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Ambiguity in social ecological system understanding: Advancing modelling of stakeholder perceptions of climate change adaptation in Kenya

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A B S T R A C T

Climate change adaptation requires understanding of complex social ecological systems (SESs). One source of uncertainty in complex SESs is ambiguity, defined as the range and variety of existing perceptions in and of an SES, which are considered equally valid, resulting in a lack of a unique or single system understanding. Current modelling practices that acknowledge the presence of ambiguity in SESs focus on finding consensus with stakeholders; however, advanced methods for explicitly representing and aggregating ambiguity in SESs are underdeveloped. Moreover, understanding the influences of ambiguity on SES representation is limited. This paper demonstrates the presence and range of ambiguities in endogenous and exogenous system drivers and internal relationships based on individual fuzzy cognitive maps derived from stakeholder perceptions of climate change adaptation in Kenya and introduces an ambiguity based modelling process. Our results indicate that acknowledging ambiguity fundamentally changes SES representation and more advanced methods are required.

1. Introduction

Referred to by popular media as "*the biggest threat facing humanity*",[1] future climate change is recognised as being hazardous for human and natural systems (IPCC, 2014). Adapting to climate change is a complex issue because of the numerous interactions between the human and natural systems (Pahl-Wostl, 2007). A leading concept in adaptive complex systems thinking is the notion of the social ecological system (SES; Audouin et al., 2013, Berkes and Folke, 1998; Biggs et al., 2015; Preise et al., 2018). In a SES, human and natural systems are inherently intertwined; human systems include elements such as values, decisions, and perceptions, and natural systems relate to biophysical elements including the ecological and hydrological cycles. Interactions are the result of any behaviour within or between the human and natural systems that reinforce or modify SES dynamics (Berkes and Folke, 1998).

Many different approaches, methods, and tools have been successfully applied to improve SES understanding (e.g. Binder et al., 2013; Levin et al., 2013; Liu et al., 2007; Ostrom, 2009), often involving modelling aimed at predicting, exploring, communicating, and learning (Brugnach and Pahl-Wostl, 2008). Common modelling approaches include system dynamics models, Bayesian networks, coupled component models, agent-based models, and knowledge-based models (Kelly et al., 2013). Recently, eight major challenges for SES modelling were identified by Elsawah et al. (2020) including bridging epistemologies, dealing with uncertainties, and integrating the human dimension, which form the broad focus of this research. First, the challenge of bridging epistemologies emerges because scientists disagree on how to represent a system due to fundamental paradigmatic differences between the social and environmental sciences. Second, the challenge of dealing with uncertainties emerges because of the disagreement between what is considered structural uncertainty (i.e. model context and model purpose) and model uncertainty (i.e. data and parameters). Third, integrating the human dimension in SES models remains challenging due to a lack of understanding about specific social systems and disagreement on the approaches to generalise social behaviour. Such a lack of understanding is compounded by limited research funding in this area as well as privacy issues associated with the use of 'big data' to study social behaviour patterns. Here, we argue that these three challenges are connected by one common theme—the presence of ambiguity within and about SESs, and the absence of mutually acceptable and replicable

Abbreviations: ABA, Ambiguity based aggregation.
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[1] https://www.nytimes.com/2018/03/29/climate/united-nations-climate-change.html.

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approaches to address ambiguity in current modelling practices.

Ambiguity is a type of uncertainty caused by the presence of multiple knowledge frames both about and within SESs, where "*there is not a unique and complete understanding of the system to be managed*" (Brugnach et al., 2008). Multiple knowledge frames are considered equally valid and have an impact on, for example, how a problem is defined (Dewulf et al., 2005). Here, we define ambiguity in SESs as the range and variety of existing perceptions in and of an SES, which are equally valid, and which result in a lack of unique or single system understanding. Ambiguity in SESs is currently addressed in models through participatory modelling (PM), which aims to generate multiple perceptions of SES system dynamics (Voinov et al., 2016). For example, some modelling approaches specifically seek to integrate the opinions and values of scientists and stakeholders (Tuler et al., 2017; Voinov and Gaddis, 2017). An advantage of PM is that it can facilitate understanding of the underlying beliefs and values of stakeholders about their environment (Paolisso and Tombley, 2017), with a broad aspiration to improve standardised reporting and reproducible methods (Gray et al., 2018). Therefore, we regard participatory modelling as an important example of how ambiguity is currently recognised and—at least partially—accounted for in SES modelling.

Group-modelling workshops are a novel PM method for addressing ambiguity in which stakeholders are facilitated towards a common understanding of an SES (e.g. Diniz et al., 2015; Henriksen et al., 2012; Simon and Etienne, 2010; van der Sluis et al., 2019). An advantage of group modelling is that ambiguity is addressed by facilitating the decision space in a way that supports collaboration; however, it is questionable whether group-modelling results in a common understanding because represented knowledge is dependent on group power dynamics (Gray et al., 2014; Turnhout et al., 2020). Alternative methods address this issue by collecting and aggregating individual perceptions of stakeholders into one model (e.g. Solana-Gutiérrez et al., 2017; Lavin et al., 2018; Mehryar et al., 2019). While this approach increases the understanding of individual SES system dynamics (Gray et al., 2014), when aggregated, heterogeneity in stakeholder perceptions is lost (Mehryar et al., 2019). Occasionally, studies have combined group-modelling workshops and the collection of individual and/or aggregated perceptions (e.g. Salliou et al., 2017).

If the goal of PM is to model how stakeholders perceive their SES, it is crucial to explicitly address the diversity of perceptions and, thereby, inherent ambiguity. Most models derived using PM aim to develop a consensus system by aggregating perspectives, assuming that each stakeholder has limited knowledge of the entire system. Therefore, models that represent ambiguity are underdeveloped (Brugnach and Ingram, 2012). We argue that explicitly representing ambiguity fundamentally changes the way we understand and represent complex SESs. Additionally, increasing transparency in the ambiguity of models is necessary to advance the field of PM and complex SES representation. Identifying how one system can be modelled whilst also explicitly representing multiple knowledge frames (i.e. ambiguity) is, therefore, a key research challenge.

Fuzzy cognitive maps (FCMs) are commonly used for PM-based group model building and/or eliciting individual perspectives. In environmental sciences, FCMs are used in a participatory setting to bridge the knowledge gap between stakeholders and scientists (Mallampalli et al., 2016; Van Vliet, 2010), qualitative and quantitative modelling (Kok, 2009; Van Vliet et al., 2017), and policy and practice (Solana-Guitiérrez et al., 2017). Moreover, FCMs are used to understand stakeholder perspectives on concepts, driving relationships, and feedback loops within a system (Diniz et al., 2015; Özesmi and Özesmi, 2004). Current FCM practices concentrate on finding consensus by group modelling or aggregating individual FCMs. Aggregation practices aim to find similarities in the internal FCM structure using, for example, mathematical simulations (Özesmi and Özesmi, 2004), whereas FCMs that represent multiple perspectives could be more beneficial when diversity and ambiguity are openly considered (van Vliet et al., 2010). Aggregating individual FCMs can aid the capture of complexity because individual FCMs tend to contain few or no feedback loops (Levy et al., 2018). However, while particularly accounting for ambiguity, advanced and mature FCM aggregation methods remain underdeveloped. To address these limitations, the main objectives of this study are to (1) explicitly represent ambiguity in complex SESs using FCMs; (2) advance the aggregation process of FCMs while explicitly representing ambiguity; and (3) understand the influence of FCM aggregation on SES representation.

2. Background

2.1. Ambiguity in SESs

Ambiguity, as a type of uncertainty described by Brugnach et al. (2008), can be approached using two broad strategies. First, a generalised 'correct' representation can be sought using epistemic strategies or, alternatively, ambiguity is accepted as an inherent structural uncertainty that is addressed via ontological strategies. Through these approaches, epistemic strategies involve the negotiation of a mutually acceptable frame, and ontological strategies relate to working with different frames, respectively. Both approaches assume that a unique system exists. In practice, the combination of these two approaches is used to simulate the heterogeneity of perceptions by, for example, splitting stakeholders into different actor groups (Mehryar et al., 2019).

Ambiguity in SESs can result from multiple system characteristics, such as poorly defined system boundaries or multi-scale interactions (Cash et al., 2006), the treatment of system entities or structures (Kelly et al., 2013), and the types of data employed (Elsawah et al., 2020). In the case of the treatment of system entities or structures, the entities of system dynamics encompass both endogenous drivers (concepts) and exogenous drivers (drivers) as well as their interrelationships. Ambiguity in concepts appears when decisions are made about whether or not a certain element is included in the system representation; ambiguity in drivers appears when decisions are made about the driving capacity of specific elements; and ambiguity in relationships appears when decision are made about the existence, influence, and direction of these relationships. All of these system entities determine the representation and understanding of a system.

Ambiguity is mainly addressed through the collection of data for multiple knowledge frames. For example, Brugnach and Ingram (2012) provide recommendations for dealing with ambiguity at the stakeholder facilitation stage, including facilitating recognition of interdependencies, building relationships, and creating a decision space that supports collaboration. Therefore, excellent facilitation and careful stakeholder interaction are crucial for addressing ambiguity. Additionally, following Bremer and Meisch (2017), who performed a comprehensive literature study on participation (or co-production) in climate change research, eight 'lenses' of participation that bridge two fundamental usages of participation. First, participation is seen as a method to reach a common 'normative' goal. Second, 'descriptive' participation focusses on how science and society shape each other and how this influences both. This framing does not, however, address methodologies aimed at processing multiple knowledge frames toward *a posteriori* models.

2.2. Fuzzy cognitive maps

A FCM is a graphical presentation of a combination of endogenous drivers ("concepts") of a system and exogenous drivers ("drivers") (Kok, 2009; Kosko, 1986; Jetter and Kok, 2014). Drivers are activated during each iteration step by the state vector and are usually 'pure' drivers, indicating concepts that do not have any incoming relationships from the system. The visualisation of FCMs takes the form of a FCM (Fig. 1, left), an adjacency matrix (Box 1), and a dynamic output (Fig. 1, right) as a result of the final state of concepts from the iterations. The dynamic

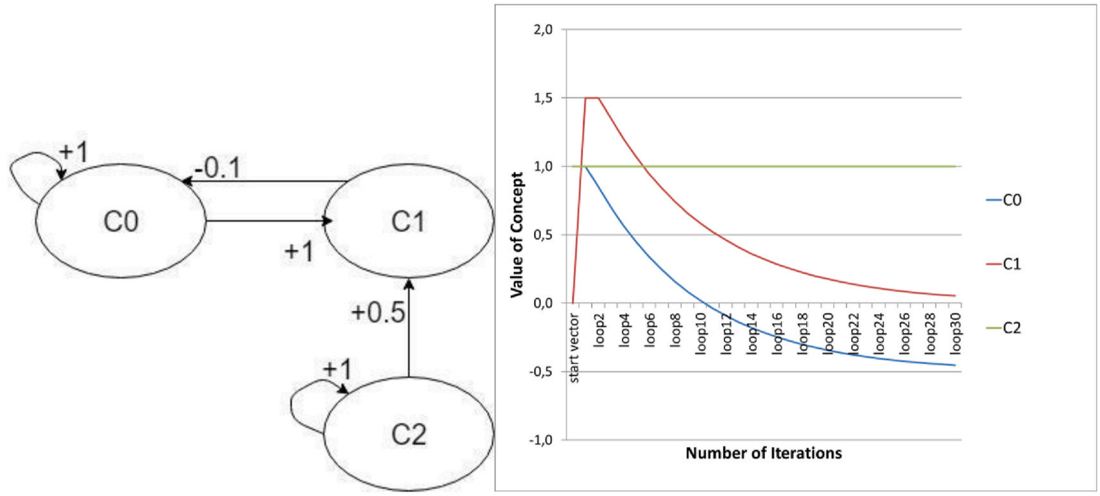

Fig. 1. Example of concepts and relationships in a fuzzy cognitive map (FCM, left) and an example of a FCM output (right) adapted from Kok (2009).

Box 1
Matrix iterations in FCM

Formula.

$A_i = A_{i-1} * E$.

In which A_i is the (new) state vector after each iteration (i); A_1 is the initial state vector for the iterations, usually set based on the drivers; and E represents the matrix of all relationships.

To use the example of Figure 6:

State vector $A_1 = (1, 0, 1)$.

Matrix E =

$A_i = A_1 * E = (1, 0, 1) * = (1, 1.5, 1)$.

The new state vector is (1, 1.5, 1).

This process can be repeated until the FCM reaches a stable state.

output can diverge, converge, be cyclic, or be stable, depending on the matrix. Only stable outputs are interpretable without a threshold (or 'clipper' function). FCMs usually have a focal issue/concept around which the system is built (Jetter and Kok, 2014).

The aggregation of individual FCMs is frequently performed using matrix algebra (e.g. Singh, 2011; Solana-Gutiérrez et al., 2017; Mehryar et al., 2019), in which numerical values are first assigned to the relationships of individual FCMs and then combined by taking the average or median values. This can be based on either individual relationships or groups of relationships (see Aminpour et al., 2020). Some alternative methods aggregate individual FCMs using Atlas.ti coding to determine the value of relationships (see Rahimi et al., 2018). Usually, all the aforementioned relationships are included in the final aggregated FCM.

Averaging solves the problem of conflicting relationships when one stakeholder indicates a strong negative relationship and another has a weak positive relationship. Nevertheless, this can result in an aggregated FCM with a majority of medium relationships. As a result, averaging can cause relationships to cancel each other out (for instance, −0.8 and + 0.8 will be 0), which results in the appearance that there is no relationship (Ozesmi, 2006). As such, the logic and reasoning of individual FCMs are lost, and relationships derived from individual stakeholders (i.e. single-stakeholder relationships) can have a large influence on the total system.

FCMs are frequently analysed using FCM indices (Özesmi and Özesmi, 2018; Özesmi and Özesmi, 2004) to explore individual concepts and relationships or the overall FCM. One example is indegree, which is used to determine the sum of weights of incoming relationships that influence a certain concept. Indices used to analyse overall FCMs include the number of concepts and density, which is a measure of complexity calculated as the actual number of relationships divided by the total maximum number of relationships in a FCM.

2.3. Project background

The 'SENSES[2]' project (2017–2020) was part of the European Research Area for Climate Services (ERA4CS) with partners from the Netherlands, Germany, Sweden, and Austria. The SENSES project aimed to make "*scenario information accessible to users in interactive transparent and comprehensible ways that help to convert scenario data into user-specific scenario knowledge*". The overall project objective of SENSES was to develop a toolkit in which scenarios are communicated and tailored to specific user groups and stakeholders by integrating climate change scenario information, participatory methods, and visualisation tools.

The project incorporated regional case studies in the Netherlands

[2] http://senses-project.org, https://climatescenarios.org/, http://www.jpi-climate.eu/ERA4CS, http://www.jpi-climate.eu/home.

and Kenya. The Kenyan case study focussed on integrating the indirect impacts of climate change—so-called transnational climate impacts (TCI; Hedlund et al., 2018)—into climate change adaptation scenarios for Kenya. In the Global South in particular, climate change can lead to increased vulnerability and the deterioration of natural resources. As such, Kenya has been classified as a water-scarce country (Falkenmark, 1989) and prolonged droughts and extreme precipitation events have already led to severe impacts across society, which will presumably aggravated by climate change in the future (NCCAP2018-2022). Therefore, societal adaptation to climate change is urgently required.

The impacts of climate change span borders, sectors, and actors including agriculture, water, energy, tourism, wildlife, and health, and the national government, civil society, and youth (NCCAP2018-2022). Agriculture in Kenya, which is mostly rain-fed, is the largest contributor to the economy and is increasingly affected by water scarcity, leading to economic losses (NWMP, 2013). Therefore, land and water use are strongly related. The involvement of multiple actors and sectors with multiple knowledge frames, and the fact that climate change can have severe impacts on land and water use, suggests that climate change adaptation in Kenya requires deeper SES understanding.

3. Stakeholder engagement and methodology

3.1. Stakeholder engagement

Our stakeholder engagement adopted a mixed method approach consisting of the following three elements: (1) performing a stakeholder analysis, (2) determining FCM concepts, and (3) eliciting individual FCMs. The stakeholder analysis was based on the grey literature, FCM concepts were derived during a stakeholder workshop, and individual FCMs were elicited during the stakeholder interviews.

3.1.1. Stakeholder analysis

The stakeholder analysis utilised an analytical categorisation (top-down) and a stakeholder-led categorisation (bottom-up) of sectors and actors (Reed et al., 2009). The analytical categorisation was based on national policy documents, with the Government of Kenya proposing several stakeholder lists via their climate adaptation policy documents (KNAP2015-2030; NCCAP2018-2022). In this context, actors were defined as having an influence on climate change adaptation or being influenced by climate change adaptation. Furthermore, the policy documents indicated several sectors involved in climate change adaptation (NCCAP2018-2022). A stakeholder analysis by Ngigi et al. (2011) identified actors and sectors in Kenya, and ranked the (formal) influence of stakeholders on smallholder farmers. Here, actors who have large-to-moderate influence (i.e. non-governmental organisations (NGOs) and ministries) and sectors that are primarily involved in climate change adaptation (environment, water, and agriculture) were selected.

3.1.2. Defining concepts in a stakeholder workshop

We used the output of a stakeholder workshop brainstorming session to define a list of concepts for the FCMs and the focal issues of the FCM. The objective of the workshop, as part of the overall Kenyan case study, was to create a skeleton (or base) for future scenarios as tools to explore future transnational climate impacts for Kenya. In the brainstorming session, participants were invited to contribute ideas on the concepts of transnational climate impacts for Kenya. Global challenges for adaptation from earlier research (Schweizer and O'Neill, 2014) were posted on the wall of the workshop room for inspiration. Additionally, the 'Big Four Agenda' from Kenya Vision2030[3] was provided to highlight issues currently addressed by the national government. The focus question of the brainstorm session was '*What are the most important drivers for understanding Kenya's vulnerability to future transnational climate risks?*', which was framed as challenges for climate change adaptation within and outside of Kenya. For the first round of brainstorming, each participant presented two concept ideas, which were written down on post-it notes. Participants could then choose to present one or two additional ideas.

All individuals' ideas were then presented to the group, collected on the wall, and grouped into named clusters by the SENSES facilitation team. At the beginning of the next session, the workshop lead facilitator verified that the participants agreed on the clusters. The concepts were subsequently labelled to determine their importance and uncertainty. Each participant received five red voting stickers to indicate the uncertainty of a concept, and five green voting stickers to indicate the importance of a concept. This exercise began the development part of the workshop but it served to determine the focal issue of the FCM. Finally, the concepts derived from the stakeholders and the concepts provided by Schweizer and O'Neill (2014) were combined to generate a comprehensive list of concepts.

3.1.3. Eliciting FCMs via interviews

Interviews were conducted to further explore stakeholder perspectives on relationships between the pre-defined concepts derived from the workshop. During the interviews, individual FCMs were created to connect the concepts, which were printed out to enable the stakeholders to indicate those that were most relevant from their own personal perspective.

The purpose of the interview was explained to each participant, and a FCM was shown to visualise the goal of the interview. The participants were assured that no direct quotes would be used, and permission was sought for the interview to be recorded for verification purposes. Subsequently, following some introductory questions, the stakeholders were invited to share their views on climate change effects in Kenya to stimulate conceptual and relational thinking.

Each stakeholder then constructed their individual FCM, placing the focal issue in the centre. Concepts were then added to the map based on the following questions:

1. Which concepts have a direct relationship with the focal issue?
2. Which concepts are directly influenced by the focal issue?

This provided the first outline of the individual's FCM, after which the following questions were used to systematically discuss positive and/or negative relationships between each concept:

3. Do you think concept C1 influences concept C2? (Yes/No, if so why?)
4. If concept C1 increases, then will concept C2 increase? (Yes/No, if so why?)

Finally, the stakeholders had the opportunity of adding concepts and defining the relative strength of their relationships based on the following questions:

5. Do you think that there are crucial concepts which are missing?
6. If concept C1 increases, how strongly does concept C2 increase? (If X doubles, will Z double too?)
7. In relative terms, will the relationship A be stronger than relationship B (Yes/No, if so why?)

3.2. Methodology

The analysis methodology consisted of three elements organised around the three objectives. First, ambiguity was elucidated based on the individual FCMs. Second, a combined FCM was constructed using an ambiguity based aggregation (ABA) process. Third, the effects of the

[3] The 'Big Four Agenda' from the Kenya Vision 2030 includes the four main governmental focus points of (1) food security, (2) affordable housing, (3) manufacturing, and (4) affordable healthcare for all.

ABA process on the FCM indices were determined and compared with the indices of the common aggregation method.

3.2.1. Elucidating ambiguity

Three important steps were considered to explicitly represent ambiguity using FCMs. The first step involved ranking the concepts, the second step involved ranking the drivers, and the third step involved summarising the individual matrices. In step 1, the predefined concepts were ranked according to how often they were included in all of the individual FCMs. For example, a rank score of 10 indicated agreement between 100% of the stakeholders, a rank score of 9 indicated 90% agreement, and so on. This approach elucidated the ambiguity regarding the inclusion of concepts in the overall SES representation.

Step 2 involved ranking the drivers of the individual FCMs. The agreement on the system drivers was tested by counting how often a concept was considered to be a driver, defined as those concepts having no incoming relationships in the individual FCMs. The driver ranks were then coupled to the concept ranks so that each rank indicated the number of concepts and drivers (i.e. rank 10 with X concepts and X drivers). Furthermore, with the intention of limiting the number of drivers in the SES representation, only those were used as concepts in more than 30% of the individual FCMs were included. This elucidated

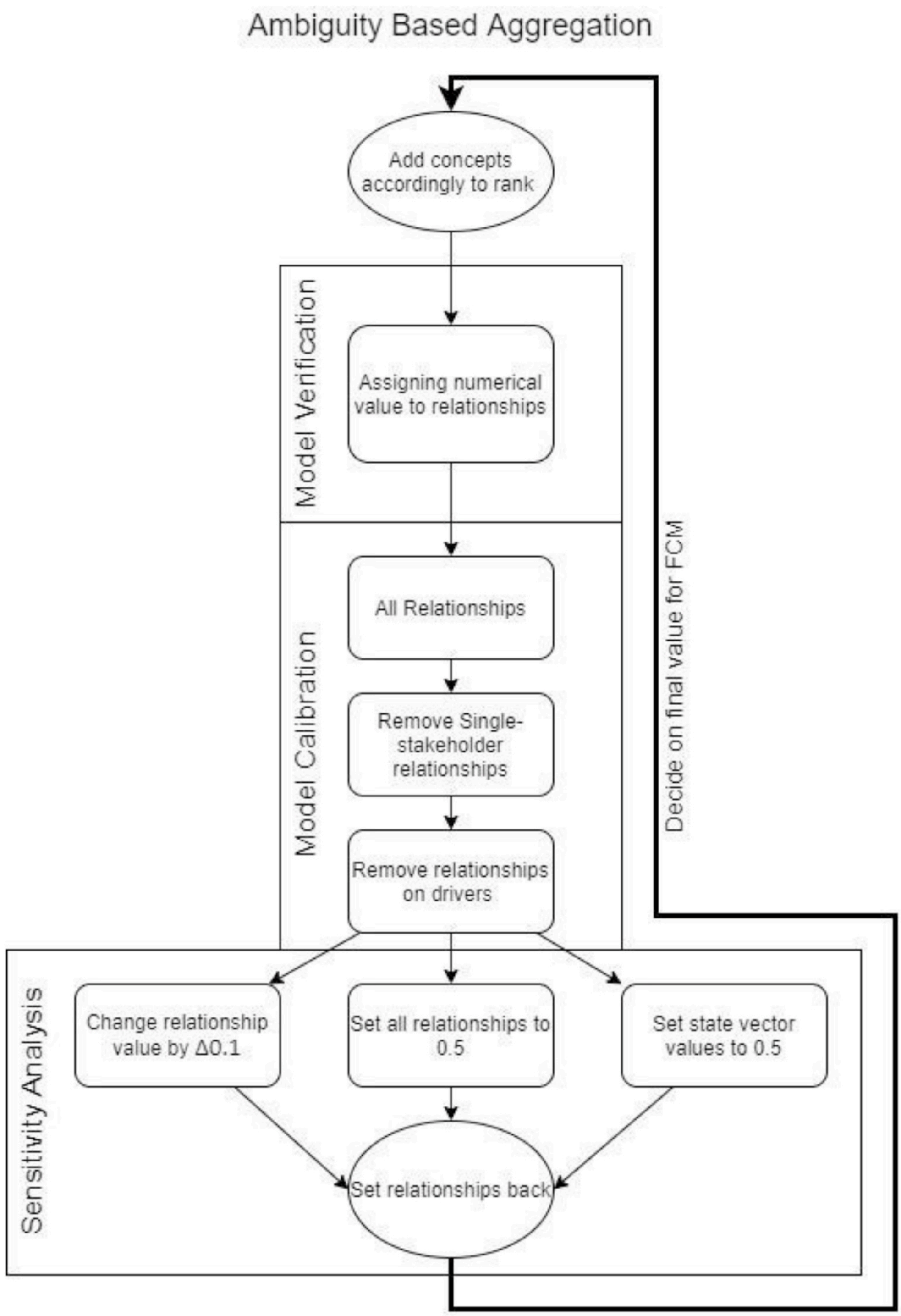

Fig. 2. Steps of ambiguity based aggregation (ABA) for fuzzy cognitive maps (FCMs).

the ambiguity regarding the inclusion of drivers in the overall SES representation.

In step 3, the individual matrices representing the individual FCMs were combined into one matrix. The relationships in the matrix were summarised as indicated in the individual FCMs (i.e. strong, medium, and weak; and positive and negative) without quantifying the relationships. This elucidated the ambiguity in the system relationships and summarised the perceptions of the presence, strength, direction, and influence (positive/negative) of the relationships in the overall SES representation.

3.2.2. Ambiguity based aggregation (ABA)

The ABA process (Fig. 2) was based on the notion of a core agreement, where we aimed to include part of the FCM characteristics (concepts and drivers) that were found to have the largest degree of agreement. Accordingly, the starting point of the ABA were the concepts with the highest rank. Subsequently, the corresponding drivers with the highest ranking were designated, and all relationships between the concepts and drivers were then included.

The ABA process adopted three common modelling procedures (verification, calibration, and sensitivity analysis) as presented by Aral (2010), where “verification is a demonstration that the modelling formalism is correct”, calibration is “the adjustment of parameters of the mathematical model such that the model agreement is maximized with respect to the observation data we have on the modelled system”, and a sensitivity analysis is “a simulation through which the modeler evaluates the response of the model to changes in input parameters or boundary condition of the model” (Aral., 2010, p.45–48).

The three modelling procedures were modified to fit the requirements for FCM development.

The modified verification step aimed to interpret the relationships between the concepts according to the collective logic of the stakeholders and quantify them accordingly. Following La Mere et al. (2020), verification was performed by comparing the summarised matrix of the directly elicited individual FCMs with the transcribed interviews. First, as described by Jetter and Kok (2014), the direction of the relationship (i.e. positive or negative) was determined; second, the relative strength (strong, medium, or weak) was determined; and third, the actual numerical integer was assigned. Strong relationships received a value between (−)0.9 and (−)0.7; medium relationships received a value between (−)0.6 and (−)0.4; and weak relationships received a value of (−)0.3 or (−)0.2. In each case, the final relationship value depended on a relative comparison with other relationships according to interview question 7 (see section 3.1). Relationships identified by only one stakeholder receive a value of (−)0.1, thereby moderating the influence of single stakeholder relationships in the dynamic output of the overall system representation. All of these verification steps and considerations were summarised in a table for the core system, which provided an overview of the core assumptions of the total ABA-FCM.

The subsequent calibration step aimed to generate an interpretable stable dynamic FCM output. For this, we used Microsoft Excel to run 45 iterations and analyse the dynamic output by visualising a graph of the iteration and corresponding state values of the concepts. Single-stakeholder relationships strongly influenced the dynamic output, despite their low values; therefore, all single-stakeholder relationships were removed. Additionally, all relationships between the concepts and drivers were removed because of their disproportionate effect on the dynamic output. These modifications generated a stable and calibrated dynamic FCM output.

A sensitivity analysis was then used to examine the behaviour of the system based on the ‘one factor at a time’ (with Δ0.1) approach (Ten Broeke et al., 2016), This generated an understanding of the influence of the final relationship weights on the overall system. Next, all the relationship values were set to medium relationships (value of 0.5) and, similarly, the state vector was halved (0.5) to examine the influence of this boundary condition on the dynamic output.

Using the calibrated output and behavioural understanding of the core FCM, the concepts and drivers with the second highest ranks (9) were added (ABA-9). This process was then repeated until a desired aggregated system representation (with a corresponding range of ambiguity) was reached. The repetition of the process can be modified regarding the objective of the FCM. For example, if the aim is to understand the core of an agreement, repetition can be limited; if the aim is to create a holistic view of stakeholder perceptions, repetition can be maximized.

3.2.3. Comparing FCM indices

FCM system representation can be analysed in several ways (Levy et al., 2018; Özesemi and Özesemi, 2004). Özesemi and Özesemi (2004) proposed a number of indices including the number of drivers (Nd), number of concepts (Nc), number of relationships (Nr), and density (D), which is defined as Nr/Nc.[2] These FCM indices were calculated for the individual FCMs as well as the aggregated FCM using standard aggregation methods (see section 2.2). To understand how FCM indices were altered by the aggregation, the average and median indices of the aggregated FCM were calculated and compared to the average and median values of the individual FCMs. Finally, to examine how the FCM indices were altered by the ABA process, they were calculated for the three calibration steps of each ABA rank and compared with the individual and standard aggregated values.

4. Results

4.1. Stakeholder engagement

4.1.1. Stakeholder participation

The stakeholder workshop, facilitated by the Swedish/Kenyan partners of the project, was organised on the 10th of January 2019 in Nairobi. To ensure consistency between the interviewees and workshop participants, stakeholders to be interviewed were first approached during the workshop. The list of stakeholders was expanded by adding missing actors from the workshop and asking the participants for additional names. A total of 11 stakeholders were interviewed in Nairobi during ten one-and-a-half hour interviews in January and February 2019, which provided ten individual FCMs. With a gender distribution of 55% female and 45% male, a workshop-interview consistency of 36%–64% no-yes, and a mix of private and public actors within climate change-affected sectors, we were able to capture a representative sample of stakeholder perceptions (Table 1).

Table 1
Stakeholders interviewed during the case study. Gender distribution, actor group, sector, and presence in the SENSES workshop are indicated (NGO = non-governmental organisation).

Actor group	Sector	Gender	Workshop attendee
Intergovernmental	Climate	F	No
National government	Agriculture & Livestock	F	Yes
National government	Water (drought)	M	Yes
National government	Environment	F	No
County government	Environment	M	Yes
University	Climate change adaptation	F	Yes
University	Climate change adaptation	M	Yes
Consultant	Climate change adaptation	F	Yes
NGO	Climate change adaptation	M	Yes
NGO	Energy	M	No
NGO	Land use	F	No

4.1.2. List of concepts

The workshop brainstorm session resulted in 19 concepts in which land and water use (C4) was prioritised. The concept list was completed with the addition of eight concepts listed by Schweizer and O'Neill (2014), giving 27 concepts considered a challenge for climate change adaptation in Kenya (see Table 2).

4.1.3. Individual FCMs

An example of an individual FCM is shown in Fig. 3. In general, stakeholders found it difficult to define relatively stronger and weaker relationships, and two stakeholders refused to do so. Some of the relationships were, therefore, only defined in terms of their direction.

4.2. Ambiguity in FCM concepts, drivers, and relationships

Considerable ambiguity was revealed in the FCM concepts, drivers, and relationships (Fig. 4). Of the 27 pre-defined concepts, all except C14 (supply chain risk management) were included in the individual FCMs. Overall, four concepts were mentioned by every stakeholder, indicating that 15% of the FCM concepts were mutually agreed upon. These four concepts were C4 (land and water use, identified as the focal issue), C6 (rapid population growth), C19 (shared natural resources), and C21 (quality of governance).

There was no mutual agreement among drivers, however, with a total of 19 identified as those concepts having no incoming relationships in the individual FCMs. The highest rank score was an agreement of 50% for drivers C6 and C21. Based on a constraint of at least 30% agreement, the following five drivers remained: C6 (rapid population growth), C9 (climate finance), C11 (national infrastructure), C20 (income per capita), and C21 (quality of governance). Two of the constrained drivers (C6 and C21) correspond to the four concepts of mutual agreement.

Ambiguity in the FCMs was also strong in the identified concept relationships, with no single relationship included in all cases. However, relationship between C6 (rapid population growth) and C4 (land and water use) was identified in 90% of the individual FCMs. The strength and influence (positive/negative) of the relationships also varied, and in some cases, relationships were undefined by the stakeholders, indicating uncertainty about their relative strengths. Table 3 displays the ABA-7 matrix and its corresponding concepts, drivers, and relationships, indicating a 70% agreement on the concepts. A fully summarised matrix is provided in the Supplementary Materials.

4.3. Ambiguity based aggregated FCM

For brevity, here we show the verification step and the calibration step of the ABA approach in detail, which accurately demonstrate the overall process using the verification step of ABA-10 and the calibration step of ABA-7. The sensitivity analysis of the ABA-7 FCM is also described for illustration.

ABA-10 (Fig. 5) included four concepts (C4, C6, C19, and C21), of which two were drivers (C6 and C21). Between the concepts and drivers, seven relationships were defined, of which two were single stakeholder relationships (and, therefore, has not yet been removed).

The verification step, in which the relationships were quantified for ABA-10, is shown in Table 4. The differences in the strength and influence (positive/negative) of the relationships occurred due to different interpretations of the concepts. For instance, as the focal issue, C4 was interpreted as the amount of land and water use as well as sustainably managed land and water use. Moreover, shared natural resources were interpreted as physical areas around the borders of Kenya by some stakeholders while others implied the inclusion of all shared resources within Kenya, such as national parks.

Using the ABA-7 FCM matrix to illustrate the calibration steps, 15 concepts were included, of which three were drivers connected by 94 relationships. Starting with all relationships (calibration step 1), the dynamic output was unstable (Fig. 6); the end state of the concepts

Table 2
List of pre-defined concepts.

Concept	Name	Description	Source
C1	Import of food	Amount and type of food that is imported in Kenya.	Workshop
C2	Regional collaboration on TCI	The degree of collaboration in East-African boarder regions to share information.	Workshop
C3	Policy implementation	The degree in which policy is transformed in to tangible actions.	Workshop
C4	Land use change in Kenya (subsequently 'land and water use', identified as the focal issue)	The amount of land and water used.	Workshop
C5	Knowledge management systems	The degree of access to information platforms and (international) sharing of data/information.	Workshop
C6	Rapid population growth	The degree of population growth in Kenya.	Workshop
C7	Access to TCI-relevant data	The degree of access to data regarding transnational climate impacts.	Workshop
C8	Importing energy	The amount of energy imported.	Workshop
C9	Climate finance	The amount and access to climate finance.	Workshop
C10	Urbanisation and cultural change	The increase of rural to urban migration and decline of rural traditions/knowledge.	Workshop
C11	National infrastructure	Infrastructure that is vulnerable to climate change, especially flooding (e.g. power dams/roads).	Workshop
C12	New economic perspective	Circular economy businesses.	Workshop
C13	Tourism in Kenya	Wildlife migration/extinction and the effect of tourism.	Workshop
C14	Supply chain risk management	An integrated and sustainable value chain of products.	Workshop
C15	Insecurity and terrorism	The decline of adaptive capacity due to (the fear of) terrorism.	Workshop
C16	Healthcare	Access to healthcare and emerging terminal illnesses.	Workshop
C17	Technology transfer	Research and development of technologies to reduce vulnerabilities.	Workshop
C18	Extreme poverty	Proportion of people in extreme poverty.	Workshop
C19	Shared natural resources	Water availability and the quality of water/land.	Workshop
C20	Income per capita	See Schweizer and O'Neill (2014)	Literature
C21	Quality of governance	See Schweizer and O'Neill (2014)	Literature
C22	Water scarcity	See Schweizer and O'Neill (2014)	Literature
C23	Proportion of population on coasts	See Schweizer and O'Neill (2014)	Literature
C24	Innovation capacity	See Schweizer and O'Neill (2014)	Literature
C25	Urbanization (subsequently merged with C10)	See Schweizer and O'Neill (2014)	Literature
C26	Educational attainment	See Schweizer and O'Neill (2014)	Literature
C27	Agricultural productivity	See Schweizer and O'Neill (2014)	Literature

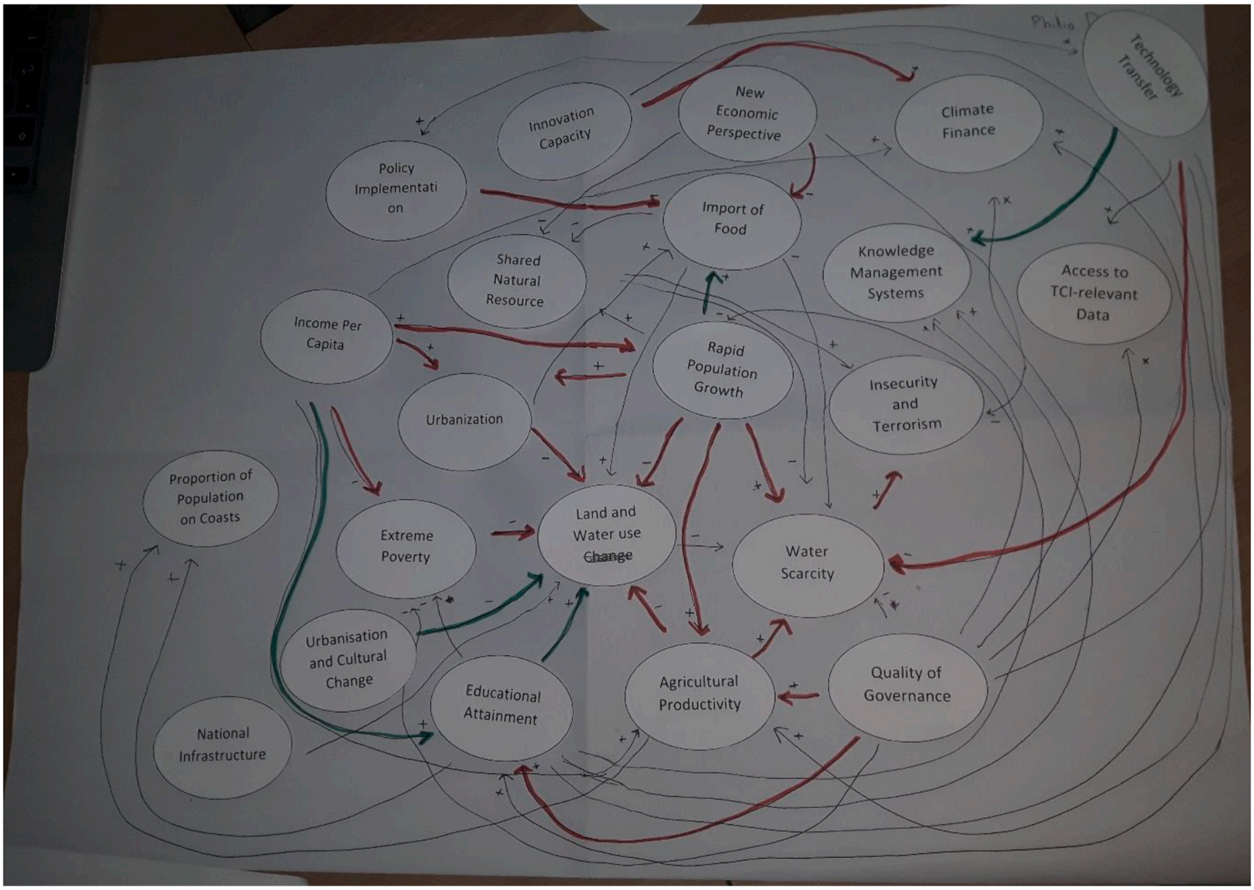

Fig. 3. An example individual stakeholder FCM. Red lines indicate strong relationships, green lines indicate weak relationships, and blue lines indicate medium-strength relationships. The + and – signs next to the arrows indicate positive and negative relationships, respectively.

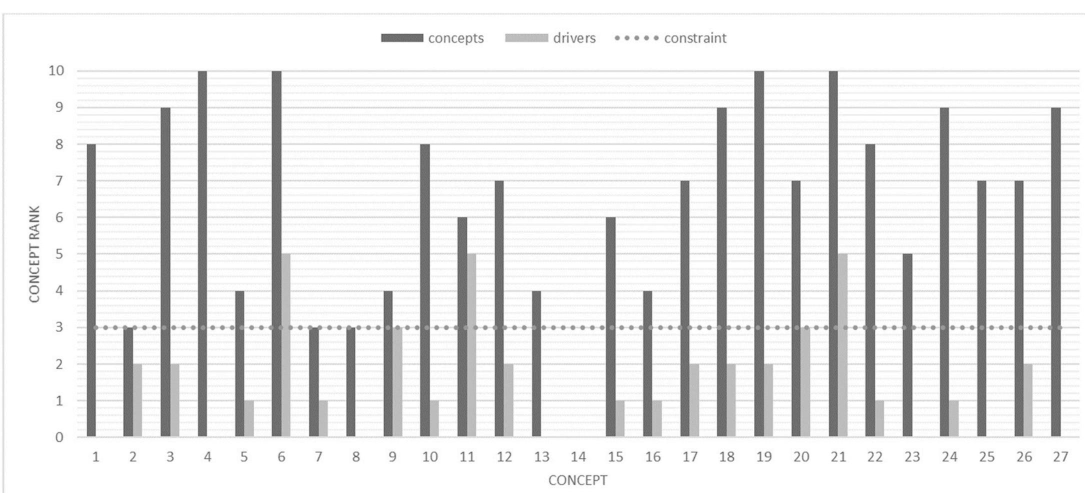

Fig. 4. Ambiguity in fuzzy cognitive map (FCM) concepts (see Table 2) and drivers. Concept rank relates to the degree of agreement where the rank 10 implies 100% agreement, 9 implies 90% agreement, etc. The dotted line demonstrates the driver constraint of more than 30% agreement.

increased exponentially between 20 and 30 iterations. As a next step (calibration step 2), all single-stakeholder relationships were removed from the matrix. This produced very similar results, with the same concepts showing positive and exponentially increasing values. In calibration step 3, the additional removal of relationships on drivers led to a stable set of concept values (Fig. 7). This shows that when calibrating a FCM, removing influences on drivers is crucial. As is common in dynamic FCM outputs, the focal issue (C4) is pushed to the highest end state. The second highest end state was C10 (urbanisation and cultural change) followed by C27 (agricultural productivity). In addition, one concept (C18, extreme poverty) was identified as having a strong negative value. This indicates that the three drivers of rapid population growth, income per capita, and quality of governance (C6, C20, and C21) increased the amount of land and water use, enhanced

Table 3
Ambiguity in relationships with a summarised matrix of up to 70% agreement (ABA-7) in which relationships between 15 concepts (see Table 2) and three drivers are displayed. “s” indicates strong relationships, “m” indicates medium-strength relationships, and “w” indicates weak relations; “o” represents relationships that were not defined in the individual FCMs. Yellow boxes indicate single-stakeholder relationships, dark shade positive and light shade negative.

Concepts	C1	C3	C4	C6	C10	C12	C17	C18	C19	C20	C21	C22	C24	C26	C27
C1			m-w+						m-			m-			
C3	so		s-m+m-m+w+	m-	m-m-	m+	m+	s-m-			s+w+m+			m+m+	m+o,m+m+
C4	s-	m+			w+o,m+s+s+				m-m+s-			m+m+s+m+s+m-	m+		m+s+w-s+
C6	m+s+m+w+		s+o,m+s+m+s+m+s-s+	driver	m+				m+			w+s+	m+m+		m+m-s+
C10	m+m+m+	s+	o,m+o,m+w-m+s+w+s+s-		s+	m+		o				m+			o,m-
C12	s-		m-m-so,m+		m+		m+	m+m-	m-				m+		
C17			m-s+m+			m+			m+			m-s+s-		m+	m+m+m+m+
C18			m-m+w-s+m+s-	m+	m-m-										m-m-
C19			m+m+s+m+m+	s+								m-			
C20	m+m+m+		s+		w+s+			s-	m+	driver				w+	
C21	m-m-	m+m+m+m+m+	s-s-s+s-s+m-		m+			m-m-	m+w+	m+	driver	m-	m+	s+	s+
C22		s+	o												m-m-
C24			m-s+		m+	o,m+	m+m+s+m+	m-				w-			m+m+
C26			w-w+w-m+w+	m-m-		m+		m-w-m-	m+	m+s+	s+m+		m+		m+
C27	m-m-m-s-s-		s+m+so,s-					s-m-		m+m+m+		s+o,s+			

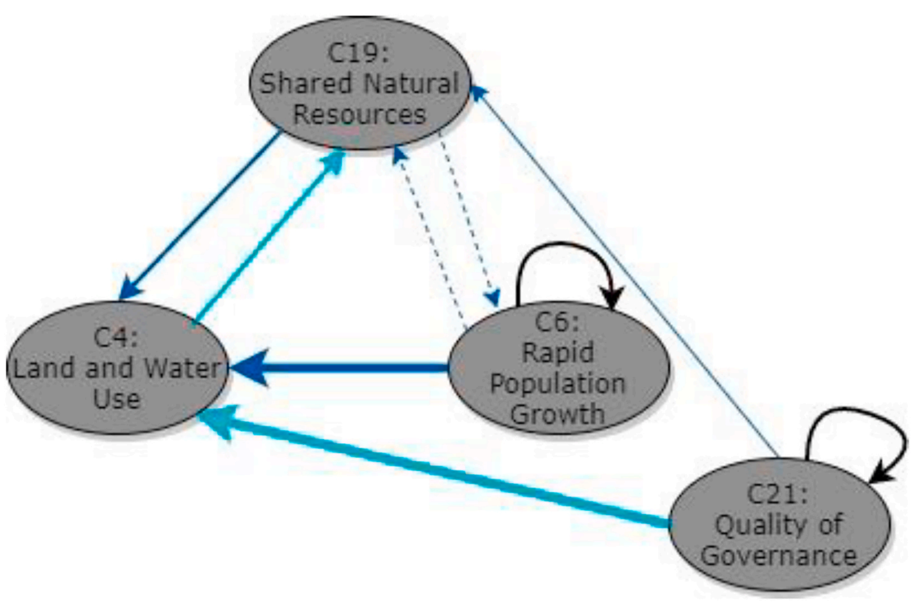

Fig. 5. Constructed ABA-10 graph. Dark blue arrows indicate positive relationships and light blue arrows indicate negative relationships. The size of the arrow (thick, medium, or small) represents a strong, medium, or weak relationship, respectively. Dotted arrows are single stakeholder relationships and black arrows are drivers.

urbanisation and cultural change, increased agricultural productivity, and reduced extreme poverty.

The FCM is sensitive to strong relationships; the Δ0.1 change making strong relationships stronger yields an explosive system that does not stabilise. Other value changes cause minor changes in the shape and end-states of the concepts. When weakening the relationships by 0.1, the

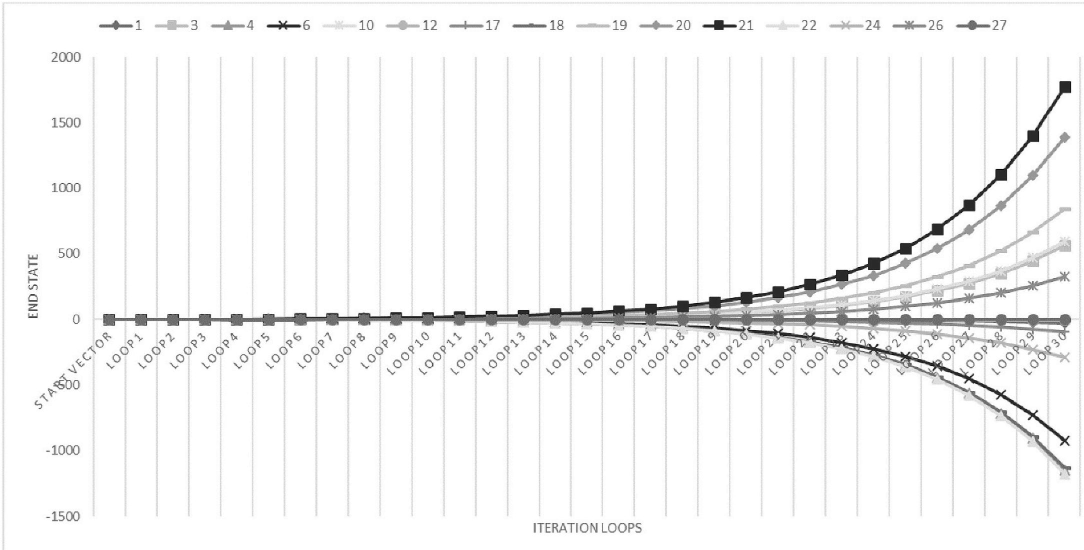

Fig. 6. Dynamic fuzzy cognitive map (FCM) output with the ABA process up to 70% agreement on 15 concepts and three drivers, at step 1 of the calibration.

ranked order of land and water use, urbanisation, and cultural change was altered, but no other considerable end-state shifts occur. A reconstruction of the ABA-7 FCM (Fig. 8) shows a strong feedback loop between land and water use, water scarcity, agricultural productivity, and back to land and water use. As a driver, rapid population growth enforces agricultural productivity and land and water use, making this loop even stronger.

4.4. *Influence of aggregation on FCM indices*

There was a wide range of drivers, concepts, and relationships in the individual FCMs (see Table 5); the number of drivers ranged from one to nine, the number of included concepts varied from eight to 18, and the number of relationships varied between 12 and 48. Importantly, the index values of the common aggregation method differ from those of the individual FCMs (Table 5); the common aggregation method produced a FCM without any drivers and with a considerably higher density value, mainly because of the high number of relationships. Although outside of the scope of this paper, it is worth noting that the dynamic behaviours of the aggregated FCMs were, consequently, also very different.

Similar to commonly used aggregation methods, the ABA method also influenced the FCM properties (Table 6), with highest the density values in each agreement rank with all relationships (e.g. for ABA-10, step 1 had the highest density, and for ABA-7, step 1 had the highest density). Importantly, the density values of almost all the steps were higher than those obtained from the common aggregation method, largely due to the low number of concepts and the relatively high number of relationships.

The two subsequent calibration steps significantly reduced the number of relationships and reintroduced drivers. This indicates that the calibrated ABA-7 included three drivers, 15 concepts, and 45 relationships, corresponding to a density of 0.22. These properties are closer to the average and median properties of the individual FCMs than the values obtained using the common aggregated method. The calibration steps were, therefore, crucial for not only providing a stable dynamic FCM output but also to change the FCM properties.

Based on Tables 5 and 6, the properties of the common FCM aggregation method do not correspond with the properties of the individual FCMs. For example, the disappearance of drivers and the high number of concepts and relationships are substantially different from individual perceptions. In comparison, after calibration, the ABA-7 properties correspond to the average and median FCM properties, and provide a more similar aggregated model compared to stakeholder perceptions. This indicates that an ABA process can produce a stable output with FCM indices similar to individual FCMs while, at the same time, elucidating and aggregating multiple perspectives.

5. Discussion and conclusions

Given that FCMs display a substantial amount of ambiguity, our ABA approach provides transparent steps for aggregating multiple FCMs. The FCM aggregation method applied substantially influences FCM indices and, therefore, SES representation. Nevertheless, explicitly representing ambiguity in complex SESs using FCMs, while advancing the aggregation process and understanding its influence on SES representation, does not come without some shortcomings, which we discuss in the following section in context of our original objectives.

5.1. *Explicitly represent ambiguity in complex SESs with FCMs*

Grey et al. (2014) discussed multiple options for collecting data to build a FCM. In this study, we focussed on consensus building and scope setting by framing FCM concepts during a stakeholder workshop. This provided predefined concepts that served as inputs for the subsequent interviews. The main advantages of using predefined concepts for FCM co-production include (1) a collaborative understanding of concepts; (2) achieving a focussed discussion on relationships instead of concepts during interviews; (3) increased comparability of individual FCMs, and (4) minimised time requirements of individual stakeholders, thus limiting stakeholder fatigue.

However, stakeholders (re-)interpreted the identified concepts differently, resulting in partially conflicting interpretations. As described by Jetter and Kok (2014), differences in the meaning of concepts are common, even after a plenary participatory discussion. Limiting conflicting interpretations of concepts could be facilitated during the interviews, by briefly explaining the concepts before discussing the relationships between them for example, although this brings the focus back on the concepts and limits stakeholders' freedom of thought. As every FCM displays an individual narrative of logic between concepts, we aimed to record this narrative rather than forcing one meaning upon them prior to the interview as this might lead to stakeholders repeating what we told them rather than voicing their own opinions. In our view, this *ex-ante* validation limits stakeholder input. When research is specifically aimed at comparing relationships in individual FCMs, an increased consensus view among stakeholders could increase comparability.

Table 4
Overview of the verification step of the ABA-10 FCM. Relationships are represented as concept → concept.

Relationship	Names	Combining individual FCMs	Verification step	FCM value
C21 → C4	Quality of governance → Land and water use	Mentioned by six stakeholders: 3 strong negative 2 strong positive 1 medium negative	It is assumed that a good quality of governance strongly decreases the amount of land and water that is used, and increases sustainable land and water use. This is because it is expected that policies will guide Kenyans to use less land and water or more sustainable land and water use.	−0.9
C6 → C4	Rapid population growth → land and water use	Mentioned by nine stakeholders: 5 strong positive 3 medium positive 1 neither positive nor negative	It is assumed that a larger population will use more land and water, primarily for food production. As most Kenyans rely on agriculture, this was identified as a strong relationship. Rapid population growth is also presumed to result in more subdivision of land because family land will be split among the children. These smaller allocations are, in some cases, not enough to provide for the family, therefore people will look elsewhere for more land and/or water.	0.8
C19 → C4	Shared natural resources → land and water use	Mentioned by five stakeholders: 4 medium positive 1 strong positive	The quality of shared natural resources influences the amount of land and water that is or can be used. ‘Low’ quality means less available land and water with sufficient quality to be used. Some transboundary rivers/lakes dry up or drop their water table due to the presumed (over)exploitation of neighbouring regions. Another example is the water quality of Lake Victoria, which results in forced changes of land and water use practices.	0.6
C4 → C19	Land and water use → shared natural resources	Mentioned by three stakeholders: 1 medium negative 1 medium positive 1 strong negative	The more land and water is used, the less the state/quality of shared natural resources will be. This is because it is assumed that Kenyans expand their agricultural or pastoral practices to transboundary areas. An example is the forced migration of pastoral groups in the northern part of Kenya resulting in more land and water use of shared natural resources, such as water and grassland, which is assumed to result in the degradation of these resources mainly due to overexploitation. Moreover, deforestation for agricultural practices is a common practice in Kenya, which also influences the shared use of natural resources, such as national parks, bordering neighbouring regions. The more sustainable land and water use is, the higher the quality of the resource.	−0.4
C21 → C19	Quality of governance → Shared natural resources	Mentioned by two stakeholders 1 medium positive 1 weak positive	It is assumed that government enforcement and legislation will increase the management of protected areas, which can increase the quality of shared natural resources.	0.3
C6 → C19	Rapid population growth → Shared natural resources	Mentioned by one stakeholder 1 medium positive	The stakeholder stated that with more people, more resources will be used, leading to the deterioration of natural resources.	0.1
C19 → C6	Shared natural resources → Rapid population growth	Mentioned by one stakeholder 1 strong positive	The stakeholder stated that with a better state of shared natural resources, more food can be produced and a better state of health will be reached, which causes population growth.	0.1

While explicitly representing ambiguity, we quantified three types of ambiguity in the studied SESs. The first type concerns the presence of concepts; the second the presence and driving capacity of concepts; and the third the presence, direction, influence, and strength of relationships between the concepts. Elucidating ambiguity in the first two types has been realised by assessing similarities and differences in individual FCMs and demonstrates that multiple knowledge frames have a large range of ambiguities. Importantly, there might be additional types of ambiguity, and more exploration is needed to quantify other potential sources including the importance of concepts and relationships, the probability of relationships, the dynamics of the system, and emerging properties. Nevertheless, our research clearly demonstrates that the

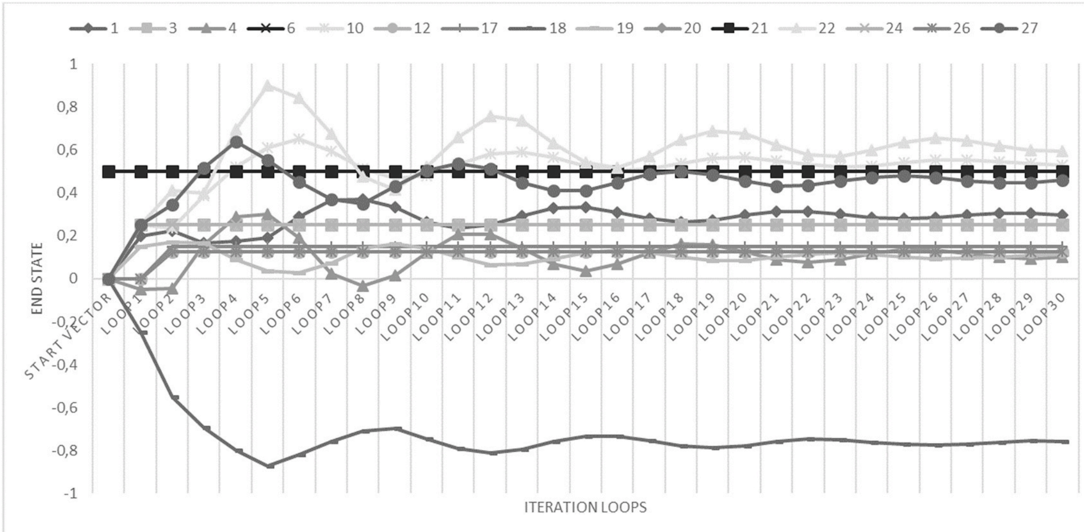

Fig. 7. Dynamic fuzzy cognitive map (FCM) output with the ABA process up to 70% agreement on 15 concepts and three drivers, at step 3 of the calibration.

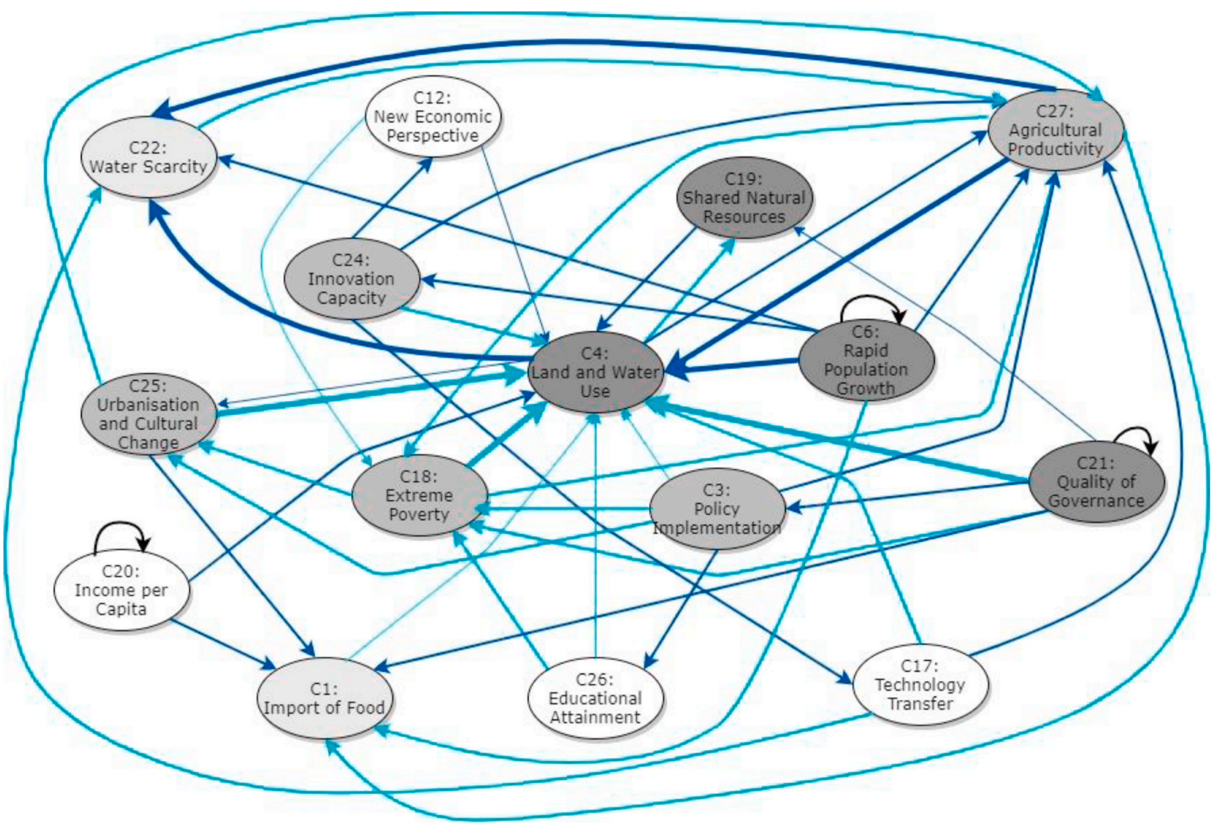

Fig. 8. Construction of the ABA-7 FCM. Dark blue arrows indicate positive relationships and light blue indicate negative relationships. Arrow thicknesses indicate strong, medium, or weak relationships, respectively. Note that this reconstruction does not show single-stakeholder relationships. The darkness of the concept (see Table 2) relates to the degree of agreement; dark grey, grey, light grey, and white correspond to ABA-10, ABA-9, ABA-9, and ABA-7, respectively.

range of ambiguities in complex SESs is already extensive. Furthermore, it is evident that dealing with ambiguity is essential when attempting to understand SESs in a participatory setting owing to its strong influence on the represented system.

5.2. Ambiguity based aggregation

The ABA process involves verification, calibration, and sensitivity analysis. These three steps create a stable FCM with a coinciding range of ambiguities. By adding concepts according to their agreement rank, a FCM can be constructed with a transparent and flexible method that accounts for the degree of common understanding among all stakeholders.

A central matter in FCM aggregation remains the translation of the linguistic valuation of relationships (strong/weak) to numerical integers. As presented, the most commonly used method for quantifying

Table 5
Fuzzy cognitive model (FCM) properties of individual FCMs, averages, median, and sum. Abbreviations Nd, Nc, Nr, and D represent the number of drivers, concepts, relationships, and density, respectively.

FCM properties	Nd	Nc	Nr	D
FCM1	3	16	31	0.12
FCM2	6	10	23	0.23
FCM3	2	16	33	0.13
FCM4	5	15	33	0.15
FCM5	4	14	30	0.15
FCM6	1	11	27	0.22
FCM7	9	18	32	0.10
FCM8	2	8	12	0.19
FCM9	6	15	48	0.21
FCM10	4	15	32	0.14
Average individual FCMs	**4**	**14**	**30**	**0.17**
Median individual FCMs	**4**	**15**	**32**	**0.15**
Common aggregation	**0**	**26**	**176**	**0.26**
ABA-10 aggregation	2	4	5	0.31
ABA-9 aggregation	2	8	19	0.30
ABA-8 aggregation	2	11	33	0.27
ABA-7 aggregation	**3**	**15**	**45**	**0.22**

Table 6
Fuzzy cognitive map (FCM) properties step 1–3 of the ambiguity based aggregation (ABA) calibration. Abbreviations Nd, Nc, Nr, and D represent the number of drivers, concepts, relationships, and density, respectively.

Agreement rank	ABA calibration step	Nd	Nc	Nr	D
ABA-10	Step 1	1	4	7	0.44
	Step 2	2	4	5	0.31
	Step 3	2	4	5	0.31
ABA-9	Step 1	1	8	28	0.44
	Step 2	2	8	19	0.30
	Step 3	2	8	19	0.30
ABA-8	Step 1	1	11	58	0.50
	Step 2	2	11	33	0.27
	Step 3	2	11	33	0.27
ABA-7	Step 1	0	15	94	0.42
	Step 2	0	15	49	0.22
	Step 3	3	15	45	0.22

relationships is to calculate an average value. This has the advantages of being straightforward, reproducible, and does not require value judgments from the researchers. It also solves the problem of reproducing conflicting relationships when, for example, one stakeholder indicates a strong negative relationship and another stakeholder indicates a weak positive relationship. Nevertheless, the resulting aggregated FCMs are likely to have a majority of 'medium' relationships that did not exist in the original individual FCMs and, furthermore, relationship scores might cancel each other out (Özesmi, 2006). Therefore, we argue that averaging should not be used because the advantages do not outweigh the disadvantages.

We adopted extra verification step, therefore, to quantify the relationships between concepts and drivers, providing the possibility of incorporating logic and reasoning back into the aggregated FCM. We strongly argue that such a verification step enhances FCM aggregation, and this process should not be simplified by mathematical configurations if stakeholder perceptions and ambiguity in SESs are to be fully understood. Although the proposed verification step still contains a subjective modelling choice, this choice is transparent and structured, which enhances reproducibility.

The calibration step yielded a stable FCM output in this study; however, this will not always be the case. For example, when an individual FCM contains a large number of relationships (especially feedback loops) and is highly complex, the applied calibration method will not suffice. However, in practice, FCMs developed from individual PM activities do not typically have large density values. Therefore, we hypothesise that the calibration steps proposed here will be useful for most FCMs derived through PM.

While the proposed ABA methodology provides a more systemic way to represent ambiguity, an additional validation step would be advantageous. As indicated by earlier research (Kok et al., 2011), the validation of stakeholder perceptions is an iterative process. Here, more practical reasons (e.g. budget, time, etc.) prevented us from including a validation step. Therefore, we do not claim that our methodology results in a 'correct' representation of stakeholder perceptions but primarily serves as an example of a method to explicitly account for ambiguity, offering an ontological approach for capturing the range of stakeholder ambiguities in aggregated models.

5.3. Influence of FCM aggregation on SES representation

Recognising and addressing ambiguity is essential as the manner by which we address it (or not) can fundamentally change the way we represent aggregated FCMs. often leads to FCMs that have radically different properties to any of the individual FCMs used to construct it. This is demonstrated by the large differences in the FCM indices of the common aggregation and ABA methods. Although sometimes the whole can be more than the sum of the parts, this is not desirable in this instance. In our work, we provided all identified concepts as inputs, thereby aiming for a description of the entire system from each stakeholder. In this case, it is desirable to maintain the properties that individual stakeholders attach to the system in the final product. In more general terms, we argue that it should always be an aim to maintain stakeholder views on system functioning to best represent the collective views of a stakeholder group.

FCM indices are typically used to identify the characteristics of a FCM. In addition to those used in this study, a range of additional properties have been suggested including centrality, indegree, outdegree, complexity, hierarchy, number of transmitters, and number of receivers (Grey et al., 2014; Özesmi and Özesmi, 2004). Here, we purposefully avoided using more complicated indices as these are highly correlated with the counting of concepts and relationships, and illustrate the ambiguities in other aspects of SES characteristics. Other studies (e.g. Lavin et al., 2018) have also used indices to determine whether individuals share a paradigm and categorise individual FCMs into groups. Although an interesting approach, there is no documented evidence that FCM properties are indicative of the logic of the underlying system. We argue that FCM properties are useful for comparing FCMs and matrices but they cannot be used to make conclusions about stakeholder understanding and reasoning in an SES.

5.4. Modelling with ambiguity

Our research focussed on identifying how a complex SES can be modelled with FCMs while explicitly elucidating ambiguity. We used a mix of ontological and epistemic strategies by first identifying a range of ambiguities followed by reconstructing one FCM. In line with the participatory paradigm (Heron and Reason, 1997), it is assumed that reality is co-created by an objective and subjective set of experiences. However, the aggregation stage of the research adopts a more positivist paradigm, assuming that a consistent part of perceptions on which stakeholders agree exist and can be modelled. Modelling multiple perceptions remains a careful balancing act but can provide insights into similar stakeholder paradigms. Nevertheless, a model is merely a tool to enable understanding of what is being modelled. Using a mixed-paradigmatic approach, as we did, emphasises the diversity of multiple perspectives while providing one model. A deep understanding of SESs, therefore, requires new methods to structure and quantify the range of ambiguities from different perspectives.

The strength of individual PMs might not lie in the model that is created but in the systematic understanding of the paradigms of the stakeholders involved. If a model shares a paradigm with the user, it may improve the uptake of the model. In particular, if PM is focussed on decision support, identifying these paradigms can advance the understanding of how society and science shape each other. More studies and elaborate methods are needed to understand what we model, why we model it, where we simplify a model, and which choices are made during this process. Methods remain in their infancy but have already demonstrated the importance of ambiguity and, therefore, the importance of transparent and flexible methods to account for it.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2021.105054.

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