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Drivers of tipping points in coupled human-environment systems

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Abstract. Mathematical models that couple human behaviour to environmental processes can offer valuable insights into how human behaviour affects various types of ecological, climate and epidemiological systems. In many coupled systems, gradual changes to the human system can lead to abrupt tipping points in the overall system, leading to desirable or undesirable new human-environment states. We review aspects of human behaviour–such as social norms and rates of social change–that drive tipping points in the modelling literature, finding that many affect the coupled system depending on the system type and initial conditions. Structural components in the human system, often represented through social networks, are discussed with many studies showing high structural complexity increases the potential for tipping points. Traditional and state-of-the-art techniques in early warning signals are introduced in relation to the human drivers discussed in previous sections. We conclude with an outline of challenges and promising future directions specific to furthering our understanding and informing policy interventions around promoting sustainability within coupled human-environment systems.

1 Introduction to coupled human-environment system models

The interconnectedness of environment systems with human behaviour on the global scale poses complex challenges for sustainable management and policy interventions. Traditionally, mathematical models of environment systems have represented human impact through fixed parameters or functions independent of the environments' current state. These models can be useful under short timescales, however for longer-term dynamics it is important that human behaviour is included endemically in the modelling framework. Coupled human-environment system (CHES) models combine traditional ecological, epidemiological, and climate models with human opinion and population dynamics (Farahbakhsh et al., 2022). The human and environment components of the coupled system have two-way feedbacks such that changes in each subsystem influence one another. The inclusion of these feedbacks lead to increased diversity in the qualitative behaviour of the system, such as whether the long-term behaviour converges to a sustainable or depleted environmental state, or evolves periodically. Shifts between qualitative regimes often occur abruptly at critical values of system parameters, and these tipping points are surprising due to this nonlinear dependence (Lenton et al., 2022). Additionally, in many of these regimes, the system has the potential to exist in multiple states under the same parameters, such as a forest or grassland, known as alternative stable states (Henderson et al., 2016). Gradual or fast changes in system parameters, for example, the rate of resource extraction, as well as sudden disturbances to state variables of the system, like a forest fire, can cause the

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system to abruptly transition between these states. These abrupt transitions, which are often difficult to reverse, are another example of tipping points (Ashwin et al., 2012).

There are many historical cases of human-induced tipping points that have drastically affected the trajectories of coupled environment systems and these effects can be both beneficial as well as catastrophic. Some positive examples include the rebound of the bald eagle and wolf populations following the enactment of conservation laws, as well as the banning of DDT regarding the declining eagle populations. These sudden changes were brought about by strong movements in both public and scientific spheres, putting pressure on governing bodies to enact immediate reform while simultaneously shifting public behavioural norms (Dunlap, 2014; Grier, 1982; Musiani & Paquet, 2004). An example of negative tipping is in the forests of Kumaun and Garhwal in Northern India, where prior to British conquest, wood harvest was sustainably regulated through social norms and strict rules enforced by local village councils. When the British colonial government tried to impose their own rules on the use of these commons, there was a breakdown of social norms and when protests led to these restrictions being removed, the system experienced rapid deforestation rather than a return to its levels under local management (Sethi & Somanathan, 1996).

When discussing human-induced tipping points in CHES models it is useful to understand some of the common tools used to represent human behaviour in these systems. One of the earliest models of human behaviour is the simple voter model where opinion change occurs through a single interaction. In its most basic formulation, nodes on a lattice represent individual humans who are each given an initial opinion from a predetermined set of opinions. At each time step, a randomly selected node will imitate the strategy of another individual randomly sampled from its immediate neighbours (Holley & Liggett, 1975). A frequently used extension of the simple voter model involves individuals accounting for more than just a single interaction for opinion change. In this threshold voter model, individuals only chose a different opinion if the proportion of neighbours holding that opinion exceeds a given threshold (Granovetter, 1978). Adding further complexity, we can model individuals who attribute value to holding various opinions through an associated utility that is dependent on various factors such as economic incentives, ethical considerations and social pressures. Within CHES models, these factors are informed by the basis that opinions determine how individuals interact with the environment. Most commonly, individuals will adopt a neighbour's opinion if their neighbour's utility is higher than their own. This can also be formulated in a stochastic setting, where the probability of adopting a neighbour's opinion is a function of the difference in utility between opinions. Similar approaches can be implemented from a top-down framework, where actors are assumed to be well-mixed and the proportion of humans with each opinion are state variables. Here, individuals sample others in the population at a fixed rate and adopt a different opinion if the other opinion has a higher utility, with probability proportional to the difference in utility. The evolution of the frequency of opinions in the population is represented through ordinary differential equations or difference equations. The majority of CHES models include two opinions; mitigation, which is environmentally sustainable behaviour and non-mitigation, which is detrimental to the long-term health of the environment. Common factors in the utility function are the rate of social learning, which

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determines the speed of human dynamics relative to environmental processes, social norms, which encourage the status quo or mitigation proportional to its frequency, cost of mitigation which measures the economic cost of being a mitigator relative to a non-mitigator, and rarity-motivated conservation which incentivizes mitigation as the environment approaches collapse.

Here we aim to deepen our understanding of human-induced tipping points through CHES models by exploring three crucial topics: the feedback loops and interactions between the human and environmental systems, the structural characteristics of the human system that influence tipping points, and the identification of early warning signals within social systems.

2 Aspects of human behaviour that lead to tipping points in CHES models

It is intuitive that many aspects of human behaviour have direct negative impacts on the environment, such as resource extraction and pollution, however, the severity of these impacts is often hard to predict. In many CHES models, small changes in parameters governing these rates can lead to the abrupt collapse of sustainable states through tipping points which can cascade between the social and environment systems. These transitions have the potential to be catastrophic due to their abrupt nature resulting from nonlinear feedbacks. In many cases, restoration to the system's previous state can be more difficult than anticipated, requiring additional effort than merely a return to parameters before collapse, a phenomenon known as hysteresis.

2.1 Coupling strength

The extent to which the human and environment systems are coupled can have a significant effect on the occurrence of tipping points in both systems. One common parameter representing the coupling strength is the extraction effort of humans, which when increased past a critical threshold, leads to abrupt environment collapse (Farahbakhsh et al., 2021; Richter et al., 2013; Richter & Dakos, 2015; Schlüter et al., 2016). For pollution and climate models, coupling strength is instead represented by pollution rates. The influence of this coupling is less intuitive than extraction effort, for example, in lake pollution models as the pollution output of mitigators is decreased, pollution levels also decrease until a threshold is reached, heralding a negative tipping point where mitigation collapses and pollution then reaches a high level (Iwasa et al., 2007, 2010). This occurs because when the lake water is not very polluted, there is less incentive to be a mitigator and high-pollution behaviour becomes a new norm. It is important to note that these models do not account for individuals valuing the environment in a healthy state, for example through the centering of ecosystem services, and the above example may be an artefact of this assumption. There is a need to shift both our relationship to the environment as well as the assumptions in our models so that inherent value in environment systems is centred and taken into account in any decision-making, even when it is in a state of abundance. This inherent valuing of the environment is present in many traditional indigenous belief systems, where relationships to the local natural environment are incorporated and prioritized in all aspects of life (Appiah-Opoku, 2007; Bavikatte & Bennett, 2015; Beckford et al., 2010; McMillan & Prosper, 2016).

2.2 Rarity-motivated conservation

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Rarity-motivated conservation represents the extent to which humans change their behaviour in response to the environment reaching a depleted state. A case study from Switzerland demonstrates how the perception of crises due to wood shortages and flooding following deforestation played a key role in restoring forest cover (Mather & Fairbairn, 2000). Often there are two critical thresholds for rarity-motivated conservation in CHES models. Increasing this parameter past the lower threshold induces a positive tipping point from a depleted to sustainable environmental equilibrium (Ali et al., 2015; Barlow et al., 2014; Bauch et al., 2016; Drechsler & Surun, 2018; Henderson et al., 2016; Lin & Weitz, 2019; Sun & Hilker, 2020; Thampi et al., 2018; Weitz et al., 2016). The second threshold exists at high values of rarity-motivated conservation, where the sustainable equilibrium is destabilized by overshoot dynamics or a regime of chaos in both the human and environment systems. These dynamics are caused by the human system being too sensitive to changes in the environment leading to extreme oscillations in human opinion and the environment increases the likelihood of collapse in mitigation opinion and the state of the environment (Bauch et al., 2016; Henderson et al., 2016). rarity-motivated conservation can also be represented by a threshold in the state of the environment, below which, humans shift towards sustainable behaviour. In a common-pool resource model, lowering this threshold led to a series of tipping points that surprisingly resulted in a higher biomass equilibrium, although the trajectory to this state comes close to ecological collapse. This is in contrast to a high threshold, which leads to lower final biomass, however, the trajectory remains much farther from a depleted environmental state (Mathias et al., 2020). Similarly to high coupling in pollution models, one should be very careful to not interpret these results as stating “too much conservation is detrimental to the environment”. They rest on model assumptions of a reactionary conservation paradigm, where there is less value in conserving when the environment is in a healthy state.

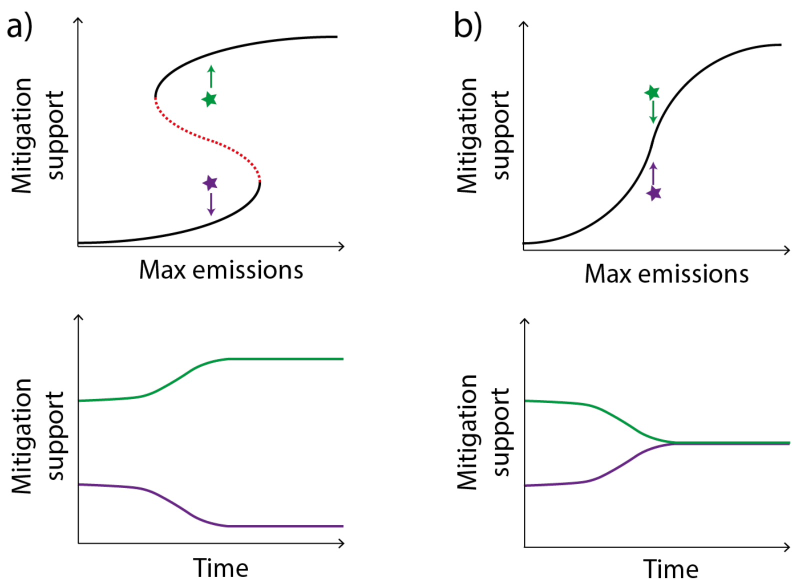

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Figure 1: Strong majority-enforcing social norms lead to bistability, in which the long-term behaviour of the system is highly dependent on initial conditions (a). This bistability is less likely in systems with weak social norms, where the system will converge to the same equilibrium regardless of initial conditions (b). In the top row, equilibrium curves are plotted as a function of the maximum emissions of non-mitigators. Black solid lines represent stable equilibria and the red dotted line represents unstable equilibria. The green and purple curves in the bottom row are the trajectories for initial mitigation support and max emission value given by the stars of the corresponding colour in the upper row.

2.3 Social norms

Social norms are also a significant human driver of tipping points in CHES models. They are often represented as majority-enforcing, incentivizing the opinion of the majority, or mitigation-enforcing, such as sanctions, which only incentivize mitigation opinion, relative to the proportion of mitigators in the current state of the system. When modelling social norms, increasing the strength of majority-enforcing norms leads to an increased number of regimes as well as bistable regimes, which often include extreme equilibria of a single opinion that is highly dependent on the initial state of the system (Ali et al., 2015; Barlow et al., 2014; Bauch et al., 2016; Bury et al., 2019; Phillips et al., 2020; Sigdel et al., 2017; Thampi et al., 2018). Since these norms are indifferent to the type of behaviour they enforce (i.e. sustainable vs harmful actions), they act as a double-edged sword that reinforces the status quo, such that when they are at high levels, bistability occurs as the system dynamics become very sensitive to the initial proportion of opinions in a population (Fig. 1). On the other hand, increasing mitigation-enforcing social norms lead to a transition of the environmental system into a sustainable equilibrium (X. Chen & Szolnoki, 2018; Iwasa et al., 2010; Lafuite et al., 2017; Moore et al., 2022; Schlüter et al., 2016; Tavoni et al., 2012), sometimes through an intermediate regime of oscillatory dynamics (Iwasa et al., 2007). In a lake pollution model, along with decreasing the likelihood of environmental collapse, this increase in mitigation-enforcing social norms also led to the appearance of alternate stable states (Sun & Hilker, 2020).

2.4 Cost of mitigation

Models of coupled human-environment systems have shown that reducing costs associated with mitigative action can lead to positive tipping (Bauch et al., 2016; Milne et al., 2021; Moore et al., 2022; Sigdel et al., 2017; Thampi et al., 2018). This can also be represented through increasing economic incentives to conserve which have similar benefits (Drechsler & Surun, 2018). In coupled epidemiological models, mitigation cost is represented through the cost of vaccination, often through economic cost or the perceived risk of a vaccine. Decreasing this cost leads to positive tipping points from a state with low pro-vaccine opinion and vaccine coverage to high pro-vaccine opinion and vaccine coverage (Phillips et al., 2020). Conversely, increasing this cost leads to a state of high infection and low vaccination. This negative tipping point occurs in the social system at lower levels of cost when majority-enforcing social norms are low, leading to widespread anti-vaccine opinion before the infection becomes endemic again (Phillips & Bauch, 2021). Decreasing profits of actors engaging in environmentally detrimental behaviour can also lead to an abrupt shift to a state of pure mitigators (Shao et al., 2019; Wiedermann et al., 2015), however, this transition can be dependent on a low rate of social change (Wiedermann et al., 2015). Other models demonstrate

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tipping in the other direction where increased non-mitigators' payoff brings about a regime shift to pure non-mitigation and environmental collapse (Richter et al., 2013; Tavoni et al., 2012). An analogue to mitigation cost is taxation rates, which resource users pay towards public infrastructure mediating resource extraction. In a model where actors have the ability to work outside of the system, pushing taxation rates to high or low levels tips a sustainable regime where institutions are at full or partial capacity transitions to a collapse of institutions (Muneepeerakul & Anderies, 2020). In another model, only actors with high extractive effort are subject to taxation and increasing this taxation rate brings about a positive tipping point to a sustainable regime, however, the size of this sustainable region is smaller with multiple governance nodes evolving through social learning compared to a single taxing entity (Geier et al., 2019).

2.5 Rates of social change and time horizons

Human and environmental change often occur on different timescales and their relative speed plays a major role in the long-term dynamics of the coupled system. In CHES models, this relative speed is usually controlled by the rate of social learning which determines how frequently individuals interact and consequently, the pace of opinion change within a population. Changes in the speed of the social system can have very different outcomes depending on the nature of human-environment coupling. In input-limited models, where humans are extracting from an environmental resource such as fishery models, increasing the speed of the social system relative to the environment often destabilises sustainable equilibria, leading to oscillations in both systems and, in many cases, abrupt collapse of the environmental state. These overshoot dynamics occur as humans change their opinions too quickly to allow for the environment to stabilise. On the other hand, decreasing the relative speed of social dynamics brings about positive tipping points increasing the stability of the high forest cover (Figueiredo & Pereira, 2011), and supporting mitigators for a generalised resource (Hauert et al., 2019; Shao et al., 2019). These positive effects have also been observed in adaptive network models where agents imitate their neighbours depending on the profitability of their strategies (Barfuss et al., 2017; Geier et al., 2019; Wiedermann et al., 2015). The reduced speed of social change leads to positive outcomes as the resource is allowed more time to stabilise before decisions regarding extractive levels occur. There are also other relative rates of change that significantly influence the existence of a sustainable regime. For example, in an agricultural land use model, increasing the speed of agricultural expansion and intensification relative to human population growth leads to the collapse of both the natural land cover and human population (Bengochea Paz et al., 2022).

In output-limited models, where human activity increases levels of harmful outputs, such as pollution models, increasing the speed of social interaction is more model-specific. In some cases, such as forest-pest and climate systems, increasing the speed of the human system leads to better mitigation of environmental harms in the short term, however, long-term sustainability often requires additional social interventions such as reducing mitigation costs and increasing levels of environmental concern (Ali et al., 2015; Barlow et al., 2014; Bury et al., 2019). In lake pollution models, higher relative speeds of social dynamics were shown to destabilise low-pollution equilibria, leading to limit cycles and eventually a polluted state with no mitigation (Iwasa et al., 2007, 2010; Sun & Hilker,

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2020). This is a similar phenomenon to the overshoot dynamics that occur when the human system is extremely reactive to the environment discussed in the case of rarity-motivated conservation. However, these outcomes are highly dependent on other social parameters since a similar model found that under no social hysteresis, represented by mitigation-enforcing social norms, and strong ecological hysteresis, represented by a high phosphorus turnover rate, fast social dynamics had the ability to stabilise oscillations to a low-pollution equilibrium (Suzuki & Iwasa, 2009). The emergence of oscillations under low rates of social learning, which was not observed in similar models is likely due to the ecological system being in a bistable state under strong hysteresis, such that even slow changes in the human system could tip the lake system into an alternative stable state.

When looking at relative timescales of human and environmental systems, it is clear that rates of change in the human system have much more malleability when it comes to interventions. This suggests an urgent need to further study the relationship between social and ecological timescales across a wide range of coupled systems to aid in sustainable policy-making decisions (Barfuss et al., 2017). Additionally in many models, the length of time horizons that humans take into account when deciding how they interact with the environment has a significant beneficial effect on conserving natural states and mitigating harmful action (Barfuss et al., 2020; Bury et al., 2019; Henderson et al., 2016; Lindkvist et al., 2017; Müller et al., 2021; Satake et al., 2007). A high degree of foresight in decision-making is a fundamental basis for many indigenous belief systems across the world. One manner in which this shows up is in land stewardship where care for the environment is prioritized as a means to ensure the health of many generations in the future (Appiah-Opoku, 2007; Beckford et al., 2010; Ratima et al., 2019).

3 Structure of human system that affects tipping points in CHES models

3.1 Social traits

In agent-based CHES models, humans are represented as individual agents that follow a set of rules. The inclusion and distribution of traits within agents as well as the structure of social networks can play a large role in determining the occurrence and types of tipping points within the coupled system. Many models discussed in the previous section allow humans to choose between two strategies, often one that is beneficial to the environment and one that is harmful. The inclusion of additional strategies, determining how actors interact with the environment and each other, can alter the potential for tipping points. For example, a common-pool resource model included a third strategy of conditional mitigation (Richter & Grasman, 2013). Under this strategy, agents act as mitigators until the number of non-mitigators reaches a certain threshold, where they then shift their behaviour to non-mitigation. The addition of this third strategy alters tipping dynamics in opposite ways, depending on the value of maximum harvesting efforts. When efforts are high, the system is less prone to tipping, however, when they are low, tipping points are more likely to occur. This third strategy also affects tipping points by masking internal social dynamics, leading to more abrupt transitions, even when the system appears to be stable. This occurs when mitigators gradually change their strategy to conditional mitigators which can go unnoticed as their interaction with the environment system does not change. However, when non-mitigation reaches high enough levels, there is a cascade of conditional mitigators choosing non-mitigation, in an example of herd behaviour, which puts abrupt harvesting

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pressure on the resource. Another three-strategy model, where agents are partitioned by resource extraction rates, contrasts dynamics with and without the trait of environmental concern (Mathias et al., 2020). In the absence of this trait, the human system either tips to high-extraction or low-extraction actors, triggering either a negative or positive environmental tipping point, respectively. Including environmental concern, however, leads to an increased number of cascading tipping points between both social and environmental systems. In a coupled agricultural model, where human traits include management strategies that respond to socio-economic and climate changes, decreasing the diversity of these traits among agents in the system, transitions the system from a sustainable state with high food production, landscape aesthetics and habitat protection to a state with low habitat protection (Grêt-Regamey et al., 2019).

3.2 Social networks

In terms of social structure between humans, CHES models have shown that a higher number of connections in social networks increases the potential for tipping points, often through the emergence and growth of a bistable regime (Holstein et al., 2021; Sugiarto et al., 2015; Sugiarto, Chung, et al., 2017). Additionally, the distributions of these connections play an important role. For example in networks with the same average number of connections, higher heterogeneity of connections among nodes leads to tipping points occurring earlier under Ising model dynamics (Reisinger et al., 2022). The distribution of resources in human-environment networks also affects the potential for environmental collapse. This can be controlled through coupled human-environment network models where both human and environment dynamics occur on a multi-layer network. Resource heterogeneity can be controlled through the distribution of carrying capacities or the amount of resource flow between nodes in the network, where higher flows lead to homogeneous resource distributions. In both cases, increasing this heterogeneity can tip the system to a state of low extraction and high sustainability. Heterogeneity in carrying capacities increases the likelihood of sustainable harvesters extracting from a resource with a large capacity, which they can maintain at high levels, eventually convincing neighbouring nodes to imitate their strategy (Barfuss et al., 2017). Heterogeneity through lower resource flows also leads to high-extraction nodes over-exploiting their resource and losing profits in the long run, de-incentivizing neighbours to imitate. Interestingly, optimal resource flow, which minimises the likelihood of resource collapse is found to be close to the critical threshold of resource flow, above which the coupled system collapses. As this optimal resource flow decreases the likelihood of collapse by supplementing resources harvested at high levels, this confers an advantage to high resource extraction. Increasing past optimal levels lead to similar resource levels among high and low-extraction nodes, resulting in higher profits from high-extraction nodes, incentivizing the entire human system to eventually choose the high-extraction strategy (Holstein et al., 2021).

Homophily, the extent to which alike actors interact in social networks, is another structural component in human systems that can play a large role in the occurrence and behaviour of tipping points in CHES models. In a common-pool resource model with two distinct communities, increasing segregation by lowering the probability that agents in separate communities will have a link, softens the abruptness of a single negative tipping point compared to when

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the communities are well mixed. This is due to the occurrence of multiple intermediate tipping points within each segregated community, however, increased segregation adds more hysteresis to the system increasing the difficulty of reversing this transition returning to a sustainable state (Sugiarto, Lansing, et al., 2017). In a public goods game modelling climate change mitigation, where humans are partitioned into rich and poor agents, a transition to group achievement of mitigation goals occurs at a lower perceived risk when there is no homophily and agents are influenced by others from both economic classes equally (Vasconcelos et al., 2014). Another human-climate model that included wealth inequality displayed an abrupt transition to lower peak temperature anomalies when homophily between economic classes approached zero (Menard et al., 2021).

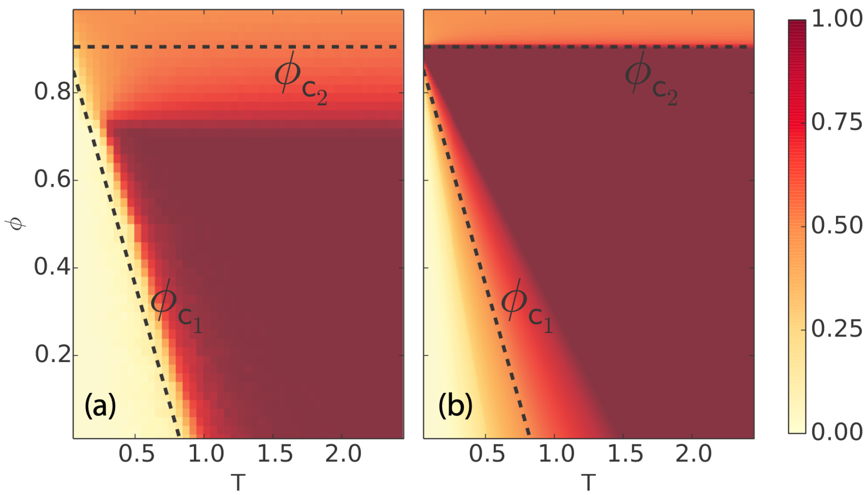

Figure 2: Mean proportion of nodes that are mitigators for network model (a) and ODE model (b). ϕ is the rewiring probability and T is the time between social interactions. ϕ_{C1} is the lower threshold and and ϕ_{C2} is the upper threshold, above which a fragmentation regime occurs. From (Wiedermann et al., 2015)

Social networks are rarely static and their ability to evolve over time is represented in adaptive network models where agents can rewire their social links. Often this rewiring is homophilic, meaning that agents are more likely to create a new social connection with others who share a similar opinion. In these models, the level of homophilic rewiring can trigger regime shifts at both low and high levels, where intermediate ranges correspond to the sustainable equilibrium. As these models are formulated where agents can either choose to rewire or imitate their neighbour, a low level of rewiring corresponds to a high speed of social interaction, which as discussed earlier can lead to negative tipping points. On the other hand, although high-rewiring leads to slower social learning, it also brings about a fragmentation regime where social dynamics are dominated by homophily and the network fragments into components based on strategy type, which makes widespread mitigation infeasible (Barfuss et al., 2017; Geier et al., 2019; Wiedermann et al., 2015) (Fig. 2).

4 Identifying early warning signals in the social system

4.1 Traditional early warning signals

Much research has been done in the past few decades to develop tools that can predict the onset of tipping points using time series data, known as early warning signals (EWS). Originally motivated by the concept of critical slowing down in bifurcation theory, where systems approaching a bifurcation show a slower recovery to equilibrium under perturbations, traditional early warning signals measure trends in this "slowing down". The most commonly used methods compute the lag-1 autocorrelation and variance of the residuals from detrended time series data. Other widely used methods involve metrics such as skewness, measuring the asymmetry of fluctuations over time, and kurtosis, representing the likelihood of extreme values in the time series data. A phenomenon known as flickering occurs when there is sufficient noise to force the system between alternate stable states. In these cases an increase in skewness and kurtosis is observed. As lag-1 autocorrelation does not account for correlation beyond a single time step, power spectrum analysis has been used to look at changes in complete spectral properties, finding higher variations at low frequencies to commonly occur before a tipping point (Dakos et al., 2012; Scheffer et al., 2009). In spatial systems, many EWS are similar to those used in well-mixed systems, while also accounting for spatial variability. For example, Moran's I is a spatial analog of lag-1 autocorrelation, which measures the correlation between neighbouring nodes in a network (Kéfi et al., 2014).

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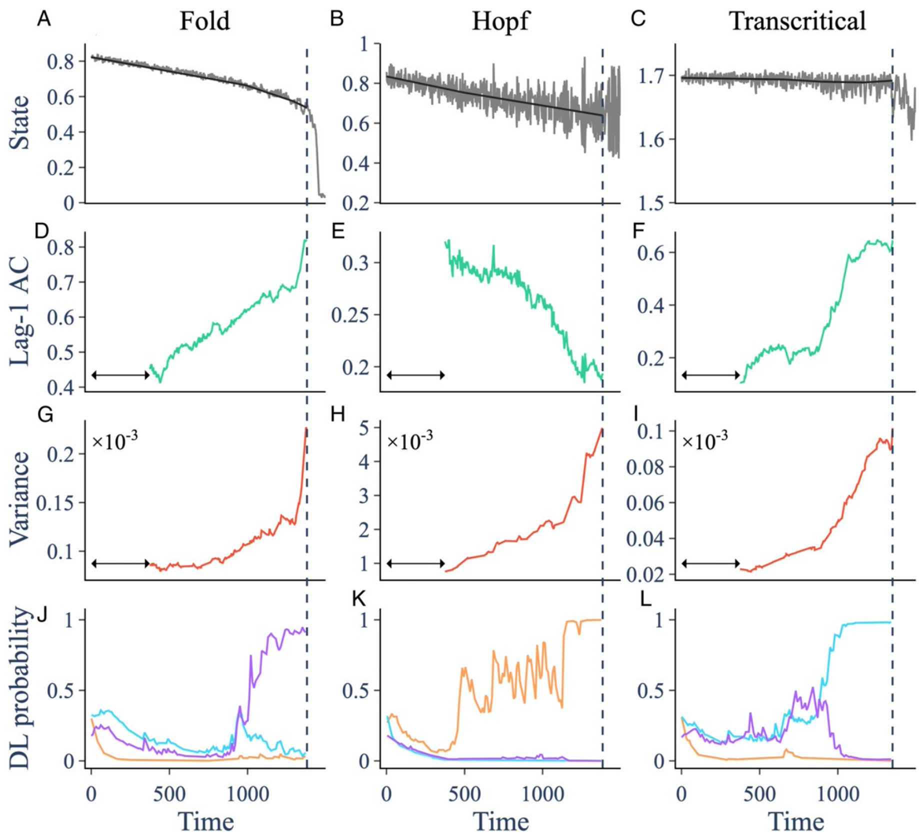

Figure 3: Traditional EWS (second and third row) as well as deep learning EWS (bottom row) from three time series exhibiting different types of bifurcations (top row); fold (left), Hopf (middle), and transcritical (right). As well as being more reliable, deep learning EWS can also distinguish between the type of bifurcation being approached. Image taken from (Bury et al., 2021).

Many spatial ecological systems have been observed to exhibit patterns in patchiness preceding a tipping point. For example, in drylands, spotted vegetation patterns are hypothesised to be an EWS for the system approaching desertification (Kéfi et al., 2014). Coupled human-epidemiological models have also shown that spatial properties in the distribution of opinions on a social network offer potential EWS for the onset of disease outbreaks. Approaching this regime shift, the number of anti-vaccine clusters increases, and very close to the transition point, these communities coalesce into larger groups (Jentsch et al., 2018; Phillips et al., 2020). This behaviour can be quantified using a number of metrics, such as an increase in modularity as well as the mean number, size, and maximum size of communities and pro-vaccine echo chambers (Phillips & Bauch, 2021). This is also in agreement with previous work done in percolation theory showing that phase transitions follow a breakup of connected components on the network (Newman, 2010).

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4.2 Recent advances in early warning signals

One downside to the traditional metrics discussed above is that they have the potential to fail when the system has large amounts of noise and is prone to transitions occurring farther from the critical point. A technique called dynamical network markers increases the dimensionality of the time series by transforming it from state variables to probability distributions of the mean and variance over a given window of time. This reduces the magnitude of noise in each dimension and in approaching a tipping point, one dominant group of variables will show a drastic increase in variance and correlation between other variables within that group. Additionally, the correlation between one variable in this dominant group and others outside the group will decrease. This technique has shown success with empirical data, such as predicting critical transitions in time series data for a eutrophic lake as well as the bankruptcy of Lehman Brothers (Liu et al., 2015), and flu outbreaks (P. Chen et al., 2019). Dynamical network markers have also been used on spatial systems such as those occurring on social networks through the use of hierarchical network representations. Here, networks are transformed into binary trees where leaves are the nodes from the original network and branches group nodes together at multiple resolutions. Through this hierarchical model, dynamical network markers use these multi-scale communities as the groups of variables which are analyzed (Li et al., 2023).

A very recent addition to the early warning signals toolkit uses concepts from statistical physics such as average flux, entropy production, generalized free energy, and time irreversibility to predict tipping points in a shallow lake model much earlier than traditional methods such as autocorrelation and variance, showing promise for use in real-time monitoring (Xu et al., 2023). Additionally, the field of machine learning has motivated data-driven approaches to EWS which do not explicitly make use of any statistical metrics in the time series data. Instead, deep learning algorithms are trained on large synthetic datasets using models that have and have not approached bifurcation points. In the majority of cases, these algorithms have performed significantly better at predicting tipping points than traditional EWS methods when tested on empirical datasets that exhibit abrupt transitions (Bury et al., 2021) (Fig. 3). Deep learning algorithms are also able to distinguish between different types of bifurcations as they are being approached which can offer vital information regarding the potential for catastrophic collapse.

4.3 Social data for early warning signals

In CHES models, the strength of EWS from environmental data has been shown to be muted compared with the environmental system in isolation (Bauch et al., 2016) or the same system with weak coupling between the human and environment subsystems (Richter & Dakos, 2015). This is likely due to the effects of human behaviour acting to mitigate variability in the environment system, for example, rarity-motivated conservation creates a negative feedback loop where incentives to conserve increase as the environment becomes further depleted, serving as a mechanism to avoid collapse. The muting of EWS provides a unique challenge for monitoring tipping points in CHES using environmental data, especially as they occur more frequently in these coupled systems as discussed in Sect. 2. There are a small number of studies that have directly compared the strength and efficacy of EWS between various state or auxiliary variables in CHES models. In these studies, traditional EWS from data in the human system were shown to be the only reliable indicators of the coupled system approaching a tipping point. Examples of

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human data used include the fraction of conservationists in a forest cover model (Bauch et al., 2016), average profits by resource harvesters and catch per unit effort common-pool resource models (Lade et al., 2013; Richter & Dakos, 2015). In agreement with traditional methods, a state-of-the-art machine learning algorithm for EWS showed much higher success in detecting tipping points generated from a coupled epidemiological model using pro-vaccine opinion in the human system compared to total infectious in the epidemiological system (Bury et al., 2021).

The improved reliability of EWS from social data demonstrated through CHES models shows a significant promise for monitoring resilience in CHES through the analysis of socio-economic data. This confers a practical advantage as socio-economic data is often more frequently collected and readily available than environmental data (Hicks et al., 2016). Some examples of this are monitoring profits tied to resource extraction as well as using sentiment analysis on social media data, such as the number of tweets in a given area raising concern over the health of a coupled natural system. Furthermore, citizen science not only generates ecological data but also provides social metadata through the participation of users who monitor specific areas. Leveraging existing platforms like CitSci.org, we can use this data to estimate trends in conservationist frequency over time (Wang et al., 2015). This approach allows for the implementation of real-time monitoring of ecological systems using data that is currently being generated, reducing the need for extensive knowledge or complex mechanistic models of the system.

5 Conclusion and future directions

From a wide range of theoretical models, we are able to gain some insight into human drivers that lead to tipping points in CHES systems. Many aspects of human behaviour, such as reducing mitigation costs and extractive effort or increasing the time horizon in decision-making lead to positive tipping points regardless of the system modelled. The positive effect of these interventions is intuitive, however, the non-linear response to these changes manifested as tipping points may not be and is important to highlight. Additionally, these interventions are perhaps the most clear in their implementation, compared to others that are modelled and occur through simple government policy changes. We can reduce mitigation costs through subsidies for land preservation and green technology, extraction effort through limits on land development and the expansion of protected natural areas (i.e. the Haudenosaunee-led protection of the Haldimand Tract), and increase time horizons through passing long-term legislation that centers the well-being of environment and social systems such as the Green New Deal.

Other aspects of human behaviour are much more nuanced and system-specific in how they affect tipping points. For example, rarity-motivated conservation can act to negatively tip the environment system when it crosses both an upper and lower threshold. Social norms, especially when majority-enforcing increase the likelihood of tipping points through the emergence of bistable regimes that are made up of both sustainable and unsustainable environmental equilibria. The speed of social change relative to environmental change can have different effects depending on the type of environment system being modelled. All these interventions are much more difficult to implement as they require a deeper mechanistic understanding of how to influence social dynamics. Further work in CHES modelling as well as empirical studies on these aspects of human behaviour can aid in the formulation and

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implementation of informed policy. This can be further supported by exploring the interactions of multiple human drivers of tipping points as a recent study has shown that multiple drivers can both reduce the time until tipping or lead to a tipping point that would not occur with a single driver (Willcock et al., 2023). Additionally, as the majority of the work in modelling tipping points has focused on slow gradual changes in the driver, fast changes in drivers require further research as they can exhibit different tipping behaviour (Ashwin et al., 2012).

Studies show that greater structural complexity via the number and diversity of human traits as well as the number of social connections can increase the potential for tipping points and mask social dynamics making these transitions much harder to predict. Directly controlling these structural components would be unethical, however, the model findings allow for a more nuanced understanding of how changes in social structure may affect the resilience of CHES. The literature remains sparse, however, with the diversity of environmental systems coupled to structured human systems, such as those occurring on a social network. This is especially true in output-limited models which are important to improving our understanding of how our social structures affect pressing global issues such as pollution and climate change.

In complement to developing a mechanistic understanding of the many ways human behaviour can drive tipping points through modelling CHES, early warning signals show great potential in predicting these tipping points without requiring a full understanding of the system being monitored. There have been many advances in using state-of-the-art machine learning algorithms to provide accurate EWS from 1-D time series, and very recent work is now developing similar techniques to predict tipping points from spatial data (Dylewsky et al., 2022) as well as predicting the time until a tipping point, a valuable piece of information that traditional EWS do not provide.

CHES models ubiquitously demonstrate the resounding impacts human behaviour has on environment systems, which often occur as human-driven tipping points in the coupled system. Although these models offer valuable insight in understanding key feedbacks and qualitative behaviour of CHES, their predictive power is limited. Additionally, as many model findings can depend on the type of system modelled as well as assumptions in the model formulation, translating this work into policy remains a significant challenge. However, further work in both diversifying model systems and assumptions paired with research in universal real-time indicators of EWS shows considerable promise in both improving our understanding and predicting human drivers of tipping points in the environment.

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