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Automated regolith landform mapping using airborne geophysics and remote sensing data, Burkina Faso, West Africa

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ABSTRACT

We have studied the regolith landform distribution in the area of Gaoua, western Burkina Faso, using an integration of geophysical and remote sensing data. Concentration maps of K, Th, U, as well as their ratios, were computed from airborne gamma-ray spectrometry data to assess the geochemical composition of the regolith. The mineralogy of the surfaces was mapped via the analysis of multispectral ASTER and Landsat scenes. Pauli-decomposition data retrieved from polarimetric ALOS PALSAR and Radarsat-2 images were included to characterize the surface properties of the regolith material. Morphometric variables such as slope, curvature, and relative relief were derived from the SRTM digital elevation model to quantify the topographic parameters of the different regolith landforms. An artificial neural network implementation, ADVANGEO, was then employed to extract four basic regolith landform units from the satellite and airborne data. Relic ferruginous duricrusts rich in hematite and goethite belonging to the High glacis, erosional surfaces represented by rock outcrops and sub-outcrops, alluvial sediments, and soft pediment materials of the Middle and Low glacis were mapped successfully in the region. The results were compared with the existing geomorphological maps, an independent visual classification, and field observations. We found that the distribution and shape of the iron-rich duricrusts are more accurate than portrayed in the current maps. The best results, with an overall accuracy of 94.21% and a kappa value of 0.92, were obtained for a dataset consisting of gamma-ray spectrometry data combined with derivatives of the SRTM digital elevation model augmented by Landsat, and polarimetric radar data. The approach demonstrates for the first time the potential of machine learning in regolith landform mapping. The proposed combined analysis of airborne geophysics and remote sensing data can be adopted easily in other regions with similar long-term lateritic weathering histories worldwide.

1. Introduction

The term regolith refers to all the lithospheric material including possible interbedded fresh rocks above the unweathered and consolidated bedrock (Taylor and Eggleton, 2001). Tardy (1997) estimates that nearly one-third of the area of all continents is covered by regolith resulting from lateritic weathering. Although the regolith represents an important economic resource (Taylor and Eggleton, 2001; Wright et al., 1985), it also acts as a hindrance to exploration for mineral deposits under cover (Anand, 2016; Salama et al., 2016) and geological mapping in general.

Except in regions where rocks are exposed without major interruption, a knowledge of the distribution of regolith landform units and an understanding of the processes that led to their formation is essential for any successful geological mapping, geochemical or geophysical survey, or mineral exploration campaign. West Africa remains poorly covered by regolith landform maps such as those commonly used in Australia (Pain et al., 2007). Detailed and comprehensive regolith-related datasets for West Africa are lacking, as most of the regolith maps are still produced by field mapping and visual interpretation of

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orthophotographs or Landsat images. This standard practice can be tedious, often further complicated by difficult access to remote and large survey areas. Some of these limitations may be reduced or overcome by employing airborne geophysical data and remote sensing data (Cracknell et al., 2015; Papp, 2002; Wilford et al., 1997; Woolrych and Batty, 2007), which assess the physical properties of regolith materials from afar. These datasets provide superior data coverage and may be utilized via both visual interpretation and automated classification methods. In countries such as Australia or Canada, pre-competitive (i.e. government supplied, moderate resolution) datasets that include airborne geophysics (magnetic, gamma-ray spectrometry), digital elevation models, and their derivatives are readily available at no cost and provide a wealth of information that can be exploited (Cracknell et al., 2015).

Indeed, one can estimate the chemical composition or mineralogy of regolith material from airborne gamma-ray spectrometry or multispectral/hyperspectral remote sensing (providing the terrain is not extensively covered by vegetation), terrain morphology from digital elevation models (e.g. SRTM), and surface roughness or prevailing geometric shapes from radar imagery (ALOS PALSAR, Radarsat-2).

Gamma-ray spectrometry senses down to a depth of approximately 30 cm and reveals the chemical properties of the material present (Minty, 1997). Different techniques have been proposed for the analysis of airborne gamma-ray spectrometry data ranging from the ratios of the radiometric channels (Dickson and Scott, 1997; Wilford et al., 1997), color composites, and color space transformations (Jaques et al., 1997), to integration with optical and near-infrared datasets (Anderson and Nash, 1997; Schetselaar et al., 2000). Martelet et al. (2006) used Agglomerative Hierarchical Clustering algorithm to classify airborne gamma-ray spectrometry data in French Guyana and noticed that ferralitic and bauxitic duricrusts display elevated U, Th content relative to K. In West Africa, Grimaud et al. (2015) used the Th/K ratio images to map the extent of the High glacis regolith surface. Wilford et al. (1997, 2007) derived regolith landform maps from gamma-ray spectrometry data and recently used gamma-ray spectrometry data as one of the parameters used during continental-scale regolith depth estimation (Wilford et al., 2016)

Unlike the gamma-ray data, optical remote sensing allows us to map the spectral reflectance of a thin surficial layer and characterize its mineral composition (Drury, 1993). Landsat imagery is routinely employed in regolith mapping (Craig et al., 1999), including directed principal component analysis (DPCA). The DPCA technique enhances the response of clay minerals and suppresses the effects of vegetation (Fraser and Green, 1987). While the spectral resolution of Landsat imagery enables us only to distinguish certain mineral groups, hyperspectral remote sensing may help us to analyze the individual mineral components of regolith (Dehaan and Taylor, 2004; Lau et al., 2003; Laukamp et al., 2016). Cudahy et al. (2006) studied the relationship of kaolinite disorder to the depth of the Al-OH absorption in transported versus in situ regolith and observed that poorly crystalline kaolinite is found mostly in transported regolith material. Various techniques were applied in the classification of optical data in regolith applications ranging from visual interpretation of enhanced images (Deller, 2006) to automated approaches, e.g. Matched Filtering (Dehaan and Taylor, 2004).

Synthetic Aperture Radar (SAR) imagery complements optical images in geological applications (Baghdadi et al., 2005), as radar images provide unique information about structural, morphological or sedimentary features, and moisture content. This information is directly tied to the physical properties of different terrain surfaces (Drury, 1993; Henderson and Lewis, 1998). Tapley (2002) showed that polarimetric AIRSAR (Airborne Synthetic Aperture Radar) data band combination C_{VV} (vertical receive-vertical transmit), L_{HV} (horizontal receive-vertical transmit), and P_{HV} was best suited for geological mapping of arid to semi-arid Australia. In regolith landform mapping, radar data have the capability of distinguishing between flat lying, uniform units such as alluvial sediments and rock outcrop with rougher, irregular surfaces. AIRSAR P_{VV} and L_{VV} data were found useful in mapping erosional landforms, while band C_{VV} provided clear discrimination between alluvial deposits and erosional features (Tapley, 2002). Automated classifications of polarimetric SAR are usually performed on the four polarimetric channels, or on polarimetric decompositions of the scattering matrix (Cloude and Pottier, 1997; McNairn et al., 2009).

Digital elevation models and their derivatives are frequently used for landform mapping in conjunction with other remote sensing data (Giles, 1998; Henquin and Totté, 1993; Irvin et al., 1997; Jakob et al., 2016; Liberti et al., 2009; Saadat et al., 2008; Siart et al., 2009). Slope, curvature, and aspect were used by Bolongaro-Crevenna et al. (2005) to characterize simple morphometric features such as valleys, peaks, ridges, or planes. With the advent of high-resolution DEMs (Digital Elevation Models) acquired by LiDAR (Light Detection and Ranging) or by UAV (Unmanned Aerial Vehicle) photogrammetry, these techniques show great potential and have been successfully applied in many studies (e.g. Grebby et al., 2010; Grebby et al., 2011; Hugenholtz et al., 2013; Mulder et al., 2011). In regolith science, Henquin and Totté (1993) and Woolrych and Batty (2007) suggested the use of morphometric variables such as slope in mapping regolith landforms in West Africa, as these are generally formed by morphologically discernible units, e.g. flat lying residual plateaus or alluvial deposits, gently sloping colluvial deposits or high relief erosional features related to rock outcrops.

Dense vegetation cover may limit the application of most of the described techniques. Indeed, the best results in mapping of the diverse regions around the world would require the integration of several data sets to characterize both the chemical and morphological properties of different regolith landform units and overcome the masking effects of vegetation. Such integration may be facilitated by simple overlaying of various layers in a GIS followed by visual interpretation (Arhin et al., 2015; Craig et al., 1999; Craig, 2001; Grimaud et al., 2015; Papp, 2002; Woolrych and Batty, 2007) or via automated classification methods which are not as common (Cracknell et al., 2015; Iza et al., 2016; Wilford et al., 2007). While visual classification can provide good results, it is often subjective and requires a long time to complete. In contrast, automated methods, which can achieve similar levels of accuracy, are considered more objective, repeatable, and faster.

Machine learning methods such as artificial neural networks (ANN) have been applied in geoscience remote sensing data analysis previously, including multi perceptron networks (An et al., 1995), probabilistic networks (Zhang et al., 2009), Kohonen self-organizing maps (Cracknell et al., 2015; Grebby et al., 2010, 2011), or quantile regression forests (Kirkwood et al., 2016).

This study aims to evaluate artificial neural network classification of regolith landform units in a moderately vegetated region of West Africa through the joint analysis of airborne geophysical and remote sensing data. Gamma-ray spectrometry, SRTM, Radarsat-2, ALOS Palsar, Landsat, and ASTER data were combined sequentially to examine the influence of particular sensor/technique on the classification accuracy. A maximum-likelihood classification was performed on the same set of data to compare the non-linear neural network classifier to a traditional statistical method.

2. Study area description

The study area is located in the Paleoproterozoic Baoule Mossi domain of the West African Craton near the town of Gaoua (Fig. 1) in southwest Burkina Faso and encompasses 686 km^2.

The planation surfaces of Burkina Faso (Fig. 2) developed on the basement rocks of the West African Craton (Fig. 1). The surfaces are a result of long-term deep weathering and erosion of the African continent under varying climatic conditions (Beauvais et al., 2008; Michel, 1973; Tardy and Roquin, 1998), mainly after the breakup of Gondwana in the Mesozoic (Chardon et al., 2006; King, 1962; Wright et al., 1985).