RGB color model (Figure 7a). In some images, only two covers were used to combine the output color (Figure 7b, c, and d). Colors seen in the output image represent a percentage of each of the three covers according to mentioned relations.

Also in discrete fields, RGB color combinations can be used for display. In discrete fields, every category defines the type of output color according to the value it bears; and the percentage of each cover in color images can be specified using relations 4 to 6. Figure 8 shows RGB color images from discrete fields.

An important issue here, also seen in the display of RGB color combination of sub-pixel images, is the map guide issue. In conventional displays of satellite images by RGB color combination method, different bands are combined for better visualization of the effects on the Earth's surface.

The outcome of this process gives a qualitatively good insight to the user to visually separate the objects on the Earth's surface. But in showing fuzzy sub-pixel objects, our data is quantitative, and each data displays a percentage of a special cover on a pixel. So a guide is needed which can provide the user with both qualitative and

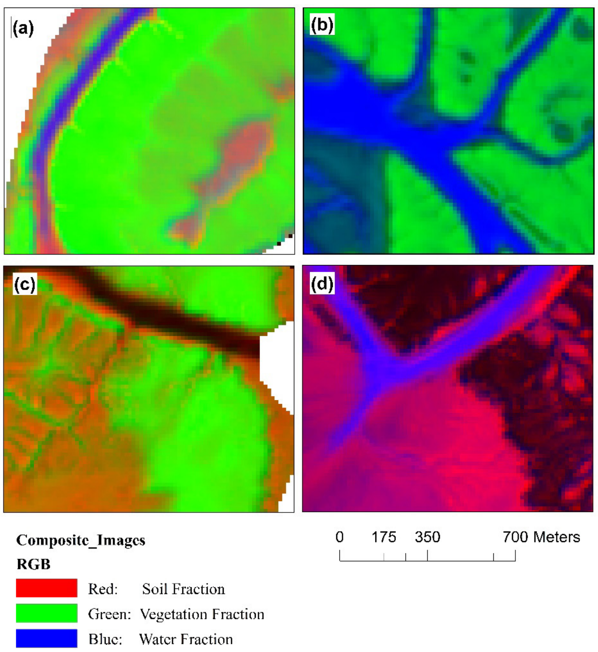

Figure 7. RGB displays of (vegetation, water, and soil) cover in the continuous area: a – RGB color combination (soil: red, vegetation: green and water: blue); b – RGB color combination (soil: off, vegetation: green and water: blue); c – RGB color combination (soil: red, vegetation: green and water: off); d – RGB color combination (soil: red, vegetation: off and water: blue)

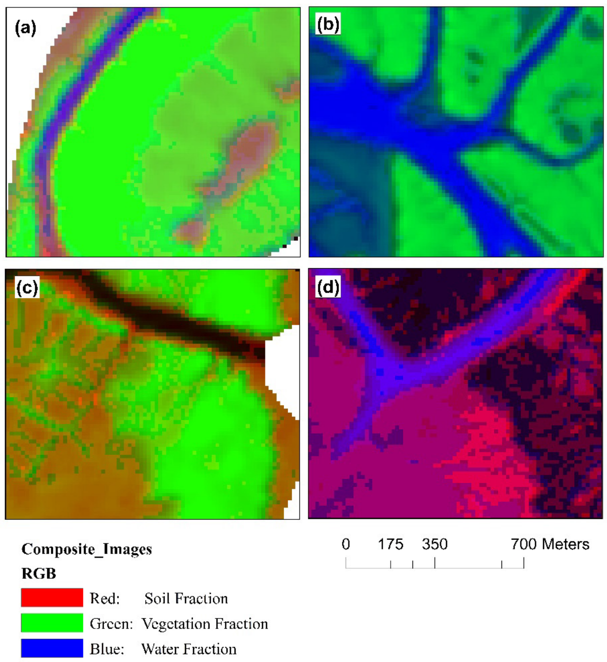

Figure 8. RGB displays of (vegetation, water, and soil) cover in the Discrete area: a – RGB color combination (soil: red, vegetation: green and water: blue); b – RGB color combination (soil: off, vegetation: green and water: blue); c – RGB color combination (soil: red, vegetation: green and water: off); d – RGB color combination (soil: red, vegetation: off and water: blue)

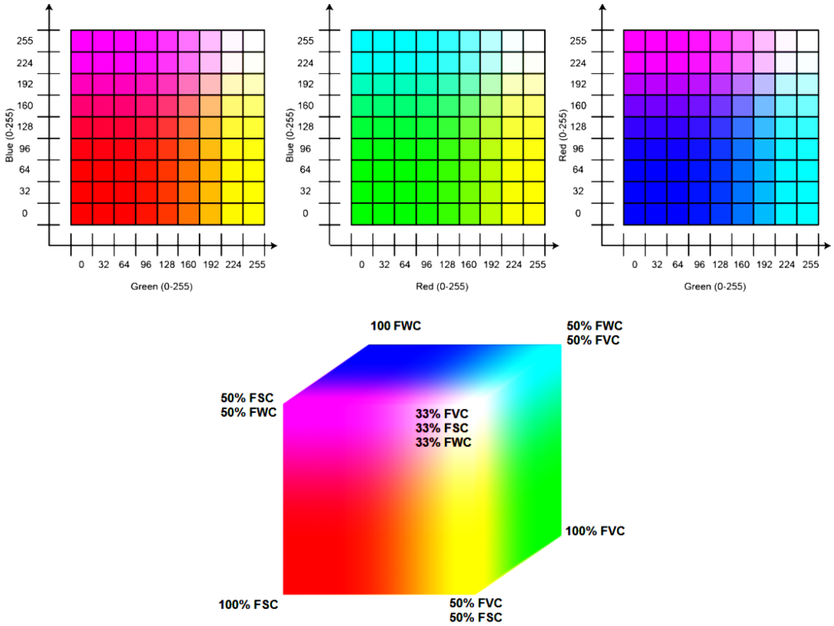

Figure 9. Gradual changes in the combination of the primary colors

quantitative information. That requires the color guide to be representative of the special cover (for example, the green color range for the vegetation cover), and to use a special number range for each color combination which would represent the percentage of different covers.

Figure 9 shows the Gradual changes of the primary color combinations. The numbers 0 to 255 of color combinations can be turned into number range of 0 to 100 using relations 4 to 6 and can be used as a guide for color images resulting from mixed pixels.

Since the studied area in this research is mangrove forests, and in these areas, there are three covers of vegetation, soil, and water in mixed pixels, then RGB color cube was used as a guide. In this guide, primary colors of red, green and blue represent the membership grades of 100% for soil, vegetation and water covers, respectively. Turquoise color shows pixels with 50 percent vegetation and 50 percent water cover. Purple and yellow colors show pixels with 50% water and 50% soil, and 50% soil with 50% vegetation, respectively. White color shows pixels with a membership equal to 33 percent of each three covers, and since the sum of outputs of SMA model equals 1, therefore there is no pixel which displays no color, and the black color does not exist in the created color image.

Figure 10 shows the RGB color image of the three covers present in the entire region, as well as the RGB cube as

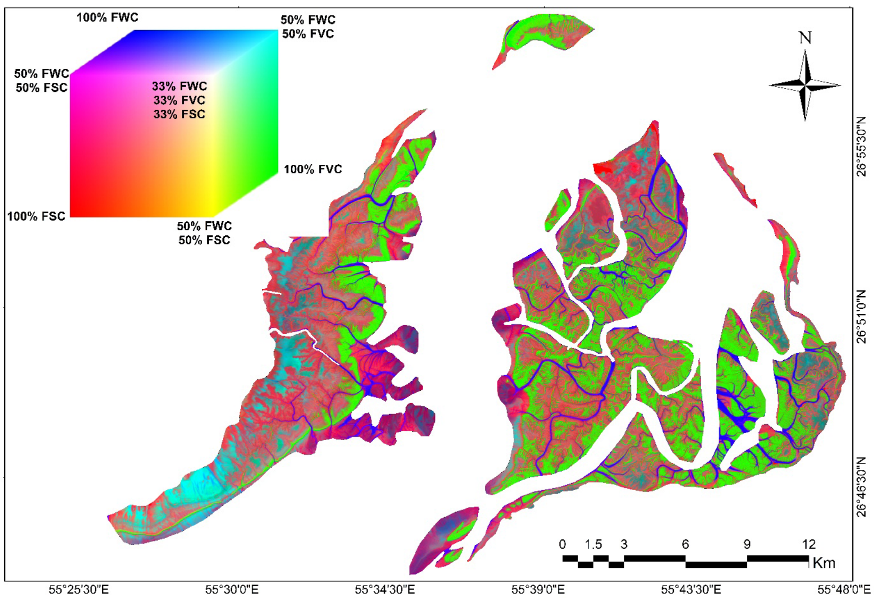

Figure 10. RGB color image from three covers in the entire region with RGB cube as a guide

a guide. By looking at the map guide, the user not only can identify the present covers, but also can have an insight of the percentage of mixed pixels in the area.

Conclusions

This study aimed to provide a method for improving the visualization of satellite images with mixed pixels as well as a better display and understanding of the fuzzy phenomena and different classes of ground cover. A common method of visualizing the digital satellite images is using RGB-color coordinates system based on additive color theory and the three primary colors red, green and blue.

In this method, images for different bands are placed on the banks of colors, red, blue and green, for a color image to be created for visual interpretation. Typical color combinations include true color combination, infrared color combination, and false color combinations. The resulting color combinations contain qualitative information from a certain area and don't provide the users with quantitative information.

A method of extracting quantitative information from land covers, is the practice of sub-pixel methods on satellite images, the output of which is continuous images from a special cover. Visualization of multiple fraction cover maps from one area is still challenging.

As discussed earlier, borders of fuzzy phenomena cannot be clearly demonstrated. Thus, a continuous and discrete display of different covers on earth's surface in areas of mangrove forests (water, soil and vegetation cover) which are considered part of fuzzy phenomena was provided using the RGB color space and the membership grade of each class in a particular pixel.

Adopting additive RGB color combination theory, images of two or three raster classes from fraction cover images were displayed simultaneously on the map, and the obtained colors are a certain percentage of each cover in a specific pixel.

To fix and have a better visual perception of the extracted maps by users, a guide was used in the form of RGB color cube. One of the benefits of using this color cube in map legend is to shed more light on the available covers in images' pixels, and the percentage of mixed pixels, which is perfectly tangible and visible for users.

References

Adams, J. B., Sabol, D. E., Kapos, V., Almeida Filho, R., Roberts, D. A., Smith, M. O., & Gillespie, A. R. (1995). Classification of multispectral images based on fractions of endmembers: Application to land-cover change in the Brazilian Amazon. *Remote sensing of Environment*, *52*(2), 137–154. https://doi.org/10.1016/0034-4257(94)00098-8

Adams, J. B., Smith, M. O., & Johnson, P. E. (1986). Spectral mixture modeling: A new analysis of rock and soil types at the Viking Lander 1 site. *Journal of Geophysical Research: Solid Earth*, *91*(B8), 8098–8112. https://doi.org/10.1029/JB091iB08p08098

Atkinson, P. M. (1997). Mapping sub-pixel boundaries from remotely sensed images. In Z. Kemp (Ed.), *Innovations in GIS 4* (pp. 166–180). Taylor and Francis.

Atkinson, P. M. (2009). Issues of uncertainty in super-resolution mapping and their implications for the design of an inter-comparison study. *International Journal of Remote Sensing*, *30*, 5293–5308. https://doi.org/10.1080/01431160903131034

Barré, B. A. (2013). *Techniques for the visualization of positional geospatial uncertainty* [Master thesis]. University of New Orleans.

Burrough, P. A., & Frank, A. (1996). *Geographic objects with indeterminate boundaries* (1st ed.). CRC Press.

Foody, G. M. (2002). The role of soft classification techniques in the refinement of estimates of ground control point location. *Photogrammetric Engineering and Remote Sensing*, *68*, 897–903.

Franke, J., Roberts, D. A., Halligan, K., & Menz, G. (2009). Hierarchical multiple endmember spectral mixture analysis (MESMA) of hyperspectral imagery for urban environments. *Remote Sensing of Environment*, *113*(8), 1712–1723. https://doi.org/10.1016/j.rse.2009.03.018

Gong, Z., Cui, T., Pu, R., Lin, C., & Chen, Y. (2015). Dynamic simulation of vegetation abundance in a reservoir riparian zone using a sub-pixel Markov model. *International Journal of Applied Earth Observation and Geoinformation*, *35*, 175–186. https://doi.org/10.1016/j.jag.2014.09.004

Hengl, T. (2003, January). Visualisation of uncertainty using the HSI colour model: Computations with colours. In *7th International Conference on GeoComputation*. University of Southampton, United Kingdom.

Hengl, T., Walvoort, D. J., & Brown, A. (2002, January). Pixel (PM) and colour mixture (CM): GIS techniques for visualization of fuzziness and uncertainty of natural resource inventories. In *5th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences (Accuracy 2002)*. Delft University Press.

Hengl, T., Walvoort, D. J., Brown, A., & Rossiter, D. G. (2004). A double continuous approach to visualization and analysis of categorical maps. *International Journal of Geographical Information Science*, *18*(2), 183–202. https://doi.org/10.1080/13658810310001620924

Jensen, J. R. (2005). *Introductory digital image processing* (3rd ed.). Prentice Hall.

Myint, S. W., & Okin, G. S. (2009). Modelling land-cover types using multiple endmember spectral mixture analysis in a desert city. *International Journal of Remote Sensing*, *30*(9), 2237–2257. https://doi.org/10.1080/01431160802549328

Peng, Y., Chen, G., Tian, G., & Yang, X. (2009). Niches of plant populations in mangrove reserve of Qi'ao Island, Pearl River Estuary. *Acta Ecologica Sinica*, *29*(6), 357–361. https://doi.org/10.1016/j.chnaes.2009.09.017

Powell, R. L., Roberts, D. A., Dennison, P. E., & Hess, L. L. (2007). Sub-pixel mapping of urban land cover using multiple endmember spectral mixture analysis: Manaus, Brazil. *Remote Sensing of Environment*, *106*(2), 253–267. https://doi.org/10.1016/j.rse.2006.09.005

Reschke, J., & Hüttich, C. (2014). Continuous field mapping of Mediterranean wetlands using sub-pixel spectral signatures and multi-temporal Landsat data. *International Journal of Applied Earth Observation and Geoinformation*, *28*, 220–229. https://doi.org/10.1016/j.jag.2013.12.014

Reynolds, R. (2002). *Oceanography. The Gulf ecosystem: Health and sustainability* (pp. 55–64). Backhuys Publishers. https://doi.org/10.14321/j.ctt1tm7jkg.11

Roberts, D. A., Gardner, M., Church, R., Ustin, S., Scheer, G., & Green, R. O. (1998). Mapping chaparral in the Santa Monica Mountains using multiple endmember spectral mixture models. *Remote Sensing of Environment*, *65*(3), 267–279. https://doi.org/10.1016/S0034-4257(98)00037-6

Roberts, D. A., Adams, J. B., & Smith, M. O. (1990, May 20–24). Transmission and scattering of light by leaves: Effects on spectral mixtures. In *Proceedings of IGARSS* (pp. 1381–1384). College Park, Maryland, USA. IEEE. https://doi.org/10.1109/IGARSS.1990.688757

Shahraki, M., Saint-Paul, U., Krumme, U., & Fry, B. (2016). Fish use of intertidal mangrove creeks at Qeshm Island, Iran. *Marine Ecology Progress Series*, *542*, 153–166. https://doi.org/10.3354/meps11546

Small, C. (2005). A global analysis of urban reflectance. *International Journal of Remote Sensing*, *26*(4), 661–681. https://doi.org/10.1080/01431160310001654950

Thu, P. M., & Populus, J. (2007). Status and changes of mangrove forest in Mekong Delta: Case study in Tra Vinh, Vietnam. *Estuarine, Coastal and Shelf Science*, *71*(1), 98–109. https://doi.org/10.1016/j.ecss.2006.08.007

Westland, S., & Cheung, V. (2012). RGB systems. In J. Chen, W. Cranton, & M. Fihn (Eds.). *Handbook of visual display technology* (pp. 147–153). Springer. https://doi.org/10.1007/978-3-540-79567-4_12

Wu, C. (2004). Normalized spectral mixture analysis for monitoring urban composition using ETM+ imagery. *Remote Sensing of Environment*, *93*(4), 480–492. https://doi.org/10.1016/j.rse.2004.08.003

Zhang, Q. (2008). *Animated representation of uncertainty and fuzziness in spatial planning maps* [MSc Thesis]. ITC, Enschede.

Zlinszky, A., & Kania, A. (2016, June). Will it blend? Visualization and accuracy evaluation of high-resolution fuzzy vegetation maps. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XXIII ISPRS Congress* (Vol. XLI-B2, pp. 335–342). https://doi.org/10.5194/isprsarchives-XLI-B2-335-2016