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Exploring the challenges with soil data in regional land use analysis

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ABSTRACT

Over recent decades, environmental models have gradually replaced traditional, qualitative land evaluation in regional land use analysis (RLUA). This changed the data requirements as the environmental models require quantitative, high resolution and spatially exhaustive data. As resources to collect new data are limited, RLUA often relies on already existing data. These data often do not meet the data requirements for the environmental models. Hence, a gap developed between the supply and demand of data in RLUA. This study aims to explore and analyse the effect of using different soil datasets in a case study for Machakos and Makueni counties (Kenya). Six soil datasets were available for the study area and showed large differences. For example, average clay percentages varied between 11.7% and 44.4%. The soil datasets were developed under different assumptions on e.g., soil variability. Four assumptions were verified using a field survey. An ongoing RLUA, the Global Yield Gap Atlas (GYGA) project, was taken as a case study to analyse the effect of using different soil datasets. The GYGA project aims to assess yield gaps defined as the difference between potential or water-limited yields and actual yields. Rain-fed maize is the dominating cropping system in Machakos and Makueni counties. The GYGA project uses soil data for the selection of the most dominant maize growing areas and to simulate water-limited maize yields. The protocols developed by the GYGA project were applied to the six soil datasets. This resulted in the selection of six different maize-growing areas and different water-limited maize yields. Our study clearly demonstrates the large differences between soil datasets. Main challenges with soil data in RLUA are: i) understand the assumptions in soil datasets, ii) create soil datasets that meet the requirements for regional land use analysis, iii) not only rely on legacy soil data but also collect new soil data and iv) validate soil datasets.

1. Introduction

There is an increased pressure on our natural resources due to e.g., population growth, economic growth and climate change. Globally, the increase in agricultural production does not keep up with population growth resulting in a decline in food security (Van Ittersum et al., 2013). This increases the need to study the interactions between our natural resources and land use. To study these interactions, regional land use analysis (RLUA) was adapted. In the past, RLUA mainly focused on qualitative land evaluation. The change in RLUA in combination with the increased information technology and data availability opened the possibility to use environmental models for RLUA (e.g., models simulating crop growth, soil erosion, water quality, land use change) (McBratney et al., 2000). These developments coincided with changing data requirements. In general, the environmental models need quantitative, high resolution and spatially exhaustive data. As many research programmes lack the resources to collect new data, most RLUAs rely on already existing data. However, existing soil data do often not match with the data requirements resulting in a gap between the supply and demand of soil data in RLUA. This gap may lead to operational problems in RLUA. This study aims to identify the main challenges with soil data in RLUA by exploring and analysing the effect different soil datasets have on RLUA.

In general, we distinguish four types of soil data:

1. Conventional soil survey (CSS). The CSS is originally established for qualitative land evaluation and is the most common type of soil data. Spatial soil variability is represented by discrete mapping units. Each mapping unit is described by one (in the case of a consociation) or more (in the case of a soil complex or association) soil types. The boundaries of the mapping units in CSS are abrupt (Cambule et al., 2013; Heuvelink and Webster, 2001). The compound mapping units are described by multiple soil types for which often relative area coverages are provided. Less abundant soil types are sometimes left out. Soil types are characterized by soil morphology and, chemical and physical analyses of representative soil profiles, before they are classified using e.g., Soil Taxonomy (Soil Survey Staff, 2014) or World Reference Base (IUSS Working Group WRB, 2014). By providing representative soil profile descriptions for the soil types, their internal variation is often ignored, i.e., the soil types are considered to be homogeneous. Nowadays, 31% of the global land surface is mapped by

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CSS at 1:1 million scale or larger (Nachtergaele and Van Ranst, 2003). The reconnaissance survey of the Kapenguna area (Gelens et al., 1976) is a good example of a CSS in Kenya. Those conventional exploratory maps and more general maps like the 1:2 million scale provisional soil map of East Africa (Milne et al., 1936) formed the basis for the Exploratory Soil Map of Kenya (Sombroek et al., 1982).

2. Point data. These data are available from a wide range of sources. They can accompany the CSS as representative soil profiles, but they can also be provided along with e.g., agronomic experiments. Point data can be qualitative or quantitative. For example, the Fertilizer Use Recommendation Project (FURP) in Kenya carried out a large number of agronomic experiments in different agro-ecological zones in Kenya (FURP, 1987; FURP, 1994). Each experiment was accompanied by a soil profile description including chemical and physical soil characteristics.
3. Digital soil maps. Digital soil mapping (DSM) spatially predicts soil characteristics by deriving statistical relationships between observed soil characteristics and auxiliary information representing the soil forming factors (e.g., digital elevation models representing topography and satellite imagery representing vegetation) (McBratney et al., 2003). The quality of digital soil maps depends on the quality and sampling density of the soil data, on the quality of the auxiliary information, and on the used mapping techniques. An example of DSM in Kenya is presented by Mora-Vallejo et al. (2008).
4. Remotely sensed soil data. These soil data are derived from a broad range of sensing platforms and sensor types. This technique is a relatively new inventory technique. Ge et al. (2011) and Mulder et al. (2011) provide an overview of the various techniques that are available. Most remote sensing studies so far have been performed locally (e.g. Palacios-Orueta and Ustin, 1998) and no standardized remote sensing based methodology for soil inventory has been established yet (Mulder et al., 2011).

Each soil data type describes soil variability in its own specific way and presents opportunities, but also drawbacks for its use in RLUA. For example, the CSS gives spatially exhaustive data and quantitative data come from representative soil profiles. However, CSS does not describe the soil variability within a soil type and the scale of CSS is often not detailed enough for RLUA (Nachtergaele and Van Ranst, 2003). Point data provide quantitative data, but the data are not spatially exhaustive. Digital soil maps provide quantitative, spatial continuous data. However, the soil characteristic maps resulting from digital soil mapping are often established independently. In comparison to conventional soil surveys, digital soil mapping has no unified (soil classification) system. Different digital soil maps of the same area can therefore vary depending on which source data are used, which assumptions are made and how the data are processed.

Our study focuses on Machakos and Makueni counties (Kenya), a semi-arid area where agriculture and food security play an important role. For this area, six soil datasets are compiled from available soil data sources. The study consists of three steps. In the first step, the six soil datasets are compared. In the second step, we verify assumptions that are made to establish soil dataset using a field survey. In the third step, the effect of selecting a soil dataset for a study on RLUA is analysed. The Global Yield Gap Atlas (GYGA) project[1] was taken as a case study. GYGA assesses yield gaps to study food security and guide potential investments in agricultural research and development (Van Ittersum et al., 2013).

2. Materials and methods

2.1. Study area

The major staple food crop in Kenya is maize. The total harvested maize area is estimated at 2.16 million ha with an average maize yield of 1.8 tons/ha (FAO Statistics Devision, 2015), which is far below the average water-limited maize yield potential of approximately 7.1 tons/ha[1]. Main causes for this large yield gap are i) nutrient depleted soils, ii) low application of mineral fertilizer, iii) scarcity in manure, iv) variable rainfall patterns, and v) lack of resources to improve degraded soils (Claessens et al., 2012). Narrowing the gap between the actual yield and the potential yield is at the top of the agenda of Kenyan governmental agencies. Problems faced by the Ministry of Agriculture and Ministry of Livestock and Fisheries Development (2004) are for example: lack of resilience during droughts and floods, low and declining fertility of land, crop diseases, and lack of coherent land policies.

An important maize cropping area in Kenya, which is also selected as a study site by the GYGA project, is located in the Eastern Province and includes Machakos and Makueni counties (Fig. 1). The counties are 1.35 million ha and half of that area is under agriculture (Mora-Vallejo et al., 2008). The area is hilly with elevations varying between 418 m and 2053 m above sea level. It has a semi-arid climate with low and highly variable rainfall distributed over two seasons. Average rainfall for each season ranges from 100 mm to 350 mm and the mean annual temperature varies between 15 °C and 25 °C. The main geological parent material originates from the Basement System and contains old intrusive and metamorphic rocks. Deep and friable soils developed in this parent material. The soils are inherently poor in nutrients with the exception of some volcanic areas. The textures range from clay to sandy clay and the soils generally have good drainage. According to the Kenya Soils and Terrain Database (KenSOTER) (Batjes and Gicheru, 2004), the most dominant soil types in Machakos and Makueni counties are Rhodic Ferralsols, Chromic Cambisols, Eutric Vertisols, Haplic Lixisols and Chromic Luvisols.

The study area has several seasonal rivers and the permanent Athi River in the East. Due to fast runoff in seasonal rivers and steep topography around the permanent river, the possibilities for irrigation are limited. Maize is often intercropped with beans, legumes and sorghum. Other cultivated crops are vegetables, fruits and root crops. Mixed smallholder farming systems are prevalent in the area. Due to increased agricultural activities in the early 1930s, caused by population growth, soil erosion took place (Tiffen et al., 1994). Governmental enforcement in erosion control, e.g. by terracing agricultural fields and reforestation of highly degraded areas and steep areas, slowed down the land degradation. Despite these measures and the willingness of people to voluntarily maintain the terraces (De Jager et al., 2005; Tiffen et al., 1994), the yields are low. Nowadays, still 59.6% of the population in Machakos and 64.1% in Makueni fall below the poverty line of 1 US$/person/day (Commission on Revenue Allocation, 2011). These numbers underline the need for RLUA.

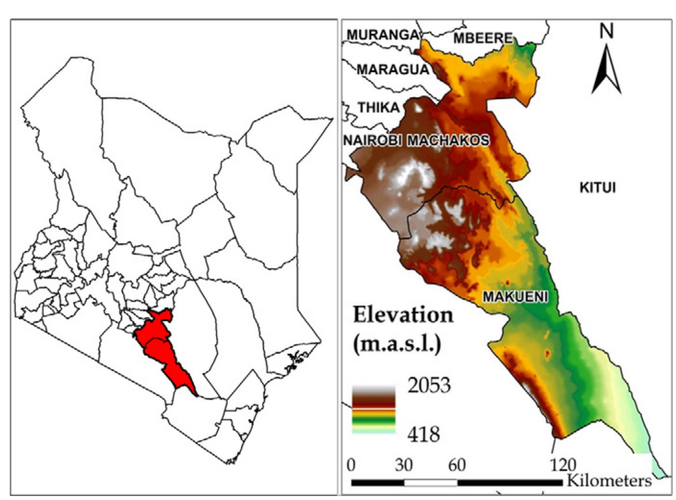

Fig. 1. Machakos and Makueni study area in the Eastern Province of Kenya.

[1] http://www.yieldgap.org/.