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How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework “targetCSA”

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ABSTRACT

Planning for agricultural adaptation and mitigation has to lean on informed decision-making processes. Stakeholder involvement, consensus building and the integration of comprehensive and reliable information represent crucial, yet challenging, pillars for successful outcomes. The spatially-explicit multi-criteria decision support framework “targetCSA” presented here aims to aid the targeting of climate-smart agriculture (CSA) at the national level. This framework integrates quantitative, spatially-explicit information such as vulnerability indicators (e.g. soil organic matter, literacy rate and market access) and proxies for CSA practices (e.g. soil fertility improvement, water harvesting and agroforestry) as well as qualitative opinions on these targeting criteria from a broad range of stakeholders. The analytic hierarchy process and a goal optimization approach are utilized to quantify collective, consensus-oriented stakeholder preferences on vulnerability indicators and CSA practices. Spatially-explicit vulnerability and CSA data are aggregated and coupled with stakeholder preferences deriving vulnerability and CSA suitability indices. Based on these indices, relevant regions with the potential to implement CSA practices are identified. “targetCSA” was exemplarily applied in Kenya exploring group-specific and overall consensus-based solutions of stakeholder opinions on vulnerability and CSA under different consensus scenarios. In this example, 32 experts from four stakeholder groups who participated in two surveys were included. The subsequent analyses not only revealed consistently regions with high CSA potential but also highlighted different high potential areas depending on the applied consensus scenario. Thus, this framework allows stakeholders to explore the consequences of scenarios that reflect opinions of the majority and minority or are based on a balance between them. “targetCSA” and the application example contribute valuable insights to the development of policy and planning tools to consensually target and implement CSA.

1. Introduction

Addressing climate change is crucial to safeguard food provisioning from agricultural systems. Hence, planning efforts are urgently needed to target and implement agricultural adaptation and mitigation options in line with governmental strategies, such as national climate change action plans (Preston et al., 2011; Conway and Mustelin, 2014). Climate-smart agriculture (CSA) as a global development goal was introduced to guide the transformation of agricultural systems integrating adaptation, mitigation and food security (FAO, 2013). Alleviating vulnerability and fostering resilience of agricultural systems to climate change to secure the sustainable provisioning of food while reducing greenhouse gas (GHG) emissions are the major objectives of CSA (Harvey et al., 2014a).

The targeting of CSA at the national level is fraught with several challenges that, if not properly dealt with, potentially hamper the legitimacy and outcome quality of made decisions. First, relevant stakeholder groups have to be involved in the decision-making process that not only contribute their valuable expert knowledge but also might disagree due to conflicting interests and views (Nordström et al., 2010). Second, high complexity and uncertainty may arise from the multitude of criteria that need to be considered for the selection and prioritization of CSA practices at specific locations (Greene et al., 2011). Third, reliable quantitative and spatially-explicit data are required to identify regions suitable for targeting certain CSA practices. Such a database should include biophysical, social and economic determinants on agricultural vulnerability to climate change, consequently, offering a demand-based perspective on CSA (Fellmann, 2012; FAO, 2013). A framework that integrates knowledge and opinions from a broad range of expert stakeholders weighs those opinions based upon consensus and couples them with spatially-explicit datasets on vulnerability and CSA practices is of paramount interest to

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support robustly the decision-making on targeting CSA. To the authors' knowledge, such a framework has not been published so far.

The aim of this study was to develop a decision support framework for the spatially-explicit targeting of CSA, named "targetCSA", which includes multiple stakeholders, vulnerability indicators and suitable CSA practices. The applicability of this framework is demonstrated through an example from Kenya. Large parts of the country are characterized by arid or semi-arid climate with agricultural production dominated by smallholder farming. Erratic weather patterns, frequent droughts and reduced growing seasons are threats that will increase the vulnerability of the agricultural sector in Kenya (Molua et al., 2010; Gachathi and Eriksen, 2011). The national climate change action plan recently passed by the Kenyan government calls for urgent implementation of CSA practices, thus, rendering "targetCSA" highly relevant for the development of policy and planning instruments (Government of Kenya, 2012).

2. Methods

2.1. Conception of the decision support framework "targetCSA"

2.1.1. Background

Supporting decision makers in their assessment of options based on several criteria can be achieved through multi-criteria decision-making (MCDM) analyses (Romero and Rehman, 2003). MCDM aims to elicit transparently individual and subjective stakeholder judgments, aggregate them to collective preferences and help to explore their implications for decision-making processes (Greene et al., 2011). Spatial information has to be integrated into MCDM since implementing CSA involves landscape planning. Geographic information systems (GIS) can be applied to link the spatial attributes of criteria to stakeholder preferences (Boroushaki and Malczewski, 2008). MCDM is based on a well-established set of methods that have been frequently applied to different planning contexts such as the targeting of projects on the mitigation of GHG-emissions or the design of ecological reserves and corridors (cf. Ferretti and Pomarico, 2013; Lin et al., 2014; Tammi and Kalliola, 2014).

Adaptation and mitigation planning is the centrepiece of coping strategies for climate change such as action plans passed by national governments (Preston et al., 2011). The decision support framework proposed here is designed to aid planners and decision makers that aim to implement CSA at the regional or national level. Such a planning process involves several sectors such as governmental institutions, civil society, science and the private sector making it mandatory to involve respective stakeholder organizations (FAO, 2013). Therefore, the framework integrates multi-sectoral stakeholder groups to contribute expert knowledge on the selection and importance of vulnerability indicators as well as CSA practices that fit into a country's or regional profile due to prevailing environmental and socio-economic conditions. However, stakeholder perceptions on what is important might differ and result in conflicting judgements and trade-offs among decision options (Nordström et al., 2012). Hence, an adequate decision support framework should allow the exploration of trade-offs and minimize dissent. Integrating expert knowledge and spatial information into MCDM is crucial for informed and robust decisions based on evidence and acceptance (Preston et al., 2011). "targetCSA" uses an optimization-based approach developed by González-Pachón and Romero (2007) that applies distance minimization algorithms to reduce disagreement among the stakeholders' opinions and to facilitate the exploration of different consensus scenarios. Moreover, consensus-oriented opinions from stakeholders are coupled with quantitative and spatially-explicit vulnerability and CSA data building the factual foundation for decisions on where to target CSA. "targetCSA" is structured into three main stages (Fig. 1).

2.1.2. Climate change vulnerability and climate-smart agriculture

The vulnerability of a system to stressors such as droughts or floods depends on its sensitivity to perturbations, the degree of exposure, and its capacity to adapt on the impact (Challinor et al., 2007; Abson et al., 2012). Climate change is expected to increase the vulnerability of farmers by threatening their livelihood strategies as well as entire food productions systems (Challinor et al., 2007; Harvey et al., 2014b; Thornton et al., 2014).

The concept of CSA couples climate change and food security through the integration of adaptation and mitigation measures. It aims to reduce vulnerability by improving the adaptive capacity of agricultural systems to climate stress and, hence, securing the provision of food while reducing GHG-emissions from agricultural practices and land uses contributing to climate change (Scherr et al., 2012; Campbell et al., 2014; Harvey et al., 2014a). Thus, a short (adaptation) and long term (mitigation) perspective are integrated into the CSA concept which should be considered in proper targeting and planning processes.

By explicitly including the vulnerability concept into CSA-targeting, a demand-based perspective is taken, meaning that regions with higher climate change vulnerability require more urgently interventions that strengthen their adaptive capacity. The vulnerability of the agricultural sector to climate change is influenced by environmental and socio-economic factors (Abson et al., 2012; Fellmann, 2012). Thus, information about relevant biophysical (e.g. climate), social (e.g. education) and economic (e.g. market access) dimensions should be taken into account to inform an assessment of where specific CSA practices are suitable.

2.1.3. Stage 1: structuring the decision-making problem

2.1.3.1. Stakeholder involvement and data collection. Relevant stakeholders should be identified at the beginning of the planning process (Nordström et al., 2010). During the first stage (Fig. 1), meetings with cross-sectoral stakeholders are conducted, e.g. from governments, civil societies, science and private sectors to develop a structured catalogue of context-specific vulnerability indicators and CSA practices (cf. Patt et al., 2010; Fellmann, 2012; Scherr et al., 2012). Related datasets can be obtained from publicly available geo-databases such as the FAO GeoNetwork, HarvestChoice and GEO-Wiki branches or compiled and made spatially-explicit based on sub-national census data using GIS.

2.1.3.2. The analytic hierarchy process. The analytic hierarchy process (AHP) is widely used in MCDM with numerous applications (Wind and Saaty, 1980; Saaty, 1994; Nordström et al., 2012). A complex problem is decomposed into pairs of criteria (decision options) through pair-wise comparisons (PC), where two criteria are compared with each other at a time (Wind and Saaty, 1980). Stakeholders assign numerical preference weights as expression of their opinion to one of the paired criteria that are compared on a measurable scale known as the Saaty scale (Saaty, 1977). It orders the importance of potential judgments from 1 = equal preference to 9 = extreme preference towards one of the paired criteria. Finally, the individual stakeholder preferences are aggregated deriving a normalized vector of overall preferences for considered criteria (Saaty, 1977).

2.1.4. Stage 2: eliciting stakeholder preferences and consensus building

2.1.4.1. Multi-criteria decision-making model. The second stage integrates and aggregates formalized stakeholder opinions (Fig. 1). Individual preference weights are queried through PC questionnaires that are administered through workshops, expert surveys or interviews (cf. Diaz-Balteiro et al., 2009; Sae-Lim et al., 2012).

A commonly used technique to aggregate individual stakeholder preferences in group decision-making processes is to calculate overall priority vectors (Eigenvectors) through geometric or arithmetic mean methods (Ishizaka and Labib, 2011; Nordström et al., 2012). "targetCSA", however, utilizes a goal programming (GP) approach by implementing a set of MCDM models that are based on linear optimization. These models were developed by González-Pachón

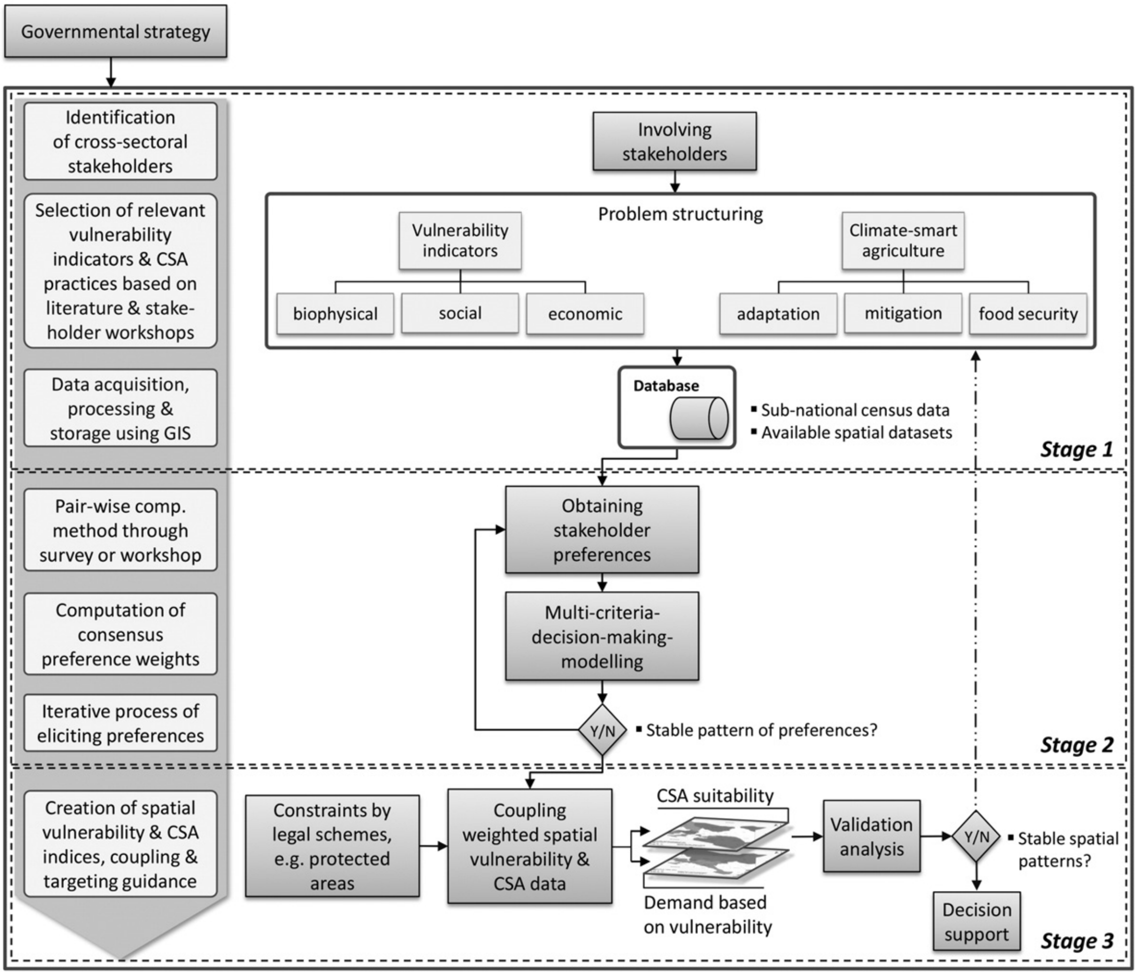

Fig. 1. Conceptual overview of the decision support framework "targetCSA".

and Romero (2007) and applied by Diaz-Balteiro et al. (2009) as well as Gebrezgabher et al. (2014). The GP approach has two advantages compared to the conventional Eigenvector-based aggregation methods: i) stakeholder preferences do not have to be consistent throughout the PC questionnaire (González-Pachón et al., 2003; González-Pachón and Romero, 2007) and ii) the MCDM models are designed to minimize distances among obtained PC questionnaires enabling the search for a collective consensus. Hence, this approach offers integrated support for participatory management and planning processes that rely on consensus (Sae-Lim et al., 2012; Gebrezgabher et al., 2014).

In a nutshell, the GP approach computes a consensus matrix that shows minimized differences to the input PC matrices attained from the questionnaires and infers the consensus preferences from this matrix using a distance minimization algorithm. During this process, optimization can be controlled following different consensus scenarios moving along a trade-off curve between majority and minority consensus (González-Pachón and Romero, 2011). The majority consensus represents the closest solution to all stakeholder preferences whereas the solution based on the minority consensus seeks to satisfy preferences of the stakeholder far apart from the majority. The MCDM models were numerically programmed in R (v. 3.1.1) using the linear programming library 'lpsolve' (v. 5.6.10). A detailed description of the models can be found in the Appendix (A1–3).

2.1.4.2. Eliciting stakeholder preferences. Stakeholder preferences represent a source of uncertainty in the decision making process (Mosadeghi et al., 2013). Therefore, it is recommended to elicit preferences iteratively (Nordström et al., 2010). The iterations allow to capture, assess and to reduce the variability of preferences which result from adjusted stakeholder opinions that might affect the targeting outcome (Mosadeghi et al., 2013). Evaluating the robustness of preferences is important to obtain a transparent measure of how reliable the included expert knowledge is for final decision-making (Xu and Zhang, 2013).

2.1.5. Stage 3: spatial aggregation and coupling of vulnerability and CSA indices

2.1.5.1. Deriving vulnerability and CSA suitability indices. The third stage combines elicited preferences with spatial data representing quantitative vulnerability indicators and data reflecting CSA practices (Fig. 1).

Weighed linear combination (WLC) is a widely applied aggregation rule where high values of one criterion can be offset by low values of another criterion (Eastman et al., 1995; Greene et al., 2011; Lin et al., 2014). In "targetCSA", values of standardized spatially-explicit criteria are multiplied with related stakeholder preferences and finally summed up deriving combined vulnerability and CSA suitability scores using WLC. Spatial information of constraints, such as regions with legal restrictions or a lacking relevance are masked and excluded from the decision-making process.

Finally, two standardized and spatially-explicit indices depicting climate change vulnerability and CSA suitability are generated. Subsequently, a re-scaling of both indices into low, mid and high vulnerability as well as CSA suitability allows to superimpose them and to assess overlaying classes for the identification of areas with high potential for selected CSA practices. Maps showing these indices can be used to explore the consequences of different consensus scenarios on the CSA targeting and guide decision-making.

2.1.5.2. Validation. If stakeholder preferences are elicited at several occasions they can be used to validate the robustness of the calculated spatial indices (Fig. 1). This is crucial to assess how reliable and, hence, how useful the vulnerability and CSA suitability indices are as source of information in a decision-making process (Delgado and Sendra, 2004). Several sets of aggregated and coupled indices can be spatially compared. Large differences in areas of CSA potential could point to high uncertainties associated to blurred stakeholder opinions and knowledge gaps which have to be addressed (Nordström et al., 2010; Mosadeghi et al., 2013).

2.2. Application example from Kenya

2.2.1. Study area

Kenya covers a total area of 581,881 km^2 and has a population of about 38 million people (Fig. 2) (Wiesmann et al., 2014). While the most productive land is situated in the central and western, sub-humid parts of Kenya, about 80% of Kenya is characterized as semi-arid or arid lands with erratic rainfall, droughts and sporadic floods (Molua et al., 2010; Gachathi and Eriksen, 2011). The agricultural sector plays a pivotal role for food provisioning and the country's economy. However, it suffers from recurring crop failure, livestock mortality and food insecurity (Grace et al., 2014). A large part of Kenya's labour force works in the agricultural sector, which makes about 75% of the national gross domestic product (Odera et al., 2013). The vulnerability of the mainly rainfed agricultural sector to climate change is marked by its exposure and sensitivity to harsh biophysical factors relating to climate and soil as well as low adaptive capacity determined by the socio-economic context, e.g. poverty, poor access to education and health facilities as well as to markets (Eriksen and O'Brien, 2007).

2.2.2. Selection of stakeholders, vulnerability indicators and CSA practices

The CSA targeting process started in 2013 through discussions between the Kenyan Ministry of Environment, Water & Natural Resources and the Research Program on Climate Change, Agriculture and Food Security (CCAFS). Stakeholders were selected from four groups representing governmental organizations (GOs), civil society

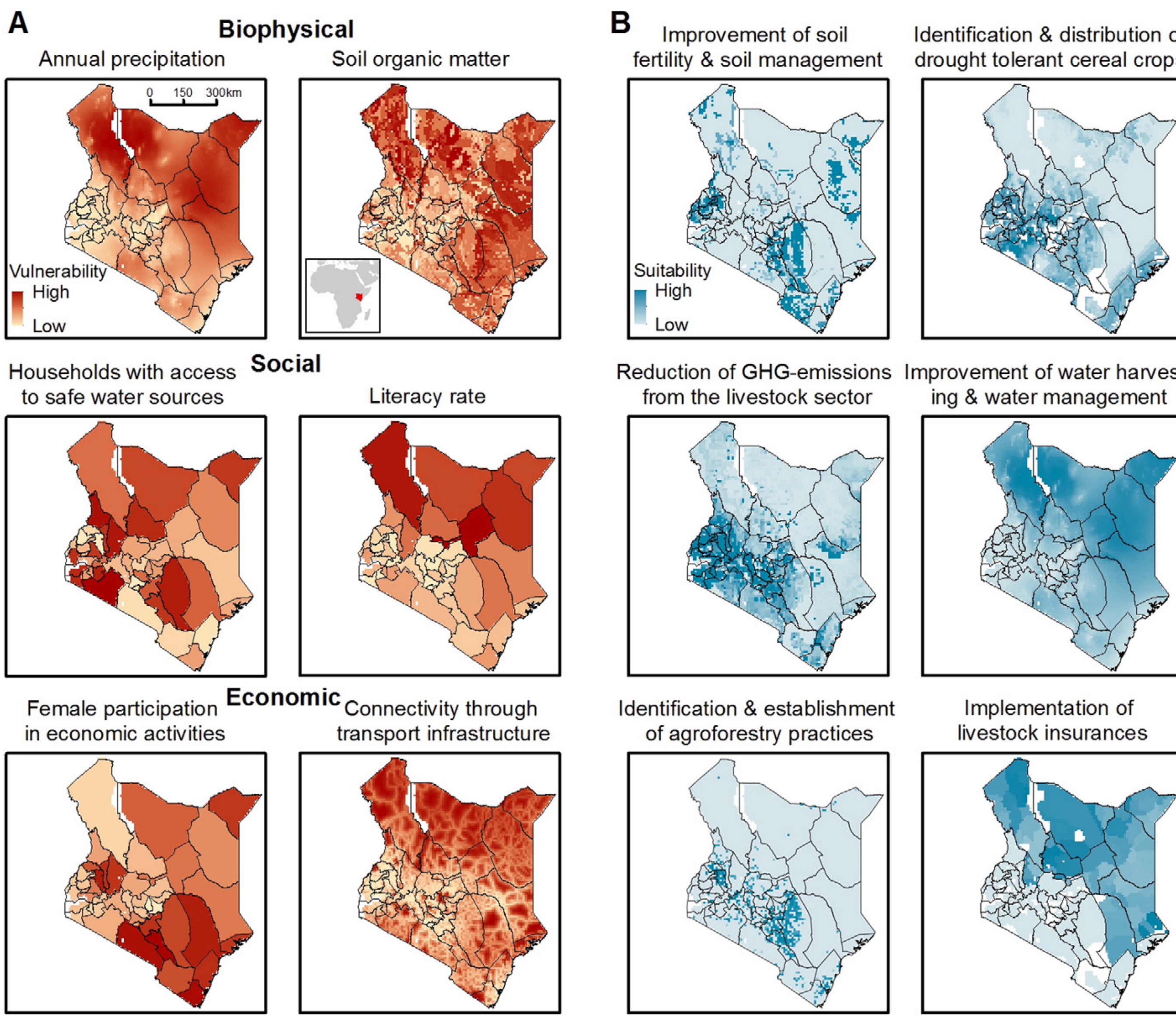

Fig. 2. Maps show the spatial distribution of consistently re-scaled datasets used to represent (A) vulnerability indicators and (B) CSA practices ranging from 0-1. For the vulnerability maps, dark red colour means highly vulnerable, for the CSA suitability, dark blue colour means highly suitable for the selected CSA practice. Included CSA practices are reflected by proxy datasets explained in Table 1.

Table 1
Overview of the stakeholder-based selection of climate change vulnerability indicators and CSA practices for the application example in Kenya, including descriptions as well as linkages between indicators and practices.

Indicators of climate change vulnerability	Data description and sources	Linkages climate change vulnerability — CSA
Biophysical		
Annual precipitation	Annual precipitation based on the period: 1950–2000 (Hijmans et al., 2005).	'Annual precipitation' was selected as indicator for water availability and ecosystem productivity. The availability of water largely determines agricultural productivity. The improvement of water harvesting and management and the introduction of drought tolerant crop varieties represent viable CSA practices to deal with vulnerability to water shortages (Harvey et al., 2014a).
Soil organic matter	Organic carbon content in the top soil layer, up to 30 cm depth, contained in (decomposed) plant and animal residues, tissues and cells (Nachtergaele et al., 2012).	'Soil organic matter' is an indicator of soil fertility and, thus, ecosystem productivity. Regions with low soil organic carbon need CSA practices that alleviate nutrient depletion such as measures to stop erosion to build up soil carbon through organic fertilizers and integrated practices such as agroforestry (Lal et al., 2011).
Social		
Percentage of households with access to safe water sources	Proportion of households per county with access to safe water sources such as: boreholes, protected wells and springs, piped water and collected rainwater (Government of Kenya, 2009; Wiesmann et al., 2014).	'Percentage of households with access to safe water sources' was selected as an indicator of household well-being. Required CSA practices should, thus, improve the management of water that is used for agricultural purposes as well as drinking water and thereby safeguard its availability (Harvey et al., 2014a).
Literacy rate	Proportion of the population (aged 15+) per county that is able to read and write (Government of Kenya, 2013).	'Literacy rate' is an education indicator. High illiteracy reflects reduced capabilities (adaptive capacity) of making informed decisions regarding viable coping strategies under climate change (Atela et al., 2014). Thus, it reflects obstacles for implementing CSA due to lack of knowledge and information. CSA practices in turn have to contribute necessary knowledge, thus, help to reduce information gaps as well as facilitate relevant practical skills.
Economic		
Female participation in economic activities	Active female labour force divided by the total female labour force per county (Government of Kenya, 2009; Wiesmann et al., 2014).	'Female participation in economic activities 'is understood as an indicator for women empowerment and economic development. Gender inequality increases the susceptibility to sudden changes and threats as such climate change. Integrated CSA practices such as conservation agriculture and agroforestry have the potential to promote gender equality and improve livelihoods for women and men while supporting mitigation and adaptation (Beuchelt and Badstue, 2013).
Connectivity through transport infrastructure	Degree of connection between places across Kenya, based on time needed for travelling to the next city >50,000 inhabitants (Uchida and Nelson, 2009).	'Connectivity through transport infrastructure' indicates farmers' accessibility to markets for selling farm produces and buying inputs as well as accessing extension services such as vaccination. A reduced access adds additional risks for farmers under climate change (Abson et al., 2012). CSA practices are supposed to support farmers to deal with the impacts of climate shocks such as losses of livestock or crop failures. CSA examples are insurance schemes and drought tolerant varieties/breeds improved soil and water management (Harvey et al., 2014a; Vrieling et al., 2014).
CSA practices	Examples, proxy datasets and assumption of use	Link to indicators of climate change vulnerability
Improvement of soil fertility and soil management	Example: low-cost soil fertility enhancement options, such as green manures, legumes, composting, and animal manure management, improved fallows and conservation agriculture Proxy dataset: low nutrient capital reserves (Sanchez et al., 2003) Assumption: depleted nutrient stocks in soils call for improved soil fertility management through CSA.	Biophysical: 'soil organic matter' Social: 'literacy rate'
Identification and distribution of drought tolerant cereal crops	Example: sorghum, millet and maize Proxy dataset: suitability of rainfed cereal crops assuming an improved management scenario in terms of labour, fertilizer use, pest control and conservation measures (van Velthuizen et al., 2007) Assumption: The biophysical suitability for cereals under region-specific farm management reflects the potential to grow drought tolerant cereal varieties.	Biophysical: 'annual precipitation' Social: 'literacy rate'
Reduction of greenhouse gas emissions from the livestock sector	Example: manure management, more efficient breeds, species, feeds and biogas technologies Proxy dataset: methane and nitrous oxide emissions from livestock per kg protein, including cattle, sheep, goats, pigs and poultry (Herrero et al., 2013) Assumption: high livestock-based emission intensities show high demand for GHG mitigation practices.	This is a mitigation practice that, in a long-term perspective, reduces the vulnerability to climate change in general. Therefore, it links to all vulnerability indicators included here.
Improvement of water harvesting and water	Example: community water pans, micro-catchments and dams constructed to harvest,	Biophysical: 'annual precipitation'

management	store and distribute water for crop irrigation and livestock Proxy dataset: aridity index (Zomer et al., 2008) Assumption: agricultural practices in drylands, such as pastoralism, are prone to water deficits. Hence, these regions reflect high demands to improve the harvesting and management of water.	Social: 'percentage of households with access to safe water sources', 'literacy rate' Economic: 'connectivity through transport infrastructure'
Identification and establishment of agroforestry practices	Agroforestry integrates trees into croplands and pastures. Example: identifying agroforestry practices (based on surveys etc.), establishing community agroforestry, tree nurseries Proxy dataset: percentage of cropland area (Fritz et al., 2015) restricted to regions with a tree cover <10% (Hansen et al., 2013). Assumption: regions with higher proportions of cropland show potential for integrating trees into agricultural landscapes that lack a minimum tree cover aligning this CSA practice with the national policy target in Kenya to achieve a tree cover of at least 10% (Government of Kenya, 2007).	Biophysical: 'soil organic matter' Economic: 'female participation in economic activities'
Implementation of livestock insurances	Example: monetary subsidies for farmers in cases of severe climate mediated livestock mortality Proxy dataset: insurance premium rates for livestock mortality based on remote sensing time series data (normalized difference vegetation index, NDVI) from 1981 to 2012 (Vrieling et al., 2014). Assumption: regions with increased drought risks and water shortages have a higher demand for livestock insurance schemes.	Biophysical: 'annual precipitation' Social: 'percentage of households with access to safe water sources', 'Literacy rate' Economic: 'connectivity through transport infrastructure'

(NGOs), scientific institutions and the private sector (Table B1). A stakeholder workshop was held in early 2014 to select vulnerability indicators and CSA practices. Subsequently, related quantitative data were collected, compiled and processed in ArcGIS (v. 10.1). All datasets were derived from publicly accessible databases or censuses conducted by governmental institutions in Kenya. Resulting grid data were resampled to match a consistent resolution of approximately 10×10 km. A subset of six vulnerability indicators and CSA practices was selected, suitable to test the applicability of "targetCSA" (Table 1).

This choice was based on three criteria. First, the selection of vulnerability indicators was based on the scientific vulnerability literature dealing with climate change in Africa (cf. Challinor et al., 2007; Abson et al., 2012; Atela et al., 2014). Selected CSA practices are also listed in a catalogue that is part of the Kenyan National Climate Change Action Plan (Government of Kenya, 2012). Second, the data quality was ensured through peer-reviewed published datasets and consultation of experts. Third, there was no high collinearity among vulnerability and CSA datasets (Spearman's rho < 0.75).

There was no information about the effectiveness of selected CSA practices on alleviating vulnerability of the agricultural sector in Kenya. Therefore, this application example represents a spatially-explicit *ex-ante* assessment that explores the potential to target CSA practices consensually by focusing on regions that are shown to be vulnerable and suitable.

2.2.3. Expert survey

The designed questionnaire comprised two parts. The first part dealt with the pair-wise comparison of six selected vulnerability indicators, while the second part focused on comparing the six selected CSA practices. The number of PC items was restricted to six avoiding potential reductions in consistency and quality of the answers (Saaty, 1977). The leading questions in both parts were formulated to elicit preference weights according to the relative importance of the items compared to each other. For this application example, a slightly reduced rating scale was used compared to the original Saaty scale, ranging from 1 to 7, based on results from a pre-test. In order to separate the different intensities of possible preferences more clearly, they were defined as: 1 = equal preference, 3 = slight preference, 5 = moderate preference and 7 = strong preference. Five different versions of the questionnaire were created differing in their sequence of comparisons based on randomization to prevent a possible bias resulting from a fixed order of comparisons (Podsakoff et al., 2003).

The survey took place between September and November 2014 interviewing eight experts from each of the four stakeholder groups ($n = 32$). Each interview took approximately 20 min. Before an interview started, the questionnaire was explained and put into the CSA targeting context to avoid misguided judgments due to potential misconception of queried items (Keeney, 2002).

During a stakeholder workshop conducted in November of 2014, the survey results were presented and preferences re-elicited using the identical PC questionnaire for the validation of spatial indices. Furthermore, the questionnaire was sent to stakeholders that could not attend, including supplementary information about the workshop results. Finally, 16 validation questionnaires were filled covering 50% of each originally sampled stakeholder group.

2.2.4. Multi-criteria decision-making model

Applying the GP optimization approach developed by González-Pachón and Romero (2007) allowed us to explore both conflicting group interests and consensus solutions regarding stakeholder preferences for vulnerability indicators and CSA practices. The MCDM models were fitted i) to aggregate group specific preferences separately keeping the experts in each group as individuals and ii) to search a consensus based on the entire set of included expert opinions, referred to as the overall consensus, assuming a collective interest in striving for consensus in a decision-making process.

The ability of the MCDM models to move towards mutually exclusive majority or minority oriented consensus scenarios was tested by González-Pachón and Romero (2007). In this example, three scenarios were applied to explore results that reflect the preferences of the i) majority, ii) minority, and iii) the optimal trade-off indicating the consensus solution that is most balanced in representing the stakeholder opinions (González-Pachón and Romero, 2011). The latter is especially interesting in a decision-making context where no information is available about the socially desired outcome of the negotiation process. A detailed description of the applied optimization model used to find the consensus with the most balanced trade-off can be found in the Appendix (A4). The modelling procedure was applied on stakeholder preferences obtained from both expert surveys enabling the assessment of changes in opinions among stakeholders.

2.2.5. Spatial aggregation and coupling of weighted vulnerability and CSA suitability indices

The WLC rule was used to combine linearly each of the two sets of spatial data (Table 1), excluding constraints such as protected areas, forests, lakes and settlements, with preferences inferred from the overall consensus deriving combined vulnerability and CSA suitability indices (Eastman et al., 1995). Spatial datasets reflecting these constraints were obtained during the initial data collection process. A detailed description of the WLC rule can be found in the Appendix (A5).

By overlaying the indices of vulnerability and CSA suitability, it was possible to assess the targeting potential of selected CSA practices based on their suitability in regions that bear high vulnerability. The indices were computed for three different consensus scenarios (majority, minority, and the most balanced trade-off) to explore differences in regions with high CSA potential. For validation, the CSA potential was computed based on stakeholder preferences derived from both surveys applying the consensus scenario with the most balanced trade-off. Through comparison of CSA potentials, areas where the survey results (dis)agree were investigated.

3. Results

3.1. Vulnerability indicators and CSA practices

Both biophysical indicators, 'annual precipitation' and 'soil organic matter' show relatively high vulnerability in Northern and Eastern parts of Kenya (Fig. 2A). The social indicator 'households with access to safe water sources' reveals a more heterogeneous pattern of vulnerability than the indicator 'literacy rate' which shows higher illiteracy in the North and, thus, elevated vulnerability compared to the rest of the country. The two economic indicators depict a contrasting pattern. Whereas 'female participation in economic activities' highlights the South-Eastern regions as more vulnerable, the indicator 'connectivity through transport infrastructure' emphasizes the North and partially the East as more remote and, hence, potentially more vulnerable.

Focusing on CSA practices, the dataset on soil nutrients shows a scattered pattern of areas in the North-East, West and South of Kenya where CSA practices relating to the 'improvement of soil fertility and soil management' are potentially suitable (Fig. 2B). For the 'identification and distribution of drought tolerant cereal crops' regions in Western, Central and coastal Kenya indicate favourable conditions using the dataset on suitability for cereal crops. The arid areas in the North and East are shown as not or marginally suitable for cereals due to prevailing biophysical conditions rendering crop-based agriculture impossible in general, except for the narrow belts along rivers that are not captured by this dataset due to its grid cell resolution of 10×10 km. Relatively high methane and nitrous oxide emissions due to livestock production identify Western, Central and partially Eastern as well as Southern regions as suitable for mitigation interventions focusing on the 'reduction of GHG-emissions from the livestock sector'. Increased aridity in the entire North and North-East of Kenya compared to its Western and Central regions reveal areas for the 'improvement of water harvesting and water management'. The percentage of croplands, constrained by low tree cover, used as proxy for the 'identification and establishment of agroforestry practices' delineates Western and Central regions from the rest of the country emphasizing them as suitable for related interventions. Insurance premium rates for livestock mortality as proxy for the 'implementation of livestock insurances' reveals Northern and Eastern areas as prone to higher risks offering eligible conditions for implementing this practice.

3.2. Aggregated group-specific and overall consensus-based preferences

The distribution of preference weights inferred from each stakeholder group separately and based on the overall consensus, including all experts, are shown for vulnerability indicators (Fig. 3A) and CSA practices (Fig. 3B). Illustrated preferences result from the consensus scenario that shows the most balanced trade-off between majority and minority. The results for majority and minority scenarios can be found in the Appendix (Fig. B1–2). Stakeholder groups differed in their preferences for each of the vulnerability indicators and CSA-practices indicated by across group standard deviation (*SD*) ranging from 0.02 - 0.09 for vulnerability indicators and from 0.00 - 0.12 for CSA practices. However, the vulnerability indicator and CSA practice that were weighed low across all groups, namely 'connectivity through transport infrastructure' and 'implementation of livestock insurances', show a relatively homogenous pattern of preferences with the lowest across group *SD*. Highly preferred vulnerability indicators across stakeholder groups are 'annual precipitation' and 'households with access to safe water sources'. These indicators relate to the biophysical and social dimensions of vulnerability to climate change. The economic vulnerability indicator 'connectivity through transport infrastructure' and the social indicator 'literacy rate' were weighed low throughout the stakeholder groups except for the science group, which assigned slightly lower preferences to 'female participation in economic activities'. For CSA-practices, high preferences were assigned to 'improvement of water harvesting and water management' and 'identification and distribution of drought tolerant cereal crops'. Yet, NGOs deviated from this pattern giving higher importance to 'identification and establishment of agroforestry practices'. Low weighed CSA practices across stakeholder groups are 'implementation of livestock insurances' and 'reduction of GHG-emissions from the livestock sector'.

The preferences based on the overall consensus largely resemble the distribution of group-specific preferences. However, they rank within the ranges of group preferences for each of the indicators and CSA practices except for 'implementation of livestock insurances' indicating minimized distances among stakeholder opinions by using consensus matrices to infer the overall consensus.

3.3. CSA potential: coupling spatial indices of vulnerability and CSA suitability under different consensus scenarios

The combined indices for vulnerability and CSA suitability derived from the overall consensus preferences, including all experts, as well as CSA potential maps that resulted from coupling the indices are shown for the majority (Fig. 4A), minority (Fig. 4B) and the most balanced trade-off (Fig. 4C) consensus scenarios. In general, high vulnerability to climate change based on the included indicators is shown for the North and to some degree in Eastern parts of Kenya whereas high CSA suitability is indicated for Western, Central, coastal and partly in Northern parts throughout applied consensus scenarios. However, there are differences in vulnerability among the consensus scenarios at county level. The majority consensus led to higher vulnerability for Turkana and Kitui counties than the minority consensus which identified the same counties as medium or marginally vulnerable. In contrast, the minority consensus indicated higher vulnerability for Wajir and Tana river counties. The consensus scenario with the most-balanced trade-off shows a pattern of vulnerability intensities that lays

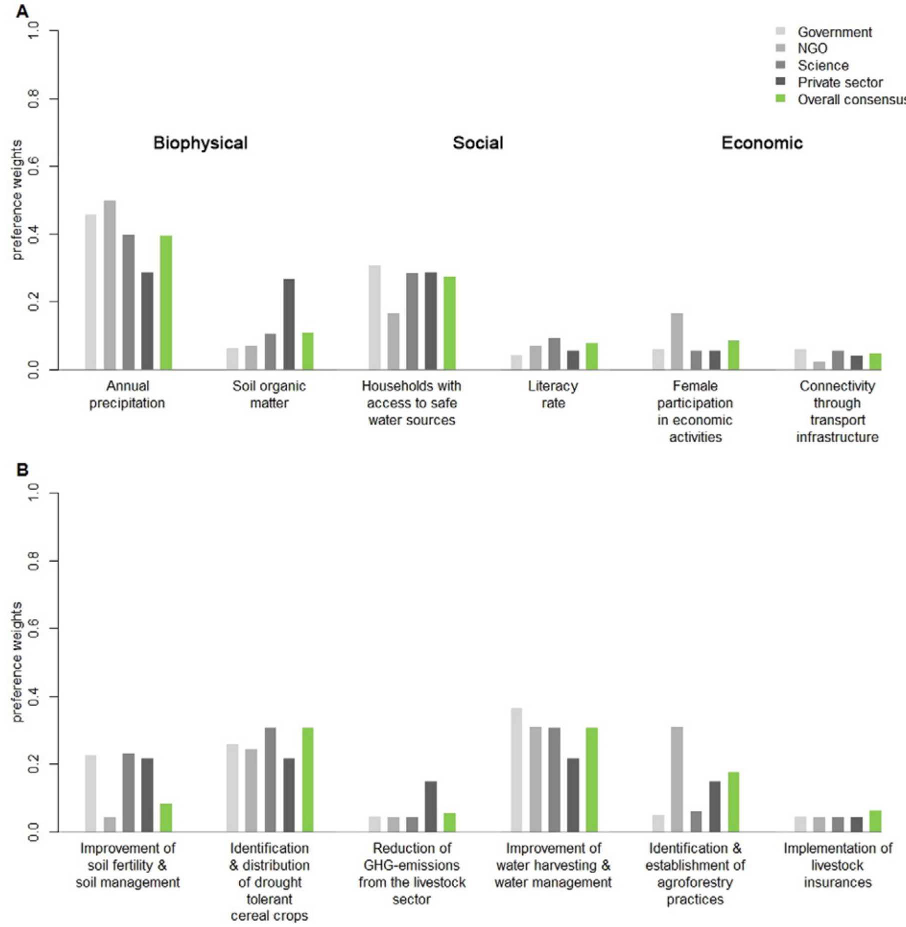

Fig. 3. Preference weights for each stakeholder group and the overall consensus, including all experts, resulting from the consensus scenario showing the most balanced trade-off between majority and minority for (A) vulnerability indicators and (B) CSA practices.

between those indicated by majority and minority for these counties. Differences in CSA suitability between the consensus scenarios are less pronounced, yet obvious in several parts of Kenya.

Overlaying CSA suitability on top of high vulnerability regions reveals areas with high CSA potential in Baringo, Mandera and Wajir counties in agreement with all three consensus scenarios. The consensus scenarios disagree on areas of high CSA potential in Turkana, Kitui and Marsabit counties. Comparing majority and minority consensus scenarios, these differences become most obvious for Turkana and Kitui counties. The most-balanced trade-off consensus reflects areas with high CSA potential whose extents rank between those indicated in the majority and minority consensus scenarios.

3.4. Validation

The preferences inferred from the overall consensus based on two expert surveys differed as shown for vulnerability indicators (Fig. 5A) and CSA practices (Fig. 5B) under the consensus scenario with the most-balanced trade-off between majority and minority. These differences are less pronounced for vulnerability indicators than for CSA practices indicated by mean differences between the preferences from the two surveys of 0.08 and 0.13 respectively. However, Wilcoxon signed-rank tests did not reveal significant median difference among the two sets of vulnerability indicators and CSA practices ($p > 0.05$).

Mapping the CSA potential based on the two sets of vulnerability and CSA suitability indices under the consensus scenario with the most-balanced trade-off depicts agreement among surveys on areas with high CSA potential in the North and North-East of Kenya mainly located in Wajir and Mandera counties (Fig. 5C). Areas of disagreement due to differing stakeholder preferences derived from the two surveys are distributed across the North and Central-East of Kenya.

4. Discussion

4.1. Informing decisions with "targetCSA" using spatially-explicit vulnerability and CSA suitability indices

The combined and spatially-explicit indices reveal a picture of where to target stakeholder selected CSA practices to reduce agricultural vulnerability to climate change at the national level. For Kenya, areas of high vulnerability contrast with areas potentially suitable for implementing CSA practices based on the empirical information included here. This study showed that regions of high vulnerability in Kenya mainly coincide with semi-arid and arid climate resulting in harsh biophysical conditions, confounded by low availability of education and health infrastructure as well as reduced access to markets (Odera et al., 2013; Wiesmann et al., 2014). High vulnerability to climate change for arid and semi-arid areas was also reported at the global scale (Allen et al., 2007). In contrast, high suitability for selected CSA practices concentrated around sub-humid, to some degree semi-arid areas and is discontinuously spread across arid climate (Grace et al., 2014). Nevertheless, areas of high CSA potential were identified and could be targeted for CSA pilot projects. The Western and Southern parts of Mandera county in the North-West of Kenya represent an example of high CSA potential consistently shown for specific areas across different consensus scenarios as well as expert surveys. The introduction of drought tolerant cereals on moderately suitable lands, the improvement of water management in areas of high aridity, or the implementation of livestock

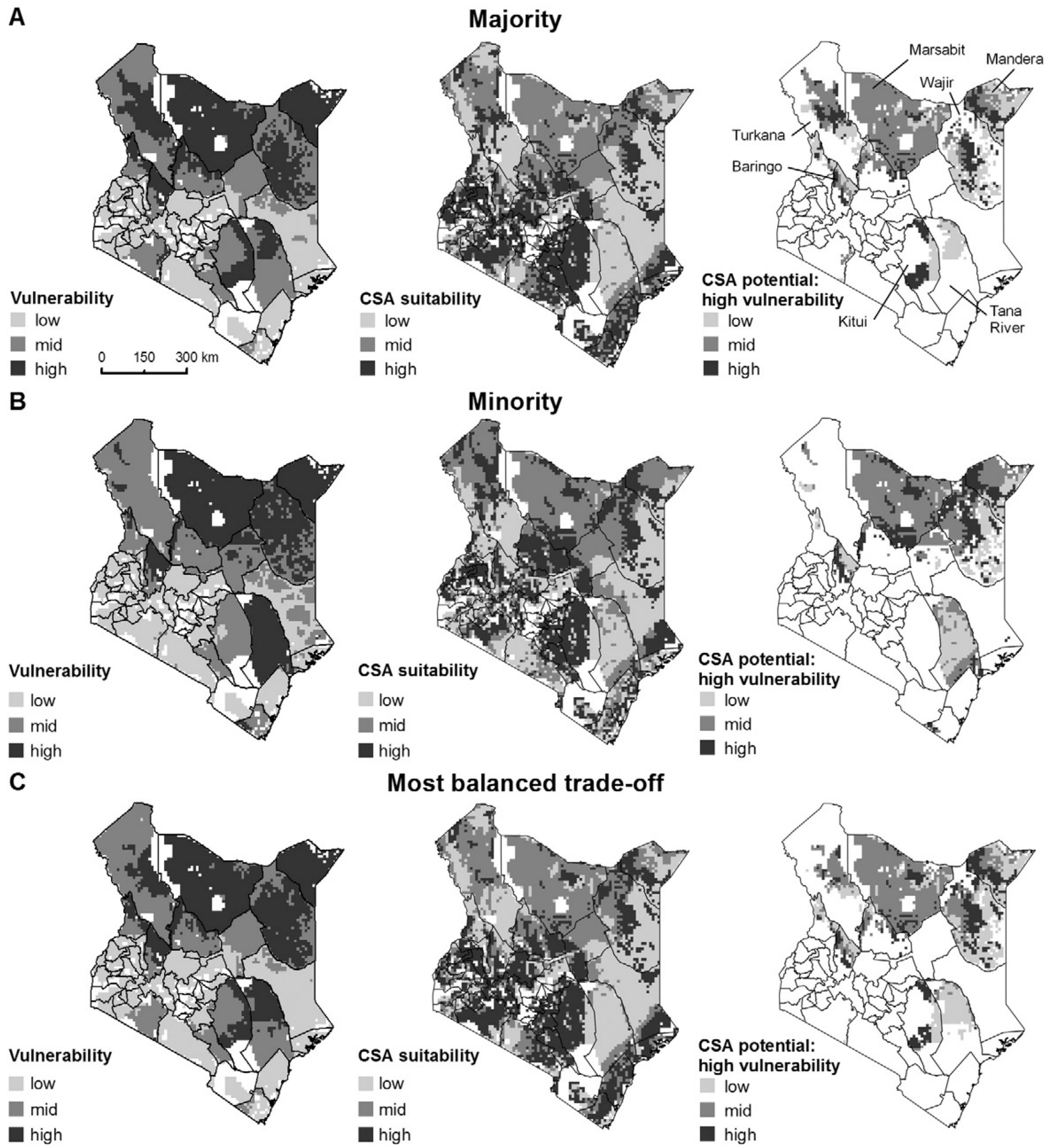

Fig. 4. Maps show the spatially-explicit indices of vulnerability and CSA suitability as well as the CSA potential for high vulnerability regions based on consensus scenarios of the (A) majority, (B) minority and (C) most-balanced trade-off. Underlying stakeholder preferences were inferred from the overall consensus, including all experts. Classes of vulnerability and CSA suitability indices (low, mid and high) resulted from quantile splits to preserve equal *n* sizes per class.

insurances addressing high mortality risk may represent promising CSA measures (Fig. 4). By coupling the computed spatial indices, the originally unrestricted space could be narrowed to specific regions of high CSA potential enabling a targeted exploration of areas of interest, potentially leading to decisions that are informed by quantitative data and expert opinions.

4.2. CSA-targeting as a consensus-driven approach

Climate change adaptation planning calls for stakeholder participation integrating perceptions and opinions from a broad range of stakeholders to strive for legitimate decisions and sustainable planning solutions (Conway and Mustelin, 2014; Krellenberg and Barth, 2014). However, stakeholder integration may lead to dissent about the importance of planning objectives reflected by measurable preferences on multiple AHP-criteria as shown in this example (Fig. 3). This has also been reported for group decision processes in forest planning (Linares and Romero, 2002; Kangas et al., 2010). Different interests, highly complex problems and resulting uncertainties are common causes of dissent in multi-criteria decision-making applications (Nordström et al., 2010). Approaching consensus solutions by finding a PC matrix that shares the highest degree of similarity with the stakeholder-derived PC matrices reduces discrepancy and hence dissent inherent to group-specific preferences.

The question of what is the appropriate consensus scenario should be asked in a certain decision-making context though. Following different consensus scenarios, changes the patterns of inferred preferences, which determine the location of regions with high potential for targeting selected CSA practices (Fig. 4). Other studies have shown similar effects on the distribution of stakeholder preferences (Diaz-Balteiro et al., 2009; Nordström et al., 2012). The ability to choose between consensus scenarios and to explore their potential impact on decisions grants higher flexibility and legitimacy to the democratic modes that shape group decision-making processes.

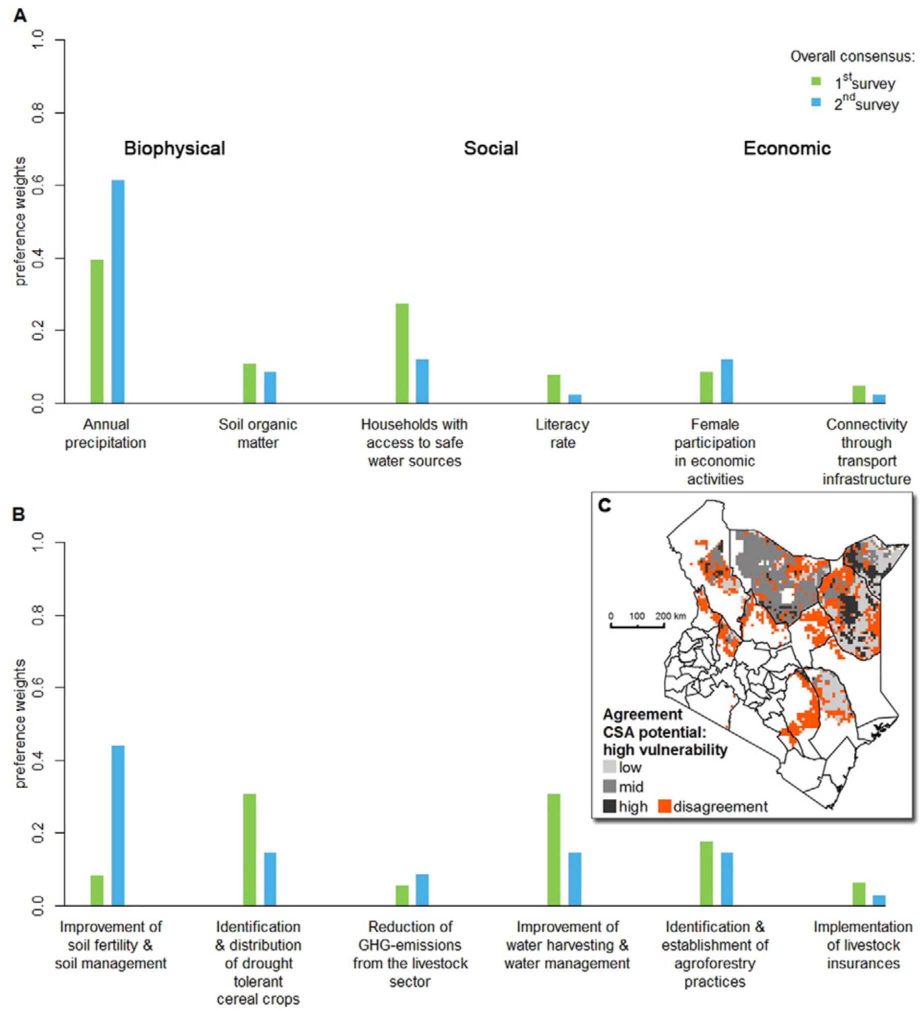

Fig. 5. Comparison of preferences inferred from the overall consensus (including all experts) based on two expert surveys for (A) vulnerability indicators and (B) CSA practices under the consensus scenario with the most-balanced trade-off. Inset map (C) illustrates agreement on low, mid and high CSA potential in areas with high vulnerability among the two expert surveys under the same consensus scenario. Regions where the surveys disagreed on CSA potential are coloured in orange.

Relying on the majority could be a proper principle when all stakeholders possess similar influence on decisions. Instead, giving more weight to the minority might be suitable when marginalized stakeholders such as indigenous people are involved who usually have low influence on decision-making. If no agreement on opting for the majority or minority principle is achievable, a compromise solution, such as the one adopted here, is to select the most balanced trade-off between these two mutually exclusive alternatives (González-Pachón and Romero, 2011). Hence, the explicit role of "targetCSA" is to structure decision-making problems and to facilitate the exploration as well as the discussion of discrepancies among stakeholder opinions to eventually achieve consensual solutions that aid decision-making processes where a broad range of stakeholders are involved.

4.3. Sticking points of a decision support framework for targeting CSA

4.3.1. Capturing and reducing uncertainty from stakeholder preferences

Stakeholder opinions may vary over time, as shown here (Fig. 5) and represent a source of uncertainty for decision-making processes (Xu and Zhang, 2013). The detected discrepancies regarding the preferences for some of the CSA practices are most likely an effect of shifts in stakeholder opinions due to changes of knowledge or interests. A reduction of this uncertainty is attainable through an iterative mode of preference elicitation, e.g. by following the Delphi method (Chung et al., 2014). Yet, this might be unfeasible in very conflict prone decision-making situations that are not consensually manageable or due to time and budget constraints (Nordström et al., 2010). Alternatively, additional experts may be involved in case of controversial situations to integrate specific knowledge that was missing but has the potential to mitigate such situations. An approach to analyse and understand social dynamics behind preference changes and their effects on decision-making systems is the use of agent-based models (Bousquet and Le Page, 2004).

4.3.2. Applicability of "targetCSA"

This example demonstrated the applicability of the presented decision support framework for targeting selected CSA practices. For instance, "targetCSA" could be used in different CSA related planning initiatives at national level such as Kenya's national CSA framework or the Nationally Appropriate Mitigation Action (NAMA) that is currently developed for the dairy production sector in Kenya to support the decision-making on the prioritization of adaptation and mitigation options. The framework is applicable on a stratified, regional scale, capturing the heterogeneous characteristics within a given country by involving region-specific stakeholders, vulnerability indicators and CSA practices. Furthermore, the restricted sets of vulnerability indicators and CSA practices that were chosen for this application example are easily extendable and adoptable to other countries differing in their biophysical, social and economic conditions. This includes vulnerability indicators that reflect projected changes of temperature and precipitation, e.g. trends of decreasing precipitation and increasing temperature would translate into higher vulnerability and vice versa.

The main objective of "targetCSA" is to support decisions for adaptation and mitigation planning at the national and regional level by structuring decision-making problems as well as exploring and building consensus among different stakeholder groups. However, several scales have to be integrated eventually into a comprehensive planning for adaptation and mitigation (FAO, 2013; Conway and Mustelin, 2014). Hence, this framework could be coupled with bottom-up approaches to properly deal with local realities and to allow for fine-scale planning (Rosenstock et al., 2014; Chaudhury et al., 2014).

4.4. Further research

Research efforts should be invested into elucidating the impact of CSA practices on vulnerability alleviation and analyses of synergies and trade-offs among adaptation and mitigation options in specific areas, including assessments of implementation costs and benefits for farmers (Harvey et al., 2014a). Information that links the implementation of CSA practices to their local effects could be derived from household surveys and exhaustive meta-analyses of CSA case studies relating costs and profitability to biophysical and social conditions prevailing in regions of interest. The resulting spatially upscaled indices of CSA costs and benefits would represent further layers of information supporting the decision-making on CSA prioritization together with the aggregated vulnerability and CSA suitability indices. Moreover, vulnerability indicators need to be further elaborated to meet the needs of the planning process and to allow for quantitative analyses of interactions and feedback mechanisms between biophysical indicators mostly pointing to exposure and sensitivity as well as social and economic indicators mainly determining the adaptive capacity of agricultural systems (Fellmann, 2012). Shedding light on how to couple the national top-down approach of CSA-targeting with bottom-up initiatives is necessary to synchronize local and broad scale adaptation planning (Conway and Mustelin, 2014).

5. Conclusions

Climate change adaptation and mitigation efforts need to be coordinated through national planning processes that implement properly climate change action plans. Related decisions should be made in accordance with relevant stakeholders and guided by quantitative information including biophysical, social and economic conditions. Especially the latter point might be challenging in data-deficient regions, yet, the exemplary application of "targetCSA" in Kenya showed that it is potentially feasible.

The main benefits of "targetCSA" for decision-makers are:

1. Problem structuring and complexity reduction by using AHP and pair wise comparison methods.
2. Spatially-explicit indices are built upon consensual preferences from cross-sectoral stakeholders on multiple criteria reflected by included vulnerability indicators and CSA practices.
3. The ability to choose between different consensus scenarios and to explore their potential effects on decisions may lead to more sustainable planning outcomes due to higher acceptance.
4. By using a three-dimensional concept of vulnerability, including biophysical, social and economic factors a demand-based assessment of CSA potential becomes possible.
5. Its transferability to other countries makes the applicability of the framework highly flexible.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2015.12.011.

References

Abson, D.J., Dougill, A.J., Stringer, L.C., 2012. Using principal component analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. Appl. Geogr. 35, 515–524. http://dx.doi.org/10.1016/j.apgeog.2012.08.004.

Allen, V.G., Baker, M.T., Segarra, E., Brown, C.P., 2007. Integrated irrigated crop-livestock systems in dry climates. Agron. J. 99, 346–360. http://dx.doi.org/10.2134/agronj2006.0148.

Atela, J.O., Quinn, C.H., Minang, P.A., 2014. Are REDD projects pro-poor in their spatial targeting? Evidence from Kenya. Appl. Geogr. 52, 14–24. http://dx.doi.org/10.1016/j.apgeog.2014.04.009.

Beuchelt, T.D., Badstue, L., 2013. Gender, nutrition- and climate-smart food production: opportunities and trade-offs. Food Secur. 5, 709–721. http://dx.doi.org/10.1007/s12571-013-0290-8.

Boroushaki, S., Malczewski, J., 2008. Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in ArcGIS. Comput. Geosci. 34, 399–410. http://dx.doi.org/10.1016/j.cageo.2007.04.003.

Bousquet, F., Le Page, C., 2004. Multi-agent simulations and ecosystem management: a review. Ecol. Model. 176, 313–332. http://dx.doi.org/10.1016/j.ecolmodel.2004.01.011.

Campbell, B.M., Thornton, P., Zougmoré, R., van Asten, P., Lipper, L., 2014. Sustainable intensification: what is its role in climate smart agriculture? Curr. Opin. Environ. Sustain. 8, 39–43. http://dx.doi.org/10.1016/j.cosust.2014.07.002.

Challinor, A., Wheeler, T., Garforth, C., Craufurd, P., Kassam, A., 2007. Assessing the vulnerability of food crop systems in Africa to climate change. Clim. Chang. 83, 381–399. http://dx.doi.org/10.1007/s10584-007-9249-0.

Chaudhury, A.S., Helfgott, A., Thornton, T.F., Sova, C., 2014. Participatory adaptation planning and costing. Applications in agricultural adaptation in western Kenya. Mitig. Adapt. Strateg. Glob. Chang http://dx.doi.org/10.1007/s11027-014-9600-5.

Chung, E.-S., Won, K., Kim, Y., Lee, H., 2014. Water resource vulnerability characteristics by district's population size in a changing climate using subjective and objective weights. Sustainability 6, 6141–6157. http://dx.doi.org/10.3390/su6096141.

Conway, D., Mustelin, J., 2014. Strategies for improving adaptation practice in developing countries. Nat. Clim. Chang. 4, 339–342. http://dx.doi.org/10.1038/nclimate2199.

Delgado, M.G., Sendra, J.B., 2004. Sensitivity analysis in multicriteria spatial decision-making: a review. Hum. Ecol. Risk. Assess. 10, 1173–1187. http://dx.doi.org/10.1080/10807030490887221.

Diaz-Balteiro, L., Gonzalez-Pachon, J., Romero, C., 2009. Forest management with multiple criteria and multiple stakeholders: an application to two public forests in Spain. Scand. J. For. Res. 24, 87–93. http://dx.doi.org/10.1080/02827580802687440.

Eastman, J.R., Jin, W., Kyem, P.A.K., Toledano, J., 1995. Raster procedures for multi-criteria/multi-objective decisions. Photogramm. Eng. Remote. Sens. 61, 539–547.

Eriksen, S.H., O'Brien, K., 2007. Vulnerability, poverty and the need for sustainable adaptation measures. Clim. Pol. 7, 337–352. http://dx.doi.org/10.1080/14693062.2007.9685660.

FAO, 2013. Climate-Smart Agriculture Sourcebook Food and Agriculture Organization of the United Nations.

Fellmann, T., 2012. The assessment of climate change-related vulnerability in the agricultural sector: reviewing conceptual frameworks. In: Meybeck, A., Lankoski, J., Redfern, S., Azzu, N., Gitz, V. (Eds.), Building Resilience for Adaptation to Climate Change in the Agriculture Sector, Proceedings of a Joint FAO/OECD Workshop. FAO/OECD, Rome (Italy), pp. 37–61.

Ferretti, V., Pomarico, S., 2013. Ecological land suitability analysis through spatial indicators: an application of the analytic network process technique and ordered weighted average approach. Ecol. Indic. 34, 507–519. http://dx.doi.org/10.1016/j.ecolind.2013.06.005.

Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., Abdel Aziz, S., Cipriani, A., Cumani, R., Cecchi, G., Conchedda, G., Ferreira, S., Gomez, A., Haffani, M., Kayitakire, F., Malanding, J., Mueller, R., Newby, T., Nonguierma, A., Olusegun, A., Ortner, S., Rajak, D.R., Rocha, J., Schepaschenko, D., Schepaschenko, M., Terekhov, A., Tiangwa, A., Vancutsem, C., Vintrou, E., Wenbin, W., van der Velde, M., Dunwoody, A., Kraxner, F., Obersteiner, M., 2015. Mapping global cropland and field size. Glob. Chang. Biol. http://dx.doi.org/10.1111/gcb.12838 (n/a–n/a).

Gachathi, F.N., Eriksen, S., 2011. Gums and resins: the potential for supporting sustainable adaptation in Kenya's drylands. Clim. Dev. 3, 59–70. http://dx.doi.org/10.3763/cdev.2010.0066.

Gebrezgabher, S.A., Meuwissen, M.P.M., Oude Lansink, A.G.J.M., 2014. A multiple criteria decision making approach to manure management systems in the Netherlands. Eur. J. Oper. Res. 232, 643–653. http://dx.doi.org/10.1016/j.ejor.2013.08.006.

González-Pachón, J., Romero, C., 2007. Inferring consensus weights from pairwise comparison matrices without suitable properties. Ann. Oper. Res. 154, 123–132. http://dx.doi.org/10.1007/s10479-007-0182-4.
González-Pachón, J., Romero, C., 2011. The design of socially optimal decisions in a consensus scenario. Omega 39, 179–185. http://dx.doi.org/10.1016/j.omega.2010.06.004.
González-Pachón, J., Rodriguez-Galiano, M.I., Romero, C., 2003. Transitive approximation to pairwise comparison matrices by using interval goal programming. J. Oper. Res. Soc. 54, 532–538. http://dx.doi.org/10.1057/palgrave.jors.2601542.
Government of Kenya, 2007. Kenya Vision 2030. Ministry of Planning and National Development, Nairobi (Kenya).
Government of Kenya, 2009. Kenya Population and Housing Census. Kenya National Bureau of Statistics, Nairobi (Kenya).
Government of Kenya, 2012. National Climate Change Action Plan. Ministry of Environment and Mineral Resources, Nairobi (Kenya).
Government of Kenya, 2013. County Development Profiles. Ministry of Devolution and Planning, Nairobi (Kenya).
Grace, K., Husak, G., Bogle, S., 2014. Estimating agricultural production in marginal and food insecure areas in Kenya using very high resolution remotely sensed imagery. Appl. Geogr. 55, 257–265. http://dx.doi.org/10.1016/j.apgeog.2014.08.014.
Greene, R., Devillers, R., Luther, J.E., Eddy, B.G., 2011. GIS-based multiple-criteria decision analysis. Geogr. Compass 5, 412–432. http://dx.doi.org/10.1111/j.1749-8198.2011.00431.x.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853. http://dx.doi.org/10.1126/science.1244693.
Harvey, C.A., Chacón, M., Donatti, C.I., Garen, E., Hannah, L., Andrade, A., Bede, L., Brown, D., Calle, A., Chará, J., Clement, C., Gray, E., Hoang, M.H., Minang, P., Rodríguez, A.M., Seeberg-Elverfeldt, C., Semroc, B., Shames, S., Smukler, S., Somarriba, E., Torquebiau, E., van Etten, J., Wollenberg, E., 2014a. Climate-smart landscapes: opportunities and challenges for integrating adaptation and mitigation in tropical agriculture. Conserv. Lett. 7, 77–90. http://dx.doi.org/10.1111/conl.12066.
Harvey, C.A., Rakotobe, Z.L., Rao, N.S., Dave, R., Razafimahatratra, H., Rabarijohn, R.H., Rajaofara, H., MacKinnon, J.L., 2014b. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. Philos. Trans. R. Soc., B 369. http://dx.doi.org/10.1098/rstb.2013.0089.
Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blümmel, M., Weiss, F., Grace, D., Obersteiner, M., 2013. Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proc. Natl. Acad. Sci. U. S. A. 110, 20888–20893. http://dx.doi.org/10.1073/pnas.1308149110.
Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978. http://dx.doi.org/10.1002/joc.1276.
Ishizaka, A., Labib, A., 2011. Review of the main developments in the analytic hierarchy process. Expert Syst. Appl. 38, 14336–14345. http://dx.doi.org/10.1016/j.eswa.2011.04.143.
Kangas, A., Saarinen, N., Saarikoski, H., Leskinen, L.A., Hujala, T., Tikkanen, J., 2010. Stakeholder perspectives about proper participation for regional forest programmes in Finland. For. Policy Econ. 12, 213–222. http://dx.doi.org/10.1016/j.forpol.2009.10.006.
Keeney, R.L., 2002. Common mistakes in making value trade-offs. Oper. Res. 50, 935–945. http://dx.doi.org/10.1287/opre.50.6.935.357.
Krellenberg, K., Barth, K., 2014. Inter- and transdisciplinary research for planning climate change adaptation responses: the example of Santiago de Chile. Interdiscip. Sci. Rev. 39, 360–375. http://dx.doi.org/10.1179/0308018814Z.00000000097.
Lal, R., Delgado, J.A., Groffman, P.M., Millar, N., Dell, C., Rotz, A., 2011. Management to mitigate and adapt to climate change. J. Soil Water Conserv. 66, 276–282. http://dx.doi.org/10.2489/jswc.66.4.276.
Lin, L., Sills, E., Cheshire, H., 2014. Targeting areas for reducing emissions from deforestation and forest degradation (REDD+) projects in Tanzania. Glob. Environ. Chang. 24, 277–286. http://dx.doi.org/10.1016/j.gloenvcha.2013.12.003.
Linares, P., Romero, C., 2002. Aggregation of preferences in an environmental economics context: a goal-programming approach. Omega 30, 89–95. http://dx.doi.org/10.1016/S0305-0483(01)00059-7.
Molua, E.L., Benhin, J., Kabubo-Mariara, J., Ouedraogo, M., El-Marsafawy, S., 2010. Global climate change and vulnerability of African agriculture: implications for resilience and sustained productive capacity. Q. J. Int. Agric. 49, 183–211.
Mosadeghi, R., Warnken, J., Mirfenderesk, H., Tomlinson, R., 2013. Spatial uncertainty analysis in coastal land use planning: a case study at Gold Coast, Australia. J. Coast. Res. 1003–1008. http://dx.doi.org/10.2112/SI65-170.
Nachtergaele, F., van Velthuizen, H.T., Verelst, L., Wiberg, D., Batjes, N., Dijkshoorn, J.A., van Engelen, V., Fischer, G., Jones, A., Montanarella, L., Petri, M., Prieler, S., Teixeira, E., Shi, X., 2012. Harmonized World Soil Database (Version 1.2). FAO, IIASA, ISRIC, ISSCAS, JRC, Rome (Italy), Laxenburg (Austria).
Nordström, E.-M., Eriksson, L.O., Öhman, K., 2010. Integrating multiple criteria decision analysis in participatory forest planning: experience from a case study in northern Sweden. For. Policy Econ. 12, 562–574. http://dx.doi.org/10.1016/j.forpol.2010.07.006.
Nordström, E.-M., Öhman, K., Eriksson, L.O., 2012. Approaches for aggregating preferences in participatory forest planning — an experimental study. Open For. Sci. J. 5, 23–32.
Odera, M., Thomas, T.S., Waithaka, M., Kyotalimye, M., 2013. Kenya. In: Waithaka, M., Nelson, G.C., Thomas, T.S., Kyotalimye, M. (Eds.), East African Agriculture and Climate Change: A Comprehensive Analysis. International Food Policy Research Institute, Washington, DC (USA), pp. 183–212.
Patt, A.G., Tadross, M., Nussbaumer, P., Asante, K., Metzger, M., Rafael, J., Goujon, A., Brundrit, G., 2010. Estimating least-developed countries' vulnerability to climate-related extreme events over the next 50 years. Proc. Natl. Acad. Sci. U. S. A. 107, 1333–1337. http://dx.doi.org/10.1073/pnas.0910253107.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88, 879–903. http://dx.doi.org/10.1037/0021-9010.88.5.879.
Preston, B.L., Westaway, R.M., Yuen, E.J., 2011. Climate adaptation planning in practice: an evaluation of adaptation plans from three developed nations. Mitig. Adapt. Strateg. Glob. Chang. 16, 407–438. http://dx.doi.org/10.1007/s11027-010-9270-x.
Romero, C., Rehman, T. (Eds.), 2003. Multiple Criteria Analysis for Agricultural Decisions, Developments in Agricultural Economics. Elsevier, Amsterdam.
Rosenstock, T.S., Mpanda, M., Rioux, J., Aynekulu, E., Kimaro, A.A., Neufeldt, H., Shepherd, K.D., Luedeling, E., 2014. Targeting conservation agriculture in the context of livelihoods and landscapes. Agric. Ecosyst. Environ. 187, 47–51. http://dx.doi.org/10.1016/j.agee.2013.11.011.
Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. J. Math. Psychol. 15, 234–281. http://dx.doi.org/10.1016/0022-2496(77)90033-5.
Saaty, T.L., 1994. Highlights and critical points in the theory and application of the analytic hierarchy process. Eur. J. Oper. Res. 74, 426–447. http://dx.doi.org/10.1016/0377-2217(94)90222-4.
Sae-Lim, P., Komen, H., Kause, A., van Arendonk, J.A.M., Barfoot, A.J., Martin, K.E., Parsons, J.E., 2012. Defining desired genetic gains for rainbow trout breeding objective using analytic hierarchy process. J. Anim. Sci. 90, 1766–1776. http://dx.doi.org/10.2527/jas.2011-4267.
Sanchez, P.A., Palm, C.A., Buol, S.W., 2003. Fertility capability soil classification: a tool to help assess soil quality in the tropics. Geoderma 114, 157–185. http://dx.doi.org/10.1016/S0016-7061(03)00040-5.
Scherr, S.J., Shames, S., Friedman, R., 2012. From climate-smart agriculture to climate-smart landscapes. Agric. Food Secur. 1, 12. http://dx.doi.org/10.1186/2048-7010-1-12.
Tammi, I., Kalliola, R., 2014. Spatial MCDA in marine planning: experiences from the Mediterranean and Baltic Seas. Mar. Policy 48, 73–83. http://dx.doi.org/10.1016/j.marpol.2014.03.015.
Thornton, P.K., Ericksen, P.J., Herrero, M., Challinor, A.J., 2014. Climate variability and vulnerability to climate change: a review. Glob. Chang. Biol. 20, 3313–3328. http://dx.doi.org/10.1111/gcb.12581.
Uchida, H., Nelson, A., 2009. Agglomeration Index: Towards a New Measure of Urban Concentration (Background Paper for the World Bank's World Development Report), Reshaping Economic Geography.
van Velthuizen, H., Huddleston, B., Fischer, G., Salvatore, M., Ataman, E., Nachtergaele, F.O., Zanetti, M., Bloise, M., 2007. Mapping Biophysical Factors that Influence Agricultural Production and Rural Vulnerability. Food and Agriculture Organization of the United Nations, Rome.
Vrieling, A., Meroni, M., Shee, A., Mude, A.G., Woodard, J., de Bie, C.A.J.M., Rembold, F., 2014. Historical extension of operational NDVI products for livestock insurance in Kenya. Int. J. Appl. Earth Obs. Geoinf. 28, 238–251. http://dx.doi.org/10.1016/j.jag.2013.12.010.
Wiesmann, U., Kiteme, B., Mwangi, Z. (Eds.), 2014. Socio-Economic Atlas of Kenya: Depicting the National Population Census by County and Sub-Location. KNBS, CETRAD, CDE, Nairobi, Nanyuki (Kenya), Bern (Switzerland).
Wind, Y., Saaty, T.L., 1980. Marketing applications of the analytic hierarchy process. Manag. Sci. 26, 641–658.
Xu, E., Zhang, H., 2013. Spatially-explicit sensitivity analysis for land suitability evaluation. Appl. Geogr. 45, 1–9. http://dx.doi.org/10.1016/j.apgeog.2013.08.005.
Zomer, R.J., Trabucco, A., Bossio, D.A., Verchot, L.V., 2008. Climate change mitigation: a spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. Agric. Ecosyst. Environ. 126, 67–80. http://dx.doi.org/10.1016/j.agee.2008.01.014.