SYNTHETIC APERTURE RADAR FOR MARITIME DOMAIN AWARENESS: SHIP DETECTION IN A SOUTH AFRICAN CONTEXT

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ABSTRACT

Maritime Domain Awareness is an initiative started to help each sea-bordering country improve its understanding of its Exclusive Economic Zone. A country that improves its Maritime Domain Awareness ensures that activities such as piracy and Illegal, Unreported and Unregulated fishing are identified more quickly and the appropriate actions for each are taken. For instance, having better awareness of the ships entering and leaving a country’s Exclusive Economic Zone could prevent illegal fishing that, in some cases, accounts for up to a 40% loss of legal catches. Various sources of data can be used to keep track of ships at sea including ship transponders (such as the Automatic Identification System and Long Range Identification and Tracking systems) and active radar sensor systems such as Synthetic Aperture Radar satellites. With the advent of new, freely available Synthetic Aperture Radar imagery from Sentinel-1, the observation of large coastal areas is becoming more and more feasible for countries such as South Africa. Synthetic Aperture Radar satellites are able to monitor large tracts of the Earth, day or night, in any weather condition. This allows for the tracking of hundreds of square kilometres of sea area in a single image. By combining and processing imagery from these satellites and ship transponders, a better picture of a country’s maritime domain can be captured thereby allowing countries to respond to environmental, commercial or security threats at sea. Furthermore, if South Africa can implement its own SAR asset, Maritime Domain Awareness for the entire country would be improved tremendously. This paper aims to give an overview of the research being done to detect ships in Synthetic Aperture Radar imagery within a South African context. It presents the current and future of Synthetic Aperture Radar satellites, how methods such as the Constant False Alarm Rate and Wavelet Transform are used to detect ships at sea and how techniques such as Simulated Annealing and Cascade Classifiers are currently being used to further improve ship detection accuracies.

INTRODUCTION

This paper is intended to give an overview of the work that is presently being done in the area of ship detection using Synthetic Aperture Radar (SAR) satellites and imagery. This introduction will provide motivation for why ship detection is necessary in terms of maritime awareness as well as give a short introduction to ship transponders, SAR and how the two can supplement one another to improve the detection of ships at sea. The paper is structured as follows: following the introduction, an overview of each of the steps in a ship detection system is given. Next, a look at some of the...
future advances in the field of ship detection and SAR imagery is shown followed by a conclusion on the state of the detection of ships for the improvement of maritime awareness.

**Maritime Domain Awareness**

Maritime Domain Awareness (MDA) is a term used to describe all factors relating to the maritime including a “all areas and things of, on, under, relating to, adjacent to, or bordering on a sea, ocean, or other navigable waterway, including all maritime-related activities, infrastructure, people, cargo, and vessels and other conveyances,” (DoD 2005). Each country is required to monitor its own Exclusive Economic Zone (EEZ) for actions that may negatively affect the country’s environment, commerce or security such as Illegal, Unreported and Unregulated (IUU) fishing. This task is impractical on a global scale and as such the purpose of the MDA initiative is to allow various parties to participate in improving their own and other’s MDA through collaboration. Some key MDA participants include the United States of America, Canada, Norway, and the Arctic Council. South Africa is becoming an increasingly important MDA participant due to its large coast and unique positioning. South Africa’s EEZ covers a larger area than its land and it is positioned at a maritime choke point in that it is surrounded by three oceans – the Indian, South Atlantic and Southern Ocean. In this way the improvement of South Africa’s own MDA is important to ensure that the country can police its coast. Various technologies have been introduced that allow for improved monitoring of ships at sea and these include ship transponders and synthetic aperture radar.

**Ship Transponders**

Ship transponders are devices installed on ships that transmit ship details to a ground or space-based receiver. There exists a number of ship transponder technologies including Automatic Identification System (AIS), Satellite AIS (Sat-AIS), Long Range Identification and Tracking (LRIT) and Vessel Monitoring System (VMS) (IMO, 2011). Despite the simplicity of the ship transponder system one inherent problem exists: it is a collaborative tracking method. In order to effectively track ships, the transponder on-board needs to switch be on and transmitting. If it is damaged or switched off then the ships cannot be tracked in this manner. Ships that have their transponders turned off are known as “dark” targets. To track dark targets, especially those not covered by coastal radar, ship transponder based tracking can be supplemented using a remote sensing technique known as Synthetic Aperture Radar.

**Synthetic Aperture Radar**

Synthetic Aperture Radar (SAR) satellites observe large tracts of the Earth from space. SAR is an active sensor that utilises radar technology at specific electromagnetic (EM) frequencies to pierce cloud cover and other materials. This allows SAR satellites to observe areas remotely and can do so in any weather condition, day or night (Oliver, 2004). The extent of coastal area that two SAR images can cover is shown in Figure 1.
Ocean water has a low backscatter because the EM signals disperse within the water whereas highly metallic objects such as ships and oil rigs will reflect the signals back to the SAR satellite. Ships appear as bright pixels and ocean as darker pixels within SAR imagery. An example of how ships look in SAR images as well as how SAR images can supplement ship transponder tracking is shown in Figure 2.

SAR Preprocessing

The SAR pre-processing step is the step that affects many basic attributes of the image and includes techniques to geo-locate the image and filter speckle noise from the image. Geo-locating is an important step in that it ensures that results obtained from the processing of SAR images can be compared to real-world positions.

CURRENT METHODS

This section will discuss the basic flow of imagery through a ship detection system and will provide some insight into some of the most prominent systems used for the detection of ships at sea within SAR imagery. It should be noted that only a brief overview of the possible methods used to detect ships is given. Specific, detailed methodology for each of these methods can be found in the papers referenced (for instance much more detail about the Constant False Alarm Rate prescreening method can be found in (Crisp, 2004; Peterson, 2012; Kleynhans 2013; Schwegmann, 2014).

Ship Detection System

A ship detection system is typically composed of a number of steps that are used to process a SAR image (Crisp, 2004).
Figure 2. SAR intensity image with the bright spots indicating ships. In some cases SAR images can highlight “dark” targets which could typically not be tracked using ship transponder data only.

Each of the steps plays an important role in the detection of ships at sea however some of the following steps are omitted because subsequent steps provide similar functionality. Figure 3 shows an example of a typical SAR ship detection system.

SAR pre-processing

Speckle noise is a multiplicative noise that is often found in SAR images (Oliver, 2004). Speckle is usually dealt with using filters such as the Lee (Crisp, 2004) and Sigma (Zhong, 102) filters. Newer techniques to despeckle SAR images includes Wavelets (Peterson, 2012; Vijaykumar 2012), signal subspace techniques (Yahya, 2012), and maximum a posteriori (MAP) filters (Peng, 2014). Sometimes speckle filtering is forgone altogether because the pre-screening methods take the noise within the SAR images into account when detecting ships.

SAR pre-screening

Once the image has been pre-processed the next step in the ship detection system is known as pre-screening. Pre-screening of SAR images has been given the most attention in literature and is typically split into three distinct groups: Global, Local and Other methods.
**Global:** These pre-screening methods consider the whole SAR image at once. Each pixel is compared to a reference threshold to determine if the pixel under test is a ship or not (Crisp, 2004). Global methods are simple and highly efficient in terms of run-time but are not typically used anymore because one single threshold is often not descriptive enough to differentiate amongst the various pixel values within an image. The results for this group of method tend to be very good for the number of correct detections but due to lack of proper discrimination many false alarms are generated by these methods.

**Local or adaptive methods:** These pre-screening methods consider pixels and their neighbours when determining whether a pixel is a ship or not. These methods allow for a more adaptive approach to ship detection by accounting for local variations in pixel intensity across a SAR image. The most widely-used of the local-based ship detection methods is a method known as Constant False Alarm Rate (CFAR). CFAR was designed to ensure an acceptable level of false alarms for a given threshold when detecting ships. The Cell-Averaging CFAR (CA-CFAR) method (Crisp 2004; Kleynhans, 2013; Lombardo, 2001) detects ships using the following

\[
\text{Ship detected} = \begin{cases} 
\text{true}, & \text{if } x_t > \mu_b t \\
\text{false}, & \text{if } x_t < \mu_b t 
\end{cases}
\]  

(1)

Where \( \mu_b \) is the mean pixel value for the neighbours around the test pixel \( x_t \). The symbol \( t \) is known as the threshold and determines how many times larger the test pixel needs to be above the mean pixel value to be detected as a ship. The selection of \( t \) is a complex task and the computation of the threshold value using the K-distribution (upon which the CFAR method is based) requires to be solved numerically (Crisp, 2004). As such CA-CFAR (a special case of the K-distributed CFAR method) allows for the selection of a single threshold value that creates a threshold plane against which the mean pixel neighbourhood value is compared. Adoptions to this concept are discussed in the section title “Future Methods”. Previously, noise within SAR images has been modelled using either the Gaussian, Rayleigh or K distributions. The first two were used in the early days of SAR processing but more recent research showed that sea noise would be better modelled using the K-distribution. Despite this, however, some authors argue that the K-distribution is not a sufficient distribution model for background pixel intensities such as the alpha-stable (Ferrar, 1998) and Cauchy–Rayleigh (Peng, 2014) distribution models. Adaptive methods typically have both excellent detection rates and low to very low false alarm rates. These methods are the ones most used in practice due to their real-world performance.

**Other:** These pre-screening methods do not specifically fall into one of the two previous categories. These methods typically use some form of machine learning to help discriminate sea pixels from ship pixels. Excellent examples of other pre-screening methods including Wavelet Transform (WT) ship detection (Gao, 2011), Genetic Algorithm Radial Basis Function (GA-RBF) Neural Network (Leung, 2002) and Ant Colony Optimization (Li, 2012). Ship detection using these methods is typically on par with that of adaptive methods.

**SAR ship discrimination**

A final step to improve detection results is that of the ship discrimination stage. This stage is sometimes omitted from the ship detection process because much of the discrimination is done in
the pre-screening stage. The ship discrimination step is typically implemented to group similar pixels to form simpler representations of ship pixels or further filtering to improve detection accuracy or decrease false alarm rate. In some cases, ship discrimination can improve the results of previous steps by an order of magnitude (Crisp, 2004).

Ship discrimination can be performed using a variety of methods from simple filters to advanced machine learning systems. The simplest example of ship discrimination is that of a Butterworth filter (Eldhurst, 1988). More advanced methods of ship discrimination include: morphological filtering (Lin, 1997), using an additional two-parameter CFAR stage (Crisp, 2004; Ji, 2010), Resonance Agglomeration and Elimination of Local Noise (Schwartz, 2002) and Mean Shift Clustering (Comanicius, 2002). A novel usage of machine learning combines output from multiple classifiers in the pre-screening stage with a Support Vector Machine (SVM) in the discrimination stage to identify ships (Ji, 2013).

FUTURE METHODS AND SAR IMAGERY

This section is split into two parts: the first details some of the current and upcoming SAR imagery sources and the second details some future methods of ship detection.

Current and future SAR imagery

SAR imagery has been used for the detection of ships at sea as far back as 1979 (Evans, 1979). Since then a number of prominent SAR satellites have been utilised such as: European Remote-Sensing (ERS) 1 and 2 satellites, Environmental Satellite (ENVISAT) and the radar satellite (RADARSAT) 1 and 2 (Oliver, 2004). These have all played important roles in the development of ship detection systems that are available today.

Looking towards the future there are two SAR satellites that will be providing modern SAR imagery. The first is the Spanish PAZ SAR satellite planned to launch in Q3 of 2014 (Kramer, 2014). The mission plans to provide over 200 SAR images daily. This level of observation will allow for a more up-to-date view of the Earth and oceans. Sentinel-1 is a two satellite constellation that is a follow up to the European Space Agency’s (ESA) ERS-2 and ENVISAT missions. The first of the two satellites is a C-band SAR sensor and was launched on the 3rd of April 2014 with one of its objectives been to provide SAR imagery of the ocean (Earth Online, 2014). This mission will improve MDA of any country because the imagery will be freely available to use for any purpose.

Future SAR Ship detection methods

Many of the ship detection methods discussed above use SAR satellite imagery and very little auxiliary data to help detect ships. One of the important advancements of the field going forward is the integration of data such as ship transponder data with SAR imagery for the improvement of ship detection. Ship transponder can be used reliably as historical, ship positioning and movement data (Kleynhans 2013; Schwegmann, 2014). By gathering historical ship positions, a ship distribution map of a given area can be created. A novel usage of this ship distribution map is using the map as a probability distribution and using it to decide when a CFAR threshold is too high. Two papers recently written employ the usage of the ship distribution map to select the threshold where the change of average ship probability over a number of thresholds is greatest (Kleynhans 2013; Schwegmann,
The first paper determines when a single threshold (flat plane) changes the average ship probability the most, whereas the second paper expands this idea by trying to find the non-flat threshold plane.

Another ship detection method uses facial image features as descriptors for ships in images and then detects ships using these features and a cascade classifier (Schwegmann, 2014). Even though these image features are simple they are enough to describe complex objects such as faces and as such simpler objects such as ships in SAR imagery can be described with very few features. This means that the system can be trained to detect ships more quickly and with fewer errors.

CONCLUSION

Ship detection is becoming an increasingly important activity for countries wishing to improve their MDA. Usually, only countries with large military budgets could afford to focus on ship detection at sea. With the advent of freely accessible SAR imagery such as Sentinel-1, countries that were previously unable to research ship detection may do so now. The detection of ships within SAR imagery is a complicated procedure with a number of steps that need to be carefully considered before implementation. Newer methods use a variety of data sources to improve ship detection performance. Governments can improve their own maritime domain awareness by investing into various sources of maritime data. The integration of ship transponder data and SAR imagery, acquired either with various assets (international and/or South African owned satellites) will lead to more advanced ship detection systems and thus improved understanding and policing of South African Waters.

REFERENCES


ADDING TEMPORAL DATA ENHANCEMENTS TO THE ADVANCED SPATIAL DATA INFRASTRUCTURE PLATFORM

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ABSTRACT

Users of Spatial Data Infrastructure (SDI) increasingly require provision to data holdings beyond the traditional static raster, map or vector based data sets within their organisations. The modern GIS practitioner and Spatial Data Scientist are required to work with data that not only has a spatial component but also a temporal component. The traditional SDI has been well suited for providing capabilities relating to governance, discovery, exploration, access and basic collation of static data sets. Across the world, Geonode is emerging as a framework for building spatial data infrastructures as it covers all of these aspects of traditional SDI. However, there is an increasing need for the capabilities of Geonode to be extended to data sets with a temporal component. Geonode is an Open Source Platform that was originally developed by the World Bank in collaboration with OpenGeo in response to the World Bank’s need for an SDI on which to build a disaster management platform for reducing risk in Central America. Geonode has since been adopted in Europe and America as well as South Africa, with a growing user base. Similar to other open source programs, a number of enhancements have since been developed. Based on the realisation that more and more scientists are using and acquiring geospatial data, and the importance of time series in geospatial research, we have developed enhancements to the Geonode platform that enable the handling of temporal data. These tools enable the user to discover, explore, visualise and access temporal data. This paper begins with a discussion of the traditional and current SDI practices, in terms of governance, discovery, exploration, access, and collation of data. We review the Geonode platform and discuss its suitability and compliance with the requirements of a Spatial Data Infrastructure. Methods used for developing the enhancements to Geonode are discussed. The results of the project are presented and challenges and further work in this project are discussed.

INTRODUCTION

Increasingly users of Spatial Data Infrastructure (SDI) require provision to data holdings beyond the traditional static raster, vector or in-situ point based datasets available within their organisations. The modern GIS practitioner and Spatial Data Scientist are required to work with data that not only has a spatial component but also a temporal component.

Traditional SDI has been well suited to providing capabilities relating to governance, discovery, exploration, access and basic collation of static data sets. For instance the capabilities provided by the popular Geonode platform cover all of these aspects of traditional SDI. However, there is an increasing need for these capabilities to be extended to data sets with a temporal component.
This paper begins with a background discussion about SDI. Following that, Geonode as an open source based SDI platform is introduced and the short comings of Geonode as it stands are discussed setting a background of why the enhancements that we made were necessary. The development of the temporal data enhancements is then presented and results discussed. The paper closes off with a discussion of the result achieved, and recommendations on future work are made.

SDI BACKGROUND

The GSDI defines an SDI as the sum of technology, policies, standards, human resources and related activities that facilitate the acquisition, processing, distribution, use, maintenance and preservation of geospatial data, throughout government, private sector and academia (Nebert, 2000; Groot and McLaughlin, 2000; Maguire and Longley, 2005). Following Masser (1998) SDI's are developed to enable users to discover, explore and use geospatial data according to the needs of their applications. A number of discussions around the definition and development of SDIs can be found (Groot and McLaughlin, 2000; Williamson et al, 2003; Cooper et al, 2007), however most authors agree on aspects and components to be considered in the development of an effective SDI, and these can be found in the GSDI cookbook (Nebert, 2000). Amongst others a good SDI must facilitate data discovery, visual exploration of data, as well as data access and delivery (Nebert, 2000; Alders and Moellering, 2001; Crompvoets et al, 2004).

Data Sharing in an SDI Environment

It has been deemed impractical to expect centralisation of data holdings as the production of data has escalated in recent years. Data is housed and owned by different organisations; therefore the focus has shifted to distributed networks of data holdings that can communicate. Ability to share data requires harmonisation and interoperability of the data. Albrecht (1999) provides a definition and detailed discussion into the concepts of Interoperability with respect to an SDI. Albrecht’s discussion provides justification for the need for standardisation to govern, facilitate and aid the data sharing processes in an SDI.

The internet is continuously growing as an effective means to share data across multiple networks and data holdings, enabling a wide range of geospatial data users to be reached. Standardised web services have therefore been used to facilitate this movement and transfer of data across multiple platforms. Crompvoets et al (2004) and Mohammadi et al (2010) provide further, detailed clarifications into interoperability issues with respect to web services.

GEONODE AS AN ADVANCED SDI PLATFORM

Why Geonode and Background

Geonode was developed by World Bank in corporation with OpenGeo as an underpinning SDI for the CAPRA program, a disaster risk management project for Central America. It is an open source based platform. The decision to make Geonode open source was in order to allow it to be improved and expanded at later stages. A study of other SDI’s was undertaken by the World Bank team to
investigate whether they could meet their requirements. The findings of the team were that most SDIs were lacking in terms of effective data sharing and collaboration (Pickle, 2010):

What is Geonode?

Geonode is based on open source components: Geoserver, PyCSW/GeoNetwork, Django and GeoExplorer/GeoExt. Together these provide a platform for spatial data discovery, access, exploration, summed up with a view on data access permissions for the security and integrity of data. It also has a social networking component in order to allow quick and easy well known communication amongst the users (Pickle, 2010). Geonode is highly interoperable and can be easily integrated into existing platforms, for example QGIS has a Geonode plugin.

Geonode has been used successfully across the world, and most notably in this context, it has been applied in Malawi, Kenya and Mozambique. Kenya, in collaboration with the World Resources Institute (WRI) developed a program called Virtual Kenya. The project was in order to provide access to the countries important datasets and maps, with a view to encourage and enable the knowledge users as well as ordinary users to develop interest in geospatial data. The World Bank’s Global Facility for Disaster Reduction and Recovery organisation (GFDRR) developed two instances of Geonode in Malawi and Mozambique, MASDAP and Moz-ADAPT, respectively. The purpose of the Geonode projects was to empower the two countries to better understand and be prepared for activities that result from climate change. The emphasis was on natural disaster reduction and resilience in a changing world. The Malawian project provides weather and infrastructure data, whilst the Mozambican project also includes modelled climate change projection data both historical (from 1980) and projections up to 2100.

Principles of Geonode:

According to Pickle (2010) Geonode, and hence its components, is based on the following key principles:

- To promote collaboration amongst geospatial scientists as users, by making it easy to share data, social networking (for example adding comments, rating datasets) and allowing connectivity with multiple Geonode instances.

- Distribution: automatic metadata creation on uploading of a data file and search via catalogues.

- Cartography: this can be referred to in general terms as the data visualisation component. It provides a mapping capability that allows for styling of data, saving maps and sharing.

- Data collection: providing a mechanism and an interface for uploading of data.

Main Components of Geonode Explained:
The three main components of Geonode, namely PyCSW, Geoserver and GeoExplorer are discussed below followed by a brief discussion about the development framework.

- **Geoserver**: An open source geospatial data server that allows users to edit and share geospatial data. It is able to publish data using the OGC WMS, WFS, WCS and WPS standards. It allows for editing of data using the SLD (Stylised Layer Descriptor) which is presented in XML (Extensible Markup Language). Geoserver can serve both raster and vector data as well as data from other databases such as PostGIS. Geonode uses Geoserver as its main geospatial data server.

- **PyCSW**: is a python based implementation of the OGC's Catalogue Service for the Web (CSW) server. It allows for the discovery and publishing of metadata for geospatial datasets. It can be deployed as a standalone server or can also be embedded in other applications. Geonode uses PyCSW for harvesting and serving metadata, in order to make data searchable.

- **GeoExplorer**: is a JavaScript based web mapping application, which is built on GeoExt. The map application allows users to interactively navigate, organise and analyse geospatial data. It uses the OGC's WMS to collect and arrange geospatial data. GeoExplorer is used as the data viewer for geonode, for previewing data and also for map compositions.

- **Django Web Development Framework**: is a python based web development framework, which follows the Model-View-Controller architecture pattern. The main purpose is to ease web development and its strong point is that the components need to be reusable and pluggable. It also implements web security through its administrative interface. This allows for different users to manage use rights of components.

**TIME SERIES EXPLORATION IN GEONODE**

As discussed in earlier sections, many geospatial and earth observation scientists depend on spatio-temporal data to do their analysis in their domain specific projects. This data has until recently not been catered for in SDIs. The OGC provides a couple of standards for dealing with time series data. The focus of this paper will be on the OGC's Web Map Service Time (WMS-T) and adding support for this to Geonode.

WMS-Time is a time aware extension of the Web Map Service (WMS) that was discussed earlier. According to Kolodziej (2004), the main advantage of WMS is that software that uses this standard is able to pull map layers from multiple other conforming web applications, and present them in an aggregated WMS. This data may not necessarily be similar in map scale, map projection or coordinate system, and may also result from geoprocessing services offered by other WMS servers (De la Beaujardiere, 2006). Figure 1 shows the flow of information from database to web client facilitated by WMS service.

WMS supports the GET method of the HTTP internet protocol and has three main requests that can be sent from the client to the server, namely, GetCapabilities, Getmap, GetFeatureInfo. The GetCapabilities in summary, requests to get service or layer metadata, the client asks the server for
the layers that are available to a service, what map projection system and data output formats are available; the server presents the response as an XML document. In the case of the Getmap request, the client asks for a map providing specifics such as projection, format, bounding box. These would have normally been acquired from the GetCapabilities request that a client issues before requesting for data. The GetFeatureInfo request: the client asks for attribute information about the features on the map layers. This request is only available to services that advertise themselves as queryable. (Becker, 2009; De la Beaujardiere, 2006)

If data is available for a phenomenon such as weather in the same geographical location for multiple time steps, such as hourly rainfall data, it can be represented in a WMS server as a WMS-Time. The time attribute will need to be configured in a way that the WMS will be aware of it, these time format specifications are provided in annex C and D of the specification document (De la Beaujardiere, 2006). For example:

    name="time" units="ISO8601" default="2003-10-17">1996-01-01/2003-10-17/P1D

The time units are in ISO8601 and the format shown above indicates the start and end times of available data. If the time is properly configured, the WMS server will be able to provide available times in the GetCapabilities response document. When requesting a map using the GetMap request the client can include the time instance they require as part of the request URL.

Using the WMS Standard in Geonode

Data is uploaded into geonode in two ways, either directly through Geonode or through the linked instance of Geoserver. Once data has been uploaded using the two mechanisms discussed, a record of the data becomes available in the Geoserver instance of Geonode. The Geonode client is
then able to request data from the Geoserver data store using the WMS mechanism described above, however it is not able to interpret the time based layer. When presented with a WMS request for a layer that is time aware Geonode returns data for the last available time stamp. This inability to display time based data resulted in the modifications presented below.

Currently uploading a time series dataset into Geonode is done through Geoserver. Geoserver is able to upload raster time series data using the ImageMosaic plugin. The plugin takes individual raster images that are georeferenced and cover the same area and named according to their timestamps e.g. *Pretoria_20091001.tif*. These images are then transformed into a single time queryable layer. It is worth mentioning that the ImageMosaic plugin can also be used to create a mosaic of spatially overlapping areas. When Geoserver registers a WMS-Time dataset through the Image Mosaic plugin, the metadata is sent to Geonode via models that also harvest the metadata information, and at the same time send it to the catalogue service PyCSW. It was realised at this stage that the WMS response from Geoserver already provides the desired WMS-time information, however this information was unused in Geonode.

**Time Series Based Extensions to Geonode**

Since the information about the WMS-Time is already passed into Geonode from Geoserver, the next step was to harvest this information and create a dynamic visualisation of the time stamps within a layer. An enhancement plugin in the form of an animation widget was added to the Geonode's GeoExplorer viewer to this effect. This widget was written such that it gets activated automatically in the viewer when the time variable is detected in the layer's metadata. The client does not see the time based animation widget in the viewer if there is no time series data available. Since GeoExplorer is built using the GeoEXT javascript framework, and the viewing tools are based on the GXP components, the plugin is written as a GXP tool that plugs into the GeoExt built GeoExplorer viewer. The code is thus written in javascript programming language.

**Accessing Time Series Data from Other Servers**

Another problem arises when one wants to load data from other WMS-Time servers. Geoserver connects to other WMS servers through the cascading WMS operation. However this does not allow the loading of WMS-Time and only brings back the last time stamp of the dataset. This is a problem because Geonode only displays and loads data from a single co-registered Geoserver. An alternative route for accessing time series data into Geonode had to be sought.

A web based implementation of the WMS server for multidimensional data, ncWMS was used. ncWMS is an extension of the OGCs WMS service, that is meant for multidimensional data including data with a time component. Unlike in Geoserver where data is stored in a mosaic of tiff images, ncWMS takes data stored in netCDF format which is CF (Climate and Forecast Metadata Convention) compliant. More information on ncWMS is provided in Blower et al. (2013). Methods for converting data between the netCDF and Tiff formats are well known within the geospatial community. With ncWMS a direct GetCapabilities request was able to be made for time series data from within Geonode to the respective servers. This is facilitated by the WMS standard being able to read the metadata that is in the known Climate and Forecast (CF) convention. The servers return a list of
available time aware layers which can then be previewed on the customised viewer using the animation widget.

The WMS from the time aware layers can also be overlaid with data from the Geonodes geoserver to create an aggregated map that gives more information. The map can then be saved, published and shared with other users using Geonode’s map publishing service.

The methods described above show the short comings of Geonode in terms of accessing and visualising time series data. The ways in which these shortcomings are overcome include the incorporation of functionality to read from ncWMS servers, as well as the use of Geoserver’s Image Mosaic plugin for overlaying tiff images as bands in a single layer with time component. The viewer is then enhanced to support the visualisation of time series data.

RESULTS

The visualisation was tested using the European Centre for Medium Range Weather Forecasting’s (ECMWF), relative humidity data. The data was acquired for a whole month cycle, for the Southern African region. The ECMWF data was acquired from their download server in netCDF, CF-1.5 compliant format. Which made it easy to put it behind our local ncWMS server as is. The server was then queried using the specific dataset URL that is provided by the server through a GetCapabilities request. The process is simplified such that the user only supplies the URL of the ncWMS server they want to query. Geonode is configured in this case such that a GetCapabilities request is performed in the background and a list of available data sets is then displayed. The user then clicks on the link to the dataset they are interested in and this is then displayed in the animation aware viewer for exploration.
The same dataset was used to test the upload of data into Geoserver as a time aware ImageMosaic. In order to display this data in Geonode through Geoserver, it was first converted from netCDF to tiff files using an automated script. The tiff files were then loaded into Geoserver as an Image Mosaic. Geonode is then made aware of this data using an update layers command that notifies Geonode of new data that has been loaded into Geoserver. The linked PyCSW catalogue service loads all the necessary metadata from Geoserver for Geonode to be aware of. Once Geonode has been made aware of the time aware data, when the user views it in the Geonode GeoExplorer viewer, the animated time slider is activated and the user is hence able to explore all available time steps of the data. This is illustrated in figure 2.

**CONCLUSIONS AND RECOMMENDATIONS**

**Further Work**

The results of the time-series enabling process in Geonode so far have been presented in the section above. However in a complete SDI platform just viewing of data is not enough, the user may want to download the full time series data or parts thereof. The download function is under development currently and results of this will be presented in due course.
Conclusions

It was found that Geonode performed all the functions that are necessary for a successful SDI platform. However it did not cater for spatio-temporal datasets. This was the basis on which the enhancements discussed above were implemented.

Since Geonode is based on the Django Web development framework, the source code is well structured and hence easy to read. This ensured that it was easy to implement the new code changes, and test the additions that were made.

Once the additions have been fully tested the changes can be contributed back into the main Geonode source code for the community to adopt following a thorough review process.

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COMPARISON OF PIXEL-BASED AND OBJECT-ORIENTED CLASSIFICATION APPROACHES USING LANDSAT-8 OLI and TIRS SPECTRAL BANDS
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KEY WORDS: Object oriented classification, supervised classification, Accuracy assessment, Land cover and Land use classes.

ABSTRACT
Image classification based on traditional pixel-based approaches is limited. The traditional pixel-based image analysis is limited because it relies only on the spectral information without taking into account the spatial information of the objects in the scene. Different from pixel-based method, object-oriented approach takes the form, textures and spectral information of the objects of the scene into account. Object-based Image Analysis (OBIA) works on (homogeneous) objects produced by image segmentation and more elements can be used in the classification. In this study, land cover types in the Free State province, South Africa were analysed and compared on the basis of the classification results acquired using the pixel-based and object-oriented image analysis approaches. Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) image with all spectral bands was used to carry out the image classification. Ground truth data were collected from field survey, personal knowledge and communication with the local people. Ten classes were determined and subsequently spectral separability analysis between classes was calculated. The results of separability analysis indicated that Landsat 8 image provided adequate spectral discrimination of different selected classes (Maize, sorghum, soybean, sunflower, grassland, cloud, bare soil, urban areas, water bodies and other land cover types). In pixel-based image analysis, supervised classification was performed using four different approaches of minimum-distance, parallelepiped, Spectral angle mapper, and maximum-likelihood. On the other hand object-oriented approach involved the segmentation of image data into objects at multi-resolution scale levels and objects were assigned class rules using spectral signatures, shape and contextual relationships. Sample based nearest neighbourhood was used as classifier for Object-oriented classification (OOC). Accuracy assessments of both classification approaches (OOC and PBC) were undertaken. Outcome from the classification works show that the object-oriented approach gave more accurate results (including higher producer’s and user’s and overall accuracy for most of the land cover classes) than those achieved by pixel-based classification approaches.

INTRODUCTION
Remotely sensed image analysis is a challenging task. One popular and commonly used approach to image analysis is digital image classification (Matinfar et al., 2007). The purpose of image classification is to label the pixels in the image with meaningful information of the real world (Jensen and Gorte, 2001). The classification of land use and land cover from remotely sensed imagery can be divided into two general image analysis approaches: i) Pixels based classifications, and ii) objects based classifications. Pixel based image classification utilizes spectral information-digital values (DNs) stored in the image and classifies images by considering the spectral similarities with the pre-defined land cover classes (Gao and Mass, 2008). In contrast to pixel-based classification, image objects (or segments) are the basic units of object-based classification. Each object is composed of spatially adjacent pixels clustered based on homogeneity criteria and image objects are generated using an
image segmentation procedure, which partitions an image into non-intersecting regions (Blaschke, 2005). Object-based classification can use not only spectral information but also other information such as shape, texture, and contextual relationships (Yinghai et al., 2010). Classification based on pixel-based approaches is limited due to the development of robust object-based image analysis (OBIA) methods that are suitable for the classification of medium (pixel size 10–30 m) to high (pixel size 2–10 m) spatial resolution satellite imagery. Thus OBIA provides a valid alternative to the ‘traditional’ pixel-based (PB) methods of analyzing and categorizing remotely sensed data (Baatz et al., 2004 and Benz et al., 2004).

Previous comparative research has been conducted that examine the relative performance of different classification algorithms using pixel-based or object-based image analysis. Yan et al. (2006) compared pixel-based image analysis using Maximum likelihood classification (MLC) and object-based image analysis using nearest neighborhood (NN) on Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery. The authors claimed in their study that the overall accuracy of the object-based K-NN classification drastically outperformed the pixel-based MLC classification (83.25% and 46.48%, respectively). Ouyang et al. 2011 compared pixel-based and object-oriented approaches to QuickBird imagery for mapping saltmarsh plants and they found that object oriented classification (OOC) performed better than Pixel based classification (PBC) in terms of accuracy. Robertson Dingle and King (2011) compared pixel-based and object-based image analysis for classifying broad land cover types for two time periods (1995 and 2005) using Landsat-5 TM imagery. They compared land cover maps produced using MLC (pixel-based) and K-NN (object-based) algorithms. Quantitative and visual analyses showed no significant difference in overall accuracy between these classification approaches. Despite the similar map accuracies produced by the two methods, temporal change maps produced and analyzed using post-classification comparison (PCC) revealed that object-based maps depicted change more accurately than MLC derived change maps.

In this research, pixel-based approaches (Maximum likelihood, Maximum distance classifier, Spectral angle mapper, and parallelepiped classification) and object-oriented approach (sample-based nearest neighbor classifier) image classifications were utilized to perform land-cover and land use mapping in North east of Free State, Province of South Africa. Ten land-cover classes were classified: Grass, Maize, Sorghum, Soybean, Sunflower, Urban, Water bodies, bare soil, Cloud (as the image had 7.7% of cloud cover) and shadows. The aim was to evaluate the performance of these two methods in land use and land cover mapping. The accuracy and visual assessment was conducted from classification outputs using medium spatial resolution (30m) Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) sensor. Authors, finally compare the pixel-based and object-based approaches with the detailed explanation of the obtained results.

STUDY AREA DESCRIPTION

The study area is located between 27°, 2’, 09”S and Long 028°, 07’, 27” E. It covers approximately 37607.26km2. It is situated in the northeastern Free State (Fezile Dabi and Thabo Mofutsanyane District Municipality respectively) and south of Gauteng (Sedibeng District Municipality) (Figure 1). The area is situated on flat boundless plains in the heart of South Africa. The region is high-lying, with almost all land being 1,000 m above sea level. The area is dominated by agricultural land use (dominant plant types are: Maize, soybean, sunflower, Sorghum and Grassland) and other land use and land cover types such as urban areas, bare soils and water bodies. Apart from agriculture, land use in the region consists of mining, tourism and manufacturing, industrial areas and other urban land use types.
With more than 30,000 farms that produce over 70% of the country’s grain (33% and 49% of national maize and wheat production respectively) (Maphalla and Salman, 2002), the abundance of agricultural land use was the main reason for the selection of the area for this study as the current situation requires up-to-date and accurate information about agricultural land use to support the decisions affecting the area and to manage crops in the most suitable way.

Figure 1: Spatial location of the study area. The satellite image is presented with false color composite of R.G.B bands represented by Near Infrared, Green and Blue.

METHODS

Landsat 8 Characteristics and Ground Truth Data

One Landsat 8 scene was used in this research with path 170 and row 79; it was captured on 17 February 2014. The standard Landsat 8 product consists of calibrated digital numbers (DN) representing multispectral image data acquired by both the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (USGS, 2014). Landsat 8 carries two instruments: The Operational Land Imager (OLI) sensor which acquires visible, near infrared, and short wave infrared image data and the TIR sensor which acquires thermal infrared image data. Both Landsat 8 sensors provide improved high signal to noise (SNR) radiometric performance quantized over a 16-bit dynamic range. It has a revisit period of 16 days. The image consists of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9 (USGS, 2014). The resolution for panchromatic Band (Band8) and thermal bands (Band10 and 11) is 15 and 100 meters respectively. It was acquired in GeoTIFF data format with Universe Transverse Mercator (UTM) map projection and World Geodetic System (WGS) 84 datum.

The Landsat 8 scene used for this study had 7.7% cloud cover. This was the only low cloud cover image available during the entire cropping period (crop full canopy) over the study area hence it was not possible to mask out the cloudy part of the study area. In order to avoid the potential effects of cloud on the classification, the cloud was taken as a separate class during the classification.
Ground truth data is important to understand the features in the real world and to map a mental picture of the type of land cover and land use (Bhaskaran et al. 2010). A hand held Garmin GPS receiver was used to collect sample farms (cultivated with Maize, Soybean, Sorghum and Sunflower), grassland, bare soil, settlements, water bodies and other land use types from the study site. X and Y coordinates were recorded and the map features (polygons) were uploaded using the ArcGIS software (ESRI, 2012). A data table with different types of samples (classes) was created from the study site. This set of data was divided into two parts; one part was used as training samples (40 points for each class); the other part was used as the test area (ground truth) to assess the accuracy of classification (40 points for each class).

Spectral separability analysis for land-use classes

Separability is a measure with which patterns can be correctly associated with their classes using statistical pattern classification (Richards and Jia 2006). Ten classes were determined in the study area including Maize, Sorghum, Soybean, Sunflower, Grassland, bare soils, water bodies, urban areas, other land use types and Cloud (as the images has 7.7% cloud cover). These 10 classes were subsequently used for both the pixel- and object-based classifications. Separability of the training data for all class pairs was assessed using the Jeffries Matusita (J–M) distance index (Richards and Jia, 1999). These are the average distance between two class density functions (Schmidt and Skidmore, 2003). These values range from 0 to 2.0 and indicate how well the selected pairs are statistically separate. In this study we used a J–M distance of ≥ 1.90 (≥ 95% of 2) as a threshold of spectral separability between group pairs, which is commonly used in remote sensing practice (Thomas et al., 2003).

Pixel based classification

Initial classification of the image was carried out using per-pixel supervised classification techniques. Pixel based approaches such as supervised classification identifies the class of each pixel in the image by comparing the n-dimensional data vector of each pixel with the prototype vector of each class. The data vectors typically consist of pixel's gray level values from multi-spectral channels (Shackelford and Davis, 2003). Among the conventional methods of classifying the multispectral imagery, such as parallelepiped, minimum distance to mean, and MLC, the latter is the most widely used algorithm for pixel-based classification, and has been shown to give the best results for classification among the algorithms of parametric classifiers (Yan et al., 2006). Therefore for this study we used the maximum likelihood, parallelepiped, minimum distance to mean and spectral angle mapper classification methods. By a detailed visual examination, the 40 training data samples for each class were identified from the image. In the second stage parallelepiped, neural net, minimum-distance, spectral angle mapper and maximum-likelihood classification algorithms have been applied respectively to the Landsat 8 image based on the determined training patterns and reference materials. For comparative analysis of each method, same training sites have been utilized. The accuracy assessment was carried out using primary ground truth data. The classification accuracy was measured by using a standard error matrix. Classification results with ground truth image data were compared in order to assess the overall accuracy. An error matrix was computed to obtain the user’s and producer’s accuracy. The producer’s accuracy represents the measure of omission errors that correspond to those pixels belonging to a class of interest that the classifier has failed to recognize. The user’s accuracy, on the other hand, refers to the measure of commission errors that correspond to those pixels from other classes that the classifier has labeled as belonging to the class of interest (Richards and Jia, 1999). All pixel based classifications have been undertaken using ENVIS.0 software package (Exelis Visual Information Solutions, 2012).
Object oriented classification

Object-oriented classification is driven by an understanding of image object rather than pixels (Bhaskaran et al., 2010) therefore object-oriented classification does not operate directly on single pixels, but objects consisting of grouped homogeneous, continuous and contiguous pixels/regions that have similar spectral and/or spatial characteristics. This is commonly known as image segmentation and it is one of the fundamental steps in object-oriented classification. Object-oriented classification starts with the crucial initial step of segmenting neighbouring pixels into meaningful areas thus multi-resolution segmentation was used to generate new image objects. After segmentation, image was classified using sample-based nearest neighbour classifier of eCognition software (Trimble, 2011). In addition the accuracy assessment was carried out using test area ground truth data collected during the field survey. Producer’s, user’s as well as overall accuracy were computed to evaluate the accuracies of the obtained object based classified image.

RESULTS AND DISCUSSIONS

The result shows that there are no overlaps between land use and land cover classes in all the combinations of the spectral feature space in other words all classes were spectrally separable. Furthermore the overall accuracy of all pixel based classification algorithm ranged from 64.04% to 92.38%, with a kappa coefficient that ranged from 0.45 to 0.87 (Table 1). The OOC algorithm (NN) reached an overall accuracy of 95.61% and a kappa coefficient of 0.88, which was the highest among all algorithm (PBC and OOC algorithms). In general, amongst the pixel-based approaches, maximum-likelihood classification gives the most accurate results, which had the overall accuracy (92.38%) and kappa coefficient (0.87) and this was significantly higher than all other used pixel based algorithm.
The reason behind is that the average vector and the covariance matrices are estimated with the higher accuracy for maximum likelihood algorithm. Such a condition depends definitely upon the availability of enough training patterns for each class and this requirement has already been realized in this research. However, object-oriented classification produced more accurate results with a 95.61% overall accuracy and 0.88 kappa statistics. The reason for this is that the compactness of the segments. Although there is no established standard for accuracy assessment, a commonly recommended accuracy is 85% (Foody, 2002). Even though classification accuracy of maximum likelihood of PBC and nearest neighbor of OOC may not be significantly different, object-based classification detected more realistic land use and land cover with fewer illogical errors than did the MLC (Figure 3).

Table 1. Overall accuracy and Kappa coefficient for pixel-based and object-oriented classifications techniques. SAM refers to Spectral Angle Mapper, ML to Maximum Likelihood, MDM to Minimum distance to mean and NN to Nearest Neighbour classifier.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Accuracy (%)</th>
<th>Parallelepiped</th>
<th>SAM</th>
<th>MDM</th>
<th>ML</th>
<th>NN (OOC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall accuracy</td>
<td>64.04</td>
<td>69.09</td>
<td>84.67</td>
<td>92.38</td>
<td></td>
<td>95.61</td>
</tr>
<tr>
<td>Overall kappa</td>
<td>0.45</td>
<td>0.57</td>
<td>0.75</td>
<td>0.87</td>
<td>0.90</td>
<td></td>
</tr>
</tbody>
</table>

To illustrate the individual classes’ performance, user’s and the producer’s accuracies were compared as they measure the commission and omission errors respectively for each class (Table 2). Evidently, most of PBC classifiers had lower user’s and producer’s accuracies than those calculated.
for the OOC. The PBC had more misclassified classes than the OOC and, therefore, the OOC appeared to overcome some of the problems encountered by the PBC methods. According to table 1 and table 2, it can be seen that the error matrix results of the OOC approach were higher than that of PBC approach. When comparing these two classification results class by class, the producer's and user's accuracies associated with the OOC approach were generally higher than those of the PBC approach. This is due to various advantages of the OOC approach, such as its capability of combining spatial as well as spectral information into the classification and thereby enhancing the accuracy of the output classification. It started with segmentation in which objects were created using spatial and spectral information, this way is similar to the way humans comprehend the landscape. The poor producer's and user's accuracies of the land cover classes “soybean and sorghum” in the OOC approach was attributed to the fact that during OOC processing, small objects were merged into larger objects and soybean and sorghum existed in limited and small areas throughout the used Landsat 8 image. In addition, a larger area cultivated by sorghum and soybean in the study area is obscured by cloud in the used Landsat 8 image.

Table 2. User's and producer’s accuracy results of both classification approaches (pixel-based classifications to object-oriented image analysis).

<table>
<thead>
<tr>
<th>Class Name</th>
<th>MDM</th>
<th>SAM</th>
<th>ML</th>
<th>Parallelepiped</th>
<th>NN (OOC)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prod.ac (%)</td>
<td>User ac (%)</td>
<td>Prod.ac (%)</td>
<td>User ac (%)</td>
<td>Prod.ac (%)</td>
</tr>
<tr>
<td>Bare soil</td>
<td>73.22</td>
<td>33.07</td>
<td>70.43</td>
<td>50.69</td>
<td>56.19</td>
</tr>
<tr>
<td>Cloud</td>
<td>100</td>
<td>100</td>
<td>74.36</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Grass</td>
<td>49.07</td>
<td>60.31</td>
<td>34.16</td>
<td>22.28</td>
<td>71.69</td>
</tr>
<tr>
<td>Maize</td>
<td>98.55</td>
<td>73.05</td>
<td>98.09</td>
<td>75.66</td>
<td>60.82</td>
</tr>
<tr>
<td>Others</td>
<td>38.24</td>
<td>100</td>
<td>0.00</td>
<td>0.00</td>
<td>99.85</td>
</tr>
<tr>
<td>Sorghum</td>
<td>84.86</td>
<td>55.95</td>
<td>83.54</td>
<td>90.52</td>
<td>62.15</td>
</tr>
<tr>
<td>Soybean</td>
<td>16.86</td>
<td>22.68</td>
<td>21.65</td>
<td>25.86</td>
<td>9.96</td>
</tr>
<tr>
<td>Sunflower</td>
<td>40.58</td>
<td>32.76</td>
<td>37.12</td>
<td>32.99</td>
<td>94.81</td>
</tr>
<tr>
<td>Urban</td>
<td>49.16</td>
<td>91.87</td>
<td>62.56</td>
<td>97.26</td>
<td>93.96</td>
</tr>
<tr>
<td>Water</td>
<td>100</td>
<td>75.00</td>
<td>81.27</td>
<td>100</td>
<td>95.65</td>
</tr>
</tbody>
</table>

In general, classifications produced using either pixel-based or object-based image analysis created similar and visually acceptable depictions of the broad land use classes present within the study area. However object-based image analysis has high accuracies compared to the pixel-based classifications. These results are consistent with those of other studies concerning the comparison between these methods (e.g., Tehrany et al., 2014; Castillejo-González et al., 2009). There seems to be an agreement about the fact that the results coming from the OOC approach are visually easier to interpret because it deals with meaningful image object (Blaschke et al., 2005). The maps obtained in these analyses with an OOC approach were more appealing, with regular polygon edges, high accuracies and less speckled results. In other words, OOC approach detects more realistically land use and land cover of the study area with fewer illogical errors than PBC approach.

**CONCLUSION**

In this paper, object-oriented image analysis technique has been compared with the classical and well-known image classification techniques (maximum likelihood, parallelepiped, minimum distance and spectral angle mapper) using Landsat 8 image of Northern part of Free state and Southern part of Gauteng, Provinces of South Africa. In the implementation of the test maximum likelihood,
parallelepiped, minimum distance and spectral angle mapper approaches are taken as pixel-based methods. Their capacity with used Landsat 8 image has been analysed based on the ground truth materials over the interest area. However, on the other hand, object based classification was performed in hierarchy, first with segmentation, and then the sample based nearest neighbor classification. Maximum likelihood had the best accuracies compared to other pixel based algorithm. However there was no significant visual difference between maximum likelihood accuracies with the sample based nearest neighbor algorithm of OOC. Although classification accuracy was not significantly different between them object-based classification detected more realistic Land cover and land use with fewer illogical errors than did the Maximum Likelihood classifier. This research shows that the object-oriented classification approach classifies Land use and Land cover more accurately than the pixel-based classifications approach.

BIBLIOGRAPHY


DIFFERENT ENTROPIES AND POLSAR LANDCOVER CLASSIFICATION SCHEMES USING THEM

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KEYWORDS: PolSAR, Landcover classification, entropy

ABSTRACT

One of the famous and widely used landcover classification algorithms for polarimetric synthetic aperture radar images, is based on entropy and complex Wishart classifier. However this algorithm, in some cases, fails to correctly classify all types of landcovers. Entropy used in this algorithm is the Shannon entropy, borrowed from information science literatures. However, there are different generalized mathematical functions which share the properties of Shannon entropy and can be used in place of it. In this paper, we present an analytical study of landcover classification schemes based on these generalized entropies. We have discussed the reasons for which a particular entropy proves to be a better choice than another. From the experiments done in the work, Rényi entropies with \(\beta=2\) and \(3\) were found to be the most suitable for crop classification.

INTRODUCTION

Landcover classification is one of the major applications of radar based remote sensing. Polarimetric synthetic aperture radar (PolSAR) imagery is well suited for landcover classification for its phenomenological capabilities (Panigrahi2011a, Panigrahi2011b, Giuli1986). One of the most popular unsupervised landcover classification schemes for PolSAR images, is based on the use of polarimetric entropy \(H\) and alpha angle \(\alpha\) (Cloude1997). To improve the classification accuracy of the original algorithm, Lee \textit{et al}. (Lee2009) introduced a combined use of unsupervised classifier based on \(H/\alpha\) and supervised maximum likelihood classifier based on complex Wishart distribution. The classified pixels in each zone in the \(H/\alpha\) plane are taken as an initial training sets for classification based on complex Wishart distribution. The classification results are then used as training sets for the next iteration. To enhance the discrimination capability of this combined technique further, zones are further subdivided into two zones based on the pixel’s anisotropy \(A\) value (polimage). This Wishart-\(H/A/\alpha\) (Pottier2000) constitutes a complete landcover classification scheme. However, this scheme in some cases, fails to correctly classify all the types of landcovers.

A Gini index based classification scheme has recently been proposed in (Panigrahi2011b), where improved classification accuracy is reported by introducing a new parameter, Gini index \((G)\) (Duda2001) as an alternative to entropy parameter in \(H/\alpha\) classification scheme. The Gini-index based classification scheme performs better because almost all the pixels in \(G/\alpha\) plane have lower entropy values in comparison to the corresponding pixels in \(H/\alpha\) plane. Even though the proposed Gini index based classification algorithm performs better than Shannon entropy based classification algorithm in crop-type discrimination, it too fails in correctly classifying all the types of crops. However from this work it has been learnt that as the entropy value of the pixels decreases, the scattering mechanisms are more easily distinguished. This led us to search for more entropy like
parameters that can move pixels more towards the lower entropy regions in the $H/\alpha$ plane. In the context of radar polarimetry, entropy is a parameter used to determine the randomness in a three-level Bernoulli statistical model employed to generate estimates of the average target scattering matrix parameters from the data (Cloude1997). The entropy used in such analysis is the classic Shannon entropy. In literature, two generalized versions of entropy, viz. Rényi and Tsallis entropy exist. Rényi entropy is the generalized version of Shannon entropy; a one-parameter family of entropies of the order $\beta$ (Renyi1961). A different version of Shannon entropy used in statistical mechanics is Boltzmann-Gibbs entropy. Tsallis generalized Boltzmann-Gibbs entropy to a one-parameter family of entropies by defining an entropy of the order $q$ which is called the Tsallis entropy (Tsallis1988).

These two generalized versions of entropy, viz. Tsallis entropy and Rényi entropy are considered in this work, based on which new landcover classification schemes are developed. A comparative study among these landcover classification schemes is carried out on the basis of their discriminating abilities. These generalized entropy functions introduce new variables ($\beta$ and $q$) which are optimized by this comparative study.

The rest of the paper is organized as follows. In the next section, a brief introduction to different forms of entropy is provided. In the next section, new landcover classification schemes based on different forms of entropy are developed. In the next section, the classification schemes are being compared as per their classification efficiency. The last section gives summary of the work presented in this paper.

**DIFFERENT FORMS OF ENTROPY**

In the early 1850s, Rudolf Clausius set forth the concept of entropy in the context of classical thermodynamics (Clausius1867). The name “entropy” is derived from the Greek word $\text{en-trepein}$, meaning energy turned to waste. Entropy is the quantitative measure of the degree of uncertainty, which exists in a system. Although entropy was originally a thermodynamic concept, it has been used in other fields of studies including information theory, psychodynamics, economics, and evolution. In information theory, entropy is a measure of the uncertainty associated with a random variable and is usually referred to as Shannon entropy.

A generalization of Shannon entropy, the Rényi entropy, is one of a family of functions for quantifying the randomness of a system. It is named after Alfréd Rényi.

Rényi entropy of the order $\beta$ is defined as

$$E_{\beta} = \sum P_i^{\beta},$$  \hspace{1cm} (1)

where $P_i$’s are the pseudo-probabilities (Cloude1997). Rényi entropy tends to Shannon entropy as $\beta \rightarrow 1$ (Reyn1).

In statistical mechanics, the Boltzmann-Gibbs entropy has been used to give a probabilistic definition of entropy (BG). It is defined as

$$H = -k \sum P_i \log P_i,$$  \hspace{1cm} (2)

where $k$ is known as Boltzmann constant.

Tsallis proposed a generalization of the Boltzmann-Gibbs entropy (Tsallis). This entropy has the form

$$H_q = \frac{1}{q-1} \left(1 - \sum P_i^q\right),$$  \hspace{1cm} (3)

where $q$ is a real positive parameter that extends the Boltzmann-Gibbs entropy. For $q \rightarrow 1$, one obtains Boltzmann-Gibbs entropy.
DIFFERENT ENTROPIES BASED LANDCOVER CLASSIFICATION SCHEMES

The two generalized versions of entropy, viz. Tsallis entropy and Rényi entropy are considered here. New landcover classification schemes based on these two generalized versions of entropy are developed. Figure 1 shows the feasible region for various entropies/alpha planes.

Rényi entropy is a function of variable β. As β tends to 1, Rényi entropy becomes Shannon entropy. Entropy in the classic entropy based landcover classification scheme is the Shannon entropy. In rest of the paper, unless it is specified, the term ‘entropy’ stands for the Shannon entropy. New landcover classification schemes based on Rényi netropy with various values of β may be developed. At first, a landcover classification scheme based on Rényi entropy with β=2 ($R_2$) is developed.

The values of $R_2$ for various scatterer types are as follows.

1. For pure target, $R_2$ is 0.
2. For distributed target, $R_2$ is $\log_2 3$.
3. For partial targets, $R_2$ is in between 0 to $\log_2 3$.

To make the same extreme values as of entropy, $R_2$ is modified as

\[ R_2 = \frac{1}{\log_2 3} \]

A new classification scheme can be realized by replacing entropy with $R_2$ in the classic entropy based landcover classification technique. Performing similar analogies, new landcover classification schemes based on Rényi entropy with various values of β may be developed. For example, a new landcover classification scheme based on Rényi entropy with β=3 ($R_3$) may be developed next.

RESULTS AND OBSERVATIONS

A comparative study among different entropies based landcover classification schemes is carried out. The motivation here is to find the entropy index that provides the optimum landcover classification accuracy. A comparative study among Tsallis entropies and Rényi entropies based classification schemes is carried out separately. The study evaluates the optimum Tsallis and Rényi entropy parameters, $q$ and β, respectively. Finally, a comparison between the classification schemes based on optimum Tsallis and Rényi entropy is carried out. The performance of different entropies based classification schemes are evaluated on Flevoland data based on their crop classification efficiency. Percentage of pixels of different classes correctly classified by different entropies based Wishart classifiers is shown in Table 1. The overall class and pixel wise accuracy for different entropy based classifiers is shown in Table 2. The termination criteria of Wishart based iterative algorithm has been set based on the following: i) percentage of pixels switching classes in each iteration is 8, ii) maximum number of iteration is 5.

A comparative study of different Tsallis entropies based landcover classification schemes is carried out here to find the optimum one. In (Panigrahi2011a), it is shown that Gini index based landcover classification technique performs better than the classic entropy based landcover classification technique. This is because almost all pixels have lower Gini index values than entropy value. When entropy in $H/\alpha$ classification technique is replaced by Gini index, the pixels moves towards the lower entropy region in $H/\alpha$ plane; thereby increasing the discrimination capability of $H/\alpha$ classification technique.
A comparative study of different Rényi entropies based landcover classification schemes is carried out here to find the optimum one. For almost all pixels, $R^2$ value is smaller than entropy value. This means that the pixels move towards lower entropy value in $H/\alpha$ plane, if entropy is replaced by $R^2$. As can be read from Table 2, the performance of $R^2$ based classification scheme is better than entropy and Gini index based classification schemes as expected.

Finally, a comparative study among Tsallis entropies and Rényi entropies based classification schemes is carried out. From the the Tables 1, 2, it can be observed that optimum Rényi entropy based classification scheme (Wishart-$R^3/A/\alpha$) is performing better than the optimum Tsallis entropy based classification scheme (Wishart-$T^2/A/\alpha$). From the performance Table 2, following observations are noted.

- Generally, classification schemes based on Rényi entropy performs better than Tsallis entropy based classification schemes.
- Rényi entropy with $\beta=3$ is the best performing index among all types of entropy.
- The overall classification efficiency goes on increasing as one moves from entropy $\to T^3 \to$ Gini index ($T^2) \to R^4 \to R^2 \to R^3$.
- Only classification schemes based on Rényi with $\beta=2$ and $\beta=3$ are able to classify all types of crops correctly.

**CONCLUSIONS**

An analytical study of different entropies based landcover classification schemes have been carried out. Different entropies based landcover classification schemes have been developed. A comparative study among different entropy based classification schemes has been carried out on the basis of their discriminating abilities. It has been observed that classification schemes based on Rényi entropy performs better than Tsallis entropy based classification schemes. For the given dataset, among all classification schemes, Rényi with $\beta=2$ and $\beta=3$ based classification schemes were able to discriminate all types of landcovers correctly. It was also found that, for the given experimental setup, Rényi with $\beta=3$ based classification scheme is the best performing landcover classification technique.
Table 1. Percentage of different classes correctly classified by different entropies based Wishart classifiers.

<table>
<thead>
<tr>
<th>Class</th>
<th>Tsallis2</th>
<th>Tsallis3</th>
<th>Rényi2</th>
<th>Rényi3</th>
<th>Rényi4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lucerne</td>
<td>86.67</td>
<td>63.65</td>
<td>44.56</td>
<td>89.34</td>
<td>×</td>
</tr>
<tr>
<td>Beet</td>
<td>59.05</td>
<td>66.03</td>
<td>75.08</td>
<td>30.80</td>
<td>80.06</td>
</tr>
<tr>
<td>Potato</td>
<td>92.17</td>
<td>88.75</td>
<td>77.30</td>
<td>89.29</td>
<td>66.22</td>
</tr>
<tr>
<td>Pea</td>
<td>80.49</td>
<td>82.70</td>
<td>78.43</td>
<td>80.58</td>
<td>76.48</td>
</tr>
<tr>
<td>Bare soil</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>98.81</td>
<td>97.89</td>
</tr>
<tr>
<td>Barley</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>84.76</td>
<td>87.97</td>
</tr>
<tr>
<td>Wheat</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>82.22</td>
<td>82.85</td>
</tr>
<tr>
<td>Rape seed</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>53.32</td>
<td>74.37</td>
</tr>
<tr>
<td>Rape seed</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>53.32</td>
<td>74.37</td>
</tr>
</tbody>
</table>

Table 2. Overall Percentage of classes and pixels correctly classified by different entropies based classifiers.

<table>
<thead>
<tr>
<th>Entropy</th>
<th>classes</th>
<th>pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tsallis2</td>
<td>50</td>
<td>79.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
<td>-------</td>
</tr>
<tr>
<td>Tsallis3</td>
<td>50</td>
<td>75.28</td>
</tr>
<tr>
<td>Entropy</td>
<td>50</td>
<td>68.84</td>
</tr>
<tr>
<td>Rényi2</td>
<td>100</td>
<td>76.14</td>
</tr>
<tr>
<td>Rényi3</td>
<td>100</td>
<td>80.63</td>
</tr>
<tr>
<td>Rényi4</td>
<td>75</td>
<td>69.43</td>
</tr>
</tbody>
</table>

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PANSHARPENING METHODS BASED ON CONTOURLET TRANSFORM
APPLIED TO URBAN AREAS

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KEYWORDS: image fusion, contourlets, NSCT, SPOT, ALSAT-2A.

ABSTRACT

This paper aims at stimulating ongoing research and development on the topic of urban remote sensing exploiting multiple data sets. Several pansharpening methods are studied and implemented in remote sensing domain, therefore, in this paper, we concentrate on fusion techniques based on multiresolution analysis called the contourlet transform (CT). Recently, the stationary version NonSubsampled Contourlet Transform (NSCT) has been proposed because of its ability to give an asymptotic optimal representation of edges and contours in image by virtue of its property of good multiresolution, shift-invariance, and high directionality.

In this work, different fusion methods were implemented and compared based on the spectral response weighting and the selection of the maximum energy in the region using the NSCT transform. In order to obtain results with spatial improvement and minimum loss of spectral features, the studied methods have been tested on two datasets representing urban areas: one is acquired by SPOT satellite and the other one is provided by ALSAT-2A satellite. The quality of the resulted images has been evaluated by visual interpretation and statistical analysis using the Relative Average Spectral Error “RASE” Relative Average Spectral Error and “ERGAS: (from the French acronym “Erreur Relative Globale Adimensionnelle de synthèse”)” parameters.

INTRODUCTION

Many image sensors provide two different types of images: multispectral images (MS) and panchromatic (PAN) image. The aim of the remote sensing image fusion, also called pansharpening of MS images, is to obtain a synthetic MS image with high spatial and high spectral resolutions simultaneously by merging the high spatial characteristic of PAN image with the high spectral one of MS images (Gonzalez-Audicana et al., 2004; Thomas et al., 2008). Several image fusion techniques are developed such as: the Intensity-Hue-Saturation transform (IHS), the Principal Component Analysis (PCA), and some approaches are based on multiresolution analysis, such as Laplacian Pyramid (Burt and Adelson, 1983), and Discrete Wavelet Transform (DWT) (Zhang and Blum, 1999).

In recent years, the pansharpening algorithm based on multiscale analysis tools, is becoming a promising technique to produce images with high spatial and spectral resolution all together such as standard contourlet transform (CT) (Choi et al., 2005), that are very different from wavelets. The SCT introduced by Do and Vetterli (Do and Vetterli, 2005) is a new extension to the DWT in two
dimensions using nonseparable and directional filter banks. The contourlet decomposition is constructed by combining two successive stages: a Laplacian pyramid (LP) and directional filter bank (DFB). While this last approach can represent smooth edges and contours in infinite orientations, the DWT lacks in this way, and can only catch point discontinuities in limited directions.

The objective of this paper is to compare methods based on the NSCT: one combines the advantage of multiresolution analysis with the characteristic of the Spectral Responses (SR) (Chu and Zhu, 2008) of objects in urban area, and the other one selects the Maximum Energy (ME) (Jia and Xiao, 2010) from the contourlet coefficients in the same urban region and combines them in the fusion rule. These methods are evaluated in order to show the effect of each one in the spatial quality improvement, and their ability to preserve the spectral aspect in the fused images. The structure of this paper is as follows. In the next section we describe the theoretical basis of the NSCT, then, we present the pansharpening methods for PAN and MS images based on the NSCT. After that, we give a qualitative and quantitative assessment to discuss the obtained results. Finally in the last section, we conclude by a comparison report between merged images illustrating the contribution of each fusion scheme in the improvement of the satellite images.

THEORY OF MULTISCALE AND MULTIDIRECTIONAL TRANSFORM

In this section, we introduce a theoretical aspect used to generate the multiscale analysis given in this work. These flexible implementations realized depending on a multitude frequency orientation offer a good tradeoff between the sparse representation of features and the perceptual quality of the reconstitute image.

NonSubsampled Contourlet Transform

In order to construct a flexible and efficient transform, a NonSubsampled Contourlet Transform NSCT has been proposed (Cunha et al., 2006). The NSCT is a non decimated version of the SCT and fully shift-invariant, multiscale and multidirection expansion whose core is the nonseparable two channels NonSubsampled Filter Bank (NSFB). The less stringent design condition of the NSFB to build filters, leads to NSCT with better frequency selectivity and regularity when compared to the SCT. To achieve the shift-invariance property, the NSCT is created upon coupling a NonSubsampled Pyramid (NSP) with the NonSubsampled Directional Filter Bank (NSDFB). Given an input image $G(x, y)$ where $(x, y)$ denotes a pixel of $G$. $G$ is transformed by $L$ scales NSP decomposition, and the resulting output consist of $L$ bandpass subbands and a lowpass subband. Each bandpass subband is further decomposed by $l^{ih}$ scale NSDFB into $2^l$ different directional subbands, $1 < l \leq L$. This decomposition can be represented like a set of subbands as follows:

$$B = \left\{ B_j \mid j = 1, 2, \ldots, \left( \sum_{l=1}^{L} 2^l \right) + 1 \right\} \quad (1)$$

Where: $B_1$ is the lowpass subband, and $B_j$, $j = 2, \ldots, \sum_{l=1}^{L} 2^l$, are directional subbands filtered by NSDFB.
In this work, the NSP decomposition stage adopts "9-7" Filter Banks generated by one dimensional prototype filters, and the NSFB decomposition stage uses the "PKVA" Ladder Filter Banks. We perform three decomposition levels \([1, 2, 3]\), it signifies: \(2^1\) directions at level 1, \(2^2\) directions at level 2 and \(2^3\) directions at level 3.

**METHODOLOGY**

In this section, we present two different fusion methods for panchromatic and multispectral images based on the NSCT transform, the first one inspired by Chu and Zhu (Chu and Zhu., 2008) using the characteristics of the multiresolution analysis and the spectral response on the decomposition subbands. The second method takes part in the detail coefficients getting by the NSCT decomposition, and selects the maximum region-energy containing in each of the corresponding subbands (Jia and Xiao, 2010). Both of these methods use the IHS transform in order to make easier their dealing with intensity image instead multispectral bands. The steps followed to implement the scheme of each technique are shown bellow.

**a) Fusion method based on NSCT and spectral response (SR)**

1. The PAN image and the original MS images are geometrically registered to each other.

2. Upsampling MS images to the size of PAN image in order to be superimposed using the bicubic interpolation technique.

3. Calculate the intensity component "I" of the upsampled MS images according to the IHS transform formula when using SPOT-MS images in one hand, and corresponding to Generalized IHS transform formula for those provided by ALSAT-2A sensor on the other hand, as follows:

   \[
   \begin{bmatrix}
   I \\
   v_1 \\
   v_2 \\
   \end{bmatrix}
   =
   \begin{bmatrix}
   1/3 & 1/3 & 1/3 \\
   -1/2 & -1/2 & 1 \\
   \sqrt{3}/2 & -\sqrt{3}/2 & 0 \\
   \end{bmatrix}
   \begin{bmatrix}
   ms_1 \\
   ms_2 \\
   ms_3 \\
   \end{bmatrix}
   \]

   \(ms_1, ms_2\) and \(ms_3\) are the multispectral bands provided by SPOT satellite, while \(v_1\) and \(v_2\) represent intermediate variables which are needed in the transform.
ALSAT2A images: 
\[ I = \frac{1}{n} \sum_{i=1}^{n} b_i \]  
(3)

We define \( i \) by the band number of the multispectral bands \( b \) given by ALSAT-2A satellite.

4. Applying the multiresolution analysis NSCT to decompose PAN and \( I \) in order to obtain an approximation subbands with low frequency coefficients and a specified number of detail subbands with high frequency coefficients for each image.

\[ \text{pan} = \text{App}_{\text{pan}} + \sum_{j=1}^{m} \sum_{i=1}^{n} \text{Det}_{\text{pan}}^{i,j} \]  
(4)

\[ I = \text{App}_i + \sum_{j=1}^{m} \sum_{i=1}^{n} \text{Det}_i^{i,j} \]  
(5)

Where \( \text{App}_{\text{pan}} \) and \( \text{App}_i \) are the coarse images of the PAN and \( I \) respectively, and \( \text{Det}_{\text{pan}}^{i,j} \) and \( \text{Det}_i^{i,j} \) are the detail images of PAN and \( I \) at \( i \) direction in the decomposition level \( j \).

5. In this step, we mainly focus on fusing the approximations, while the contourlet coefficients representing details of the fused intensity component come from the corresponding detail coefficients of the PAN, in order to inject the high frequency information of the pan into the MS images. The approximation coefficients of the merged intensity component \( \text{App}_{\text{pan}} \) are determined as follows.

\[ \text{App}_{\text{new}} = \begin{cases} \beta \cdot \text{App}_i(i, j) + (1 - \beta) \cdot \text{App}_{\text{pan}}(i, j) & \text{if } \text{App}_i(i, j) > \text{App}_{\text{pan}}(i, j) \\ \text{App}_i(i, j) & \text{otherwise} \end{cases} \]  
(6)

\( \beta \) represents a weighting parameter equal to 0.9 in this paper.

6. Performing the inverse NSCT transform, to combine \( \text{App}_{\text{new}} \) and \( \text{Det}_{\text{pan}}^{i,j} \) and obtain the new intensity \( I_{\text{new}} \).

\[ I_{\text{new}} = \text{App}_{\text{new}} + \sum_{j=1}^{m} \sum_{i=1}^{n} \text{Det}_{\text{pan}}^{i,j} \]  
(7)

7. Executing the inverse IHS transform to achieve the fused MS images according to the following expressions:

\[ \begin{bmatrix} ms_{f1} \\ ms_{f2} \\ ms_{f3} \end{bmatrix} = \begin{bmatrix} 1 & 1/3 & 1/\sqrt{3} \\ 1 & -1/3 & -1/\sqrt{3} \\ 1 & 2/3 & 0 \end{bmatrix} \begin{bmatrix} I_{\text{new}} \\ v_1 \\ v_2 \end{bmatrix} \]  
(8)

\( ms_{f1}, ms_{f2} \) and \( ms_{f3} \) are the fused multispectral bands for SPOT satellite.
Fused ALSAT2A images:

\[
\begin{bmatrix}
    b_{f1} \\
    b_{f2} \\
    b_{f3} \\
    b_{f4}
\end{bmatrix} =
\begin{bmatrix}
    b_1 + (I_{new} - I) \\
    b_2 + (I_{new} - I) \\
    b_3 + (I_{new} - I) \\
    b_4 + (I_{new} - I)
\end{bmatrix}
\]  

(9)

\(b_{f1}, b_{f2}, b_{f3}\) and \(b_{f4}\) are the fused multispectral bands for ALSAT-2A satellite.

b) Fusion method based on NSCT and maximum energy (ME)

In this method the four first steps introduced in the fusion method based on the NSCT and the SR are applied in this part, and the rest of steps goes after are given bellow.

1. Select the maximum the region energy for every coefficient of each detail subband of pan and the corresponding one of the intensity applying the related expression:

\[
Det_{new}^{i,j} = \begin{cases} 
     Det_{pan}^{i,j}(i, j) & \text{if } Det_{pan}^{i,j}(i, j) > Det_{I}^{i,j}(i, j) \\
     Det_{I}^{i,j}(i, j) & \text{otherwise}
\end{cases}
\]  

(10)

2. Apply the inverse NSCT in the framework of the fusion rule to merge the approximation \(I_{App}\), getting from the intensity after NSCT decomposition step and the details \(Det_{new}\) calculated by equation 10, and obtain the new Intensity \(I_{new}\).

\[
I_{new} = I_{App} + \sum_{j=1}^{n} \sum_{i=1}^{m} Det_{new}^{i,j}
\]  

(11)

3. Perform the inverse IHS transform like it is mentioned above in the first image fusion scheme.

The fusion methods mentioned are applied on two datasets acquired by SPOT and ALSAT-2A satellites and taken on an urban area of Algiers town. Figures 2 (a, b) show the high spatial resolution of Pan: SPOT (512x512 pixels) with resolution of 10m and ALSAT-2A (1024x1024 pixels) with resolution of 2.5m. While the colored compositions of MS images are illustrated in figures 3(a, b), provided respectively by SPOT (256x256 pixels) and ALSAT-2A (256x256 pixels), characterized in that order by resolutions of 20m and 10m.
Figure 2. Panchromatic images: a) SPOT Pan image, b) ALSAT-2A Pan image.

Figure 3. The colored composition of multispectral images oversampled to the pan resolution presented with their zoom in urban area, corresponding to:
   a) SPOT images, b) ALSAT-2A images.
EXPERIMENTAL RESULTS

Figure 4. Fused images for SPOT and ALSAT-2A stemming from different techniques: SPOT: a) NSCT+SR, b) NSCT+ME, c) IHS, d) DWT, ALSAT-2A: e) NSCT+SR, f) NSCT+ME, g) IHS, h) DWT.

The assessment of each method is based on the preservation of the spectral aspect and the injection of the spatial characteristics in the fused image.

In order to evaluate the performance of the presented methods and assess the goodness of the spatial and spectral qualities on the fused images, two well known quality indices have been used: the Relative Average Spectral Error index “RASE” and the Relative Dimensionless Global Error in Synthesis (ERGAS), and defined as follow:

\[
RASE = 100 \frac{1}{M} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \text{RMSE}^2(B_i) \right)}
\]  

(12)

Where \( M \) is the mean radiance of the \( N \) spectral bands \( B_i \) of the MS images, and the “RMSE” is the Root Mean Square Error computed in the following expression:

\[
\text{RMSE}^2(B_i) = \text{bias}^2(B_i) + \text{sdd}^2(B_i)
\]  

(13)

\[
\text{ERGAS} = 100 \frac{h}{l} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \text{RMSE}^2(B_i) / (M_i)^2 \right)}
\]  

(14)
\( h/l \) represents the resolution ratio of high and low resolutions, and \( M_i \) signifies the mean radiance of each spectral band involved in the fusion process.

Table 1. Statistical evaluation for fusion methods.

<table>
<thead>
<tr>
<th>method</th>
<th>data</th>
<th>IHS</th>
<th>DWT</th>
<th>NSCT_SR</th>
<th>NSCT_ME</th>
</tr>
</thead>
<tbody>
<tr>
<td>RASE</td>
<td>SPOT</td>
<td>14.44</td>
<td>7.97</td>
<td>7.12</td>
<td>3.15</td>
</tr>
<tr>
<td>ERGAS</td>
<td></td>
<td>9.36</td>
<td>4.08</td>
<td>3.82</td>
<td>1.66</td>
</tr>
<tr>
<td>RASE</td>
<td>ALSAT-2A</td>
<td>26.00</td>
<td>25.80</td>
<td>25.42</td>
<td>13.52</td>
</tr>
<tr>
<td>ERGAS</td>
<td></td>
<td>6.62</td>
<td>6.47</td>
<td>6.38</td>
<td>3.39</td>
</tr>
</tbody>
</table>

The visual inspection highlights, in figure 4, that the fused images presented in this paper have more information compared to that resulting from wavelet and IHS transforms. Thus, we observe the appearance of details and the clearness of the scene presenting an urban area in the resultant image stemming from the fused method based on NSCT and SR presented in figure 4 (a, e) and a good preservation of the spectral quality in the image stemming from the combination of NSCT and ME method in figure 4(d, f). In addition we notice that, the NSCT ensure the regularity of edges and lines in urban zones compared to wavelet engendering splits due to the decimations produced during this transform, and we can see in the complete image the good preservation of the spectral aspect when applying the NSCT compared to the IHS transform.

In table 1, we show the values of the quality indexes computed for the fused images obtained when applying the above mentioned fusion methods. According to these results, we notice that the NSCT+SR and NSCT+ME scheme analysis presented, provide lower RASE and ERGAS values compared for those calculated in DWT and IHS methods, in addition, this explains the injection of the details and the conservation of the spectral characteristic for each method. However, quantitative analysis of the fused images indicates best results for NSCT based fusion method with good and balanced values of RASE and ERGAS compared to other methods, and this prove the visual report where contours and edges are well defined and the spectral information is properly hold.

CONCLUSION

In this work, two image fusion algorithms based on NSCT transform are presented to merge panchromatic and multispectral images of SPOT and ALSAT-2A satellites.

The obtained results show that the NSCT transform is able to inject more details and preserve the spectral data than other methods due to its good frequency selectivity. The introduction of the new fusion methods based on NSCT represents edges better than wavelets. Since edges play a fundamental role in urban areas, one good way to enhance spatial resolution is to enhance the edges. In addition, these fusion methods provide richer information in the spatial and spectral domains at the same time.
ACKNOWLEDGMENTS

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REFERENCES


HYPERSONTAL DATA REDUCTION BASED ON WAVELET TRANSFORM

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KEYWORDS: Wavelet transform, Dimensionality reduction, Feature extraction, Band selection, Principal components analysis, Minimum noise fraction transform

ABSTRACT

The hyperspectral imaging permits to measure radiance considering hundreds of narrow spectral bands. These data are converted into reflectance to express the spectral responses that permit to precisely identify each object present in the observed scene. The spectral wealth of such data is closely related to a very large volume that makes their exploitation difficult to perform. Thus, dimensionality reduction is necessarily performed to discard redundancy and noise and mainly project these data into a lower dimensional space where only the pertinent content is likely to appear. Moreover and specifically to the hyperspectral data, this should preserve the spectral features that permit the discrimination of the imaged objects. Many methods proposed in the literature, suggest the hyperspectral data reduction by the mean of linear and statistically-based transformations such as the popular Principal Component Analysis (PCA) and the Minimum Noise Fraction Transform (MNFT) which both have the advantage of being simple and yielding to few uncorrelated, ordered and representative components. These methods answer the need of numerous applications but fail when the spectral characteristics are of interest. The Wavelet Transform (WT), which is a linear transformation, widely used for signal compression, present an interesting option for hyperspectral data reduction. The decomposition of the spectral responses with the WT implies the use of sub-sampling filters that separate low frequencies from high ones producing approximations (overall form of the spectra) and details (anomalies and noise). The sub-sampling has the advantage of reducing the dimensionality of the spectra to the half at each level of decomposition. In this paper, we present the results of the described WT principle application and which we compare to the ones obtained for the PCA and the MNFT. Spaces of different dimensionalities are constructed and whose representativeness is evaluated via an unsupervised classification. Encouraging results are assessed with real and remotely sensed data.

INTRODUCTION

The hyperspectral imaging senses the reflectivity of illuminated objects considering contiguous spectral bands, generally extended from the visible to the infrared regions with a bandwidth of few nanometres (Goetz, 2009). The spectral detail produced by the great number of the simultaneously recorded images permits to pinpoint the materials present in the observed scene and makes the hyperspectral technology suitable but not limited to the precise land cover classification (Trabalka, 2010). The high dimensional character of such images increases the computational complexity of the
algorithms to implement before the effective exploitation. As a solution, many processing have been carried out to improve the assessment of the pertinent content enclosed in the acquired datasets (Plaza, 2006). They generally consist of creating lower dimensional and more representative spaces applying some projections (Croux, 2000; Liu, 2009) that aim to discard redundancy and noise. It should be noticed that the majority of these methods hasn’t been developed specifically to the hyperspectral case but only extended or adapted to their important dimension. As a consequence, these methods usually do not preserve the spectral characteristics of these data despite the fact that it consists of the fundamental advantage of the hyperspectral technology. In order to reduce the dimensionality of the hyperspectral images and at the same time to sufficiently describe the spectral characteristics, we present in this paper an algorithm based on the Wavelet Transform (WT) which we compare to conventional methods that have been successfully used for the hyperspectral reduction that are the Principal Components Analysis (PCA) and the Minimum Noise Fraction Transform (MNFT). The WT method has the quality of being simple to implement and yielding to representative components with adjustable precision.

**DIMENSIONALITY REDUCTION PRINCIPLE**

Very often the significant components of high dimensional datasets are enclosed in a lower dimensional space whose identification is obtained via the dimensionality reduction process (Chui, 2010). This process improves the significance of the data discarding undesirable content due to redundancy and noise. This process significantly reduces the space of storage, lightens the complexity of manipulation and minimizes the time-consumption.

Most dimensionality reduction methods suggest performing two successive processing stages. The first called the features extraction is concerned with the projection of the original data using an adequate transformation in a new space of representation where specific and interesting features are likely to appear. This stage is obligatorily followed by the bands selection stage whose concern is the properly said reduction. It consists of the location of the most interesting features extracted and their collection to construct the lowest dimensional but the most representative space (Guo, 2008).

Usually and for simplicity, the described dimensionality reduction is defined on the basis of linear transformation models. One of the methods that are commonly used is the well-known Principal Components Analysis (PCA) which can be added to its noise-adjusted version called the Minimum Noise Fraction Transform (MNFT). The principles of these cited methods are described below.

**The Principal Component Analysis (PCA)**

The PCA is an orthogonal transformation that uses second order statistics and eigenvalues decomposition to condense the content of multidimensional data and construct a new dataset made of uncorrelated and ordered channels.

The ordering of these channels is based on variance calculation in a way that makes the pertinent components ranked in first orders, the reason why they are called principal components (Liu, 2009).

Dimensionality reduction suggests keeping a small and adequate number of the principal components (selected decreasingly starting from the first) which are supposed to gather the most significant components enclosed in the original data.
The Minimum Noise Fraction Transform (MNFT)

The MNFT is a linear and a statistically-based transformation that assumes that the multidimensional and highly correlated data to transform are affected by an additive white noise. This transform which can be seen as resulting from the application of two successive PCA, suggests estimating the presence of the noise that is defined as being in the origin of all radiometric variations recorded over homogeneous regions. The first PCA is processed with the aim of separating the estimated noise from the informative components where the second gives uncorrelated and informative ones ranked according to the fractions of noise that they may contain (increasingly from the noiseless to noisy ones) (Green, 1988). The components of first ranks are the noiseless hence they are called the minimum noise fraction components. They are the most interesting features that should be retained in the dimensionality reduction process. Their number defines the dimensionality of the reduced dataset constructed.

WAVELET-BASED REDUCTION

The Wavelet Transform Theoretical Basis

The Wavelet Transform (WT) is at the basis of many tools exploited in different remote sensing applications such as compression, geo-referencing, fusion and classification (Rivard, 2008). It creates a representation domain that describes simultaneously the spatial and the frequential distributions of the data. This is obtained thanks to its multi-resolution and multi-scale structure.

The WT decomposition of a mono-dimensional signal involves a function called the mother wavelet that is subject of translation and dilation when passing from one level of decomposition to another following the expression cited below where $\psi$ and $\psi_{m,n}$ denote respectively the mother and the daughter wavelets, $\alpha$ denotes dilation factor and $\beta$ the translation one.

$$\psi_{m,n}(k) = \alpha^{-1} \psi(k - \beta / \alpha^2)$$  \hspace{1cm} (1)

An algorithm proposed by Mallat (Mallat, 1989) suggests applying a complementary low pass and high pass filtering followed by dyadic decimations. This operation reduces the dimension of the decomposed signal to the half and the resulting coefficients define respectively approximation and details.

When it is judged that the dimensionality of the produced components has not been sufficiently reduced, the produced approximation is decomposed once more with respect to the scheme illustrated in Figure 1.

![Figure 1. The WT decomposition principle](image-url)
The WT which is a good candidate for hyperspectral dimensionality reduction (Kaewpijit, 2003) permits to improve the representativeness of the data by the separation of noise and anomaly (represented by high frequencies) from the pertinent content that gave a global description (described with low frequencies).

**The Wavelet-Based Reduction Algorithm**

The presented algorithm of reduction suggests performing successive steps as it is illustrated in the Figure 2 and is explained next:

Figure 2. Wavelet-based algorithm for hyperspectral dimensionality reduction

First, the hyperspectral images are organized in a way that represents the spectral responses with one dimensional (1D) vectors in the number \( P \) of the spatial cells (pixels) and whose length is equal to the spectral dimension \( N \). Dependently from the considered mother wavelet \( \psi \) and the original spectral dimension \( N \), the maximum level of decomposition \( L_{\text{max}} \) is calculated. It should be noticed that the more the form of \( \psi \) is complex, the more the number of levels to reach is small. Hence, it is suitable to use a wavelet with a simple form to reach high reduction ratios. The WT is then applied to these vectors using a sub-sampling filter that separates low frequencies from high ones and produces components with decimated dimensionality respectively called approximations and details. While the \( L_{\text{max}} \) level is not reached, the operation can be repeated applying the sub-filtering on the last approximation generated because that they give a description which is close to the original spectra.

**EXPERIMENTAL PROCEDURE AND RESULTS**

**Used Dataset Identification**

Our experiments have been applied to a remotely sensed hyperspectral image acquired over an Algerian region using the Hyperion sensor which is embedded on the EO1 spatial platform. We chose this voluminous dataset because that it illustrates a proximate region that represents an extended and heterogeneous zone with objects belonging to different themes (sea, vegetation, urban and soil). In addition, the spectral bands are contiguous which favours redundancy and because that it is acquired from a spatial platform this image is supposed to be sensitive to noise. The hyperspectral data cube associated to the observed scene is represented below in the Figure 3.
The used hyperspectral data cube represents a subset extracted from the entire collection recorded by the Hyperion sensor. Next table summarizes its main specifications:

<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Spectral Dimension</th>
<th>Spectral Range</th>
<th>Spectral Resolution</th>
<th>Spatial Dimension</th>
<th>Spatial Resolution</th>
<th>Imaged Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyperion-EO1</td>
<td>120 bands among 242</td>
<td>from 447.17nm to 2224.03nm</td>
<td>around 10nm</td>
<td>450 x 256 pixels</td>
<td>30meters</td>
<td>Algiers (Algeria)</td>
</tr>
</tbody>
</table>

**Results Presentation and Discussion**

Before the application of the presented algorithm on the described hyperspectral dataset, it was necessary to define the mother wavelet to consider. To reach the most important reduction, we suggest using the wavelet Daubechies 1 (commonly known by the Haar wavelet).

The calculation of the maximum level of decomposition that can be reached using this mother wavelet is dependent from the original spectral dimension. For our tests, starting from 120 spectral bands, the calculated value of the $L_{max}$ fixes the final decomposition order to the 6th one.

The evaluation of the representativeness of the components generated is done exploiting different tools: First, the visual inspection, comparing the lower dimensional approximations obtained by the decomposition of the original spectra that belong to different themes. Then, the unsupervised classification that estimates the confusion matrix and the overall accuracy of classification ratio taking as reference the classified image obtained with the consideration of the entire original hyperspectral dataset. And finally, the comparative study that estimates the similarity or difference in the reduction performance and representativeness preservation between the algorithms based on the WT and the conventional methods PCA and MNFT.

**Spectral signatures reduction**: The decomposition of the collection of the spectral responses gave approximation components with decreasing dimensionalities as it is illustrated in the Figure 4 for samples extracted from the original scene over zones representing different themes. Original spectra are illustrated in the left and their associated and successive approximations are ordered in the right:
Original spectra and their successive approximations representing different themes

Figure 4 demonstrates that the decomposition of the original spectra yields to highly reduced approximations that preserve the original overall form. As it is shown, these components basically permit to distinguish the nature of the elements represented despite the fact that they are of a considerably reduced dimension (approximation 5 illustrates a good example with only 4 components).

Unsupervised classification: We consider the entire image and perform an unsupervised classification using the K-means classifier which has been run under the ENVI software platform knowing that the number of classes is fixed to 6 based on a prior knowledge and a visual inspection of the imaged scene. The obtained results are illustrated next from the 1st level (on left) to the 6th (on right):

The evaluation of the constructed collections based on generated approximations has been realized computing the confusion matrix and taking as reference the classified image obtained for the entire hyperspectral dataset.

Next table exposes the impact of the decomposition level on the reduced dimensionality reached starting from a dimensionality of 120 spectral bands. In addition, it gives a quantitative estimation via the accuracy of classification that has been rated for each class among the 6 defined.

<table>
<thead>
<tr>
<th>Level of Decomposition</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Produced Dimensionality</td>
<td>60</td>
<td>30</td>
<td>15</td>
<td>8</td>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>
Comparative study: To assess the performance of the presented algorithm with comparison to a conventional method of reduction, a comparison has been carried out taking into account the results obtained for both PCA and MNFT. These transformations were developed and implemented, then selections have been made on the extracted components to create spaces of representation as dimensional as the ones obtained with the WT-based algorithm.

Unsupervised classifications have been performed on both PCA and MNFT components and produce the results illustrated below for decreasing dimensionalities (60 on left and 2 on right):

The following tables express quantitatively the representativeness of the results obtained by the PCA and MNFT implementation and which have been illustrated before in Figure 6 and Figure 7.

Table 3. Classification accuracy estimated for the reduced datasets using the PCA

<table>
<thead>
<tr>
<th>Constructed Dimensionality</th>
<th>60</th>
<th>30</th>
<th>15</th>
<th>8</th>
<th>4</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification Accuracy (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class 1</td>
<td>99.95</td>
<td>96.76</td>
<td>80.05</td>
<td>55.14</td>
<td>24.36</td>
<td>78.46</td>
</tr>
<tr>
<td></td>
<td>Class 2</td>
<td>Class 3</td>
<td>Class 4</td>
<td>Class 5</td>
<td>Class 6</td>
<td></td>
</tr>
<tr>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>99.95</td>
<td>96.76</td>
<td>90.01</td>
<td>55.09</td>
<td>24.33</td>
<td></td>
</tr>
<tr>
<td></td>
<td>99.95</td>
<td>96.80</td>
<td>89.95</td>
<td>54.97</td>
<td>24.28</td>
<td></td>
</tr>
<tr>
<td></td>
<td>99.95</td>
<td>96.91</td>
<td>89.83</td>
<td>54.98</td>
<td>24.50</td>
<td></td>
</tr>
<tr>
<td></td>
<td>99.95</td>
<td>97.96</td>
<td>89.03</td>
<td>54.52</td>
<td>24.66</td>
<td></td>
</tr>
<tr>
<td></td>
<td>100.00</td>
<td>83.83</td>
<td>76.63</td>
<td>68.88</td>
<td>68.28</td>
<td></td>
</tr>
<tr>
<td></td>
<td>78.48</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Overall Accuracy Ratio (%)</th>
<th>80.338</th>
<th>74.238</th>
<th>74.146</th>
<th>74.000</th>
<th>83.000</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>74.123</td>
<td>74.113</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Classification accuracy estimated for the reduced datasets using the MNFT

<table>
<thead>
<tr>
<th>Constructed Dimensionality</th>
<th>60</th>
<th>30</th>
<th>15</th>
<th>8</th>
<th>4</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification Accuracy (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class 1</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Class 2</td>
<td>97.38</td>
<td>97.43</td>
<td>97.46</td>
<td>97.70</td>
<td>97.76</td>
<td>83.83</td>
</tr>
<tr>
<td>Class 3</td>
<td>92.83</td>
<td>92.92</td>
<td>92.97</td>
<td>93.26</td>
<td>92.85</td>
<td>76.73</td>
</tr>
<tr>
<td>Class 4</td>
<td>92.94</td>
<td>93.16</td>
<td>93.21</td>
<td>93.47</td>
<td>92.53</td>
<td>68.88</td>
</tr>
<tr>
<td>Class 5</td>
<td>97.69</td>
<td>97.90</td>
<td>98.01</td>
<td>98.29</td>
<td>97.68</td>
<td>66.28</td>
</tr>
<tr>
<td>Class 6</td>
<td>98.02</td>
<td>98.04</td>
<td>98.07</td>
<td>98.22</td>
<td>98.58</td>
<td>86.31</td>
</tr>
<tr>
<td>Overall Accuracy Ratio (%)</td>
<td>96.477</td>
<td>96.575</td>
<td>96.620</td>
<td>96.823</td>
<td>96.567</td>
<td>80.333</td>
</tr>
</tbody>
</table>

The reading of the measures mentioned in tables 2, 3 and 4 permits to conclude that the presented algorithm can be considered as an interesting tool that reduces the dimensionality of the original spectra, preserves the most significant features and offers an adjustable degree of precision dependent from the dimensionality to retain. Moreover, it yields to good representativeness if compared to the PCA and MNFT which are recognized for their satisfying reductions.

CONCLUSION

This paper presented an effective method of dimensionality reduction that beyond its advantage of considerably lowering the volume of the hyperspectral images it preserves the original spectral descriptions that consist of the basic characteristics of these datasets but is generally lost with usual methods of reduction. Experiments show that this algorithm yields to significant results despite the fact that it was implemented with high dimensional real hyperspectral images obtained over a spatial platform which favours noise presence. The comparison of the obtained results to the ones given by the recognized PCA or MNFT proves that it can be efficiently adopted especially because that it offers the possibility of adjusting its performance according to the need either in term of the representativeness precision or the reduction degree. Both parameters are functions of the decomposition level reached which is dependent from the initial hyperspectral dimensionality and the form of the mother wavelet considered. Finally, it is worthy to notice that the presented algorithm gives better results when the imaged scene is made of distinct materials whose spectra are sufficiently separated when superimposed.
REFERENCES


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POTENTIAL UTILITY OF THE WORLDVIEW-2 MULTISPECTRAL DATA AND SUPPORT VECTOR MACHINES ALGORITHM TO CLASSIFYING LAND USE/COVER IN DUKUDUKU LANDSCAPE, KWAZULU-NATAL, SOUTH AFRICA

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KEYWORDS: Land use/cover, WorldView-2, support vector machines algorithm, fragmented landscape

ABSTRACT

Land use/cover (LUC) is a fundamental variable that influences and link with many parts of the human and physical systems and is a vital data component for many aspects of environmental change. There is a lack of information on how support vector machines (SVM) classification algorithm can perform on delineating LUC patterns in a fragmented landscape using WorldView-2 (WV-2) multispectral data. The objective of the present study was to classify LUC patterns using WV-2 data and SVM algorithm in Dukuduku landscape, South Africa. The study successfully classified eight LUC patterns; achieving an overall accuracy of 78.00% (total disagreement = 22.0%). The study concludes that WV-2 multispectral data and SVM classifier have the potential to classify LUC patterns in Dukuduku landscape. The study also offers relatively accurate information that is important for the indigenous forest managers in KwaZulu-Natal, South Africa for making informed decisions regarding conservation and management of LUC patterns.

INTRODUCTION

Land use/cover (LUC) is a fundamental variable that influences and link with many parts of the human and physical systems and is a vital data component for many aspects of environmental change (Foody, 2002). The changes in LUC have significant effects on the basic ecosystem processes, including biogeochemical cycling and land degradation (Foley et al., 2005). Such effects are most visible in the ecosystem processes when introduced to land cover patterns in a large area where landscapes are highly fragmented. Despite this important role, LUC classification is still facing a complex challenge in relation to ambiguous classes used (Herold et al., 2008). Therefore, effective techniques for classifying and monitoring LUC patterns in large landscapes are needed. Traditional ground based mapping techniques are a costly, time-consuming process that often lacks the necessary geometric accuracy. Complementary techniques that may offer synoptic, timely and fairly accurate classifications for LUC
patterns are required, particularly in a highly fragmented landscape. In this regard, remote sensing offers economic means and effective techniques and has successfully been used for classifying LUC with rapid return intervals and high accuracy (Pu and Landry, 2012).

Moreover, multispectral data such as SPOT and Landsat have proved inefficient in classifying LUC due to the lack of spectral and spatial resolution (Cho et al., 2012; Foody, 2002). Particularly when used for classifying LUC patterns in a fragmented landscape (Cho et al., 2012; Foody, 2002). Conversely, the advent of hyperspectral data has overcome the limitations of multispectral data by providing spectral data of many and contiguous bands (Melgani and Bruzzone, 2004) for more accurate and reliable LUC maps (Pal, 2006; Petropoulos et al., 2012). However, the use of hyperspectral data has its own limitations in terms of cost, availability, processing, and high dimensionality (Mutanga et al., 2012). Recently, high resolution multispectral sensors like WorldView-2 were launched with a few strategically located bands to overcome the limitations of spatial and spectral capabilities over other high resolution multispectral sensors of conventional bands (Peerbhay et al., 2014). Many classification algorithms such as artificial neural networks, random forest, and support vector machines (SVM) (Breiman, 2001; Civco, 1993; Petropoulos et al., 2012) have been used to extract LUC information from multi-sensor and multispectral remote sensing images. Amongst these classification methods, attention has been paid to the use of SVM due to its superior image handling capability (Cortes and Vapnik, 1995). SVM provides an accurate way to classify LUC from remote sensing images without having to rely on statistical assumptions (Ghosh and Joshi, 2014; Mountrakis et al., 2011). To the best of our knowledge, there is a lack of information on how SVM classification algorithm can perform on delineating LUC patterns in a fragmented landscape using WV-2 multispectral data. Therefore, the objective of the present study was to classify different LUC patterns using WV-2 data and SVM algorithm in Dukuduku landscape, South Africa.

**METHODOLOGY**

**Study Area**

The study area is located in Dukuduku area, in the northern part of KwaZulu-Natal, South Africa (28°25′S, 32°17′E). This study focuses on approximately 19887.00 ha of land use/cover located on Dukuduku area. The subtropical climate dominating the study area has warm moist summers and mild dry winters. The mean daily maximum temperatures are 26°C in January and 21°C in July, while mean daily minimum temperatures are 19°C in January and 9°C in July (Ngema, 2009). The rainy season falls between November and March with a mean annual rainfall of 1250 mm (Ngema, 2009). The Dukuduku forest is undergoing fragmentation as a result of indigenous forest clearance for agriculture, plantation forestry, and settlements (Cho et al., 2012; Cho et al., 2013). The area is covered by various natural indigenous vegetation species with different age groups and other forms of LUC patterns. These include sugarcane farms and commercial plantation forests occurring on the artificially drained floodplain to the south of the area and grassland to the north (Cho et al., 2012).

**Image Acquisition and Pre-processing**
For this study, cloud-free WV-2 multispectral image covering the study area was acquired on the 1st December 2013. WV-2 image consists of eight multispectral bands in the 400-1040 nm spectral range with a spatial resolution of 2 m and swath width of 16.4 km at nadir. The spectral bands of WV-2 are coastal blue (400–450 nm), blue (450–510 nm), green (510–580 nm), yellow (585–625 nm), red (630–690 nm), red edge (705–745 nm), NIR-1 (770–895 nm), and NIR-2 (860–1040 nm). The image was calibrated to at-sensor radiance (Wm$^{-2}$/sr$^{-1}$/μm). Radiance image was atmospherically corrected and transformed to canopy reflectance using the Quick Atmospheric Correction (QUAC) extension (Bernstein et al., 2005) in Environment for Visualizing Images (ENVI 4.7) software (ENVI, 2006). The image was referenced to the Universal Transverse Mercator (UTM zone 36 South) projection using WGS-84 Geodetic datum.

Field Data Collection

A field campaign was carried out on 7th December 2013, within a week of the WV-2 imagery acquisition. This was done in order to collect ground reference data of eight LUC patterns, namely: dune forest (DF), indigenous forest (IF), degraded forest (DEF), Eucalyptus spp (ES), Pinus spp (PS), mature sugarcane (MS), young sugarcane (YS), and grassland (GL). During the field visit, a total of 75 sample data points were collected for each pattern. The ground reference data were collected using random sampling protocol to adequately sample LUC patterns based on their representative sizes within the study area.

STATISTICAL ANALYSIS

The effectiveness of SVM algorithm to classify LUC patterns was investigated in this study. The algorithm was trained on 70% (n = 53) of a randomly selected holdout sample and final accuracy assessments were evaluated using the remaining 30% (n = 22) of each class dataset. When the training positions and patterns were allocated, classification signatures were created for the eight LUC patterns in the study area. After assessing and adjusting the signatures, SVM supervised classification method was then employed to classify the WV-2 image.

Support Vector Machines Algorithm

SVM (Cortes and Vapnik, 1995) was originally introduced as a binary algorithm. However, real remote sensing problems usually include identification of multiple classes. Amendments were made to the simple SVM binary algorithm to run as a multi-class classifier using methods such as one-against-one and one-against-all procedures. The algorithm was then assigned to the correct class by using a voting mechanism (Krahwinkler and Rossman, 2011; Mathur and Foody, 2008). SVM attempts to maximize the margin; that is the distance between the data points of each class to the optimal separating linear hyperplane axes created from each variable (Petropoulos et al., 2012). There are two supporting hyperplanes in the boundaries of the data distribution and the data points on the margin of these hyperplanes are the support vectors of the algorithm and the optimal hyperplane is in the middle of the margin. Many classes are not linearly separable, hence SVM uses kernel trick to adjust for finding a non-linear (e.g., polynomial) separating hyperplane in a high-dimensional feature space using an
optimization function (Hornik et al., 2006; Yang, 2011). For detailed description on SVM theory and principles see Cortes and Vapnik (1995), Burges (1998), Hornik et al. (2006) and Mathur and Foody (2008).

In the present study, all eight bands of WV-2 image were used for defining the space feature of SVM. A radial basis function (RBF) was used to find an optimal hyperplane that can differentiate amongst LUC patterns in the Dukuduku landscape. The two parameters of RBF; the cost function ($C$), which controls the tradeoff between maximization of the margin width and minimizing the number of misclassified data points in the training dataset samples, and gamma ($\lambda$) which is the width parameter of the RBF kernel (Hornik et al., 2006) were optimized using a 10-fold cross validation method. The e1071 library version 2.15.2 in R statistical packages (R Development Core, 2012) was employed for SVM parameters optimization.

Accuracy Assessment

A confusion matrix was constructed to compare the true class with the predicted class assigned by SVM and to calculate the overall accuracy (OA), producer’s accuracy (PA) and user’s accuracy (UA) (Congalton and Green, 2008). In addition, two parameters were calculated from the cross-tabulation matrix to evaluate the reliability of SVM algorithm. These include quantity disagreement (QD) and allocation disagreement (AD), which were developed by Pontius Jr and Millones (2011). The quantity disagreement is the amount of the contrast between the number of test data and predicted data, while the allocation disagreement describes the number of expected classes that have less than optimal spatial location in comparison to the test data.

RESULTS

Optimization of Support Vector Machines Algorithm

The results of grid search and 10-fold cross validation methods indicate that SVM achieved minimum classification error (32.2%) when $\lambda$ and $C$ were set at 0.1 and 100, respectively (Figure. 1).
Figure 1. Optimization of the SVM parameters (λ and C) using WorldView-2 multispectral data

Accuracy Assessment

Figure 2 shows the spatial distribution of eight land use/cover patterns in Dukuduku area, South Africa using SVM classifier. The map shows that the Dukuduku indigenous forest was mainly surrounded by grassland and commercial forest plantation, while the grassland on the north eastern part of the study area was degraded. Most of sugarcane farms in the study area were at a mature growth stage.
Furthermore, the overall accuracy assessment of the LUC classifications was 78.0% (total disagreement = 22.0%) (Table 1). SVM algorithm obtained quantity and allocation disagreement values of 5.0% and 17.0%, respectively (Table 1). Generally, all LUC patterns achieved over 70% producer’s and user’s accuracies, with exception of degraded forest (PA = 63% and UA = 68%) and indigenous forest (PA of 68% and UA of 59%) (Table 1). Our results indicate that the values of the PA were very high (100%) for young sugarcane and UA for *Eucalyptus spp* (91%) (Table 1). Table 2 shows areas under each LUC pattern obtained using SVM classification algorithm and WV-2 data. The study area is dominated by indigenous forest, commercial plantation and grassland.

<table>
<thead>
<tr>
<th>Patterns</th>
<th>DEF</th>
<th>ES</th>
<th>IF</th>
<th>GL</th>
<th>MS</th>
<th>DF</th>
<th>PS</th>
<th>YS</th>
<th>Total</th>
<th>PA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEF</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>24</td>
<td>63.0</td>
</tr>
<tr>
<td>ES</td>
<td>1</td>
<td>20</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>27</td>
<td>74.0</td>
</tr>
</tbody>
</table>

Table 1. Classification confusion matrix of support vector machines (SVM) algorithm using WorldView-2 data for the 30% test data sets. The confusion matrix includes overall accuracy (OA), quantity disagreements (QD) and allocation disagreements (AD).
Table 2. Area of each LUC pattern in the study area obtained using WorldView-2 data and support vector machines classification algorithm

<table>
<thead>
<tr>
<th>Land use/cover patterns</th>
<th>Code</th>
<th>Area ha⁻¹ for WorldView-2 data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degraded forest</td>
<td>DEF</td>
<td>1918.52</td>
</tr>
<tr>
<td>Dune forest</td>
<td>DF</td>
<td>2146.92</td>
</tr>
<tr>
<td>Eucalyptus spp</td>
<td>ES</td>
<td>1579.09</td>
</tr>
<tr>
<td>Indigenous forest</td>
<td>IF</td>
<td>4292.60</td>
</tr>
<tr>
<td>Grassland</td>
<td>GL</td>
<td>2762.34</td>
</tr>
<tr>
<td>Mature sugarcane</td>
<td>MS</td>
<td>2348.33</td>
</tr>
<tr>
<td>Pinus spp</td>
<td>PS</td>
<td>1848.63</td>
</tr>
<tr>
<td>Young sugarcane</td>
<td>YS</td>
<td>2991.09</td>
</tr>
</tbody>
</table>

DISCUSSIONS

This study highlights the utility of new generational multispectral image (Worldview-2) in classifying LUC patterns in large landscape where there are limited training samples. The study demonstrates that WV-2 multispectral data are effective for classifying LUC patterns using SVM classification algorithm in Dukuduku landscape. This result is in conformity with Cho et al. (2013) and Ghosh and Joshi (2014) who concluded that using WV-2 data with advanced classification methods in a fragmented landscape leads to improved classification accuracy. There are two reasons that may have led to the delineation of LUC classes in Dukuduku area with high classification accuracy. Firstly, the LUC patterns in Dukuduku forest consists of vegetation and WV-2 strategically located bands are effective in...
differentiating vegetated surfaces (Yang, 2011). Secondly, the SVM classification algorithm is useful, because SVM reduces classification error on test data points without a prior assumption about their distribution (Ghosh and Joshi, 2014; Mountrakis et al., 2011).

In the present study, we used a non-linear kernel function to perform SVM classification. A non-linear kernel is an efficient method to solve inseparability problems that may be found in the LUC patterns. The good performance of SVM algorithm obtained in this study is consistent with Kavzoglu and Colkesen (2009) and Petropoulos et al. (2012) who utilized a kernel function of SVM for classifying remotely-sensed data and concluded that the algorithm leads to improved classification accuracy. A number of authors have found that SVM was the best classification technique for mapping LUC using high spatial resolution imagery such as WV-2 (Pal, 2006; Petropoulos et al., 2012). To our knowledge, WV-2 data have never been used for classifying LUC patterns in areas with limited training samples, such as the fragmented landscape in the Dukuduku area of KwaZulu-Natal, South Africa. Our study shows that SVM algorithm was unable to fully deal with the high spectral variation inherent in some LUC patterns like mature sugarcane and grassland. This is a common problem when classifying heterogeneous landscapes using high spatial resolution (WV-2 image) based on per-pixel classification techniques (Lu and Weng, 2007).

The relatively high allocation disagreements shown in table (1) of the confusion matrix was expected since pixels covered by multi-classes could probably be mismatched in terms of spatial pattern between test ground truth instances and predicated test samples. In summary, our findings are promising for accurate classification of LUC in fragmented areas using WV-2 multispectral bands and SVM algorithm. Moreover, the relatively accurate classification result obtained in this study provides reliable information on LUC patterns in the Dukuduku area. That could be used for the design of management plans and policies as a basis for assessing and monitoring natural resources, ecological fragmentation and the ecosystem function in Dukuduku area. Further research is needed to widen the use of WV-2 imagery in identifying the threatened forest species within the indigenous forest in the north-western part of the study area.

**CONCLUSIONS**

The present study shows a successful application of WorldView-2 multispectral data and the machine learning SVM algorithm in classifying eight LUC patterns in a fragmented landscape. The results show that WV-2 data have the potential to classifying LUC patterns, achieving an overall accuracy of 78%. Our study provides LUC maps that could be used as essential information for decision-making regarding land management and policy making strategies in the fragmented Dukuduku landscape.

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MULTI-FREQUENCY SAR FOR LAND COVER CLASSIFICATION OF SEMI-ARID AND FORESTED REGIONS OF AFRICA, USING RANDOM FORESTS

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KEYWORDS: multi-frequency, SAR, land cover, classification, random forests

ABSTRACT

Multi-frequency Synthetic Aperture Radar (SAR) systems have the potential for increased classification accuracies over single-frequency SAR for several land cover classes. In this study, test sites in Cameroon and Tanzania are compared and analysed with data from ALOS PALSAR, ENVISAT ASAR and TerraSAR-X. Calculations of texture layers and inter-channel ratios increase the dimensionality of the available feature space. Land cover classes are defined as bare soil, dense trees, thinner dense trees (degraded / mosaic forest), sparse vegetation, water and settlements. The primary classifier used is the Random Forests classification algorithm. Recommendations and comparisons of classification accuracies are made for single-frequency vs multi-frequency SAR systems, i.e. L, C, X, LC, LX, CX and LCX-band combinations. Finding the best configuration for a multi-frequency SAR image acquisition strategy is important for future rapid land cover mapping or reference mapping during crisis situations, and more generally for any area of interest with frequent cloud cover. Different image channel combinations to represent different permutations from current and future SAR missions can be derived depending on which land cover types are of most interest.

INTRODUCTION: WHY MULTI-FREQUENCY SAR?

With several Synthetic Aperture Radar (SAR) missions in orbit, including the newly launched Sentinel 1A (C-band) on 3 April 2014 and ALOS-2 (L-band) on 24 May 2014, there exists a real potential of utilising multi-frequency SAR from satellite, even from different platforms. Apart from these two sensors, there are several X-band sensors (TerraSAR-X and Cosmo-Skymed, and planned Paz), Radarsat-2 (C-band) (Aschbacher and Milagro-Pérez, 2012) and planned SAOCOM L-band satellites (CONAE, 2011), which will ensure global sensor availability from L-, C- and X-band for at least the next 5-10 years. In addition to this, SAR satellites utilising non-traditional frequencies from S-band is currently in orbit by the Chinese HJ-1C (Barbosa, 2012), with NovaSAR-S (SSTL, 2011) and the P-band BIOMASS mission (Le Toan et al., 2011) planned for the near future.

Within the projects leading up to the European operational Earth Observation programme, Copernicus (formerly known as GMES), SAR has almost only been used for flood mapping (Henry et al., 2006) in the context of crisis mapping. SAR is also utilised for specialist applications of deformation mapping and landslides using interferometry, but this study will focus on the use of SAR
for land cover classification. Therefore, the motivation of using multi-frequency SAR can be summarized as follows:

- The well-known all-weather, day-night image acquisition capabilities of SAR. This is particularly of interest for areas around the world with persistent cloud cover.
- SAR observes different phenomena to optical. Bio-physical parameters such as soil moisture and surface roughness, can be inferred from the SAR signal (Barrett, Dwyer and Whelan, 2009).
- Studies conducted using multi-frequency SAR from SIR-C / X-SAR for land cover classification (Pierce et al., 1995), and more recently from TerraSAR-X, ENVISAT ASAR and ALOS PALSAR for general land cover classification (Turkar et al., 2012), showed satisfactory results of ~90% overall classification accuracy.
- As mentioned, the availability of several spaceborne SAR sensors (Aschbacher and Milagro-Pérez, 2012) make the use of multi-frequency SAR an operational possibility.

The objective for this study is to compare the accuracy of land cover classification using single frequency L, C, X and images, with dual-frequency combinations of LC, LX, CX-bands and three-frequency LCX-band images. What is the added benefit of using two or three frequencies, compared to only one frequency? In order to achieve this objective a comparison is done of Random Forests (RF) classification of the different band combinations (L, C, X, LC, LX, CX, LCX) for each of the available study site-season scenarios, i.e. for Cameroon-Dry, Cameroon-Wet, Tanzania-Dry and Tanzania-Wet.

DATA AND STUDY SITES, METHOD, ALGORITHM, RESULTS AND DISCUSSION

Data and Study sites

The data is selected based on images available in the TerraSAR-X, ENVISAT-ASAR and ALOS PALSAR archives. The constraints for the data selection are that the images should be overlapping in space and close in time, ideally from the same year and season. The imagery has to be high spatial resolution in the order of 5-15m pixels. The sites had to be located on the African continent, to increase the research related to SAR Earth Observation of African landscapes. Previous work was done using data from these areas, to allow follow on research (SAFER, 2012). The starting point is the high spatial resolution TerraSAR-X images, since there were only a select few available across Africa.

After selecting TerraSAR-X images, corresponding ENVISAT ASAR and ALOS PALSAR data are compared to these sites, to achieve a combined data-stack from all three SAR sensors. The images are grouped by either wet or dry season images, and if a certain polarisation image is not available, an image from the same season from a different year is chosen. Over the whole of Africa, only eight potential sites are available with images from all three sensors of the same season available. This shows a scarcity of available high resolution SAR images across the African continent, especially with regards to the TerraSAR-X archive.

The two sites with the most data are in Cameroon and Tanzania, which are used as the main study sites. The locations of these sites are shown in Figure 1. Apart from the data availability limitations with regards to overlapping in time, the overlapping areas from all the available imagery are
highlighted in bright yellow, which is only a small portion of the image extent from any of the single scenes. This is because these images were not necessarily planned to be used together. Therefore for a future acquisition strategy, the region of interest will need to be specified to ensure maximum coverage by each of the sensors.

![Figure 1. The locations of the Cameroon and Tanzania study sites.](image)

The available SAR images for the Cameroon site are shown in Figure 2 and for the Tanzania site in Figure 3. The monthly rainfall data from 2008 to 2012 is shown in the graphs. From this the dry and wet season images are chosen, which are highlighted in bright red and bright blue.

The images are multi-looked and then resampled to closest 5m spatial resolution with the TerraSAR-X images resampled to 5m, ENVISAT ASAR to 15m and ALOS PALSAR to 10m. To be able to combine the data into a layer stack, all the images are subsequently resampled to 5m spatial resolution. This is to be able to make the most of the high spatial resolution from TerraSAR-X, to identify relatively small features on the ground, and to be able to utilize the high spatial resolution from TerraSAR-X for meaningful texture measures.
Method

The methodology followed in this study is a standard supervised classification methodology of sample selection, training / test data split, model development and testing the model on the test data. First of all, the dimensionality of the data of the two sites is increased by computing several additional layers of:

- Image ratios, additions and subtractions (e.g. HH/HV, HH+HV, HH-HV).
• Selected texture measures, namely contrast, correlation and entropy (Clausi, 2002) is calculated at window sizes 5x5, 7x7, 9x9, 11x11, 13x13. The neighbourhood mean is also calculated for the same window sizes.

• Elevation, slope and aspect from SRTM data are added as additional input layers.

Image ratios, additions and subtractions enhance the information content from the dual-polarisation layers compared to only the single polarisation view (Lönnqvist et al., 2010). Texture measures aims to enhance differences in texture, at different window sizes between the various land cover classes (Haralick, Shanmugam and Dinstein, 1973). The inclusion of elevation, slope and aspect has been shown to increase the accuracy of land cover mapping (Peng, Wang and Zhang, 2005).

Land cover samples are chosen, by visually identifying land cover types on DigitalGlobe imagery available on Google Earth, for both the Cameroon and Tanzania sites. For the Cameroon site, the land cover classes are bare soil, dense trees, thinner dense trees, sparse vegetation, settlements and water. For the Tanzania site the land cover classes are agriculture, bare soil, dense trees, thinner dense trees, sparse vegetation and settlements. The land cover class definitions are mapped to the land cover classes used in the GLC2000 map of Africa (Mayaux et al., 2004). There is a slightly different interpretation for the land cover classes for the Cameroon and Tanzania sites as laid out in Table 1, which highlights the different landscapes between the two study sites.

Table 1. Land cover classes in this study mapped to the land cover class definitions and numbers of the GLC2000 map of Africa (Mayaux et al., 2004).

<table>
<thead>
<tr>
<th>Broad Land cover class</th>
<th>Cameroon interpretation</th>
<th>Tanzania interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense Trees</td>
<td>Closed evergreen lowland forest (1)</td>
<td>Submontane forest (3)</td>
</tr>
<tr>
<td>Thinner Dense Trees</td>
<td>Degraded evergreen lowland forest (2)</td>
<td>Mosaic forest/savanna (8)</td>
</tr>
<tr>
<td>Sparse Vegetation</td>
<td>Open Deciduous Shrubland (12)</td>
<td>Open grassland with sparse shrubs (14)</td>
</tr>
<tr>
<td>Bare Soil</td>
<td>Sparse grassland (16)</td>
<td>Sparse grassland (16)</td>
</tr>
<tr>
<td>Agriculture</td>
<td>Inland waters (26)</td>
<td>Croplands (18)</td>
</tr>
<tr>
<td>Water</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

The sample polygons are split between 80% training samples and 20% test samples. From these polygons 2000 pixels per land cover class are selected as training data and 500 pixels per land cover class as test data. The input layer-stack of data is split into different input scenarios, of L, C, X, LC, LX, CX and LCX band combinations. All input scenarios included the elevation slope and aspect SRTM-derived layers. A RF model based on 5000 trees is trained on each of these input scenarios and the classification accuracies based on the test data is compared to assess the models.
Algorithm: Random Forests

The classification algorithm used in this study is the Random Forests (RF) classifier (Breiman, 2001). RF is an ensemble of many decision trees, and is an extension to ‘bagging’. Bagging is where several decision trees are constructed based on a bootstrap sample of the training data set. RF extends the bagging model by randomly selecting a subset of the input features for each decision tree. Each decision tree is built without pruning. Finally, a majority vote is cast to determine the classification outcome.

RF has the ability to determine variable importance as a result of training the RF model, and is robust against overfitting. RF is also user-friendly as there are only two parameters to alter, namely the number of variables in the random subset (with default: the square-root of the number of input variables), and the number of decision trees to grow. The RF built in this project is built using the randomForest package in R (Liaw and Wiener, 2002).

The classification accuracies of the RF classification based on the test data is shown in Figure 4. The graphs are split between Cameroon Dry, Cameroon Wet, Tanzania Dry and Tanzania Wet classification accuracy results. The classification accuracies are shown for each of the land cover classes for the Cameroon and Tanzania sites. The frequency combinations (L, C, X, LC, LX, CX, LCX) are sorted by overall classification accuracy from left to right, with the highest classification accuracy towards the right of each of the four graphs.
Results

Figure 4. Top left: Classification accuracies for Cameroon Dry study site. Top right: Classification accuracies for Cameroon Wet study site. Bottom left: Classification accuracies for the Tanzania Dry site. Bottom right: Classification accuracies for the Tanzania Wet site.

Discussion

The classification accuracies on the test data for the four groups of images (Cameroon Dry, Cameroon Wet, Tanzania Dry and Tanzania Wet) are shown in Figure 4. The highest overall classification accuracy is 88% for Cameroon Dry, 82% for Cameroon Wet, 73% for Tanzania Dry and 57% for Tanzania Wet.

The Dry season images give better classification accuracies, which can be explained by the sensitivity of the SAR signal to moisture. The classification accuracies for the wet season are lower than the dry season for both sites. One explanation could be that the different land cover classes look similar to the SAR signal with more moisture throughout the scene. Another and related explanation could be that with all the rainfall, there is overall a lot more vegetation in the scene, blending the different land cover classes of thinner dense trees, sparse vegetation, bare soil and settlements into much more similar and less distinguishable land cover areas. The wet season will
therefore correspond to a period of enhanced vegetation growth, and therefore blending the
different land cover classes to be more similar, leading to lower classification accuracy

It is notable that for the forested Cameroon site, the X-band images have the largest contribution
to classification accuracies for all the chosen land cover classes. This can be explained by the high
spatial resolution of the X-band images being able to capture the different texture characteristics of
the different land cover classes. For the semi-arid Tanzania site, the L-band images seem to have the
largest contribution to classification accuracy. This highlights the difference between the two study
sites, and confirms the need for distinct models for different landscapes.

The best dual-frequency combination is an LX-combination, for the majority of the site-season
scenarios. The only exception is the Tanzania Wet, for which the classification accuracy is the lowest
and clearly in need of some more refinement and more detailed investigation. The LX-combination is
in line with the planned Italian/Argentinian L and X-band constellation for emergency management
(SIAGSE), combining Cosmo-Skymed and SAOCOM acquisitions (Caltagirone et al., 2010; Pierdicca,
Pelliccia and Chini, 2011).

Next steps

The next steps in this research are first to select a core set of variables to define a compact
classification model for the forested wet and dry; and semi-arid wet and dry test sites. Secondly, a
Support Vector Machine (SVM) classification will be run on the same data as in this study. This will
enable a comparison between SVM and RF classification approaches. Thirdly, the transferability of
the models will be tested by applying the models on additional data available in different locations in
the DRC for forested areas, and in Sudan for semi-arid areas.

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Part 4
Agriculture, Forestry, Geology, Mineral Exploration and Water Wetlands
INTEGRATING IMAGE TEXTURE DERIVED FROM HIGH RESOLUTION WORLDVIEW-2 IMAGERY AND NEURAL NETWORKS TO PREDICT THAUMASTOCORIS PEREGRINUS (BRONZE BUG) DAMAGE IN PLANTATION FORESTS

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KEYWORDS: Image texture, neural networks, WorldView-2

ABSTRACT

This study assessed the potential of image texture derived from the new generation WorldView-2 sensor in predicting T. peregrinus damage in forest plantations. T. peregrinus is a sap sucking insect which is causing significant damage to eucalypt plantations globally by reducing tree growth and even death of severely infested trees. Image texture and the WorldView-2 sensor bands were entered into a multiple layer perceptron neural network algorithm to predict T. peregrinus damage. The integrated approach involving neural networks and image texture predicted damage with an R² value of 0.74 and a RMSE of 1.32 % on an independent test dataset. The study develops innovative remote sensing techniques that can accurately predict insect infestation in plantation forests, using image texture measures derived from a new multispectral sensor which contains key vegetation wavelengths. The result is significant for plantation health monitoring in South Africa.

INTRODUCTION

Image texture is a key visual criterion when interpreting information on the spatial distribution of forest vegetation from airborne surveys (Franklin et al., 2001). Texture refers to the visual roughness or smoothness of features across an image, due to the spatial variability of tonal values, which result in a repetition of patterns across the image (Tso and Mather, 2001). With the increased availability of new and improved high spatial resolution imagery, texture can be considered as a potentially important source for forestry purposes (Franklin et al., 2001). Stress in forest plantations due to insect infestation displays a variety of symptoms such as reduction in moisture, loss in chlorophyll content and leaf colour changes; all of which have been conventionally studied using leaf spectral reflectance (Le´vesque and King, 2003, Stone et al., 2001). Forest structural changes caused by insect infestation is also displayed at an individual crown scale or canopy level and has been studied using image based indices (Barry et al., 2008, Coops et al., 2004, Coops et al., 2006). However, several studies have argued that focusing solely on the spectral properties limits the ability to adequately extract information housed within remotely sensed imagery (Cohen and Spies, 1992, Franklin et al., 2001). Furthermore, vegetation indices do not behave linearly and saturate at low or high vegetation
cover depending on the index used (Levesque and King, 2003). This limitation can be overcome by using texture and semivariance measures. Unlike pixel by pixel analysis, image texture considers the relationships between pixels and has often improved the classification of forest damage (Franklin et al., 2001, Levesque and King, 2003, Moskal and Franklin, 2004). In the aforementioned studies, texture analysis produced stronger models than those obtained using only raw spectral data or vegetation indices (Levesque and King, 2003).

Numerous studies have used texture analysis to assess insect infestation in plantation forests (Dye et al., 2008, Ghitter et al., 1995, Moskal and Franklin, 2004). Ghitter et al. (1995) showed that image texture derived from high spatial resolution airborne imagery could successfully classify insect caused structural damage on individual trees, whereby damaged trees had flat tops and were asymmetrical. Franklin et al. (1995) used texture analysis to classify western spruce budworm defoliation with an accuracy of 78% using high spatial resolution aerial videographic data and 75% accuracy using Landsat TM data. More recently, Dye et al. (2008) used texture measures calculated from high spatial resolution imagery to successfully predict and map Sirex noctilio infestations in plantation forests. Successful use of image texture with airborne and multispectral imagery indicates the importance of these techniques in accurately assessing forest damage caused by insect infestation.

According to Coppin (1991) textural and spectral features are inter-related and complement each other. Both spectral and textural properties are present in an image but the degree to which one is dominant over the other is dependent on spatial resolution. When spatial resolution is high in relation to the scale of tonal variation, texture can improve classification in forest plantations (Tso and Mather, 2001). Image texture derived from a new and improved multispectral sensor such as WorldView-2 which contains 8 bands with a spatial resolution of 2 metres could be valuable in predicting Thaumastocoris peregrinus damage. T. peregrinus is a significant pest causing damage to eucalypt plantations by reducing the photosynthetic ability of the tree resulting in stunted growth and even death of severely infested trees (FAO, 2007, Jacobs and Neser, 2005). Trees that are infested display a reddening of the leaves and have a ‘washed out’ appearance (Jacobs and Neser, 2005). In severe cases, there is branch dieback and the entire tree may die. There is an imperative need to identify trees that are infested so forest managers can take proper remediation measures before trees reach a point of no-recovery. Although numerous studies have used image texture to classify insect infestation, no studies to the best of our knowledge have used WorldView-2 derived texture measures to predict insect infestation in plantation forests. Furthermore, the utility of predicting insect infestation in plantation forest using high resolution data has been limited to general regression models (Coops et al., 2006, Dye et al., 2008) which are often prone to overfitting and less sensitive to non-linearity in a dataset. Advanced stochastic models such as artificial neural networks which model non-linearity in a dataset and perform better than traditional linear models (Atkinson and Tatnall, 1997, Skidmore et al., 1997) have not been tested in predicting insect infestation using image texture derived from high resolution data. It is against this background that the study aims to assess the relationship between image texture and the WorldView-2 bands with T. peregrinus damage. We further tested the utility of the best selected texture indices and WorldView-2 bands in predicting T. peregrinus damage using an artificial neural network algorithm.
METHODS

Study area

The study area is situated in Richmond, KwaZulu-Natal, South Africa. The study area covers an area of 875 ha. Richmond receives an annual rainfall ranging from 800 to 1280 mm and is situated at an altitude range between 900-1400 m above sea level. Richmond has a mean annual temperature of 17°C with various forest species planted across the landscape.

Leaf sampling and visual damage assessments

Three Eucalyptus smithii compartments that showed varied rates of T. peregrinus infestation were selected for sampling. Systematic sampling was carried out on the 24th and 25th of November 2010 whereby 15 transects were arranged across the three compartments. The distance between transects was 5 planted rows of trees (each row 3m apart) and every tenth tree in each transect was sampled. This was done in order to cover a wide range of T. peregrinus infestation rates across the compartments. Eighty trees were sampled and Global Positioning Systems (GPS) points were captured for each tree using a handheld Trimble, Geo-Explorer unit with submeter accuracy calculated as the average of 50 sequential coordinate readings.

Branches were cut down using a pruning saw and 50 leaves were picked from each tree for visual damage assessments. A plant pathologist divided each leaf into quadrants and the percentage of necrotic tissue was visually estimated on the fifty leaves and then averaged for each tree. A visual assessment was preferred over a computer based approach as it allowed for a larger number of samples to be analysed.

WorldView-2 imagery

WorldView-2 imagery was acquired on the 1st of December 2010. The WorldView-2 sensor captures 0.5 m panchromatic imagery and 2 m multispectral imagery. The spectral range of the WorldView-2 sensor consists of the following bands: coastal blue (400-450 nm), blue (450-510 nm), green (510-580 nm), yellow (585-625 nm), red (630-690 nm), red edge (705-745 nm), near-infrared 1 (770-895 nm) and the near-infrared 2 (860-1040 nm) (DigitalGlobe, 2010). The multispectral and panchromatic images (1 scene each) were orthorectified and georeferenced by the data providers and projected to the UTM Zone 36 S (WGS84) coordinate system. The images were atmospherically corrected to top of atmosphere reflectance using the quick atmospheric correction model (QUAC). QUAC determines atmospheric compensation parameters directly from the information contained within the scene and thus allows for the retrieval of reasonably accurate reflectance spectra (ENVI, 2006).

Texture measures

Texture measures can be divided into two classes: the grey level occurrence matrix (GLOM) and the grey level co-occurrence matrix (GLCM). The GLOM measures are obtained from the histogram of pixel intensities within a window or neighbourhood and ignore the spatial relationships between pixels (Dye et al., 2008, St-Louis et al., 2006). The GLCM in contrast calculates the probability that each pair of pixel values within a moving window co-occur in a given direction of distance (St-Louis et al., 2006). Several window sizes may be used to calculate texture measures and this depends on the
image resolution. Due to the high spatial resolution of the WorldView-2 imagery, a 3X3 window size was selected for calculating texture measures. Moskal and Franklin (2001) argue that smaller window sizes are better suited for capturing the textural characteristics of individual objects such as trees. Five GLOM measures were calculated for each band off the multispectral image which consists of data range, entropy, mean, skewness and variance. Eight GLCM measures were calculated for each band off the multispectral image and are comprised of mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation. The texture measures were calculated in the ENVI 4.3 software (ENVI, 2006). In total, 40 GLOM and 64 GLCM texture measures were calculated. The mean texture value for each sample (n=80) was extracted from the WorldView-2 multispectral image using the ArcGIS zonal statistics tool.

DATA ANALYSIS

Relationship between image texture and WorldView-2 bands with T. peregrinus damage

The Shapiro-Wilk test was run to test the normality of the data. Pearson correlation coefficient $r$ was then calculated between the texture measures and WorldView-2 bands with T. peregrinus damage. In order to simplify the modelling process, the texture measures and WorldView-2 bands of statistically significant correlation (p < 0.05) were then entered into a neural network algorithm to predict T. peregrinus damage. A neural network algorithm was chosen for the prediction of T. peregrinus damage as it has the competency to deal with non-linearity, non-normality and collinearity within a system (Ingram et al., 2005). It is therefore not affected by collinearity of the input data.

The neural network algorithm

An artificial neural network algorithm was used to predict T. peregrinus damage. A neural network is composed of highly interconnected nodes working in union to solve a problem through a learning process. Although various types of neural network models have been developed, the most widely used is the multiple layer perceptron (MLP), a feed-forward artificial neural network algorithm which has the ability to learn to weight significant variables and ignore less important ones.

Figure 1 shows the neural network structure that was used to predict T. peregrinus damage. A back propagation algorithm was used which consist of a three layer network and contains an input, hidden and output layer. The back propagation algorithm is designed to minimize the root mean square error (RMSE) between the actual output of a multiple layer perceptron and the desired output (Mutanga and Skidmore, 2004, Oumar and Mutanga, 2010).
The back-propagation algorithm comprises a forward and a backward phase through the neural network. The forward phase occurs when the input values which are the texture measures and the WorldView-2 bands \((O_i)\) are presented to a node and are multiplied by a weight factor \((W_{ji})\) (Skidmore et al., 1997). The products are then summed at the hidden nodes \((O_j)\) to create a value \(Z_j\) for the \(j\)th layer. The following description is after Skidmore et al. (1997):

\[
Z_j = \sum_j W_{ji} \cdot O_i
\]  

For a three layer network with the layers \(i, j, k\) with \(k\) being the output layer \(Z_k\) may be calculated as equation (1). Non-linearity is added to the network when the value \(Z_j\) is passed through a sigmoidal activation function for each node. The output of this function is defined as:

\[
O_i = \frac{1}{1 + e^{-(Z_j + \theta_i) / \theta_0}}
\]

Where \(z_j\) is defined from equation (1), \(\theta\) is a threshold or bias and \(\theta_0\) is a constant (Skidmore et al., 1997).

The forward phase stops once the output values \(T. peregrinus\) damage \((ok)\) are calculated for each output node. The second phase involves the back-propagation whereby the output node values are compared with the target values (measured damage) and involves training of the network. The difference between the target (measured damage) and calculated output values is referred to as error. This whole process whereby error is calculated represents one epoch of the back-propagation algorithm. Back-propagation of the error is achieved by changing the weights of each node during
training. The whole process is repeated and the weights are recalculated at every iteration until the error is insignificant.

The dataset was randomly divided into two parts. 70% (n=56) was used for training and the remaining 30% (n=24) was used for testing. The training process was run 5 times with random weights (Oumar and Mutanga, 2010). The neural network that yielded the highest $R^2$ and the lowest RMSE was chosen for the prediction of *T. peregrinus* damage. A sensitivity analysis was carried out on the training dataset to determine the importance of each variable in predicting *T. peregrinus* damage. The performance of the neural network algorithm in predicting damage was also compared to a stepwise multiple regression model. The strength of both the prediction models was evaluated using the independent 30% test dataset.

**RESULTS**

**Relationship between image texture and WorldView-2 bands with *T. peregrinus* damage**

The Shapiro-Wilk test revealed that the data was normally distributed. *T. peregrinus* damage measurements ranged from 0% to 80% with a mean value of 36%. The correlation analysis revealed that two GLOM texture measures (mean and skewness) calculated from the blue, red, red edge and near-infrared bands were significantly correlated with *T. peregrinus* damage. From the GLCM measures, only the mean texture was significantly correlated with *T. peregrinus* damage using the red edge and near-infrared bands. Correlating the WorldView-2 bands with *T. peregrinus* damage showed that all the bands are significant with the red edge and near-infrared bands yielding high correlations ranging from -0.60 to -0.74.

**Parameters of the neural network**

The neural network parameters shown in Table 1 were used to predict *T. peregrinus* damage. The neural network algorithm predicted *T. peregrinus* damage with an $R^2$ value of 0.81 and a RMSE of 1.71 % on the training dataset outperforming the multiple regression ($R^2 = 0.61$, RMSE = 2.42%). The strength of the prediction was validated using the 30% independent test dataset and the neural network algorithm also performed better than the multiple regression and predicted *T. peregrinus* damage with an $R^2$ value of 0.74 and a RMSE of 1.34 % as compared to the regression model ($R^2$ value of 0.54 and a RMSE of 4.16%).
Table 1. Neural network parameters used to predict *T. peregrinus* damage

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of inputs</td>
<td>16</td>
</tr>
<tr>
<td>Number of outputs</td>
<td>1</td>
</tr>
<tr>
<td>Number of layers</td>
<td>3</td>
</tr>
<tr>
<td>Number of hidden nodes</td>
<td>8</td>
</tr>
<tr>
<td>Neural network type</td>
<td>Multiple layer perceptron</td>
</tr>
</tbody>
</table>

Sensitivity analysis

A sensitivity analysis determines which input variables (texture measures and WorldView-2 bands) in the neural network are most important. Variables are ranked in terms of a ratio, with higher ratios indicating more importance in model development as opposed to variables with lower ratios. For each variable, the network is executed as if that variable is unavailable in the model. The error obtained when that variable is unavailable is then divided by the error obtained when the variable is available. Important variables have a high ratio, indicating that the performance of the network will deteriorate if that variable is no longer available to the model. Table 2 shows the sensitivity of the image texture measures and WorldView-2 bands in predicting *T. peregrinus* damage.
Table 2. Sensitivity analysis showing importance of image texture and WorldView-2 bands in the neural network model

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Near-infrared 2</td>
<td>Band 8</td>
<td>5.132</td>
</tr>
<tr>
<td>GLCM</td>
<td>Mean Band 6</td>
<td>2.417</td>
</tr>
<tr>
<td>GLCM</td>
<td>Mean Band 7</td>
<td>1.710</td>
</tr>
<tr>
<td>GLOM</td>
<td>Mean Band 7</td>
<td>1.648</td>
</tr>
<tr>
<td>Blue</td>
<td>Band 2</td>
<td>1.185</td>
</tr>
<tr>
<td>Coastal Blue</td>
<td>Band 1</td>
<td>1.180</td>
</tr>
<tr>
<td>GLOM</td>
<td>Mean Band 2</td>
<td>1.171</td>
</tr>
<tr>
<td>GLOM</td>
<td>Skewness Band 6</td>
<td>1.128</td>
</tr>
<tr>
<td>GLCM</td>
<td>Mean Band 8</td>
<td>1.127</td>
</tr>
<tr>
<td>Near-infrared 1</td>
<td>Band 7</td>
<td>1.123</td>
</tr>
<tr>
<td>Yellow</td>
<td>Band 4</td>
<td>1.103</td>
</tr>
<tr>
<td>Green</td>
<td>Band 3</td>
<td>1.086</td>
</tr>
<tr>
<td>Red Edge</td>
<td>Band 6</td>
<td>1.035</td>
</tr>
<tr>
<td>GLOM</td>
<td>Mean Band 8</td>
<td>1.023</td>
</tr>
<tr>
<td>Red Edge</td>
<td>Band 5</td>
<td>1.022</td>
</tr>
<tr>
<td>GLOM</td>
<td>Mean Band 3</td>
<td>1.017</td>
</tr>
</tbody>
</table>

DISCUSSION

Relationship between image texture and WorldView-2 bands with T. peregrinus damage

From the GLOM texture measures calculated (data range, entropy, mean, skewness and variance) only the mean and skewness statistics were significantly correlated with T. peregrinus damage. Results from the GLCM measures also show that only the mean texture statistic was significantly correlated with T. peregrinus damage. The mean statistic calculates the average texture value for each sample and the skewness measures the asymmetry of the data (Levesque and King, 2003, St-Louis et al., 2006). Correlations between these texture measures and T. peregrinus damage ranged from -0.23 to -0.44 with the mean texture measure been the most dominant. This could be due to the fact that T. peregrinus damage at compartment level showed a spatial pattern of damage with clusters of infested trees and this spatial pattern was averaged and picked up by the 3 x 3 moving window. Although the correlations between image texture and T. peregrinus damage ranged from -0.26 to -0.74. The red edge and near-infrared bands were highly correlated with T. peregrinus damage (-0.60 to -0.74) and these regions have been recommended for monitoring stress in vegetation (Barry et al., 2008, Coops et al., 2004). The high correlations between the WorldView-2 bands and T. peregrinus damage show the capability of the WorldView-2 bands which are sensitive to vegetation health in assessing T. peregrinus damage in plantation forests.
Integrating image texture and WorldView-2 imagery with neural networks to predict *T. peregrinus* damage

The integrated approach involving neural networks with image texture and WorldView-2 imagery predicted *T. peregrinus* damage with an $R^2$ value of 0.74 on an independent test dataset with a RMSE of 1.34%. Similar results were also obtained by Dye et al. (2008) who predicted *Sirex noctilio* infestations in plantation forests with a correlation coefficient of 0.70 using GLCM and GLOM texture measures. The WorldView-2 near infrared band 2 was ranked the most important variable in the neural network model for predicting damage. The near-infrared region is associated with plant physiological measures thereby making it a good indicator for monitoring plants under stress. The sensitivity analysis indicated the importance of the WorldView-2 near-infrared band 8 in assessing *T. peregrinus* damage levels. The GLCM texture measures were ranked second and third in the neural network model and performed better than the GLOM measures. The results are consistent with previous efforts by Franklin et al. (2001) and Yuan et al. (1991) who found that GLCM texture performed better than GLOM texture measures. This could be due to the fact that the GLOM texture measure ignores the spatial relationships between the pixels and therefore infestation was better deduced by the GLCM measure which takes into account the spatial distribution of the pixels. The blue and coastal blue bands of the WorldView-2 sensor which absorbs chlorophyll in healthy vegetation were also ranked as important variables in the model development followed by the GLOM texture measures. The ability to accurately predict *T. peregrinus* damage in plantation forests is crucial for monitoring the spread of infestation and for the effective deployment of suppression activities. This reduces the economic threat of large scale timber losses that is associated with insect infestation in plantation forests.

CONCLUSION

The aim of this study was to assess the relationship between image texture derived from the new high resolution WorldView-2 sensor in predicting *T. peregrinus* damage. The following conclusions can be drawn:

1. Mean and skewness texture statistics calculated from GLCM and GLOM measures are significantly correlated with *T. peregrinus* damage.
2. A MLP neural network model predicted *T. peregrinus* damage with an $R^2$ value of 0.74 and a RMSE of 1.34% on an independent test dataset.
3. The near-infrared band 8 of the WorldView-2 sensor and GLCM texture measures were ranked as the most important variables in the prediction of *T. peregrinus* damage.

Overall, this study is important for monitoring plantation health in South Africa using a new sensor which contains key vegetation wavelengths. The results show the potential of image texture derived from the new generation WorldView-2 sensor in predicting insect damage in plantation forests.

REFERENCES


