~~Drivers of tipping~~Tipping points in coupled human-~~environment systems~~ environmental system models: a review

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Abstract. Mathematical models that couple human ~~behaviour~~behavior to environmental processes can offer valuable insights into how human ~~behaviour~~behavior affects various types of ecological, climate and epidemiological systems. In many coupled ~~systems~~human-environmental systems with tipping points, gradual changes to the human system can lead ~~to abrupt tipping points in the overall system, leading~~abruptly to desirable or undesirable new human-~~environment~~environmental states. We ~~review aspects of human behaviour~~use snowball sampling to review the modelling of social processes–such as social norms and rates of social change–that ~~drive tipping points in the modelling literature~~are shown to drive tipping points, 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~~For example, tipping points can manifest very differently in input- versus output-limited systems. Some potential interventions, such as reducing costs associated with sustainable behavior, have intuitive results. However, their beneficial outcomes via less obvious tipping point behavior are highlighted. Of the models reviewed, we found that greater structural complexity can be associated with increased potential for tipping points. ~~Traditional~~We review generic and state-of-the-art techniques in early warning signals ~~are introduced in relation to the human drivers discussed in previous sections~~of tipping points and identify significant opportunities to utilise digital social data to look for such signals. We conclude with an outline of challenges and promising future directions specific to furthering our understanding and informing policy ~~interventions around promoting~~that promotes sustainability within coupled human-~~environment~~environmental systems.

Non-technical summary. Mathematical models that include interactions between humans and the environment can provide valuable information to further our understanding of tipping points. Many ~~aspects of human behaviour~~social processes such as social norms and rates of social change can affect these tipping points in ways that are often specific to the system being modelled. Higher complexity of social ~~networks~~structure can increase the likelihood of these transitions. We discuss how data is used to predict tipping points across many systems.

1 Introduction to ~~coupled human-environment system models~~¶

~~The interconnectedness of environment systems with human behaviour on the global scale~~tipping points in coupled human-environmental systems models

Humans are facing environmental catastrophes of their own making, like climate change and biodiversity declines, at local and global scales and yet avoiding these catastrophes still poses complex challenges for sustainable ~~management~~behavior and policy interventions (Steffen et al., 2017). Traditionally, mathematical models of ~~environment~~environmental systems have represented human ~~impact~~impacts through fixed, static parameters or functions independent of the ~~environments'~~environment's 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~~ (Binford et al., 1987; Bosch, 1971; Chaudhuri, 1986; Getz, 1980), and these models can be useful to inform mitigation and adaptation for short timescales. However, for longer timescales, where human dynamics can evolve, it may be necessary to include human behavior endemically in the modelling framework to allow for human-environmental feedback to occur (Bauch et al., 2016; Innes et al., 2013; Lade et al., 2013; Schlüter et al., 2012). Coupled human-~~environment~~environmental system (CHES) models combine ~~traditional~~environmental (e.g., ecological, epidemiological, and climate) models with human ~~opinion~~behavior and population dynamics (~~Farahbakhsh et al., 2022~~Bury et al., 2019; Carpenter et al., 2009; Farahbakhsh et al., 2022; Innes et al., 2013; Lade et al., 2013; Phillips et al., 2020; Sethi and Somanathan, 1996). The human and ~~environment components~~environmental subsystems of the coupled system have two-way ~~feedbacks~~(positive and/or negative) feedback, such that changes in each subsystem influence one another. For example, in Innes (2013), the amount of forest cover influences the proportion of the population that conserves forest ecosystems. The inclusion of these feedbacks ~~lead~~leads to increased diversity in the qualitative ~~behaviour~~behavior of the system, such as whether the long-term ~~behaviour converges~~dynamics converge 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 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).~~¶

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~~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)~~cycle over time. Negative feedback promotes a return to equilibrium (Figure 1a) and can increase the system's capacity to respond to disturbances and adapt in ways that allow the system to maintain the function of social and ecosystem services, which is sometimes referred to as “resilience” (Folke, 2006).

Human-environmental negative feedback loops via processes such as public concern pressuring governments to introduce environmental legislation can be powerful and there are many historical examples of it occurring (Dunlap, 2014; Grier, 1982; Mather and Fairbairn, 2000; Stadelmann-Steffen et al., 2021). Forest cover in Switzerland doubled, following an all-time low in the first half of the 19th century brought about by rapid population growth and early industrialisation. Wood shortages and floods led to public concern, triggering local regulation, the formation of the Swiss Forestry Society, and the first federal forestry law enacted in 1876 that in turn caused a recovery of forest cover (Mather and Fairbairn, 2000). Similarly, the bald eagle population in North America recovered significantly after the banning of DDT by the EPA in 1972. This was instigated by public outcry following the publication of Rachel Carson’s *A Silent Spring* in 1962 which linked DDT in the environment to low reproduction of birds and their declining population (Dunlap, 2014; Grier, 1982). In both cases, gradual recovery of the population was not brought about simply by governmental legislation. There were also strong movements in the public and scientific spheres, directly responding to perceived environmental risk which pressured governing bodies to enact immediate reform (Dunlap, 2014; Grier, 1982; Mather and Fairbairn, 2000). We interpret these two examples as negative feedback loops in a coupled human-environmental system because a decline in forest/eagle abundance stimulated a response by humans which led to the recovery of the environmental system (Figure 1a). These negative feedback loops are pervasive in the CHES models that we review here.

In contrast to negative feedback that promotes an eventual and often gradual return to equilibrium, tipping points describe a phenomenon in complex systems near an equilibrium where gradual changes in external conditions lead to abrupt and lasting shifts in the system state and characteristic behavior (also referred to as a “regime”). One way tipping points may occur is through nonlinear self-reinforcing mechanisms known as positive feedback loops, which amplify these gradual changes, propelling the system into a new stable state in ways that are often difficult to reverse. Such transitions have been extensively modelled using dynamical systems theory, where they exemplify a type of “bifurcation” (Ashwin et al., 2012; Crawford, 1991; Dakos et al., 2008; Lenton et al., 2008). Additionally, many systems with tipping points exhibit alternative stable states, where the system has the potential to persist over long periods of time in one of multiple states under the same parameters (May, 1977; Lenton et al., 2008, Henderson et al. 2016). In many cases, a return to the system's previous state can be more difficult than anticipated, requiring additional effort rather than merely a return to parameters before the tipping point, a phenomenon known as hysteresis, which can make mitigation and adaptation efforts challenging.

Bifurcation theory has been applied to study tipping points in a vast number of environmental models (May and Oster, 1976; Brovkin et al., 1998; Ghil and Tavantzis, 1983; Wollkind et al., 1988); however, more recently, researchers have identified abrupt shifts in environmental systems for which bifurcation theory has yet to be explicitly applied (Dakos et al., 2019; Lenton, 2020, 2013). For example, during the mid–Holocene, the Sahara was much more humid than at present, showing evidence of shrub and savannah biomes as well as the expansion of lakes, an alternative stable state to what we know as its current desert state. It is hypothesised that around 5,000 years ago, the gradual weakening of the North African Monsoon led to an abrupt decrease in vegetative cover, due to positive feedback between reduced surface albedo and precipitation, bringing the Sahara into a stable desert state (Hopcroft and Valdes, 2021; Pausata et al., 2020). In more dominantly human systems, many pivotal revolutions can also be framed as tipping points where gradual changes are reinforced by positive feedback loops, leading to a new political or technological stable state (Lenton et al., 2022). Social tipping points also occur in financial systems such as in the 2008 financial crisis. Here, the bankruptcy of Lehman Brothers led to a rise in public panic around the stability of markets, causing banks to increase their liquidity, amplifying the crisis in other economic sectors and leading to a global recession (Van Nes et al., 2016). These are just two of many examples illustrating how important tipping points are as a phenomenon, in both human and environmental systems, and coupling these systems using mathematical models could lead to further insights.

Since the beginning of the Anthropocene and with our growing awareness of human impacts on the environment, tipping points are increasingly being conceptualised within the context of coupled human-environmental systems (Bauch et al., 2016; Henderson et al., 2016; Lenton et al., 2022; Milkoreit et al., 2018). Tipping points can lead to highly beneficial or catastrophic outcomes for humans, especially when an environmental change occurs in the presence of social hysteresis. An example of ~~negative~~detrimental tipping is in the forests of Kumaun and Garhwal in Northern India, where, prior to British ~~conquest~~colonisation, wood harvest was sustainably regulated through social norms and strict rules enforced by local village councils. When the British colonial government ~~tried to impose~~imposed their own rules on the use of ~~these commons, there was a breakdown of social norms and when~~forests, these social norms broke down. Eventually, protests led to ~~these~~British lumber restrictions being removed, but the system subsequently experienced rapid deforestation rather than a return to its previous levels under local management (Somanathan, 1991). This system has been modelled using a dynamical systems approach that allows for a quantitative understanding of the human drivers leading to the tipping points (Sethi ~~&~~and Somanathan, 1996).¶

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~~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~~ Contrasting this example, tipping points can also result in environmental change that is beneficial to humans and the environment. The rapid response of the international community to the hole in the ozone layer has been interpreted by some as an example of a system undergoing tipping points caused by human-environmental feedback (Stadelmann-Steffen et al., 2021). First, there was a shift in public opinion regarding the use of CFC products, causing a change in behavioral norms and pressure on political institutions to follow suit. Then when policy was passed, industry shifted abruptly to producing CFC alternatives, which led to a tipping point in CFC emissions bringing about a new stable state of relatively low emissions globally (Andersen et al., 2013; Cook, 1990; Epstein et al., 2014; Stadelmann-Steffen et al., 2021).

Tipping points associated with social processes as described in the preceding paragraph can be conceptualised through positive feedback loops that capture a self-reinforcing process. In the case of social norms, this self-reinforcing process may correspond to peer pressure or conformism that reinforces the dominant opinion or belief. Depending on whether pro- or anti-mitigation opinions are currently dominant, this could lead to hysteresis (Figure 1b). The negative feedback loop that might normally regulate the CHES to exist in a state of intermediate environmental health and public support for sustainability (Figure 1a) could be overpowered by the positive feedback of social norms, leading the population to a state where either sustainability (or anti-sustainability) is strongly entrenched. If the conditions governing social learning or social norms move beyond a tipping point, the population may flip between these two norms, or alternatively it may move into a regime where social norms are instead dominated by the negative feedback loop, causing the population to exist in an interior state of partial sustainability. As such, negative feedback and positive feedback may be characteristic of any CHES and should be systematically studied.

This review aims to deepen our understanding of human drivers of tipping points in 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 human systems. By "human drivers", we refer to the gradual changes in social parameters that elicit these non-linear tipping responses in either the environment, human system, or both. However, we also discuss aspects of social structure that may be conducive to tipping points. In the following sections we review CHES model literature found using Google Scholar with the keywords: ‘human environment system’ OR ‘socio-ecological system’ OR ‘social ecological system’ OR ‘human ecological system’ OR ‘human natural system’ combined with ‘tipping’ OR ‘regime shift’ OR ‘bifurcation’. Additional literature was found through a snowball approach using references from the sources found in this search as well as papers referencing these sources (Wohlin, 2014). The findings in this review highlight commonalities between the CHES models surveyed; however, some trends may be a result of both the dynamical models chosen and the relatively low diversity and volume of these models.

2 Structures and processes in human systems that cause tipping points in CHES models

In this section, we look at how social processes and structures cause tipping points. In order to have a better understanding of how these human drivers affect tipping, it is important to understand the basics of modelling human systems. Within CHES models, various factors, such as economic incentives, environmental considerations and social pressures determine how individuals make decisions and interact with the environment. In most of the current modelling literature, individuals can choose between two behaviors (also referred to as opinions or strategies), one that is environmentally sustainable (also referred to as mitigation or cooperation) and another that is detrimental to the environment (also referred to as non-mitigation or defection). The perceived advantage of mitigation or non-mitigation relative to the current state of the human and environmental system can be quantified through a “utility function”. Common factors in the utility function are the rate of social learning, which determines the speed of human ~~dynamics~~behavior change 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~~valuation, which incentivizes mitigation as the environment approaches collapse~~.~~¶

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~~**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,~~ (Bauch et al., 2016; Farahbakhsh et al., 2022; Tavoni et al., 2012). In most models that use social learning, individuals sample others in the population at a fixed rate and adopt a different behavior if the other behavior has a higher utility, with probability proportional to the difference in utility (Hofbauer and Sigmund, 1998; Schuster and Sigmund, 1983). This can also be formulated in a stochastic setting, where the probability of adopting a neighbor's behavior is a function of the difference in utility between behaviors (Schlag, 1998). Most of the models reviewed in this paper use social learning to represent human behavioral dynamics. There are also CHES models that do not include social learning such as Motesharrei (2014) and Dockstader (2019) where the human population is influenced by its current size and the state of the environment; however, these are outside the scope of this paper.

Many human behaviors, such as resource extraction and pollution, have direct detrimental impacts on the environment; however, the severity of these impacts is often hard to predict. In many CHES models, small changes in parameters governing ~~these rates~~human behavior and social processes can lead to the abrupt collapse of sustainable states through tipping points ~~which~~that 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~~human and environmental systems (Bauch et al., 2016; Lade et al., 2013; Richter and Dakos, 2015; Weitz et al., 2016). Additionally, structural elements of the human system, such as the degree of choice and individual diversity, as well as how the social system is organised, can affect tipping. These heterogeneous model elements are often only accessible in agent-based models, where humans are represented as individual agents that follow a set of rules. CHES models do not always exhibit tipping points under realistic settings for the human system (Bury et al., 2019; Menard et al., 2021); however, in this review, we focus on models with tipping points.

2.1 Coupling strength

Coupling strength (how strongly the subsystems are coupled) can have a significant effect on the occurrence of tipping points in both systems~~. One common~~, and the nature of these transitions often depends on whether systems are ‘input-limited’ or ‘output-limited’. In input-limited systems, humans extract from an environmental resource such as in forest and fishery models. Stronger coupling in input-limited models often leads to environmental collapse. A common social parameter representing the coupling strength in these systems is the extraction effort of humans, which when increased past a critical threshold, leads to abrupt ~~environment~~environmental collapse (Farahbakhsh et al., 2021; Richter ~~et al., 2013; Richter & Dakos, 2015; Schlüter et al., 2016). For~~and Dakos, 2015; Richter et al., 2013; Schlüter et al., 2016). For output-limited systems, where human activity increases levels of harmful outputs, such as 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~~detrimental tipping point where mitigation collapses and pollution then reaches a high level (Iwasa et al., ~~2007, 2010~~2010, 2007). This occurs because when the lake water is not very polluted, there is less incentive to be a mitigator and high-~~pollution behaviour~~polluting behavior 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~~environmental systems is ~~centred and taken into account~~central in any decision-making, even when ~~it is in a state of abundance~~the environment is far from collapse. This ~~inherent~~fundamental valuing of the environment is present in many traditional indigenous belief systems, where relationships to the local natural environment are incorporated and ~~prioritized~~prioritised in all aspects of life (Appiah-Opoku, 2007; Bavikatte ~~&~~and Bennett, 2015; Beckford et al., 2010; McMillan ~~&~~and Prosper, 2016).

2.2 Rarity-motivated ~~conservation~~valuation

Rarity-motivated ~~conservation~~valuation represents the extent to which humans ~~change their behaviour~~increase their mitigative behavior 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~~environmental variable (e.g., forest cover, endangered species population size) nearing a depleted state. Model systems with rarity-motivated valuation often exhibit two tipping points at high and low levels, with a sustainable regime for intermediate values. High levels of rarity-motivated valuation lead to overshoot dynamics, however, this may not be true in empirical systems. In models, the sensitivity of human response to the abundance of the natural resource/population is represented by a ‘sensitivity’ parameter and there are often two critical thresholds ~~for rarity-motivated conservation in CHES models. Increasing this parameter past~~in the sensitivity parameter that lead to tipping. Increasing the sensitivity parameter beyond 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 ~~&~~and Surun, 2018; Henderson et al., 2016; Lin ~~&~~and Weitz, 2019; Sun ~~&~~and Hilker, 2020; Thampi et al., 2018; Weitz et al., 2016). The second threshold exists at high values of ~~rarity-motivated conservation~~the sensitivity parameter, where the sustainable equilibrium is ~~destabilized~~destabilised by overshoot dynamics or a ~~regime~~state of chaos in both the human and ~~environment~~environmental systems. These dynamics are caused by the human system being too sensitive to changes in the environment, leading to extreme oscillations in both human ~~opinion~~behavior and the environment, which 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~~Rarity-motivated valuation can also be represented by a threshold in the state of the environment, below which~~,~~ humans shift towards sustainable ~~behaviour~~behavior. 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~~environmental 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.

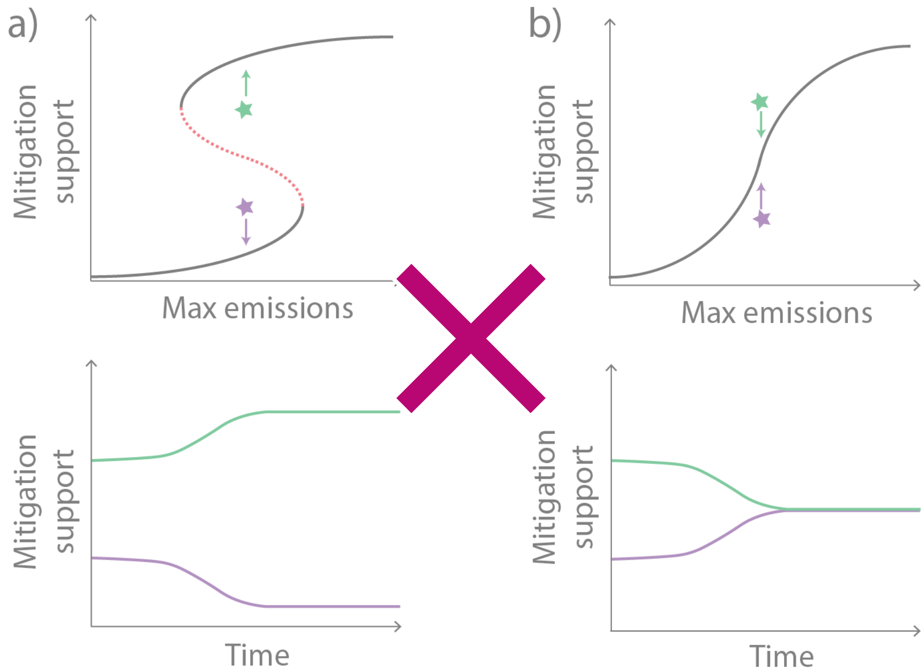

Figure 1: ~~Strong majority-enforcing social norms lead to bistability, in which the long-term behaviour of the system is highly dependent on initial conditions (a). This bistability is less likely in systems with weak social norms, where the system will converge to the same equilibrium regardless of initial conditions (b).~~ Negative feedback between the human and environmental subsystems, support convergence to the same equilibrium regardless of initial conditions (a). With strong majority-enforcing social norms, encouraging either mitigative or harmful behavior adds a positive feedback loop which makes the coupled system highly dependent on initial conditions (b). The top row shows the negative feedback loop between emissions and the proportion of mitigators, where (b) also includes the positive feedback of majority-enforcing social norms. In the ~~top~~middle 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~~color 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~~Introducing social norms can lead to alternative stable states and thus tipping points (Figure 1b), although the system dynamics are highly dependent on both the type of social norms and initial conditions. Social norms are informal rules emerging through social interaction that promote and discourage certain behaviors, especially around how humans relate to one another and the environment (Chung and Rimal, 2016). In models of small groups such as a community of fishers, they are often (rightly) assumed to support mitigative behavior by punishing those who violate norms by over-harvesting (Ostrom, 2000). However, at larger population scales, social norms can support either pro- or anti-mitigation behavior, on account of factors such as politicisation of actions relating to environmental, climate, and public health crises (Stoll-Kleemann et al., 2001; Van Boven et al., 2018; Latkin et al., 2022). Unlike a fisher for instance, a climate denier may not acknowledge themselves as a 'defector' who is harming a public good, but rather view the climate activist as 'defecting' against a free society. Thereby, social norms have the ability to encourage behavior that is harmful to both human and environmental well-being, over larger spatial and temporal scales (Bury et al., 2019; Latkin et al., 2022; Menard et al., 2021; Stoll-Kleemann et al., 2001; Van Boven et al., 2018).

Social norms can be represented as majority-enforcing, incentivizing the ~~opinion~~behavior 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~~In CHES models, increasing the strength of majority-enforcing norms leads to an increased number of regimes as well as bistable ~~regimes, which often include extreme equilibria~~(more than one stable state) regimes (Figure 1b), made up of a single ~~opinion that~~dominant behavior, which is highly dependent on the initial ~~state of the system~~proportion of behaviors in a population (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~~This occurs because these norms are indifferent to the type of ~~behaviour~~behavior they enforce (i.e. sustainable vs harmful actions), and 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~~ through a positive feedback loop, where the dominant behavior becomes more prevalent (Figure 1b). On the other hand, increasing mitigation-enforcing social norms lead to a transition of the environmental system into a sustainable equilibrium (~~X.~~ Chen ~~&~~and 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 ~~&~~and 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~~ These findings show that stronger social norms lead to a greater number of tipping points; however, the trajectories brought about by these tipping points are highly dependent on the type of social norms (mitigation- or majority-enforcing) as well as the current dominant social behavior.

2.4 Cost of mitigation

Reducing the cost of mitigation often leads to beneficial tipping points; however, these tipping points can depend on the rate of social change as well as social norms. Although it is intuitive that reducing costs or increasing economic incentives associated with mitigative action will have beneficial impacts on the environment, CHES models also show that this beneficial change can occur through tipping points (Bauch et al., 2016; Drechsler and Surun, 2018; 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~~In coupled epidemiological models, where the environmental state is the proportion of infected individuals, mitigation cost is represented through the ~~cost of vaccination, often through~~ economic cost or ~~the~~ perceived risk of ~~a vaccine~~vaccination. Decreasing this cost leads to ~~positive~~beneficial 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~~detrimental tipping point occurs in the ~~social~~human system at lower levels of vaccination cost when majority-enforcing social norms are low, leading to widespread anti-vaccine opinion before the infection becomes endemic again (Phillips ~~&~~and Bauch, 2021). Decreasing profits of ~~actors~~individuals engaging in ~~environmentally detrimental behaviour~~non-mitigative behavior 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 tipping in the other direction where ~~increased~~increasing non-mitigators' payoff brings about a regime shift to pure non-mitigation and environmental collapse (Richter et al., 2013; Tavoni et al., 2012). Similarly, a common-pool resource model that uses machine learning in a continuous strategy space shows tipping to a depleted resource regime when the costs associated with harvesting are too low (Osten et al., 2017). An ~~analogue~~analog to mitigation cost is taxation rates, which resource users pay towards public infrastructure mediating resource extraction. In a model where ~~actors have the ability~~individuals can choose 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 ~~&~~and Anderies, 2020). In another model, only ~~actors~~individuals with high extractive effort are subject to taxation, and increasing this taxation rate brings about a ~~positive~~beneficial tipping point to a sustainable regime~~, however~~. 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). However the cost of mitigation is represented, increasing the relative economic incentive of mitigation behavior has the potential to bring about beneficial tipping to a sustainable regime.

2.5 Rates of social change and time horizons

Human and environmental change often occur on different timescales and their relative ~~speed plays~~rates of change play a major role in the long-term dynamics of the coupled system~~. In CHES models, this relative speed is usually~~ and whether or not tipping points will occur. Increasing the rate of social change (in most cases, social learning) leads to collapse in input-limited models due to overshoot dynamics. Whereas, in output-limited models, the impacts of the rate of social change are more model-specific. In both types of models, increasing the time horizon in decision-making is beneficial. In CHES models, these rates of change can be controlled by the rate of social learning which determines how frequently individuals interact and consequently, the pace of ~~opinion~~behavioral change within a population. Changes in the speed of the ~~social~~human system can have very different outcomes depending on the nature of human-~~environment~~environmental coupling. In input-limited models, ~~where humans are extracting from an environmental resource such as fishery models,~~ increasing the speed of the ~~social~~human system relative to the environment often destabilises sustainable equilibria, leading to oscillations in both systems and, in many cases, the abrupt collapse of the environmental ~~state~~system. These overshoot dynamics occur as humans change their

~~opinions~~behavior too quickly to allow for the environment to stabilise. On the other hand, decreasing the relative speed of ~~social~~human dynamics usually brings about ~~positive~~beneficial tipping points ~~increasing the stability of the~~leading to a state of high forest cover (Figueiredo ~~&~~and Pereira, 2011), and supporting mitigators for a generalised resource (Hauert et al., 2019; Shao et al., 2019). These ~~positive~~beneficial effects have also been observed in adaptive network models where ~~agents~~individuals imitate their ~~neighbours~~neighbors 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~~beneficial outcomes as the resource is allowed more time to stabilise ~~before~~as decisions regarding extractive levels occur. ~~There are also other~~Other relative rates of change ~~that~~can also 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~~. 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~~can destabilise low-pollution equilibria, leading to ~~limit cycles~~oscillations and eventually a polluted state with no mitigation (Iwasa et al., ~~2007, 2010~~2010, 2007; Sun ~~&~~and Hilker, 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~~valuation; however, these outcomes are highly dependent on other social parameters~~ since a similar model found that under~~. In a related model, with no social hysteresis, represented by mitigation-enforcing social norms, and strong ~~ecological~~environmental hysteresis, represented by a high phosphorus turnover rate, fast social dynamics ~~had the ability to~~could stabilise oscillations, leading to a low-pollution equilibrium (Suzuki ~~&~~and 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~~environmental 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~~rates of change in human and environmental systems, it is clear that ~~rates of change in the human system have much more malleability when it comes to~~the pace of the human system can be more readily influenced by 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~~

2.6 Social traits

The inclusion and distribution of traits within agents can play a large role in determining the occurrence and types of tipping points within the coupled system, where ncreasing the modelled heterogeneity in social traits can lead to more tipping and also promote sustainable outcomes. The majority of models discussed in the previous section only allow humans to choose between two strategies~~, often one that is beneficial to the environment and one that is harmful~~; mitigation and non-mitigation. The inclusion of additional strategies, determining how ~~actors~~individuals 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 ~~&~~and Grasman, 2013). Under this additional strategy, agents act as mitigators until the number of non-mitigators reaches a certain threshold, where they then shift their ~~behaviour~~behavior 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~~environmental 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~~behavior, which puts abrupt harvesting 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 a state of high-extraction or low-extraction ~~actors~~behavior, triggering either a ~~negative or positive~~detrimental or beneficial environmental tipping point, respectively. Including environmental concern~~, however,~~ leads to an increased number of cascading tipping points between both ~~social~~human and environmental systems. In a coupled agricultural model, where human traits include management strategies that respond to socio-economic and climate ~~changes~~conditions, 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~~ As there are relatively few models that explicitly compare the complexity of social traits and their effect on tipping points, it is difficult to say with certainty whether higher complexity will increase the likelihood of tipping points in all CHES and whether this is due to a higher dimensionality of the system. However, these commonalities are worth highlighting and will be put to the test with future CHES models and empirical work.

2.7 Social networks

In many agent-based CHES models, individuals are structured on a social network, where they usually only interact with others whom they share a link with. These models demonstrate how 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~~2017a, 2015). 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 certain social (Ising model) dynamics (Reisinger et al., 2022). The distribution of resources in human-~~environment~~environmental networks also affects the potential for abrupt environmental collapse. This ~~can be controlled through coupled human-environment~~often occurs in CHES network models where both human and ~~environment~~environmental 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~~neighboring 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~~neighbors to imitate their behavior. 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~~leads 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~~Heterogeneity of human interaction can be quantified through homophily, the extent to which alike individuals interact. Homophily can play a large role in the occurrence and ~~behaviour~~behavior of tipping points in CHES models occurring on social networks, often having a detrimental effect on the environmental system. 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~~detrimental tipping point compared to when 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 and returning to a sustainable state (Sugiarto~~, Lansing,~~ et al., ~~2017~~2017b). 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).

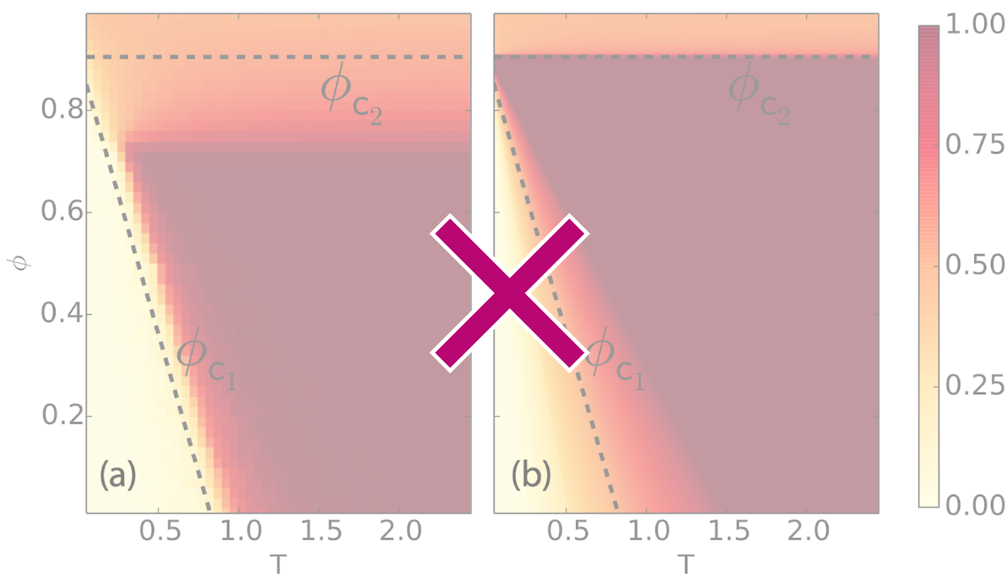

Figure 2: Mean proportion of nodes that are mitigators for network model (a) and ODE model (b). ϕ is the rewiring probability and T is the time between social interactions. ϕ_{C1} is the lower threshold and ~~and~~ ϕ_{C2} is the upper threshold, above which a fragmentation regime occurs. From (Wiedermann 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~~break existing social links and create new ones, a process called "rewiring". 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,~~behavior. Common adaptive network CHES models have nodes representing a renewable resources stock with an associated extraction level which can adopt a high extraction or low extraction level through imitating neighbors. These models show that the level of homophilic rewiring can trigger regime shifts at both low and high levels, where intermediate ranges correspond to ~~the~~a sustainable equilibrium. As ~~these models are formulated where~~ agents can either choose to rewire or imitate their ~~neighbour~~neighbor, a low level of rewiring corresponds to a high speed of social interaction, which as discussed ~~earlier~~in Section 2.5 can lead to ~~negative~~detrimental 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.~~Figure 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~~ CHES models with social networks are still relatively new and lack diversity in how they are formulated. For example, regarding the tipping points related to rewiring social links, the lower threshold may be caused by increased social learning since in all models agents can either rewire or imitate, but not both. There is still much to learn through isolating the effect of rewiring as well as exploring a wide array of different model formulations of CHES on social networks.

3 Identifying early warning signals in the CHES

Although dynamical models can offer qualitative insight into potential trajectories of CHES resulting from specific interventions, it is more difficult to use them to generate precise and reliable predictions. Given the potential for severe environmental tipping points in the coming decades, it is extremely useful to be able to predict these abrupt shifts without complete mechanistic knowledge of the system. The ability to predict tipping points with limited data can allow policymakers to have more time preparing for future disasters, and given enough warning and political will, an opportunity to avoid them or mitigate their severity. Rapidly growing research in early warning signals (EWS) offers tools to monitor empirical time series data and warn of future tipping points that are likely to occur (Bury et al., 2021; Dakos et al., 2012, 2015, 2008; Kéfi et al., 2014; Lapeyrolerie and Boettiger, 2021). Although much of the work has been conducted on synthetic data, there are many studies that successfully predict historical tipping points in both empirical human and environmental time series data such as the 1987 Black Monday financial crash (Diks et al., 2019) as well as abrupt temperature shifts from paleoclimate datasets (Dakos et al., 2008).

3.1 Recent advances for detecting early warning signals

Much research has been done in the past few decades to develop tools for EWS using both empirical and synthetic time series data (Bury et al., 2021; Dakos et al., 2012, 2015, 2008; Kéfi et al., 2014; Lapeyrolerie and Boettiger, 2021). Originally motivated by ~~the concept of~~ critical slowing down in bifurcation theory, where systems approaching a ~~bifurcation~~tipping point show a slower recovery to equilibrium under perturbations, ~~traditional early warning signals~~generic EWS measure trends in this "slowing down" (Scheffer et al., 2009). 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 rapidly force the system between alternate stable states. In these cases, an increase in skewness and kurtosis is observed (Dakos et al., 2012). 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~~neighboring nodes in a network (Kéfi et al., 2014).

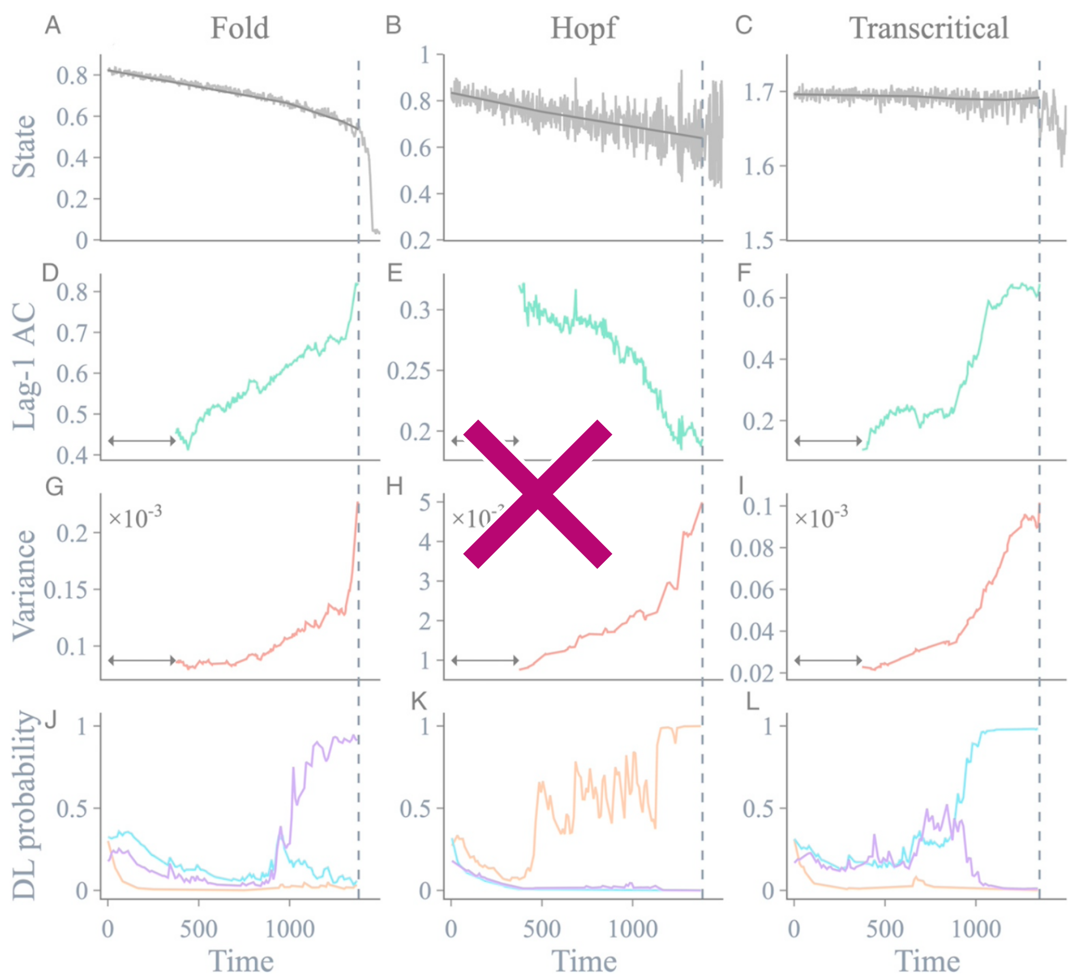

Figure 3: ~~Traditional~~Generic EWS (second and third row) as well as deep learning EWS (bottom row) ~~from three~~for time series generated by two ecological models exhibiting different types of bifurcations (top row); fold (left), Hopf (middle), and transcritical (right). As well as being more reliable, deep learning EWS can also distinguish between the type of bifurcation being approached. In the bottom row, the DL algorithm gives probabilities for the occurrence of fold (purple), Hopf (orange), or transcritical (blue) bifurcations. **Image taken from (Bury et al., 2021).**

~~Many~~Numerous 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~~show 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~~These clusters are 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 ~~&~~and 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).

~~4.2 Recent advances in early warning signals¶~~

One downside to the ~~traditional~~generic metrics discussed above is that they have the potential to fail ~~when the system has~~in the presence of large amounts of noise ~~and is prone to transitions occurring farther from the critical~~where transitions can occur far from their analytically derived tipping 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~~At the same time, 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~~that are analysed (Li et al., 2023). This spatial technique offers a novel method for predicting tipping points for CHES using human data occurring on complex social networks.

A very recent addition to the ~~early warning signals~~EWS toolkit uses concepts from statistical physics such as average flux, entropy production, ~~generalized~~generalised free energy, and time irreversibility to predict tipping points in a shallow lake model much earlier than ~~traditional~~generic 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~~tipping points. In the majority of cases, these algorithms have performed significantly better at predicting tipping points than ~~traditional EWS methods~~generic EWS indicators when tested on empirical datasets that exhibit abrupt transitions (Bury et al., 2021; Deb et al., 2022) (~~Fig.~~Figure 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~~ in CHES.

3.2 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~~to EWS from environmental systems not coupled to a human system (Bauch et al., 2016) or the same system with weak coupling between the human and ~~environment~~environmental subsystems (Richter ~~&~~and Dakos, 2015). This is likely due to the effects of human ~~behaviour~~behavior acting to mitigate variability in the ~~environment~~environmental system, for example, rarity-motivated ~~conservation~~valuation creates a negative feedback loop where incentives to ~~conserve~~mitigate 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.~~Section 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~~generic 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 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 ~~&~~and Dakos, 2015). In agreement with ~~traditional~~generic 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). It is possible that the state variable most sensitive to the forcing parameter may exhibit the strongest EWS, as seen in experimental work on tipping points in a lake food web. In this system, data from the species that had a direct trophic linkage to a driver of the tipping point (predators added to the food web) exhibited EWS earlier than those that were farther removed from the driver (Carpenter et al., 2014). If this is the case, human drivers of tipping points would most directly affect the human system, and EWS should still be stronger using social data.

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~~environmental system. Furthermore, citizen science not only generates ~~ecological~~environmental 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~~environmental 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**~~ With the potential social data offers for use with EWS, it is important to note that much of the traditional social data, often conducted through national or regional surveys, do not provide fine-grained spatial or temporal resolution. On the other hand, novel methods that use social media data can solve the resolution issue, but may not accurately represent the population it is being used to model (Hargittai, 2020). These challenges may be addressed through a hybrid approach that uses hybrid time series generated from multiple types and sources of social data (Rosales Sánchez et al., 2017).

4 Conclusion and future directions

4.1 Summary of main points

From a wide range of examined 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~~social interventions, such as reducing mitigation costs and extractive effort, or increasing the time horizon in decision-making, lead to ~~positive~~beneficial tipping points, regardless of the system modelled. The ~~positive~~beneficial effect of these interventions is intuitive, however, ~~the~~ non-linear ~~response to these changes~~responses 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~~as evident. Mitigation costs can be reduced through subsidies for land preservation and green technology, and extraction effort through limits on land development and the expansion of protected natural areas (i.e. the Haudenosaunee-led protection of the Haldimand Tract) (Forester, 2021), and ~~increase~~by increasing time horizons through passing long-term legislation that centers the well-being of ~~environment and social~~human and environmental systems such as the Green New Deal.¶

¶

~~Other aspects of human behaviour~~ (Galvin and Healy, 2020). These policy interventions become more difficult to implement at large scales, and models that are tailored to global coordination problems can give us insight into how institutions can work together to rapidly mitigate looming threats, such as the current climate crises we are facing (Karatayev et al., 2021).

Other human behaviors and social processes are much more nuanced and system-specific in how they affect tipping points. For example, models show that rarity-motivated ~~conservation~~valuation can act to ~~negatively~~detrimentally tip the ~~environment~~environmental system into a depleted state when it crosses both an upper and ~~lower threshold~~(counterintuitively) a lower threshold value. This was illustrated most clearly in the example of forest cover in the paper by Bauch et al. (2016). 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 extent of coupling between the human and environmental system as well as 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~~whether the model is input- or output-limited. Interventions related to human valuation and social norms 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 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).~~¶

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~~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.~~¶

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~~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~~ and may also have ethical considerations.

The models we reviewed also 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. The modelling literature has only explored a small sliver of the space of possible choices regarding assumed social structure and the types of environmental models coupled to them. For example, the vast majority of models only allow for a binary choice in human behavior and adaptive social networks have only recently been incorporated, with limited mechanisms of re-wiring and types of coupled environmental systems. Consequently, we still have much to learn on how shifting underlying social structures acts as a driver of tipping points. 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. Even if we include more diverse and realistic social structures and processes, CHES are composed of many non-linear feedbacks and contain high levels of uncertainty, and the reality is that we may not be able to have a complete mechanistic representation through models. EWS from empirical data show great potential in predicting 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 (Bury et al., 2021; Deb et al., 2022), and very recent work is now developing similar techniques to predict tipping points from spatial data (Dylewsky et al., 2022). As synthetic data from models have shown the value of EWS from social data, it is likely that applying these techniques to diverse and hybrid empirical social datasets can vastly improve our ability to predict tipping points caused by human drivers in the future.

4.2 Future work in CHES modelling

There are many social phenomena that are not commonly included in CHES models, yet may be important in furthering our understanding of tipping points within these systems. We know that inequality in human systems plays a large role in individuals' risk perception and ability to engage in pro-environmental behavior (Gibson-Wood and Wakefield, 2013; Pearson et al., 2017; Quimby and Angelique, 2011; Rajapaksa et al., 2018) and have mentioned two CHES models that incorporate wealth inequality in a human-climate system (Menard et al., 2021; Vasconcelos et al., 2014). However, more studies explicitly investigating the role of inequality could offer some valuable insight into interventions that can be more effective in benefiting both the environment and the most vulnerable in human systems. This could be complemented by social biases where perceptions of risk are linked to an individual's socio-economic status, and detrimental environmental outcomes are experienced disproportionally by vulnerable communities as is commonly observed globally (Banzhaf et al., 2019; Boyce, 2007). Future models could allow for alternatives to the common modelling assumption where individuals act in their own self-interest, for example by incorporating other-regarding preferences into utility functions so that individuals value their neighbors' well-being along with their own (Dimick et al., 2018). These models could also look at grassroots redistribution of wealth allowing us to explore the effects of alternative social value systems on the environment (Tilman et al., 2018).

Stochasticity (noise), especially regarding drivers of tipping points can significantly affect system dynamics including when tipping points occur. Although many CHES models are deterministic, recent work has shown that increasing noise can lead to earlier tipping (Willcock et al., 2023), or in other cases, increase the duration of time the environmental system can persist before becoming extinct (Jnawali et al., 2022). These contradictory results warrant further work in understanding how different types of noise and their magnitude within drivers of tipping points affect the resilience of these systems. With stochasticity comes uncertainty, and in real-world systems, it is impossible to know with precision the extent of social change required to bring about a beneficial or avoid a detrimental tipping point. This uncertainty around our knowledge of system thresholds adds an additional challenge in both agreeing upon and following through with policy that promotes sustainable futures while taking into account potential tipping points. Experimental games have shown that high threshold uncertainty can promote the collapse of a shared resource, often through an increase in free-riding behavior (Barrett and Dannenberg, 2014, 2012). On the other hand, field experiments in fishing communities have shown that high uncertainty can promote cooperation and sustainable resource use (Finkbeiner et al., 2018; Rocha et al., 2020). Theoretical models show that increased uncertainty can lead to increased mitigative behavior if the shared resource is highly valued, however for low-valued resources, increased uncertainty can deter mitigation, putting the persistence of the shared resource at risk (Jager et al., 2000; McBride, 2006). Uncertainty around thresholds is unavoidable, further motivating the need to offer additional incentives for mitigative action on institutional scales, rather than solely the threat of environmental collapse. In systems where uncertainty can promote mitigative action, increased communication and awareness campaigns around this threshold uncertainty could be useful to incorporate into policy.

This review has focused primarily on the effects of single drivers, however research on multiple co-occurring human drivers of tipping points, while more analytically challenging, could offer a holistic understanding of how these drivers interact. 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) and there is already a large body of empirical work exploring the diversity of these drivers which can be used to inform future CHES models (Jaureguiberry et al., 2022; Maciejewski et al., 2019; Millennium Ecosystem Assessment, 2005). Finally, as the majority of the studies in modelling tipping points have focused on slow gradual changes in the driver, fast changes require further research as they can exhibit very different tipping behavior (Ashwin et al., 2012). CHES models ubiquitously exemplify the phenomenon of tipping points, which often occur through drivers in the ~~coupled~~human system. Although these models offer valuable insight in understanding key feedbacks and qualitative ~~behaviour of CHES~~behavior, 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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