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Risk assessment and recovery trajectories of a social-ecological system after a volcanic eruption

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1 Abstract

A risk assessment for disasters is usually composed of hazard, vulnerability and exposure variables, which are hardly studied and modeled simultaneously. In volcanology, it remains ambitious to anticipate risk trajectories of pre- and post-eruption regimes. The interdependencies and feedback loops of the system's components, between geological, ecological, social and economic ones, give rise to trade-offs and synergies that should be disentangled for supporting decision-makers and helping local communities to face the risks. We developed here an innovative discrete-event and possibilistic model based on a dynamical network representation to assess volcanological multi-risk and long term post-eruption impacts of such a multifactorial system. We illustrated our method with the region around Mount Meru (Northern Tanzania), a strato-volcano with various eruption styles, located in a growing economic and touristic region (>1M.inh.).

We used qualitative and rule-based Petri nets, largely unused in environmental sciences, for an integrated assessment of the overall system dynamics and associated risks. As a central result, we showed that the region could recover from a blast eruption, irrespective of the timescale. Our study highlights the fact that agriculture and pastoralism remain key activities to favour the recovery of this region. Yet, as soon as subsidies from governmental and non-governmental organizations are lacking, the modeled region remains isolated from national and international activities and shifts to rural dynamics. Our case study can equip environmental risk assessment with innovative models, new dynamical indices (e.g. desirable and non-desirable trajectories), and rigorous reasoning for an ultimate integrated management of social-ecological systems at stake.

Keywords: volcanic hazard; integrated model; social-ecological system; dynamical system; Petri nets.

2 Introduction

Risk assessment is always a sensitive issue, as it implies political and human decisions. Complex models are nowadays available for modeling multi-hazard occurrences (Deligne et al., 2017; Neri et al., 2008), quantify probabilistic vulnerability (Neri et al., 2008; Wilson et al., 2014), and assess fine resolution exposures (Spence et al., 2008; Wild et al., 2019) in volcanic eruptions to help decision makers. Yet, a model to assess interdependencies between the various domains involved in such a complex geological, social, economic, and ecological system is still lacking. In particular, a risk assessment that would highlight all possible trajectories of the integrated and multifactorial system (Gaucherel and Pommereau, 2019) exposed to an eruption hazard is essential as a decision support tool. In current literature, only most probable trajectories of the impacted region are modeled and used (Deligne et al., 2017;

Wilson et al., 2014), which leaves out other and possibly rare trajectories that might become central after volcanic eruption.

The main objective of this paper is to demonstrate the benefits of an integrated and possibilistic model using a dynamical network-based approach to investigate the social-ecological functioning affected by a volcano eruption. We illustrate this approach with the Arusha region, Northern Tanzania, to highlight the numerous factors influencing the risk assessment and risk management. The Mount Meru (Northern Tanzania, 4566m a.s.l) is in a geodynamical active area, with seismic and volcanic activities (Roberts, 2002; Tiberi et al., 2019), located in a region famous for its biodiversity and touristic attractions, and nearby a big city (Arusha town, approx. 420 000 inhabitants). It appears critical, for the safety of local populations as well as for the economic importance of the region, to accurately assess the volcanological and associated risks of the region (Ghiglieri et al., 2012; Vye-Brown et al., 2014). In line with systems thinking (Checkland, 1999; Sword-Daniels et al., 2015), we chose to use a network-based approach to highlight variables that are connected by causal processes to describe their interdependencies and we divided the area into four sub-systems: the Arusha city, cultivated lands, the Arusha National Park and the northern Meru savanna.

The volcanological risk assessment is classically composed of hazard, vulnerability and exposure variables (GAR-UNDDR, 2019; Prasetyo et al., 2020; The-Geneva-Association, 2018), and recently conceptualized through the complex interdependencies of system components undergoing the disaster (Eiser et al., 2012; Sword-Daniels et al., 2015). The functioning complexity of these three variables and their interactions are still challenging modellers. Systems thinking approaches propose a relevant way for this purpose (Checkland, 1999; Sword-Daniels et al., 2015), although they focus on system structure and rarely model the system dynamics. Moreover, many studies quantify complex hazard assessments without taking into account all these variables simultaneously (Deligne et al., 2017; Neri et al., 2008). Several studies elaborate “vulnerability functions” without considering their possible interactions and/or other potential risk variables (Wild et al., 2019; Wilson et al., 2014). For this reason, we propose to develop a qualitative “vulnerability chain” instead of the well-known quantitative vulnerability functions used in volcanology (Spence et al., 2008; Wilson et al., 2014) to assess singular (unitarian) event sequences of the region. Such a vulnerability chain consists in the causal chains of states and events (i.e. a trajectory) possibly generated by the interactions of all vulnerability functions of the studied system. An appropriate and possibilistic model should be able to predict such event succession from the interaction network made up of these functions.

Also, spatially explicit and fine-scale studies analyse the exposure to some disasters while underestimating or oversimplifying the other risk variables (Leung et al., 2003; Spence et al., 2008). The few studies that simultaneously account for the three main risk variables in environmental sciences are usually neglecting the causal interactions between geo-hazard, social-vulnerability, economic-exposure and ecological-exposure. For understanding the whole system and providing sounding recommendations, it is mandatory, we think, to gather social, economic, physicochemical and ecological processes. Otherwise, we would gain an

uncomplete and likely biased understanding of the system at risk. Impact models also rarely combine pre- and post-eruption dynamics. Finally, most studies focus on the most probable trajectories (Deligne et al., 2017; Neri et al., 2008) and neglect rare and potentially important trajectories. This explains why cutting-edge possibilistic models may provide complementary insight about the system dynamics.

A sound decision support tool should encompass most possible system responses to ultimately inform its stakeholders (Ewing et al., 2002; GAR-UNDDR, 2019; Prasetyo et al., 2021), as forgetting some processes of the integrated system may lead to erroneous understanding. The possibilistic framework consists in exhaustively computing successive events of the system in an asynchronous way (Clarke et al., 2018; Reisig, 2013). Conversely, the probabilistic framework (e.g. Markov Chains) assigns probabilities to each event to produce several trajectories only. The possibilistic framework is *in*-deterministic, as it potentially provides many (yet deterministic) outcomes from each system state. Here, we argue that possibilistic and integrated models of volcanological risk assessment and management are useful and fully complementary to probabilistic models (Neri et al., 2008; Wild et al., 2019). In particular, Bayesian belief networks (BBNs) and dynamic Bayesian networks (DBNs) are already much used in risk analysis and risk assessment (e.g. Neri et al., 2008; Tierz et al., 2017), but they provide a probabilistic view and miss some dynamics handled by possibilistic approaches (Amin et al., 2019; Clarke, 2008). By recording event sequences in a so-called state space, they allow for finely assessing the risk and identifying relevant (e.g. recommended and dangerous) management practices. The model is explicitly assigning the reasons for rational behaviour as well as implicit and unknown causes (Checkland, 1999; Eiser et al., 2012).

Our possibilistic model is also called a qualitative discrete-event model, focusing on sharp changes in system states and identifying long term changes only (Gaucherel et al., 2017; Pommereau, 2010). Discrete-event models describe dynamics in terms of discrete changes of variables' state, which may be irregular over time (Cassandras and Lafortune, 2008). We combined such discrete dynamics with qualitative variables to model sharp changes in a parsimonious and rigorous way. Their mathematical engines are numerous yet mostly rely on formalisms such as Boolean networks (Kauffman, 1969; Saadatpour et al., 2011), Graph Transformations (Ehrig et al., 1973), or Petri nets (Aloini et al., 2012; Nyvlt and Rausand, 2012; Pommereau, 2010). We chose to use Petri nets to model ecosystem transitions with if-then rules, for their flexibility and for their ability to handle “concurrent resources”, i.e. possibly simultaneous or contradictory source-sink fluxes on complex networks. Petri nets and other discrete-event systems have already been applied in risk analysis, although they remain largely underused. For example, they allow reinforcing safety and providing diagnosis in buildings as in various process industries (Aloini et al., 2012; Nyvlt and Rausand, 2012), but they remain rarely found in environmental sciences. Nevertheless, it is possible to find stochastic petri nets used to manage flood disaster in urban environment (Nukavarapu and Durbha, 2020), and coloured Petri nets for risk assessment of wind farm development (Zeinalnezhad et al., 2021). Petri nets and discrete-event models are almost absent in environmental sciences in which technological components are usually lacking or are neglected (but see Gaucherel and Pommereau, 2019).

In this study, we aimed to model (1) undisturbed social-ecological system dynamics and (2) recovery pathways following a blast eruption. Such pathways were assessed under two contrasting environmental and economic scenarios. More specifically, we questioned whether the ecosystem was able to recover from an eruption if national/international subsidies were present or absent. Inspired by the Mt St. Helens eruption in 1980 (Dale et al., 2005), we hypothesized that a blast eruption could possibly destroy the Arusha city. Additionally, governmental and non-governmental sectors, the private sector and any other substantial external assistance are often critical in the aftermath of the eruption, especially in developing countries. For each scenario, we addressed the same two questions: Q1. Is the region able to recover its present-day state, irrespective of its timescale? Conversely, we consider the system to have collapsed in case it reaches a state or a set of states from which it can no more exit (Gaucherel and Pommereau, 2019). For Q1, we hypothesised (H1) that reference and blast scenarios (RS and BS) are resilient, while the post-eruption subsidies scenario SS is not, possibly imposing a too strong pressure on the system (Benson, 2005; Checkland, 1999). Q2. In which order do human activities, vegetation types and ecosystems recover after the Mt Meru eruption? We hypothesised (H2) that, after the eruption destructions, agricultural activities will recover before urban re-settlement and touristic activities, as was often observed in the past (Martí and Ernst, 2005). Finally, we discuss the critical roles of water supply and state political choices in the social-ecological system of reconstruction, and the model's ability in assessing the associated risks.

3 Materials and Methods

3.1 The Mount Meru region

Mount Meru is a complex strato-volcano formed through the succession of Plinian and Pelean episodes, effusive and intrusive episodes and lahars. This edifice is composed by pyroclastic deposits, debris avalanche, ash and pumice, lapilli and basaltic lava flows and phonolitic lava intrusions. This morphological signature demonstrates significant volcanic activity with very different eruptive style and dynamism (Delcamp et al., 2013; Wilkinson et al., 1983; Wilkinson et al., 1986). The volcanic activity took place in three major phases (Wilkinson et al., 1986): i) the oldest between 2 and 1.5 Ma with the construction of a center located to the west of the current summit; ii) between 0.35-0.16 Ma, volcanic activity resumes north and north west of the current center; iii) the construction of the main cone of the Mt Meru occurs between 0.16 and 0.06 Ma with the establishment of effusive and intrusive facies alternating with phases of destabilisation of the building which give rise to lahars and debris avalanche (Benson, 2005; Cosme et al., 2022; De Bélizal et al., 2012; Naldi et al., 2011). After 0.16 Ma, volcanic activity appears more sporadic.

The massive eastern flank of Mt Meru collapsed and the formation of the current caldera is the result of a large Pelean eruption (Delcamp et al., 2017; Wilkinson et al., 1983; Wilkinson et al., 1986). This last collapse left a 4×4 km² horseshoe-shaped valley filled with ash deposits (the so-called ash cone, Cattermole, 1982; Wilkinson et al., 1983; Wilkinson et al., 1986).

Lacustrine sediments above the debris avalanche give a minimum age of 8600 BP (Hecky, 1971) suggesting a Holocene age for this collapse event. This collapse led to the formation of pyroclastic flows ($20 \pm 2 \text{ km}^3$ distributed over an area of 1250 km^2) that cover the entire eastern part of the region, extending to the base of Mt Kilimanjaro (Delcamp et al., 2017). The ash cone and the crater are still active, including explosions from the ash cone in 1910 and fumarolic activity in 1911, 1926, 1936 and 1953 (Guest and Leedal, 1956). Mount Meru is located in the Arumeru district, northern Tanzania, amongst approx. 100 km^2 of Maasai steppes (Roberts, 2002; Tiberi et al., 2019). For this study, we have divided the study region into four distinct social-ecological systems, based on current land cover (Fig. 1a, Table 1): i) the Arusha National Park, established in 1960, surrounding the Mt Meru cone and composed of savanna and forest areas (Galanti, 2003; Istituto_Oikos, 2011), ii) the savanna area north of the park, inhabited by two agropastoral dominant ethnics (Maasai and Wameru), iii) the southwards urban area of Arusha city (approx. 420 000 inhabitants, Istituto_Oikos, 2011), iv) surrounded by smallholder-farming agricultural lands (Istituto_Oikos, 2011; Ministry-of-Agriculture-US, 2008). We assumed that fire is absent in these northern Tanzanian savannas.

The regional climate is characterised by a bimodal rainfall pattern with a long and a short rainy season (from March to May and November to December, respectively), which drive water availability of the region, and average temperatures ranging from 8°C (July) to 28°C (February) (Strauch and Almedom, 2011). Soil fertility and elevation favoured the settlement of an evergreen forest on the highest slopes of the volcanic edifice, surrounded by semi-arid savanna and agricultural lands (approx. 400 000 rural residents). Tanzania presents a so-called transition economy, characterised by a strong growth and a diversification of the economic sector. Its main sector of activity remains the agricultural sector, which accounts for 28% of Gross Domestic Product, 30% of exports, 65% of industry contributions and employs 70% of the local workforce (Ministry-of-Agriculture-US, 2008). Hence, we defined the central agricultural activities in the model as annual (e.g. maize, sorghum, rice) and permanent (e.g. coffee, banana, mango) productions (Table 1). These productions may be divided into “food and cash crops”, providing a reliable social-economic indicator. The tourism sector also plays an important role in the economic growth of the region (e.g. the wildlife conservation budget), with luxury tourism and Meru climbing activities.

3.2 The modelling framework

In our model, each variable had two Boolean states (Fig. 2): “present” (the variable is functionally present in the system, also denoted as '+') and “absent” (functionally absent of the system or '-'). Any system state is a list of present/absent variables (Fig. 2e). We chose such a qualitative representation of the system to model sharp changes over the long term, neglecting rapid and continuous variations. The system state changes according to “if-then” *rules*, which reflect the qualitative effects of physicochemical, bio-ecological and/or social-economic processes. A rule consists in a *condition* (“if”) and a *realisation* (“then”) part (i.e., a list of present/absent variables) as follows: [“rule's label: condition >> realisation”]. If a state satisfies a rule's condition, the rule is executed and generates a *transition* to a new system

state by updating the variables' values according to the rule's realization. Several variables may be updated simultaneously, but only one rule is executed at a time (i.e. rules are executed asynchronously).

The set of states resulting from all possible rules executions is called the *state space* (Reisig, 2013; Thomas, 1991). This state space is represented as a graph whose nodes and edges represent states and transitions, respectively, and is called the *state-transition graph* (or STG for short). STGs usually exhibit three major topological structures characterising the system trajectories: Strongly Connected Components, attractors and basins. A Strongly Connected Component (SCC) is a set of mutually reachable states (e.g. Fig. 2e). It is thus defined by the reversibility of its internal transitions, which is a form of stability. Therefore, for the sake of simplicity, SCCs will be called *stabilities*. An *attractor* is a SCC which is impossible to exit (i.e. no process exist to leave any of its states, Naldi et al., 2011). A *basin* is a set of states leading to the same stabilities. Basins are intrinsically transient dynamics as they necessarily lead to one or several stabilities, and can be seen as a bifurcation point if a basin leads to several stabilities.

The illustrative and toy-model includes two variables (the volcano (V) and the human population (H), Fig. 2a). Four rules (R1-4) are defined: R1, the sleeping volcano allows for the human population to settle; R2, an eruption impacting most people; R3, the sleeping volcano erupts; and R4, the eruption stops (Fig. 2b-c). The corresponding rules are written as *R1: V- >> H+*; *R2: V+ >> H-*; *R3: V- >> V+* and *R4: V+ >> V-* (Fig 2b). This set of four rules is translated as a Petri net (Fig. 2c) which computes the STG (Fig. 2d-e) consisting of all reachable states from the initial state (S1) and all transitions (Fig. 2b). Technical details of a similar method can be found in (Gaucherel and Pommereau, 2019).

During the modelling process, we made seven technical assumptions: first, we assumed that we know the initial state, observed transitions of the system for comparison with simulations, and the processes involved to generate them. We also assumed it is possible to represent the system by a graph (not layers or other structures), and to model its long term dynamics by using its topological changes instead of flux variations on a fixed topology as in traditional models. We defined long term changes by qualitative changes explicitly crossing thresholds, as opposed to short term quantitative variations often modeled for example by differential equations. Unlike other discrete-event models (e.g. Boolean networks, Gaucherel et al., 2017; Saadatpour et al., 2011), we assumed that rule outcomes may simultaneously modify several variables and may asynchronously manage conflicting outputs. We made four additional and reasonable assumptions about ecosystem structure and dynamics. First, the system state changes as long as it can, so that if one transition is possible, it will finally happen. Any resource (e.g. food, equipment, seeds) is always available from the market. Climate is adequate for sustaining agriculture and any additional production on an inter-annual basis. Landscapes and wild fauna always remain appealing for tourists, while we did not explicitly model local people livelihoods.

This model was event-driven: no regular time steps were applied, focusing only on the chronology (i.e., order) and causality (causes precede consequences) of events (Cassandras and Lafortune, 2008). Hence, no time frame is imposed apart from rule executions themselves (i.e. non-temporized model). In brief, alternative models proposed here are discrete, qualitative, mechanistic (all processes are explicit) and possibilistic (i.e. non-stochastic and yet non-deterministic). This allows these discrete-event and possibilistic models to account for rare events and assess all possible reactions to a given perturbation or management action, which enables identifying those leading to (un)desirable states (Aloini et al., 2012; Zeinalnezhad et al., 2021). Additional properties on the principles of such unusual models in living and environmental sciences can be found in literature of biology (Blätke et al., 2011; Machado et al., 2009; Naldi et al., 2011; Thomas and Kaufman, 2001) and more rarely in environmental sciences (Akhtar et al., 2019; Gaucherel and Pommereau, 2019; Su and Huang, 2018).

3.3 Model building and scenarios

For each of the four sub-ecosystems of the region, we selected their main bio-ecological, physicochemical and social-economic components (variables) and processes based on literature, field observations, and stakeholder interviews (Appendix 1). As said, it is mandatory to combine social, economic, physicochemical and ecological processes, even if simplified, to gain a balanced and less biased understanding of the risk propagation. The modeling results are estimated to be realistic over a period of approximately 30 years, as computed trajectories were qualitatively validated. Beyond this period, major biological or technological innovations might become apparent, likely making model predictions irrelevant, and would require the model to be redefined. Rules may describe slow (e.g. forest development) or fast events (e.g. season changes). We excluded long-term processes (e.g. ecosystem successions due to climate change or human migrations) and very short term processes, as these could not be translated into sound immediate managements.

The following ecosystem models were developed in four successive steps: a) building the geo-social-ecological system network (i.e., a set of components and their related processes) to represent the ecosystem structure centred on the leading questions (Fig. 2a); b) transforming this ecosystem network into a model based on qualitative variables and rules (Fig. 2b); c) defining the initial state by assigning an initial value to each variable and translating the model into a Petri net (Fig. 2c); and d) computing the state space and analysing it (Fig. 2d-e, detailed thereafter). Variables and processes have been selected for allowing a relevant analysis of the geo-socio-ecological dynamics and addressing our chosen questions. There is a trade-off between the number of variables limiting the model size (it should sum up to less than 40 variables to remain fully tractable) and the detailed view of the whole system changes: in our case, between four and ten variables per social-ecological system were optimal. In addition, selected variables should take into account for most component categories and be sensitive to interannual changes over the 30-year temporal extension chosen.

We first modeled the four social-ecological systems as independent modules and studied their main dynamical properties and stabilities. We then assembled them without geological hazard as a reference scenario, leading to model with 29 variables (Table 1) and 113 rules (App. 1). Based on the reference scenario (RS), we built two other scenarios: the blast scenario to assess ecosystem recovery to a blast eruption (with subsidies provided in the aftermath of the eruption, BS) and the "no subsidies" scenarios to assess recovery to a blast eruption in absence of subsidies (from NGOs, local or foreign states, SS). The chosen scenarios are defined by one-off conditions without any timeline. Yet, each scenario generates event successions computed by the three model versions. The social-ecological system was represented by its interaction network made up of material variables (nodes) connected through their related processes (edges) (Fig. 1b and Fig. 2d). The integration of these components and their relations were assessed using literature and interviews with experts at the Nelson Mandela African Institution of Science and Technology (NM-AIST) in Arusha and Istituto Oikos and local stakeholders (during the year 2018).

3.4 Model analysis

A STG is generally too large to be visually analysed (Gaucherel and Pommereau, 2019) and dynamics must be simplified in order to be intelligible. For this reason, we made a huge effort to summarize the computed dynamics into tables and oriented graphs directly derived from the state spaces (Appendix 2, Fig. S1). One method is to reduce SCCs and basins to single nodes (Béranguier et al., 2013). In such a representation, nodes are SCCs and basins, and a transition between two nodes indicates that there is a transition between at least two states of the corresponding topological structures (Cosme et al., 2021). This enabled to identify attractors and compare them with the initial stability. In this study, we removed transient dynamics (basins) to focus on stabilities only (e.g. in App. 2). Then, we merged stabilities that were connected and had the same size. Indeed, sets of stabilities sharing the same properties (of connection and size) suggest that they can be "mapped" onto each other and match, every state change having exactly the same dynamic behaviour (while having slightly different compositions). We call these set of merged stabilities the *system's regimes* and they were gathered into the *regime graph*.

Another method to simplify a STG is to merge nodes sharing a similar property. For instance, we previously indicated that we merged all neighbouring SCCs of the same size. We mostly used state properties to partition vegetation types, human activities and sub-ecosystems. Based on such partitions, we merged all states of the same class (Table 2) in a *summary graph* (Diop et al., 2019). This enabled visualizing (1) in what order vegetation, human activities and sub-ecosystem recovered and (2) which human activity profiles (i.e. sets of co-occurring activities) exist in a SCCs and the transitions between them. We analysed the reference scenario using a correspondence analysis (CA) applied on STG states for an overall view of the relations between model variables. In summary, we first built the ecosystem network (Fig. 1b) and the model (Tables 1 and Appendix 2), we then computed the dynamics (Fig. 3 and App. 2), and interpreted them by categories (Fig. 4-5 and Table 3), . Maps and CA analyses

were performed using ArcGis 10.4.1 and R 3.2.5 softwares. Models are calculated with Python 3.7 and the TINA tool (Berthomieu, 2017).

4 Results

4.1 Reference scenario (RS)

The Meru ecosystem network is partitioned into sub-ecosystems modules of this region (Fig. 1, colors). Despite several spatial relations, Arusha city, Northern Meru, the National Park and the cultivated lands display relatively independent functioning (Table 1 and App. 1). The reference scenario led to a STG with $3.9 \cdot 10^5$ states connected by $8.8 \cdot 10^6$ transitions. This STG was reversible, i.e., was a single stability. Regarding social-economic transitions, losing several activities simultaneously was possible while gaining many was not. Diseases were the only processes causing simultaneous losses of several activities while other losses were related to overgrazing, diseases, water sources over-exploitations, human-wildlife conflicts and loss of wildlife (not shown). The diversification of the regional social-economic profile was related to purchase of pesticides and fertilizers, crop production and pastoralism, respectively (not shown).

4.2 Post-eruption with financial assistance (BS)

The blast scenario led to an irreversible STG partitioned into 438 stabilities and 172 basins, including one attractor (App. 2, Fig. S2 and S3). Following the eruption (red transitions, Fig. 3), the system progressively recovered through several successive stabilities (i.e. the system reaches a stability of the same size as the initial stability). Yet, as central results, (i) human populations always resettled shortly after the eruption, within one season, and (ii) the attractor had the same size as the reference scenario STG, suggesting that they were a mutual projection and had the same dynamic behaviour. The summary graphs indicate that human activities first recover through either agriculture or pastoralism, while tourism always recovered later (Fig. 4, Table 2). The first vegetation types to recover were savanna and/or agricultural land, followed by forest (mainly found in the National Park). The regime graph led to a smaller but still complex graph (35 nodes, Fig. 3).

4.3 Post-eruption scenarios without financial assistance (SS)

The scenario combining the blast eruption and the interruption of subsidies resulted in an irreversible STG (App. 2, Fig. S4). We extracted the system's regimes, which resulted in a symmetric graph (dynamics were identical on both sides, App. 2, Fig. S6). Therefore, we merged all stabilities of the same size, regardless of their connectivity, to summarize the system regimes (Fig. 5a). In this scenario, the economy was mostly based on tourism and had a constant food production (agriculture and/or pastoralism, regimes 1 to 5, Table 3, Fig. 5b, 5d). This configuration may be transformed such that food production can be lost (regimes 2 and 7, Fig. 5c, 5e), while other transitions may lead to the disappearance of tourism (regimes 6 and 7, Fig. 5d, 5e).

In any of the regimes 1 to 7, the system may undergo a blast eruption, leading it towards two alternative transient regimes (8 and 9, Fig. 5a). These stabilities represent a bottleneck following the disaster. They display contrasting dynamics (as they have a different size), but have similar socio-economic transitions (Table 3, Fig. 5f). As in the first blast scenario (section 4.2), the system had the possibility to first recover pastoralism or agriculture which may be combined subsequently (Fig. 4). However, in absence of subsidies, tourism was unable to recover from the eruption. Moreover, infrastructures could not be rebuilt, which isolated the region. This configuration of the system made it impossible for local people to sell or buy goods such as seeds, livestock, pesticides or fertilisers purchases, and rather only relying on local (rural) social-economic drivers, without national and international connections. Forest recovery stabilized the system into an attractor (regime 11, Table 3).

5 Discussion

This study illustrates the first attempt to assess disaster risk and recovery trajectories with possibilistic models, to face the challenge of geo-social-ecological system management. As a take-home message, discrete-event models are able to integrate complex systems exposed to volcanological risks for identifying (un)desirable trajectories. By using discrete-event models borrowed from theoretical computer sciences (Ehrig et al., 1973; Giavitto et al., 2012; Pommereau, 2010), we demonstrated here their ability to handle between-domain interdependencies and to exhaustively compute possible trajectories of a complex geo-social-ecological system impacted by multi-hazard eruptions and anthropogenic disasters. In addition, the model represents a qualitative framework combining in a parsimonious way all relevant components and processes of the studied region (Cosme et al., 2022; Gaucherel and Pommereau, 2019). Our model provides an integrated assessment of the environmental risk, whatever the concerned number of hazard, vulnerability and exposure variables (Favereau et al., 2018; GAR-UNDDR, 2019; Prasetyo et al., 2020; The-Geneva-Association, 2018). Whereas most risk assessment in volcanology provide a unique index being most of the time static (Eiser et al., 2012; Selva et al., 2010), our approach is complementary in providing detailed trajectories.

As a central result in the studied region, the model suggests that, starting from the chosen initial state, human populations, economy and vegetation would recover (Fig. 4). The computed state space perfectly illustrates the “vulnerability chain” listing the causal chain responding to the vulnerability functions previously gathered into the interaction network of the system (Fig. 1b). The Mt Meru region and Arusha city would even be resilient to a blast eruption (pyroclastic flows with dense mixtures of hot volcanic fragments and gas, BS) on every slope of the volcano cone (Q1 and H1). Our exploratory model can describe in more details this resilience. Although the system may reach the attractor and fully recover its pre-eruption dynamics, it may also remain in any of the intermediate stabilities. We found that the system could thus undergo dramatic transformations through geological and economic (i.e., a lack of subsidies) disasters and reorganize itself towards a local and rural economy. The

trajectories exhibited by the exploratory model, provide a guideline to help decision makers by choosing infrastructures implementation ahead of the disaster.

5.1 The Mount Meru pre- and post-eruption risk assessments

The reference scenario (RS) exhibited a reversible state space, highlighting the potential resilience of the Mt Meru region, irrespectively of recovery time and transition probabilities, in agreement with literature for similar environments (Buisson and Le Stradic, 2019; C.E.R. and T.M., 2014). We considered the system to be resilient when it recovers a dynamic (here, a structural stability) similar to a past dynamics (the same stability). Hence, we supposed the resilience to be a set of trajectories rather than a state or a set of states of the studied system (Cosme et al., 2022; Gaucherel and Pommereau, 2019). Reversibility becomes possible in such a qualitative model as a functionally “absent” component may reappear when crossing its predefined threshold. Multivariate analyses showed a balanced distribution of the variance along principal components (CA, App. 2, Fig. S1), suggesting that processes and components were relatively complementary and non-redundant (App. 1). This illustrates the strong integration capacities of the model based on the ecosystem network (Fig. 1b).

As expected, when looking at explosive eruptions in the history of humankind, the blast scenario (BS) also showed a potentially resilient Mt Meru region. Following the blast, if the system reaches the attractor, it will recover its pre-eruption dynamics (Fig. 3). Indeed, social-ecological systems have survived to similar disasters (Ambrose, 1998; Grattan, 2006; Prasetyo et al., 2021), even to an extreme eruption as modeled here. This confirms our first hypothesis (Q1 and H1) stating that scenarios RS and BS are resilient to non-volcanic and volcanic disasters, respectively. Hence, an irreversible state space may be resilient and, reciprocally, state space reversibility does not necessarily imply resilience but provides some conditions for resilience. We also partially confirmed our second hypothesis (Q2 and H2) that agricultural activities arrive first after the volcanological impact in BS and SS (Fig. 4). However, the system had two alternative social-economic recovery trajectories, one possibly starting with pastoralism, the other with crop farming. Agriculture and pastoralism remain key sets of local activities in Mt Meru region to favour the social-ecological system resilience (Buisson and Le Stradic, 2019), another central result of our study. Hence, vegetation plays a central role in semi-arid social-ecological systems such as savanna, and as expected, agricultural areas always recovered first before forested areas (Fig. 4, Table 3). Such models are generic enough to be applied to any social-ecological systems at risk, and already helps improving our understanding of such complex systems and related dynamics (Gaucherel et al., 2020).

The eruption (in BS as in SS) destroyed the vegetation, but Northern Meru savanna and then forest recovered (Fig. 4 and Table 3), in agreement with studies of the mount St Helens eruption in 1980 (Dale et al., 2005). The Mt St. Helens eruption, similar to the BS modeled here, showed a so-called secondary succession of vegetation involving communities of species typical of disturbed habitats, while a primary succession involving pioneer species seldom appears after an eruption (Crisafulli et al., 2015). Indeed, many organisms including seeds often survive to an eruption, promoting a quick recovery. Moreover, volcanic ashes will

be progressively absorbed by leaching, enriching the soil with key nutrients, such as iron, calcium, magnesium, sodium, potassium, phosphorous, sulphur, silicon and other trace elements, which stimulate plant growth (De Bélizal et al., 2012). Touristic attractions are still lacking at this stage (e.g. the Pinatubo volcano in Philippines, Crisafulli et al., 2015).

As illustrated in the SS scenario, the Mt Meru region is strongly impacted by the absence of financial support (Q2). As a major result, the absence of subsidies yielded an irreversible state space (Fig. 5a, regimes 1 to 7), suggesting a critical role of external financial support for the resilience of the system. Without such subsidies, the social-economic system rewired and exhibited contrasting dynamics (Fig. 5a-e). Initially, the social-economic system exhibits a set of realistic states (only AT, APT or PT, Fig. 5b), but then may transform into sometimes undesirable states with only a few or no activities (Fig. 5e). As an illustration of decision-making processes, stakeholders using our model would observe undesirable trajectories such as the regime 7 exhibiting some states without any activity (Fig. 5e), but desirable trajectories of rural dynamics in the terminal regime 11 (A, P and PA, Fig. 5f). This clearly shows how decision makers could use possibilistic models differently to that of a more traditional risk index (Checkland, 1999; Selva et al., 2010). Interestingly, our models did not assume that humans behave rationally: although they explicitly assigned reasons for rational behaviours through the defined processes (App. 1), they also explored other possible trajectories with implicit causes (Checkland, 1999; Eiser et al., 2012).

Furthermore, the system could not fully recover from the disaster (H2 in SS scenario), as post-eruption social-economic transitions differ from the initial regime. The region recovers a food production (Fig. 5f) and its vegetation in all sub-systems (Table 3). However, the eruption deprived the system of tourism. The potentially stable trajectories following the eruption seemed to be dramatically different to that of the BS, which is particularly striking when comparing attractor sizes (Fig. 4). In a way, this observation contradicts our first hypothesis that the region would collapse (H1) but instead reorganises its structure to end up in an apparently economic and ecologically viable functioning. On the other hand, it confirms the second hypothesis (H2) that the region would recover through trajectories necessarily involving agricultural activities. This lack of resilience is likely due to the absence of roads, which we can expect could be rebuilt through local initiatives (and subsidies) as many examples show an intense economic boom following eruptions (Benson, 2005). Hence, as preliminary recommendations and policy implications, we suggest i) to favour local development by subsidies and organization, and ii) to rapidly rebuild the road infrastructure (Fig. 1, plain lines). As perspectives, the model will be improved to integrate more coping and mitigating strategies to infrastructure and institutional destructions. It will also be given to local authorities and hopefully used by various stakeholders.

5.2 Power and drawbacks of possibilistic models for risk analysis

We proposed here a new model family for predicting and understanding *environmental risk*. The discrete-event and qualitative model with non-deterministic and asynchronous properties allowed an exhaustive identification of possible trajectories, from the initial pre-disaster state to the disturbed ones towards possible stabilities (Fig. 2). Our model was based on Petri nets,

which are one commonly-used engine for computing discrete-event dynamics. The representation of the interaction network (Fig. 1b) combined to its topological (i.e., present/absent) transformations allows reaching this realism in social-ecological system integration, whatever the studied system and the disaster applied to it (question Q1, Fig. 3-5). The size and complexity of the model remained manageable, mainly due to the fully qualitative approach and the associated minimal assumptions, thus allowing a generic and rigorous formalization of any *ecosystem development* (Gaucherel et al., 2017). Similar models have been developed in computer sciences and in biology, for example on molecular signalling networks (Blätke et al., 2011). Other qualitative models were used in environmental studies, yet focusing on much smaller interaction networks (Dambacher et al., 2003; Gaucherel and Pommereau, 2019). To our knowledge, this is the first time these models have been applied to environmental risk assessment (here in volcanology) and to realistic social-ecological systems, although Petri nets and discrete-event models were already known in risk analysis (Aloini et al., 2012; Amin et al., 2019; Nyvlt and Rausand, 2012).

An increasing number of risk models are being developed today (Deligne et al., 2017; Leung et al., 2003; Neri et al., 2008; Wild et al., 2019), but they usually focus on relatively short term impacts (a year or less), include only some parts of the risk facets, and focus on most probable trajectories, thereby excluding rare events of potentially tremendous importance (Clarke, 2008). In this paper, we developed a discrete-event and possibilistic model inspired from computer sciences (Giavitto et al., 2012; Pommereau, 2010; Reisig, 2013) to assess volcanological multifaceted risk and long term post-eruption impacts (question Q2, Fig. 3 and 4) for helping in management. A real strength of the discrete-event model is certainly to focus on intuitive and qualitative changes of the system. As such, to focus on topological changes of the whole social-ecological network is equivalent to exploring the system changes over a relatively long time and/or to shifting to a more qualitative view on the system dynamics (Gaucherel et al., 2017). Such an approach is quite close to the systems thinking approach already proposed in disaster risk reduction in that it uses a fully integrated network to describe the system at risk (Checkland, 1999; Sword-Daniels et al., 2015). Yet, instead of analysing this network structure for itself, we propose to build a possibilistic model for handling its changes. Conversely, our approach is not similar to fuzzy logic often mentioned in the same context, as we rigorously handle here qualitative variables with discrete rules instead of numerically handling gradual variables with fuzzy operations (Chen et al., 2011).

The development of discrete-event model remains in a preliminary stage and still requires a number of improvements. One of the strengths of asynchrony update mode is the ability to account for delays between rule executions (events) and to manage concurrent processes (e.g. conflicts of interest). As in every modeling task, the model definition remains partly subjective and dependent on the network definition (Blätke et al., 2011; Gaucherel and Pommereau, 2019). A strength which may also become a limitation of our model concerned the Boolean natures of components (variables), which impede the expression of activity thresholds, e.g., an interaction effect changing between multiple ranges, or quantitative gradients. A multivalued framework (e.g. components taking three or more continuous values) would allow transforming the model toward continuous dynamics at the cost of a

higher computing time and approximations. Also, sensitivity of the model may vary depending on individual components and processes. The qualitative sensitivity analysis we performed highlighted balanced rules apart those related to subsidies (and defining the scenario SS). More research is required to develop a deep understanding of the impact of this model composition on its emergent properties in risk analysis (Aloini et al., 2012; Nyvlt and Rausand, 2012; Zeinalnezhad et al., 2021). Finally, the calibration and validation stages remain challenging for such integrated and possibilistic models. Our objective here was to provide a proof of concept for risk assessment with an exploratory and cutting-edge model, validated with expert knowledge on known trajectories. Conversely, developing a qualitative rather than a quantitative model significantly reduces the amount of data needed and the parameterisation: the model is an abstraction and remains simple and intuitive (Gaucherel and Pommereau, 2019; Machado et al., 2009).

Finally, although we illustrated our network-based and possibilistic approach in the specific case study of a volcanic disaster, the model developed here is generic enough for understanding any social-ecological system and its disaster risk. Acknowledging the deep and tangled interactions between domain-specific components, namely ecological, sociological, economic and geological variables, we first built a qualitative interaction network of the region (the so-called *ecosystem network*). Then, we connected these components through some processes representing the main interdependencies and feedbacks involved, and exhaustively computed possible trajectories of the entire modeled system from the present-day initial state with a rigorous framework. This allowed anticipating resilient regimes as well as sharp changes between regimes, depending on the disaster intensities and types applied to the social-ecological system. Our model now equips environmental sciences with a new tool and reasoning to face the challenge of an integrated risk assessment of social-ecological systems at stake.

6 Appendices

6.1 Appendix 1: Social-ecological processes and the model rules

6.2 Appendix 2: Model construction and details of dynamics

7 References

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8 Tables

Table 1. Model components with name nodes and abbreviations, concerned locations (sub-ecosystems) of the Meru region modeled, together with brief significations and descriptions.

SUB-ECOSYSTEMS	ACRONYMS	SIGNIFICATION	DESCRIPTIONS
Agricultural area, Savanna and Park	Rf	Rainfall	Dry or wet seasons
Savanna and Park	Wl	Wildlife	Wild fauna
	T	Tourists	Tourists can visit the park and the savanna (North meru) areas. They also visit ethnic populations
City	Sub	Subsidies	Government and NGO subsidies
	Lm	Land Managers	Water and conservationist managers
	Rd	Roads	Roads allow movement (for tourism and trading)
	Hc	Health centers	This component takes into account for the health budget and veterinary centers
	Bd	Buildings	City buildings with their inhabitants
Savanna	SFa	Farmers	Ethnic group farmers (agriculture and crafts)
	SFaB	Farmer budgets	Economy associated to agriculture
	SLv	Livestock	Grazers
	Sv	Savanna vegetation	Wood and grasses
	SCr	Crops	Annual crops
	SWs	Surface water	Surface water, rivers and waterholes (artificial or not)
	SWg	Groundwater	All available underground water
Agricultural area	Fa	Famers	Smallholder farmers around Arusha city
	PCr	Permanent crops	Banana, coffe, mango, pigeon peas. They take over a year to mature and can be harvested for a number of years
	ACr	Annual crops	Cereals, tuber/roots, pulse, oil seeds, fruits and vegetables
	If	Inorganic fertilizers	Such fertilizers are expensive (not all famers can afford them)
	ALv	Livestock	Grazers from pastoralism
	APif	Pesticides	Pesticides are chemicals used for controlling insects, diseases and weeds
	Aws	Surface water	Surface water, rivers and tap are the main sources of irrigation
	AWg	Groundwater	This component allows extracting underground water and use it at a waterhole

	FaB	Farmer budgets	Economy associated to agriculture obtained by crop storage (i.e., crops stored for a while as food for the household) to sell at higher prices, as well as seeds to be planted at the next season
	Ps	Pastures	Pasture lands for livestock
Park	PSv	Savanna vegetation	Typical savanna vegetation
	Ft	Forest	Evergreen forest in the park (higher elevation)
	PWs	Surface water	Surface water, rivers and waterholes (artificial or not)
	Mt	Mountain	The volcano and its cone

Table 2. Definitions of the state properties of interest in the modeled region. Each sub-component (e.g. agriculture) of a property of interest (e.g. social-economic profiles) may be associated to other in each system state, e.g. agriculture may/may not be associated to pastoralism and tourism. Human related components/variables are in bold (sec. column). When looking at stabilities, a sub-component is considered present if one or several of its variables are present in all states. It is considered as varying if one or several of its variables are present in one or several state of the stability. Agriculture: crops present (in at least one sub-ecosystem); Pastoralism: livestock present; Tourism: Tourists present; Savanna.

PARTITION	CLASSES	STATE PROPERTIES
SOCIAL-ECONOMIC PROFILES	Agriculture	SCr+ or PCr+ or ACr+
	Pastoralism	SLv+ or ALv+
	Tourism	T+
VEGETATION TYPES	Savanna	Sv+ or PSv+
	Crops / Rangeland	SCr+ or PCr+ or ACr+ or Ps+
	Forest	Ft+
SUB-ECOSYSTEMS	Agricultural area	Fa+ or PCr+ or ACr+ or If+ or ALv+ or APif+ or FaB+ or Ps+
	Savanna	SFa+ or SFaB+ or SLv+ or Sv+ or SCr+

	City	Lm+ or Hc + or Bd+ or Rd+
	Park	Ft+ or PSv+

Table 3. Summary of regimes for the SS scenario. The regime numbers correspond to those of Fig. 5a. A: agriculture; P: Pastoralism; T: Tourism; S: Savanna; C: Crops and pastures; F: Forest; N: Northern Meru; AL: Agricultural Lands; P: Park; C: City. Since regimes are aggregates of multiple stabilities with the same internal dynamics, some may differ and keep the same dynamics. We denote by "±" the fact that some stabilities have a different composition which does not affect the dynamics (e.g. regime 4 (A, T, ±P) may or may not have Pastoralism).

STABILITY IDENTIFIER		SOCIAL-ECONOMIC PROFILES		VEGETATION TYPES		SUB-ECOSYSTEMS	
		Varying	On	Varying	On	Varying	On
1	Pre-eruption	A, P	T	S, C	F	N, AL	P, C
2		A, P	T	S, C	F	N, AL	P, C
3			A, T		F, C, ±S		P, C, AL
4			A, T, ±P		F, C, ±S		P, C, AL
5		P	A,T		F, C, ±S		P, C, AL
6		A, P, T		S, C	F	N, AL	P, C
7		A, P, T		S, C	F	N, AL	P, C
8	Post-eruption	A, P		S, C		N, AL	
9		A, P		S, C		N, AL	
10		A, P		S, C	F	N, AL	P
11		A, P		S, C	F	S	P, AL

9 Figures

Figure 1. Map of the Meru region modeled (a) and its corresponding ecosystem network (b). The Meru region is located in North Tanzania (Coordinates: $3^{\circ}14'48''$ South; $36^{\circ}44'54''$ East), around the Meru volcano (a, picture), and is broadly composed of four social-ecological systems (the park and volcano: green, the savanna: brown, the Arusha town: orange, and the agricultural area: beige), interconnected with the road network (black lines) discussed in the paper. The ecosystem network gathers 46 components (Table 1) belonging to one or several social-ecological systems (same colors), simultaneously interacting through 113 processes (oriented edges, highlighting the influence direction, Appendix 1).

Figure 2. Illustration of a simplistic volcanic hazard system with (a) its simplest interaction graph, (b) its associated rule-based model, made of two components (V, H) and four rules, (c) the corresponding Petri net, (d) its illustrated state space and (e) the state space as it is produced by the model, with labels on arcs and nodes. Note that each state is a list of +/- components. Starting in the absence of both components, it is possible to compute all system states and rule executions (absent nodes are displayed in grey, d). The corresponding Petri net is made of two so-called places (V, H) and four transitions R1-4 (c). In the Petri net, arcs from places to transitions (resp. transitions to places) correspond to the condition (resp. realization) of the rule. A black (resp. white) round arrowhead indicates a positive (resp. negative) condition or realization. When a condition is satisfied, the transition "eats" and creates new tokens (black dots), according to the realization of the rule. The marking of the Petri net (i.e., the token distribution in the net) corresponds to state 2 in (d and e), and the successive states are deduced from the token circulation seen in the dynamics (d and e). Note that the state space in (d) and (e) is reversible, i.e., is a unique stability as any state can reach (directly or indirectly) the initial state.

Figure 3. Regime graph of the blast scenario (BS). Each node corresponds to a regime, i.e., one or several connected stabilities of the same size (node labels and colors). Stabilities of the same size likely share similar internal dynamics, hence the merging. Red arcs represent the blast eruption, and the following nodes correspond to the recovery sequences. This graph should be chronologically read from top to bottom, through the various trajectories connecting every regime with various processes (rules, oriented edges).

Figure 4. Schematic representation of recovery trajectories for the various properties of interest (social-economy, vegetation and sub-ecosystems recovery) in the BS model. Red arcs represent the blast eruption, and the following nodes correspond to the recovery sequences. The graph should be read from top to bottom. Following the eruption, all properties of interest

may recover one (or) or several (&) sub-components at a time. For instance, the agricultural lands always recover simultaneously with the Northern Meru and may recover with the City. Details of properties are given in Table 2.

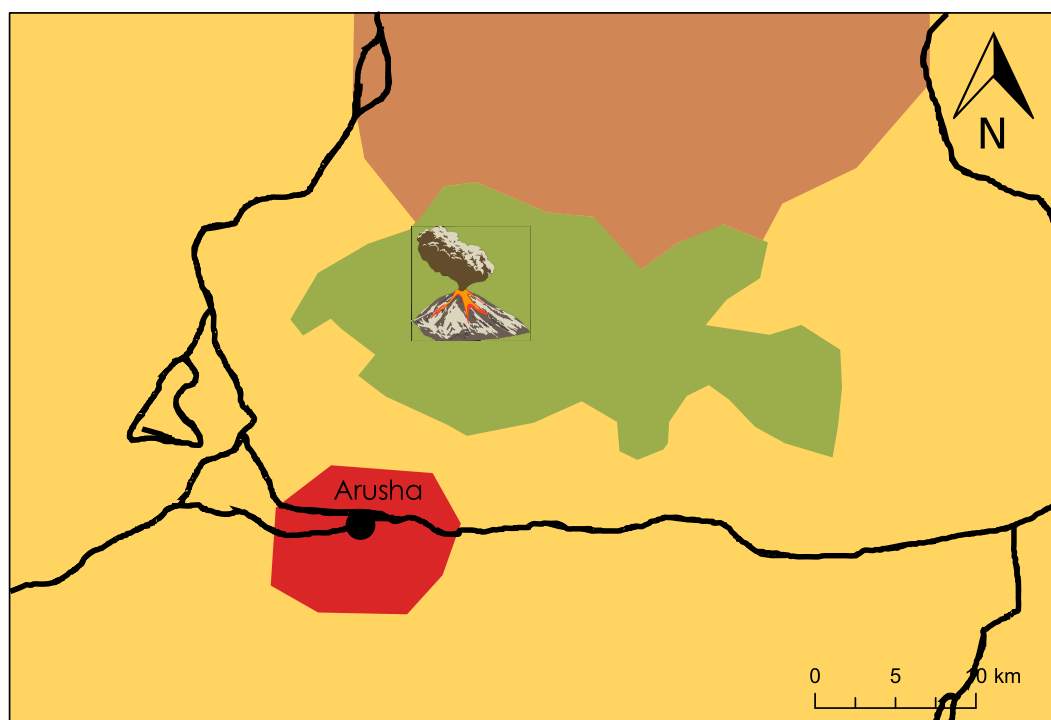
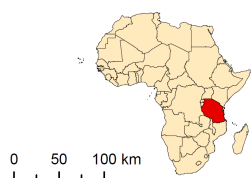
Figure 5. The merged STG of the blast scenario without subsidies. Each node corresponds to a regime, i.e., one or several connected stabilities of the same size (node labels and colors). This graph should be read from top to bottom. Node colors correspond to the sizes of the stabilities before merging them (except in blue). Below the color palette is indicated the number of merged stabilities for each regime. The biggest regimes' social-economic transitions are detailed as sub-graphs in blue (from b to f), with A: Agriculture; P: Pastoralism; T: Tourism. In sub-graphs, the node color is arbitrary. The blast eruption may occur in every state contained in the red box, leading to regimes 8 and 9. Details of regimes composition are given in Table 3.

a)

Socio-ecosystems:

- Park
- Savanna
- Urban area
- Agricultural lands

— Roads



b)

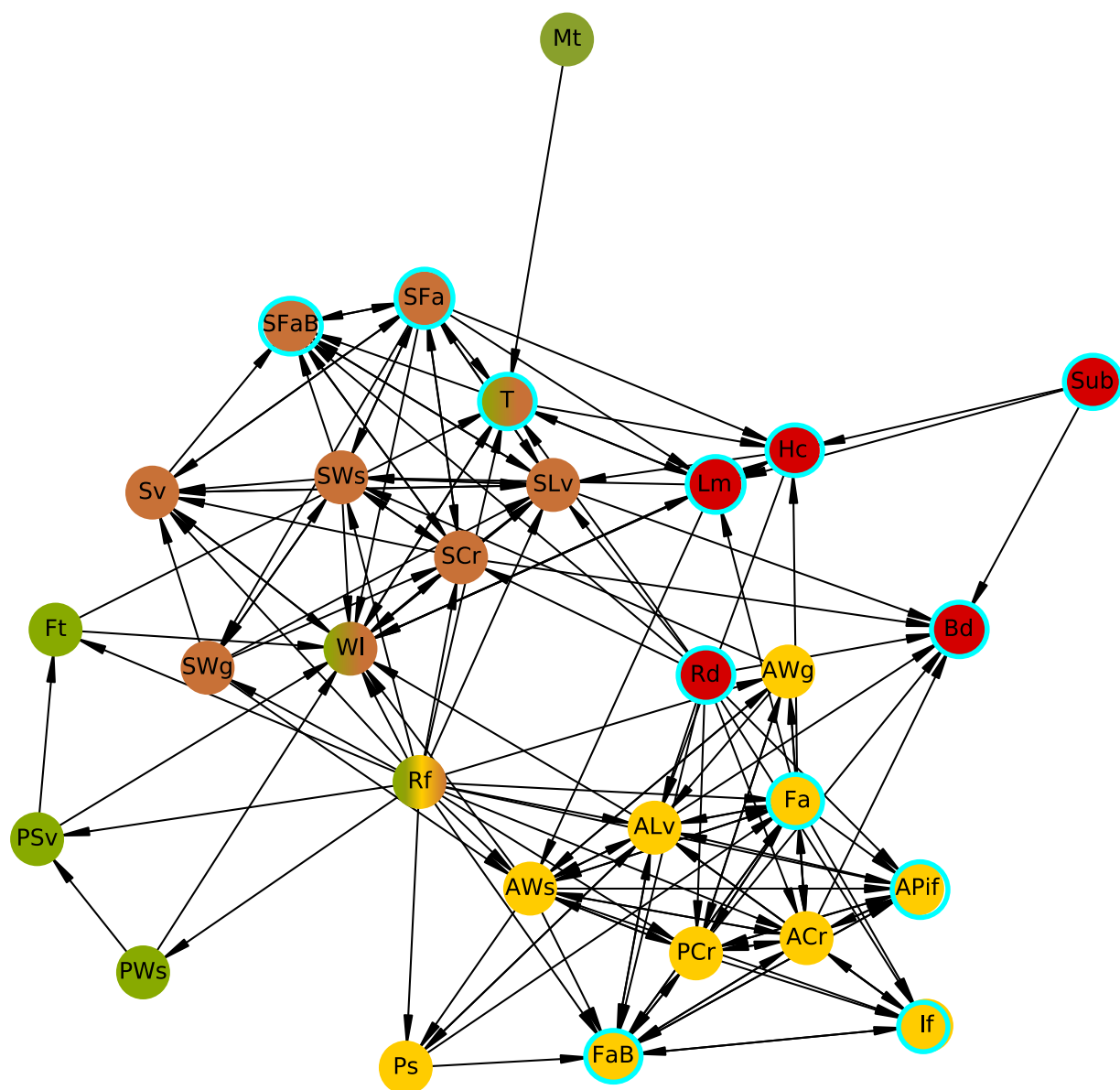
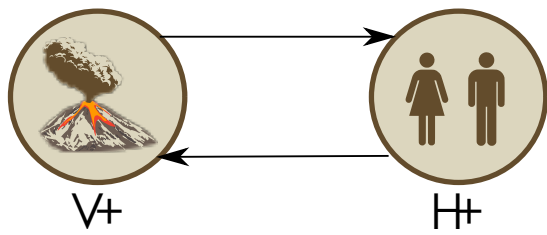


FIGURE 1

a)



b)

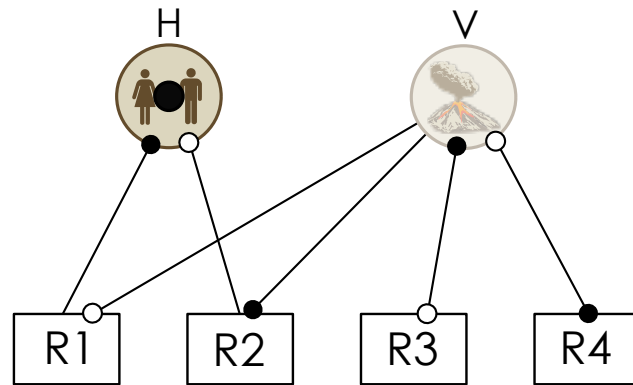
COMPONENTS:

V-: Volcano

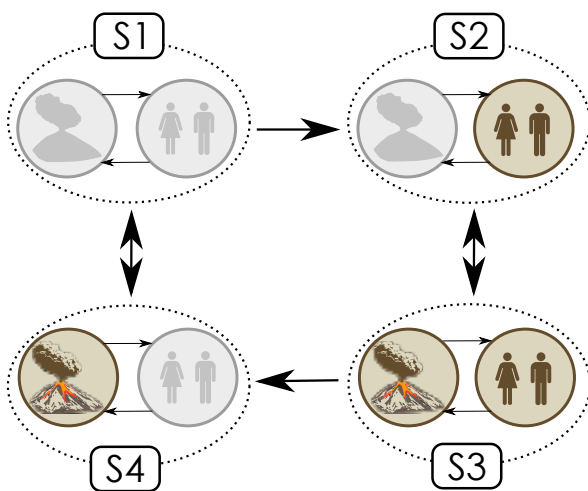
H-: Human population

RULES:R1: $V- \gg H+$ R2/C1: $V+ \gg H-$ R3: $V- \gg V+$ R4: $V+ \gg V-$

c)



d)



e)

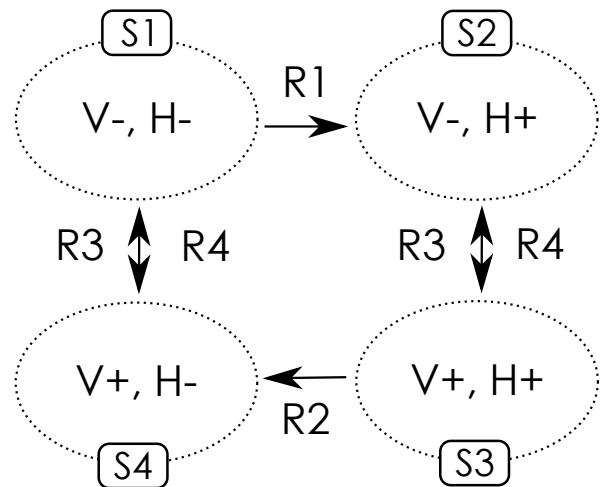


FIGURE 2

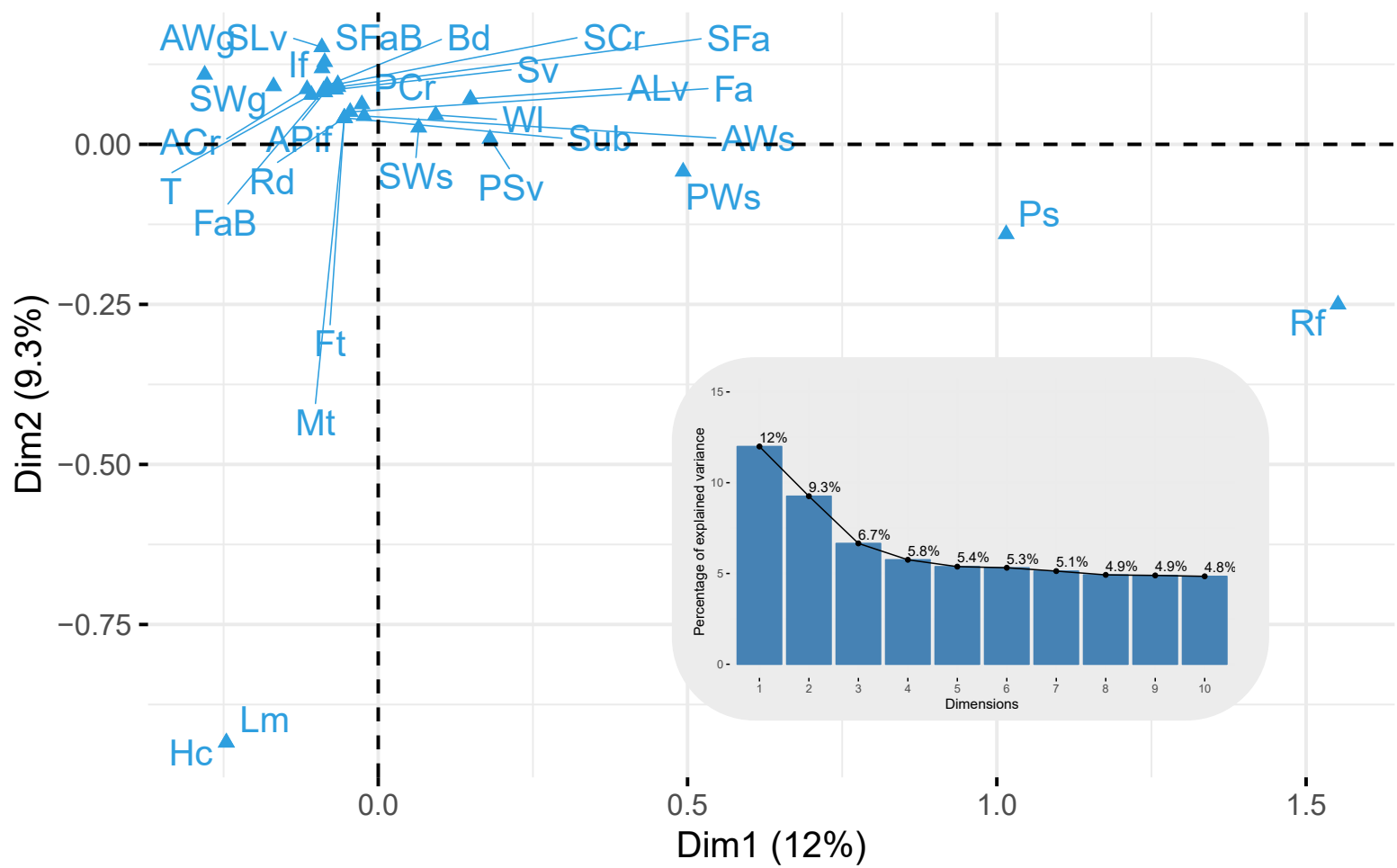


FIGURE 3

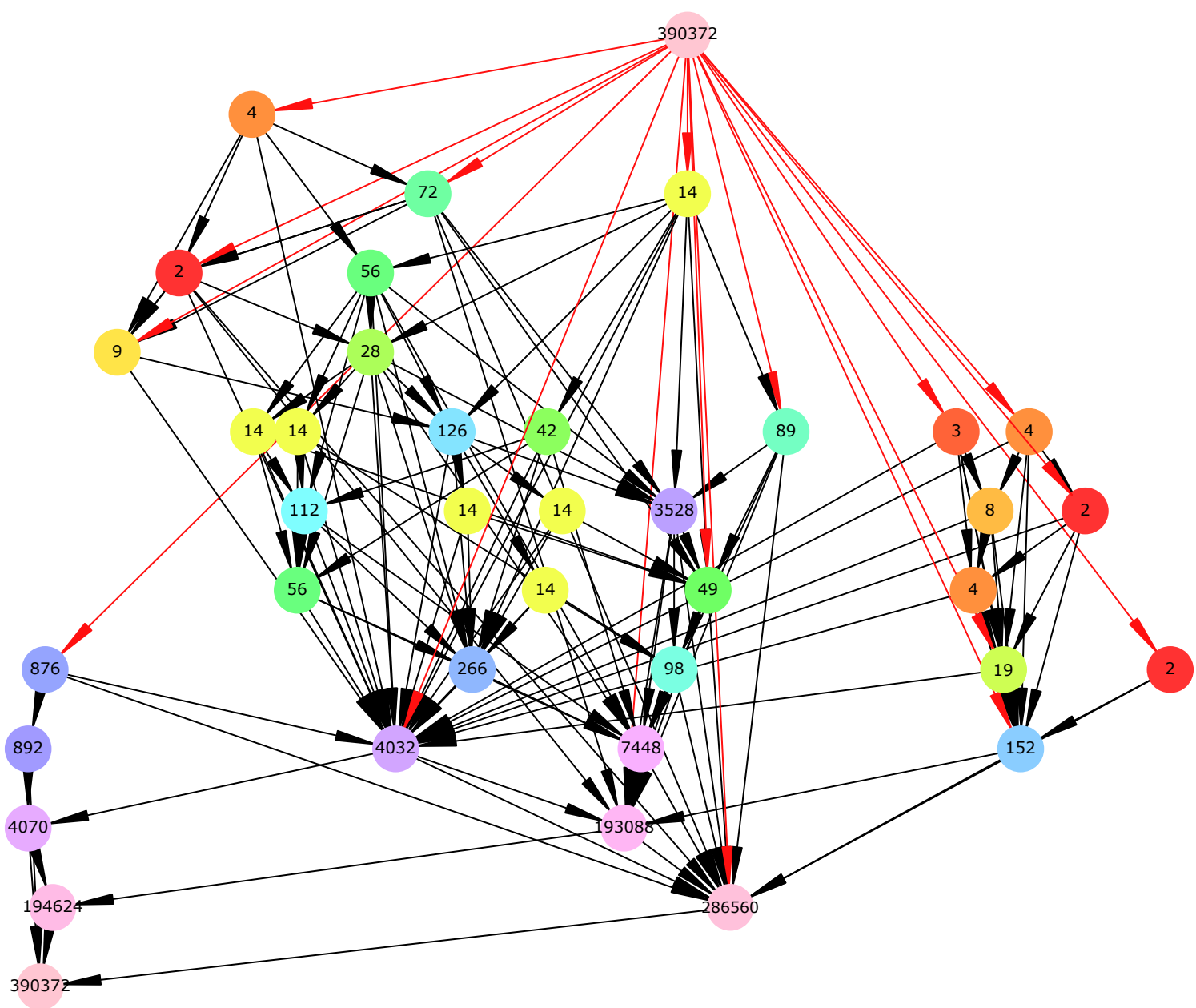


Figure 4

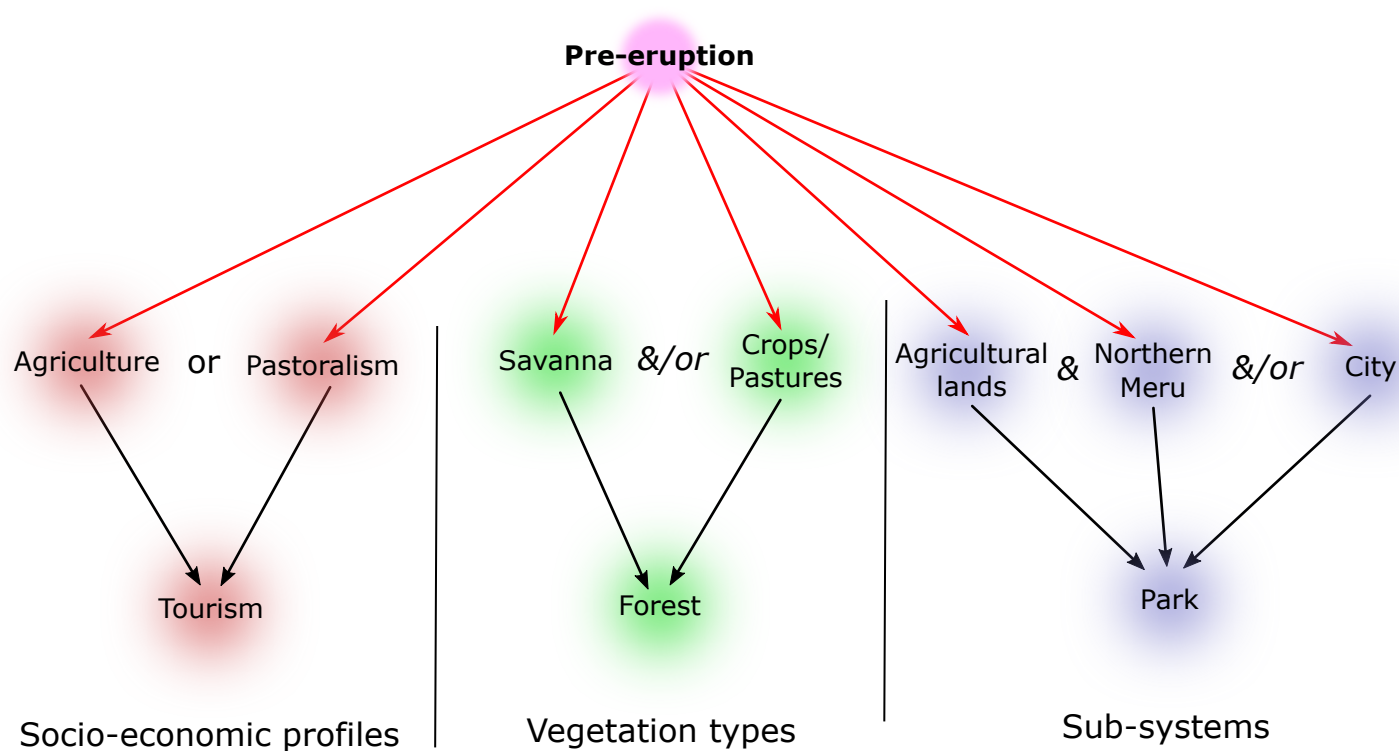


Figure 5

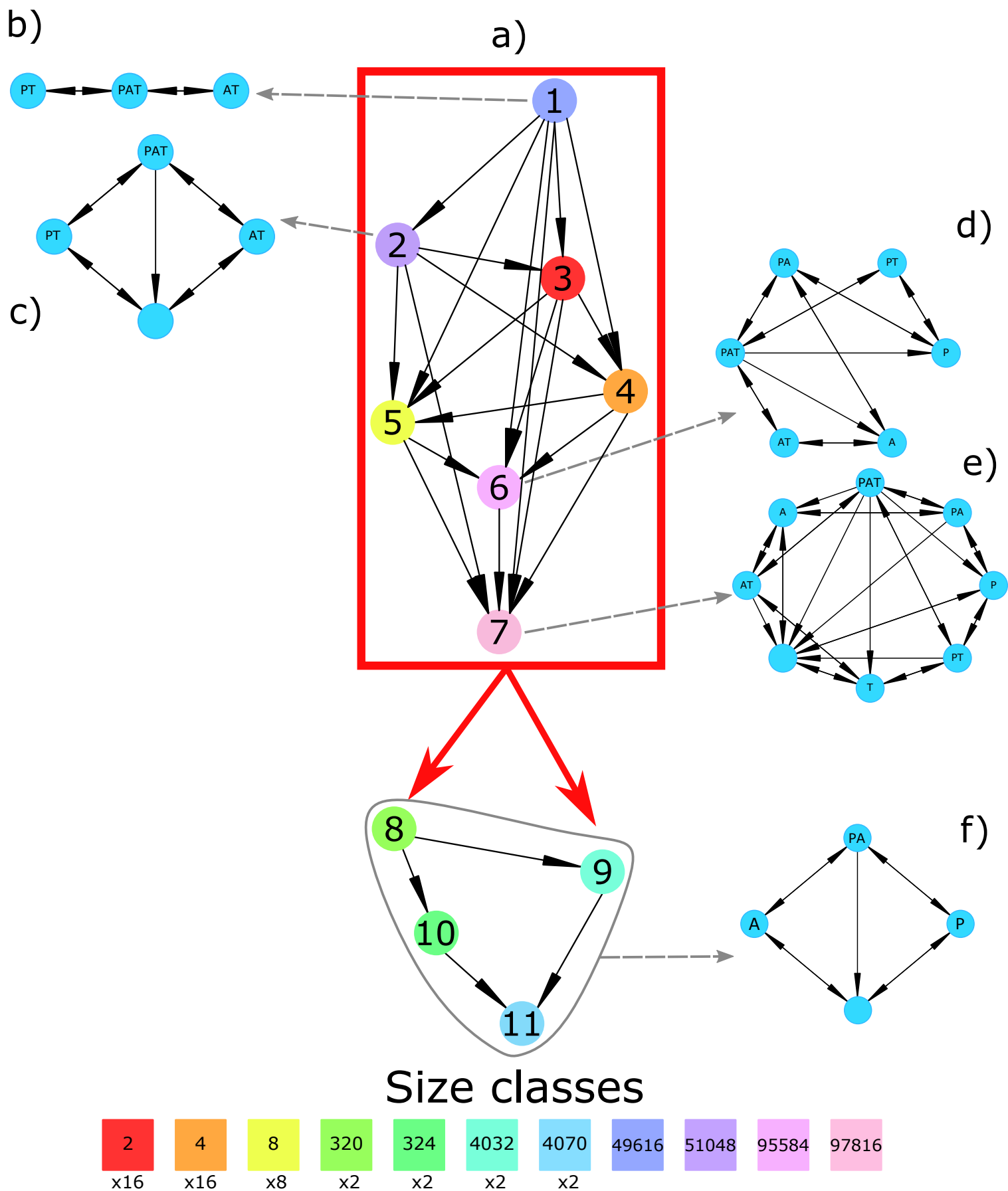


Figure 6