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Research Paper

Comparing multi-criteria evaluation and participatory mapping to projecting land use

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ABSTRACT

Projections pertaining to future land use and land use change may have diverse backgrounds. Often, both local and scientific knowledge encompass important pieces of information for such a projection. Acknowledging the diversity across the two types of knowledge, we investigated their differences and similarities in a twofold case study, conducting a participatory mapping (PM) exercise with local wine growers, as well as a Multi Criteria Evaluation (MCE) with non-local experts from science, government and industry. Hence, we not only utilised two different knowledge elicitation methods, but also two types of 'knowledges'.

Within a region dominated by vineyards, and with expected land use change, we compared the two results quantitatively, in a participatory evaluation workshop, and with annotations gained through the participatory mapping exercise. Both methods have their merits, with the results from the participatory mapping perceived as being more plausible, and the MCE scoring higher in terms of spatial resolution. Whilst the participatory mapping yields more and better contextualised information, the results from the MCE can be better compared across study areas.

1. Introduction

In land use projections, one may elicit local knowledge and hence consider the peculiarities of the respective area, whilst also consulting a scientific body of literature and incorporating general mechanisms (DeWalt, 1994). Therefore, it is promising to combine both types of 'knowledges'; however, this is usually a difficult task (Davenport & Prusak, 1998). To this end, we will use maps as an integrative platform (Payton et al., 2003).

This paper tries to answer the following research question: When projecting future land use, to what extent do the results garnered from a Participatory Mapping (PM) exercise undertaken with local wine-growers concur with the outcomes of a Multi Criteria Evaluation (MCE) based on estimations from experts from science, policy and consultancy? Both methods are assessed with respect to their potential for land use change projections in a case study on the persistence of vineyards, as a certain land use under economic pressure but with high emotional value. With this work, a contribution is made to the comparison of PM and MCE, as well as to different types of 'knowledges', which are often compared against one another in literature (Enengel et al., 2012; Raymond et al., 2010).

We assume the wine-growers in this region as holding more 'local knowledge', with the experts from science and consultancy holding more 'scientific knowledge' (Agrawal, 1995; Chalmers & Fabricius, 2007). 'Local knowledge' is generated informally, in a heuristic trial-and-error manner, mostly interacting within tacit and oral knowledge (Payton et al., 2003). 'Local knowledge' is often gathered in a participatory manner (Corburn, 2003), as in this case. 'Scientific knowledge', on the other hand, is usually very much formalised, often captured in written reports (Raymond et al., 2010). Therefore, MCE, as a formalised procedure (Belton & Stewart, 2002, p. 4), corresponds well with 'scientific knowledge'.

The decision was made that focus would be centred on the two methods MCE and PM, despite the many other methods existing in eliciting land use change (Sohl & Claggett, 2013). MCE and PM are straightforward methods, requiring a similar amount of time for establishing a comparable dataset, and farmers' knowledge has shown to deliver valuable insights for changes in a cultural landscape (Calvo-Iglesias, Crecente-Maseda, & Fra-Paleo, 2006). Further, the simplicity of the methods likely increases the overall acceptance associated with the predictions (Sohl & Claggett, 2013).

There are many reasons for eliciting and acquiring local and/or scientific knowledge (DeWalt, 1994; Raymond et al., 2010). 'Local knowledge' is usually of a small spatial and topical coverage, but likely

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covers a long-time scale, while particularly highlighting extreme events (Berkes, Folke, & Gadgil, 1995; Moller & Berkes, 2004). 'Scientific knowledge', on the other hand, is mostly detached from the concrete case, is generalised, and is only accessible with corresponding background information (Fleck, 1935; Raymond et al., 2010). Local knowledge might be 'richer' in context; therefore, it can complement scientific knowledge (Chalmers & Fabricius, 2007). However, there is a lack of studies combining and comparing the qualities and peculiarities inherent in 'local knowledge'—in our case, those gathered through participatory mapping—and the 'scientific knowledge', here formalised with an MCE.

One aspect we investigate when comparing the two methods with one another is the value of their results in terms of data quality. Data quality can be measured by various aspects and, depending on the specific study, is operationalised differently by incorporating relevance, spatial accuracy, correctness and/or completeness (Veregin, 1999; Worboys & Duckham, 2004). This is particularly important, as in regard to environmental management and monitoring, the data quality is of the greatest concern, and it might be higher with either 'local knowledge' or 'scientific knowledge' (Moller & Berkes, 2004). As there is no ground truth in land use projections, spatial accuracy, correctness and completeness cannot be measured as such. In this study, however, we compare the results of two methods and corresponding types of 'knowledges' and further investigate the reliability of either method in stakeholder consultation. Below, we present a selection of studies investigating the data quality related to either of the two types of knowledge, or methods (PM and MCE), respectively. We begin with studies making use of PM, before moving on to those studies making use of MCE, and, thirdly, studies combining both approaches.

1.1. Studies investigating the data quality of PM

Very few studies have compared PM-data with field observations. In a study by Brown (2012), a total of 260 participants mapped native vegetation, which was then compared to a land cover database. The PM points were found to have greater positional accuracy than randomly distributed points. However, this particular study does not calculate the share of native vegetation that was not identified with PM; that is, the completeness of the data. Rohrbach, Anderson, and Laube (2016) used PM with farmers for capturing past land use and validated the data with independent data sources. They found a correctness and completeness of approximately 67% and 55%, respectively. Aswani and Lauer (2014) performed a longitudinal PM study to assess the overall accuracy of PM data on benthic substrate in respect to changes due to a Tsunami. They found PM to be largely able to identify changes and their magnitude, with an overall agreement between field observations and PM between 59 and 94% depending on year and content.

1.2. Data quality of MCE models

The quality of the land use projections by multi criteria models was investigated in a larger study by Pontius et al. (2008), comparing 13 land use predictions by different models with surveyed data. In order to evaluate the quality of the predictions, the figure of merit was calculated, as the Jaccard-Coefficient (Jaccard, 1908), which is described and used later in this study. The figure of merit of the models ranges between 0 and 1, with higher values corresponding to higher data quality. On average, the models in the study of Pontius et al. (2008) yielded a figure of merit of 24%. Only one model reached a figure of merit of greater than 50%, indicating that more than half of the predicted pixels were actually correctly predicted.

1.3. Studies comparing data quality of PM and MCE methods

A couple of studies have evaluated local knowledge and scientific methods at the same time. Payton et al. (2003), for example, compared indigenous and scientific knowledge pertaining to soil types using GIS. Through their work, it was found that there is limited agreement between the two types of knowledge on specific soil types, as the different ontologies rendered the two sources largely incomparable. Other studies used predefined ontologies. For example, Brown, Weber, and de Bie (2015) evaluated results of PM with those yielded by a scientifically informed zonation software concerning conservation priority areas. They concluded that the conservation priority areas identified by software are also generally found through PM data. However, this study fails to report the number of areas identified by PM but not by the zonation software. Hence, no overall agreement could be calculated. Vergara-Asenjo, Sharma, and Potvin (2015) mapped primary forests with indigenous communities, and subsequently compared them with the digital image classification of remotely sensed data. Comparing both sets of data to 'ground truth', PM showed the greatest overall accuracy (83.7% vs. 79.9%). Selgrath, Roelfsema, Gergel, and Vincent (2016) carried out a similar comparison concerning benthic cover types in the ocean. They, however, found the PM result to be somewhat of inferior overall accuracy compared to the classification of remote sensing data (66% vs. 76%). Another way of integrating scientific methods with local knowledge was followed by Lauer and Aswani (2008), who used PM of marine habitats as seed pixels for a supervised classification of remote sensed data and accordingly validated the results with field observations. Compared to an unsupervised classification of the remote-sensed data, that with the PM seed pixels increased overall accuracy from 39% to 65%.

In summary, if the two types of knowledge are comparable, one might expect a considerable overlap between them. If the two types can be combined, the overall quality of the outcome should then be increased. However, the validity of the outcomes and strengths of either method and knowledge need to be assessed in the specific context (Raymond et al., 2010). As a consequence, guidance for the selection of appropriate types of knowledge and methods is deemed necessary.

In contrast to most of the presented studies comparing PM and MCE, this study applies both methods for a prediction of land use. Hence, there can be no 'ground truth' as such and neither of the two methods can be said in principle to score better compared to observations. However, through evaluating and contrasting insights from a PM with those from an MCE, this study nonetheless provides a threefold contribution: firstly, we quantify the agreement between the results; secondly, we qualitatively evaluate the outcomes in a participatory evaluation; and thirdly, we add rich qualitative information to the quantitative outcomes of either method by incorporating annotations.

2. Methods

2.1. General remarks

Our aim was to produce a spatial dataset for each method, namely MCE and PM, and accordingly represent the likelihood of land use change (i.e. abandonment of viticulture). The timeframe of the study—which took place in 2015—was set to 25 years into the future, as this was considered as representing the average life-span of a vine in viticulture. Therefore, somewhere between 2015 and 2040, a winegrower faces the decision to either continue growing wine and investing in re-planting or to stop the wine production on the parcel in question. Overall, the study area has been experiencing a recent downturn of the extent of vineyards. Currently, the municipal area is covered by forests (43%), unproductive land (27%), meadows (18%), built-up area (6%), arable land (2%) and viticulture (4%) (Swiss Federal Statistical Office., 2010). Fig. 1 provides the locale of the study area within Switzerland.

2.2. Participatory mapping

We projected land use change through the application of participatory mapping, adopting a pen-and-paper approach. As basemaps, we