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Evaluating the potential of image fusion of multispectral and radar remote sensing data for the assessment of water body structure

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ABSTRACT

The European Water Framework Directive (Directive 2000/60/EC) is a mandatory agreement that guides the member states of the European Union in the field of water policy to fulfil the requirements for reaching the aim of the good ecological status of water bodies. In the last years several workflows and methods were developed to determine and evaluate the characteristics and the status of the water bodies. Due to their area measurements remote sensing methods are a promising approach to constitute a substantial additional value. With increasing availability of optical and radar remote sensing data the development of new methods to extract information from both types of remote sensing data is still in progress. Since most limitations of these data sets do not agree the fusion of both data sets to gain data with higher spectral resolution features the potential to obtain additional information in contrast to the separate processing of the data. Based thereupon this study shall research the potential of multispectral and radar remote sensing data and the potential of their fusion for the assessment of the parameters of water body structure. Due to the medium spatial resolution of the freely available multispectral Sentinel-2 data sets especially the surroundings of the water bodies and their land use are part of this study. SAR data is provided by the Sentinel-1 satellite. Different image fusion methods are tested and the combined products of both data sets are evaluated afterwards. The evaluation of the single data sets and the fused data sets is performed by means of a maximum-likelihood classification and several statistical measurements. The results indicate that the combined use of different remote sensing data sets can have an added value.

Keywords: Sentinel 1, Sentinel 2, image fusion, maximum likelihood

1. INTRODUCTION

The plurality of missions for earth observation leads to an increasing amount of remote sensing data that will have an important impact on the comprehension of dynamic processes and trends of the geosphere and biosphere. The utilization of remote sensing data has proved to be an effective instrument for the observation of the earth surface and the atmosphere on a global, regional and local scale. It provides important information about the dimension and classification of natural and man-made objects and properties of the earth surface and is able to establish a relationship between these objects and properties. The utilised airborne and space-borne sensors used for earth observation are capable to acquire information at different spectral wavelengths ranging from the visible part of the electromagnetic spectrum to infrared and microwave at different temporal resolutions ranging from more than one observation per day and spatial resolutions ranging from sub-metre to several kilometres which allows the provision of a variety of information about the earth surface.¹ This gives rise to the possibility and necessity to combine these data to achieve the greatest possible benefit. The data can be acquired by different sensors at the same time or by one sensor acquiring data over a longer period of time.² The earth observation and environmental monitoring program Copernicus (formerly GMES, Global Monitoring for the Environment

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and Security) which represents the European contribution to the Global Earth Observation System of Systems program (GEOSS) under the supervision of the European Union in cooperation with the member states as well as the European Space Agency (ESA) shall provide reliable information in the fields of environment and security. It implements an operative system in the form of the Sentinel missions to provide a systematic acquisition of remote sensing data, which can also be used to support the implementation of the European Water Framework Directive.³

The European Water Framework Directive (Directive 2000/60/EC)⁴ of the European Union forms the basis for sustainable water politics with the objective of achieving the good ecological status of surface water and groundwater resources. The Working Group on water issues of the Federal States and the Federal Government (LAWA) of Germany has developed a mapping approach for on-site and overview mapping. Remote sensing data provides the basis for overview mapping. These data has served for the determination of a variety of parameters: chlorophyll-a (chl-a),⁵⁻⁷ total suspended matter, turbidity and Secchi depth⁸⁻¹⁰ and water surface temperatures.^{5,11,12} The determination of the river centreline with the help of remote sensing data was tested by Karrasch et al. (2015),¹³ the comparison of this centreline with administrative data was conducted by Karrasch and Hunger (2016).¹⁴

An additional value can be generated by the use of data from different systems at the same time which are used independent of each other. Another possibility to use these different data sets is to combine them to form a new data set which replaces the original data. The aim of this study is to test various image fusion techniques to combine the data of Sentinel-2A and Sentinel-1A and to provide information concerning their usability.

The study area (cf. Figure 1) is situated in the catchment area of the river Freiburger Mulde between the two cities Nossen and Leisnig. The Freiburger Mulde originates in the Eastern Ore Mountains in the Czech Republic. After 124 km the Freiburger Mulde merges with the Zwickauer Mulde to form the river Vereinigte Mulde. The catchment area covers an area of 2918 km² and is characterised by agricultural areas and meadows. The annual precipitation ranges from 650 mm/m² to 1230 mm/m².¹⁵

Figure 1. Study Area

2. DATA AND IMAGE FUSION

The exact definition of the term data fusion proves itself to be difficult and there exists a variety of different definitions for example formulated by Mangolini (1994),¹⁶ Mastrogiovanni et al. (2007)¹⁷ or McGirr. (2001).¹⁸ In 1996 the established working group of the European Association of Remote Sensing Laboratories (EARSeL) and the french Société de l'électricité, de l'électronique et des technologies de l'information et de la communication (SEE) had the task to find a definition which is not restricted to data acquired by a sensor, type of information, methods and techniques or system architectures. The final definition was presented in 1998: "data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application".^{19,20} The fusion of images is a branch of data fusion. For a variety of applications images acquired by only one sensor are not sufficient in order to obtain reliable information about specific objects or areas.^{21,22} The quality of an image is influenced by illumination constraints, image sharpness, image noise and image contrast. A multitude of sensors is available that capture images at wavelengths ranging from x-ray, visible and infrared to microwave.^{2,21}

Goshtasby and Nikolov (2007)²¹ define image fusion as follows: "Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task."

Smith and Heather (2005)²³ provide three essential requirements for image fusion:

- The resulting image shall contain all important information from the original data sets
- The process of image fusion shall not introduce artefacts or inconsistencies to the resulting image
- Unwanted properties of the original images such as image noise shall be decreased or removed in the resulting image

According to Pohl und van Genderen (1998)²⁴ the process of image fusion can be divided into three processing levels:

- pixel-level
- feature-level
- decision-level

Several authors provide different classifications. Ehlers et al. (2010)²⁵ classified these processing levels as iconic, symbolic and knowledge level whereas Goshtasby und Nikolov (2007)²¹ used low-, mid- and high-level to describe the different processing levels.

Image fusion on the pixel-level can be referred as the lowest processing level concerning the fusion of measured physical parameters.²⁴ The pixels of the original images are combined to a new image with the help of a well-defined algorithm. The new image can be used for classifications and feature extraction.²⁶ The co-registration and in most cases georeferenced raster data form the basis for the image fusion process. Co-registration constitutes an important processing step since an omission or inaccurate realisation will lead to a false representation of colours and objects.²⁴

The fusion on the feature level requires the detection and identification of image objects in the individual data sets.²⁴ Therefore every data set is processed on its own to emphasise the different features.^{26,27} These features can be divided into spectral features such as texture and grey value occurrence and geometrical features such as form and size.²⁸ By means of these features corresponding image objects can be extracted from the different data sets.²⁶

In contrast decision-level fusion requires the results of the individual analysis of each data set. With the help of rulesets the obtained information is combined to improve the interpretation of the data and to obtain a wide spectrum of information about the observed objects.²⁴

The existing methods for pixel-level fusion can be grouped into colour-related techniques, statistical/numerical methods and combined methods.²⁴ Ehlers et al. (2010)²⁵ also used this classification; however they distinguished between statistical and numerical methods.

The presented examples demonstrate a selection of common methods which are used in a multitude of studies to combine low resolution multispectral images and high resolution panchromatic images^{29–31} or to fuse multispectral images and radar images^{32,33} on the pixel level.

3. METHODS

3.1 Methods of image fusion

3.1.1 Colour-related techniques

Colour composites

Colour composites represent a simple possibility to combine information from different images. The original images respectively spectral bands are assigned to one of the three additive primary colours. The use of more than three spectral bands leads to an image layer stack that offers different combinations when assigning these images to the primary colours.²⁴

Intensity Hue Saturation (IHS) Transformation

The RGB colour space model is based on the idea that all possible colours can be created by combining the three additive primary colours with different fractions. To use the IHS transformation as an image fusion technique the image data has to be transformed into the IHS colour space. Each component of an image is expressed by its intensity I, its hue H and its saturation S.³⁴ In the further course of the process the intensity component is swapped for the high resolution panchromatic band or the radar data. To utilize the range of values between 0 and 1 the panchromatic or radar data is matched to the original intensity component. This results in a comparable mean and standard deviation for the panchromatic or radar data and the intensity component. The last step comprises the backward transformation to the RGB colour space of the modified data set.^{35,36} Nevertheless only three spectral bands can be used at the same time. A layer stack consisting of more than three spectral bands has to be processed successively.

3.1.2 Statistical techniques

Principle Component Transformation/ PC Spectral Sharpening

The principle component transformation is a common used method to compress and restructure the information of datasets by omitting redundant information and decreasing the dimensionality which is expressed by a fewer quantity of spectral bands. If used in the case of image fusion the histogram of the panchromatic band or radar data is matched and the data swapped for the first principle component. The fused image can be obtained by performing an inverse principle component transformation.^{35,37}

Gram Schmidt Spectral Sharpening

The developed method by Laben und Brower (1998)³⁸ utilises a panchromatic band to simulate a panchromatic band with a lower geometric resolution. The subsequent performed Gram-Schmidt transformation is a common method used in linear algebra and multivariate statistics to orthogonalise matrices which removes redundant information in the various spectral bands of a layer stack. The simulated band forms the first band of the image stack which consists of this simulated band and the multispectral bands. The original panchromatic band is swapped for the first band of the image stack. The final image results from a backward Gram-Schmidt transformation. In this study a radar data set was used instead of a panchromatic band.

3.1.3 Numerical techniques - Wavelets

The application of wavelets leads to four new images: one image is low-pass filtered in row and column direction, which is called the approximation image, one row wise high-pass filtered image, which contains the horizontal edge information, one column wise high-pass filtered image, that contains the vertical edge information and one column and row wise high-pass filtered image that contains the diagonal edge information. The column and row wise decrease in resolution leads to transformed images that have only half the size of the original image.³⁹ Both the multispectral data set and the radar data set are disassembled into the above mentioned sub-images. The low-pass image of the original radar data set is swapped for the multispectral data set. The backward transformation generates the fused image. However, each multispectral band has to be fused separately with the radar image.⁴⁰

3.1.4 Combined techniques

Ehlers Fusion

An IHS transformation combined with filter techniques in the frequency domain forms the basis for the fusion of multispectral and radar data sets. In a first step three selected multispectral bands are transformed into the IHS colour space. The histogram of the radar data set is matched to the intensity component and both data sets are transformed into the frequency domain with the help of a 2d Fourier transformation. Whereas the radar data set is filtered with a high pass filter a low pass filter is used to filter the intensity component. The next step comprises the backward transformation of both data sets to the spatial domain where they are summed up. The histogram of the resulting data set is matched to the histogram of the original intensity component. Finally the data set is transformed back to the RGB colour space by an inverse IHS transformation.⁴¹

Wavelets combined with IHS

It is also possible to use wavelets in combination with the IHS transformation. According to Hong and Zhang (2003)⁴² the multispectral data is transformed into the IHS colour space. The histogram of the radar data set is matched to the histogram of the intensity component. The radar data set as well as the intensity component is disassembled into high and low frequency fractions. The low pass filtered component of the radar data set is swapped for the low pass filtered image of the intensity component. The modified intensity component is obtained by an inverse wavelet transformation. This intensity component and the original hue and saturation components are transformed to the RGB colour space.⁴²

Wavelets combined with PCA

The utilisation of wavelets in combination with the principle component analysis is similar to the integration of the IHS transformation. The multispectral data is compressed and restructured to form the principle components. The most important component is the first component. The histogram of the radar data set is matched to the histogram of the first principle component. The modified radar data set as well as the first principle component is divided into four component images using the wavelet transformation. The detail components of the radar data set are added to the first principle component. The fused image is obtained by using the inverse wavelet transformation followed by an inverse principle component transformation.⁴³

3.2 Pre-processing of Sentinel-1 and-2 data

To evaluate the described image fusion methods one Sentinel-1A data set (02.04.2016) and one Sentinel-2A data set (04.04.2016) were acquired. The Sentinel-1A data set is provided as a ground range detected product with a spatial resolution of 10 m. The digital numbers were converted to normalised radar cross-section σ° by the help of ESAs Sentinel Application Platform (SNAP). The selection of an appropriate speckle filter was performed by visual evaluation and the utilisation of the Equivalent Number of Looks (ENL) criteria which uses the mean and the variance of the image area.⁴⁴ The selected median filter with a size of 7x7 performed very well.

$$ENL = \frac{\mu^2}{\sigma^2} \quad (1)$$

Terrain correction was carried out with the help of the implemented Range-Doppler Terrain Correction.

The Sentinel-2A data (Level-1C product) features 13 spectral bands and geometric resolutions ranging from 10 m to 60 m (4 bands in range of the visible and near infrared at 10 m, 6 bands in the range of the near and shortwave infrared at 20 m and 3 bands in the range of the visible as well as the near and shortwave infrared at 60 m). Atmospheric correction was performed using the Sen2Cor plugin in conjunction with SNAP in order to process the Top-Of-Atmosphere (TOA) reflectance data to a Level-2A Bottom-Of-Atmosphere (BOA) reflectance product. The Atmospheric model *summer* and the aerosol model *rural* were used. The visibility value of 65 km was calculated by the use of the Aerosol Optical Depth Values (AOD) derived from the MODIS Atmosphere Product MOD08, which can be acquired through NASA's Giovanni portal⁴⁵ and the formulas provided by ITT (2009):⁴⁶

$$V = \frac{3,912}{\beta} \qquad \beta = \frac{AOD}{2} \qquad (2)$$

Co-registration was carried out using the ENVI 5.0 software package. The resulting data set consist of 10 spectral bands with a geometric resolution of 10 m. The original bands with a spatial resolution of 20 m are resampled to a spatial resolution of 10 m. The bands with a spatial resolution of 60 m are only used to perform the atmospheric correction and are omitted in the final product.

3.3 Maximum Likelihood Classification and Accuracy Assessment

The maximum likelihood classifier uses training sets for every object class and evaluates both the variance and the covariance to assign an unclassified pixel to one of the classes. On the assumption that the distribution of data value forming the training set of a class is normally distributed the reflectance values of a class can be described by the mean vector and the covariance matrix. These values are necessary to compute the membership probability to a class for every unclassified pixel. Every class has its own probability density function which can be used to calculate the membership of an unclassified pixel to a certain class. The membership probability for every class and every unclassified pixel is evaluated and the pixel is assigned to the class which exhibits the maximum probability value.⁴⁷

The generation of a classification error matrix, also known as confusion matrix, is a common used technique to evaluate the result of a classification. In this context the result of the classification is compared to reference data on a category by category basis which provides the basis for several descriptive measures. The overall accuracy is determined by computing the ratio of the total number of correctly classified pixels and the total number of reference pixels. The producer's accuracy describes how well the pixels of the training set of a specific category are classified. It is computed by dividing the number of correctly classified pixels in a specific class by the number of pixels belonging to the training set of that class. In contrast, the user's accuracy is defined as the probability that a pixel assigned to a class represents that class in reality. It is calculated by dividing the number of correctly assigned pixels to a certain class by the total number of pixels that were assigned to that class. The Kappa coefficient, introduced by Cohen (1960),⁴⁸ measures the difference between the actual agreement between the reference data and the classified data and the chance agreement between the reference data and a random classification.⁴⁷ According to Landis and Koch (1977)⁴⁹ the Kappa coefficient exhibits six levels of agreement. Values between 0,81 and 1.0 indicate an almost perfect agreement, 0,61-0,8 a substantial, 0,41-0,6 a moderate, 0,21-0,4 a fair, 0-0,2 a slight and values lower than 0 indicate a poor agreement.⁴⁹

To compare the different fusion techniques five classes were selected that can be easily identified.

1. Water
2. Urban Areas / Settlements
3. Agricultural Areas (Fallow Land)
4. Meadows and Agricultural Areas (Cultivated Land)
5. Forest

4. RESULTS

As a reason of the irradiation of the different object classes and the geometric resolution of the used data sets it was not always possible to detect and classify the course of the river Freiburger Mulde. Especially in the area of the city of Döbeln and in some of the south-eastern areas of the study area where the narrow river is covered by overhanging vegetation the mapping of the water course proved to be difficult. The performed accuracy assessment revealed overall accuracy values between 55.6 % and 86.4 %. Figure 2 shows the results of the classification for a portion of the study area.

The visual evaluation revealed considerable differences between the classification results of the applied image fusion techniques. The classification of the original Sentinel-2A data provided in contrast to the other tested methods one of the best results. The discrimination of urban areas and bare agricultural areas caused some problems especially in the peripheral zones of these bare areas. All other classes were assigned without difficulties. The additional utilization of the Sentinel-1A data led to a slight decrease in overall accuracy. The classification image demonstrates an increase in misclassified bare agricultural areas which is nevertheless not observable from the confusion matrix. However the misclassified pixels that were assigned to the water class are clearly noticeable. This mainly affects the urban areas and the forests. The result of the classification of the IHS fused data along with the Gram-Schmidt fused data exhibits a poor discrimination between the employed classes. An erroneous allocation was clearly visible for all agricultural areas which were misclassified as urban areas or forests. The classification of larger water bodies performed better than for the original data. Instead the pixels of small water bodies are often assigned to other classes. The result of the PC Spectral Sharpening fused image exhibits a similar result but the amount of misclassified agricultural areas is considerable smaller. The classification shows a better performance for the larger water bodies. The application of the classification algorithm to the data set which was generated by the Gram-Schmidt transformation demonstrates an overrepresentation of urban areas that mainly affect the bare agricultural areas. It is also noticeable that the assignment of pixels to the class water occurs quite often. The result of the wavelet transformation provides only a moderate classification accuracy which is mainly caused by an incorrect assignment of pixels that originally do not belong to the urban areas but to fallow lands. The classification of the data combined with the Ehlers fusion achieved the worst result of the three utilised complex fusion techniques which is caused by the overrepresentation of urban areas that affect all other object classes. Both complex wavelet techniques provide classifications that are comparable to the classification of the original data. The results of the accuracy assessment can be found in Table 1.

Table 1. Results of Accuracy Assessment [%]; PA: Producer's Accuracy, UA: User's Accuracy

Method	Overall Accuracy	Kappa Coeff.	Water [PA/UA]	Urban Areas [PA/UA]	Fallow Land [PA/UA]	Cultivated Land [PA/UA]	Forest [PA/UA]
Original	84.4	0.77	100.0/100.0	100.0/28.0	73.7/90.3	83.5/100.0	87.8/100.0
Colour Comp.	81.6	0.72	66.7/18.3	92.0/41.1	52.5/91.3	85.5/100.0	91.9/94.4
IHS	56.0	0.41	100.0/6.0	76.5/20.3	50.0/100.0	45.0/100.0	82.6/40.9
PC Spect. Sharp.	65.6	0.53	80.0/40.0	83.3/25.4	55.8/82.8	57.8/98.7	87.8/58.9
Gram-Schmidt	55.6	0.41	100.0/27.3	95.0/23.2	50.0/90.9	46.3/100.0	73.7/42.4
Wavelets	76.4	0.66	88.9/80.0	100.0/21.4	61.9/100.0	81.6/99.1	64.6/96.9
Ehlers Fusion	66.4	0.53	100.0/60.0	100.0/18.9	46.0/81.0	70.6/99.0	53.2/92.6
Wavelets+IHS	86.4	0.80	100.0/70.0	73.9/42.5	82.6/95.0	89.8/98.3	84.8/90.7
Wavelets+PCA	84.4	0.76	100.0/100.0	100.0/35.7	75.0/96.0	82.2/99.2	90.0/97.8

Figure 2. Results of the multispectral classification

5. DISCUSSION AND CONCLUSION

The results of the multispectral classification reveal that the utilisation of additional radar data does not always improve classification accuracy. Despite the additional information it was not possible to clearly discriminate all object classes. Especially the discrimination of urban areas and bare agricultural areas remains difficult because of their high degree of similarity. Therefore a satisfying discrimination is only possible in dense urban areas where the infrastructure behaves like dihedral or trihedral corner reflectors generating double or multi bounce effects. Since the other urban areas exhibit a low building density their backscatter values are similar to those values resulting from the bare agricultural areas.

Especially the basic image fusion methods that use the IHS transformation or the principle component transformation provide a substantial lower classification accuracy. Solely the simple adding of the radar data to the multispectral image stack generates a similar accuracy compared to the original multispectral data. While the wavelet technique does not improve the classification accuracy the additional use of the IHS transformation or the principle component transformation does provide classification results of the same or a slightly greater value. As a result of this study only these two techniques can be recommended.

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