Research Directions: One Health

www.cambridge.org/one

Using a fuzzy cognitive map to assess interventions to reduce antimicrobial resistance in a Swedish One Health system context under potential climate change conditions

Results

Cite this article: Cousins M, Parmley EJ, Greer AL, Neiterman E, Lambraki IA, Graells T, Léger A, Henriksson PJG, Wernli D, Søgaard Jørgensen P, Carson CA, and Majowicz SE (2024). Using a fuzzy cognitive map to assess interventions to reduce antimicrobial resistance in a Swedish One Health system context under potential climate change conditions. *Research Directions: One Health*. **2**, e6, 1–15. https://doi.org/10.1017/one.2024.2

Received: 2 June 2023
Revised: 13 February 2024
Accepted: 14 February 2024

Keywords:
Fuzzy cognitive mapping; antimicrobial resistance; One Health; mixed methods; simulation modelling

Corresponding author:
Melanie Cousins;
Email: melaniemcousins@gmail.com

Melanie Cousins[1,2], E. Jane Parmley[2,3], Amy L. Greer[3], Elena Neiterman[1], Irene A. Lambraki[1,2], Tiscar Graells[4,5], Anaïs Léger[6], Patrik J.G. Henriksson[5,7,8], Didier Wernli[6], Peter Søgaard Jørgensen[4,5], Carolee A. Carson[9] and Shannon E. Majowicz[1,2]

[1]School of Public Health Sciences, University of Waterloo, Waterloo, ON, Canada; [2]One Health Modelling Network for Emerging Infections (OMNI-RÉUNIS), North York, ON, Canada; [3]Department of Population Medicine, Ontario Veterinary College, University of Guelph, Guelph, ON, Canada; [4]Global Economic Dynamics and the Biosphere, Royal Swedish Academy of Sciences, Stockholm, Sweden; [5]Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden; [6]Global Studies Institute, University of Geneva, Geneva, Switzerland; [7]Beijer Institute of Ecological Economics, Royal Swedish Academy of Sciences, Stockholm, Sweden; [8]WorldFish, Batu Maung, Penang, Malaysia and [9]Canadian Integrated Program for Antimicrobial Resistance Surveillance, Foodborne Disease and Antimicrobial Resistance Surveillance Division, Centre for Foodborne, Environmental and Zoonotic Infectious Diseases, Public Health Agency of Canada, Guelph, ON, Canada

Abstract

Antimicrobial resistance (AMR) is a growing One Health crisis that can be impacted by other challenges of sustainable development, such as climate change, but few interventions have been assessed with a systems-wide lens. The objectives of this study were to use a previously defined fuzzy cognitive map (FCM) of the Swedish One Health system to: 1) identify areas in the system to target interventions; and 2) test the potential ability and viability of interventions to reduce AMR under a changing climate. The FCM, based on participatory modelling workshops and literature scan, was used to assess the sustainability of eight interventions under potential climate change conditions. Network metrics were calculated to describe the system structure and identify highly impactful nodes. The network metrics identified high-leverage nodes including alternative productions systems and good farming practices. None of the scenarios evaluated were able to adequately reduce AMR within the system. Overall, fuzzy cognitive mapping provides an innovative way to analyse the AMR system, identify high-leverage interventions, and examine potential impact of interventions using a broader systems lens.

Introduction

Antimicrobial resistance (AMR) is a global One Health crisis (McEwen & Collingnon, 2017; Søgaard Jørgensen et al., 2016; van Helden et al., 2013; Shomaker, 2014; Robinson et al., 2016; The European Commission, 2018) causing economic and health burdens in humans, animals, and the environment (The European Commission, 2018; WHO Regional office for Europe, 2017). In 2019, 4.95 million deaths worldwide (23,100 deaths in western and central Europe) were associated with AMR (Murray et al., 2022). AMR has also impacted the agricultural sector by causing loss of production due to animal illness with resistant infections and has decreased trade due to a fear of resistance (The European Commission, 2018). AMR emerges from interactions in the complex One Health system that spans the human-animal-environment interface (O'Neill, 2016; McEwen and Collignon, 2017; The European Commission, 2018; WHO, 2018) and is exacerbated by globalization (Frost et al., 2019; Holmes et al., 2016; Lambraki et al., 2022a; Wegner et al., 2022). Antimicrobial use (AMU) in human medicine and food production has been at the forefront of research and the focus of targeted action to reduce AMR (The European Commission, 2018; WHO, 2018), however there are a multitude of factors that affect *why* and *how* we use antimicrobials, including: socioeconomic factors (e.g., poverty, access to nutritious food and clean water); society and social pressures (e.g., quick fix to get back to work); and economic factors (e.g., decreased losses in food production, lowering production costs) (Holmes et al., 2016; McEwen and Collignon, 2017; Alividza et al., 2018; Lambraki et al., 2022a; Wernli et al., 2017; Søgaard Jørgensen et al., 2020). Many past attempts to address AMR have failed to account for interactions in the One Health and socio-ecological system and lacked integration and communication between the multiple actors involved in the complex system (Government of Canada, 2017; The European Commission, 2018; Lambraki et al., 2022a). For example, if policies or interventions were taken in one sector (e.g., reducing antibiotic use in food animals and agriculture), this could negatively impact another sector (e.g., more costs for human consumers). Therefore, a One Health perspective is needed to adequately address AMR.

Due to the intimate relationship between the environment, humans, and animals, climate change is predicted to worsen the problem of AMR, however the impacts across the One Health system are associated with high levels of uncertainty (Fouladkhah et al., 2020; Burnham, 2021; Pepi and Focardi, 2021; Rodríguez-Verdugo et al., 2020). Furthermore, the livestock production system is both a driver of AMR and a large contributing factor of climate change, thus perpetuating both issues in tandem (Søgaard Jørgensen et al., 2020). Within Sweden, temperatures are predicted to increase (especially in the northern part of the country) with increased precipitation events and unpredictable weather patterns (Meehl et al., 2007). The changes in weather in Sweden and globally may lead to an increase of disease in humans, animals, and crops (World Health Organization, 2017; Rodríguez-Verdugo et al., 2020; Carlson et al., 2022), impact food production (Morse, 1995; Hoffmann, 2010; Van Dijk et al., 2010; Lacetera, 2019; Abirham, 2020; Reverter et al., 2020), and cause mass migrations into less vulnerable countries such as Sweden, potentially leading to overcrowding (Parry et al., 2005; Semenza and Ebi, 2019; Abirham, 2020). Overall, there is expected to be great need for effective antimicrobials in the future. Therefore, understanding how climate change will shape the One Health system and how changed in the system drive AMR, especially how it may impact AMU and AMR, and identifying sustainable interventions that can help mitigate these impacts using a One Health perspective in the future is vital.

Simulation modelling (gray and Rumpe, 2016) explores how a system may be affected by different scenarios (e.g., climate change) and assess interventions. AMR has been modelled within specific areas (e.g., agricultural system, health system), but the entire One Health system of drivers has yet to be modelled (Cousins et al., 2024). Fuzzy cognitive mapping is a semi-quantitative simulation modelling technique (Kosko, 1986) that enables a One Health lens to account for the complex socio-ecological drivers of AMR (Cousins, 2022a). First introduced by Kosko in 1986 (Kosko, 1986), fuzzy cognitive maps (FCMs) have shown promise in modelling complex dynamic systems in many disciplines (Alipour et al., 2019; Ntarlas and Groumpos, 2015; Dorokhov et al., 2017; Poomagal et al., 2021). These models use expert knowledge to construct representations of the causal relationships between components that describe a system (Kokkinos et al., 2018). FCMs consist of concepts (or components or nodes), connected by weighted causal relationships, defined in linguistic terms (e.g., strong vs weak, high vs low (Kosko, 1986; Nápoles et al., 2018). FCMs are useful for decision-making in systems with incomplete or non-specific data or undefined interactions (Sypher, 2017). As a case study, Cousins, 2022a created a FCM of AMR in the Swedish One Health system, informed by literature and expert opinion (Cousins, 2022a). Using the previously defined FCM, the objectives of this study were to: 1) identify areas in the system to target interventions; and 2) test the potential ability and viability of interventions to reduce AMR under a changing climate.

Methods

Using a previously created FCM of AMR development and transmission in the Swedish One Health system, this study further explored the system that drives AMR and assessed interventions under climate change conditions (Cousins, 2022a). The structure of the FCM was based upon a qualitative model that was created during two participatory modelling workshops held in Sweden with experts from within the European food system (Lambraki et al., 2022a,2022b). A second set of workshops were used as to help inform the interventions and compare outcomes from the scenario analyses. Together these will further be referred to as the workshops. The methods for the creation of the FCM are fully described in the initial case study (Cousins, 2022a), but a brief outline is described to provide a basis of understanding.

The participatory modelling workshops

A set of workshops took place on September 19th and 20th, 2019 at the Stockholm Resilience Centre in Stockholm, Sweden and online on September 11th and 12th, 2020 with seventeen experts from across the One Health spectrum in fields such as veterinary and aquatic sciences, consumer and public health advocacy, agricultural crops, and pharmaceutical marketing (Lambraki et al., 2022a). The purpose of these workshops was for experts from within the broad One Health system in Europe to: 1) map out the drivers of AMR including the major factors and interrelationships (Lambraki et al., 2022a), and 2) discuss the success of two interventions to combat AMR (taxation of antimicrobials (AMs) at point of sale, and increased infection prevention and control measures) under potential climate change conditions (Lambrakiet al., 2022b). During these workshops, experts discussed the major drivers of AMR and the interrelationships between these drivers, which were visually represented as a causal loop diagram (CLD) consisting of 92 nodes (drivers) and 334 relationships (). This CLD served as the base structure of the FCM.

Brief description of building the FCM

FCMs (Kosko, 1986) are dynamic models that combine fuzzy logic, neural networks, and cognitive mapping (Kosko, 1986; Kokkinos et al., 2018; Nápoles et al., 2018). The components and causal relationships between the components together form a neural network (Kokkinos et al., 2018; Nápoles et al., 2018). Each component has an activation value (AV) assigned a value from [0,1] and each relationship has a weight (reflects the degree of causality between the components) assigned a value between [−1,1], with negative values indicating an inverse relationship (Nápoles et al., 2018). Fuzzy logic (Zadeh, 1990) is used to convert quantitative data (e.g., surveillance data) and qualitative data (e.g., linguistic terms) into a common format to inform the AVs and weights.

The CLD (Lambraki et al., 2022a) served as the base structure, refined by the available data from the literature and accounts made by the participants during the workshops (Cousins, 2022a), resulting in 90 components (Cousins, 2022a, Table S1). The relationships between the remaining components were added, including those from: the CLD, identified in the literature, and the transcripts. Fuzzy logic was used to combine the data to inform the AV and weights of the relationships were converted into levels using fuzzy logic (Figure 1); AVs were divided into eight categories that represented the level of the component, and weights were

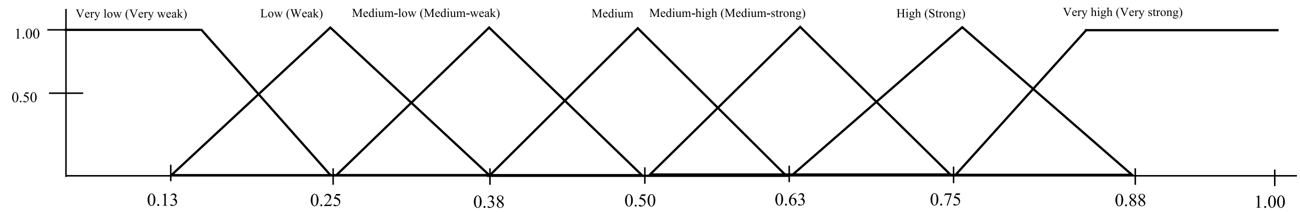


Figure 1. An example of how fuzzy logic was used to create the categories for the activation values for the components (and the weights of the relationships) in the fuzzy cognitive map of the development and transmission of antimicrobial resistance in a Swedish One Health system context. Fuzzy logic uses "degree of truth" as opposed to "true or false," or Boolean logic (0 or 1). Therefore, the degree of membership refers to the relative amount the factor belongs within each category. If the factor belongs fully to a category, it will have a degree of membership of 1.

divided into 15 categories. Intercoder reliability (Lavrakas, 2008) was assessed for the AV and weights on a subset (10%) of the components ($n = 11$) and relationships ($n = 43$). All decisions and deviations from the CLD were documented in a decision matrix (Cousins, 2022b).

Components and relationships and their initial AVs and weights were inputted into the software FCM Expert (Nápoles et al., 2018). An inference process was performed and the model reached equilibrium (Lavin and Giabbanelli, 2017). Structural measurements of the model were calculated using Mental Modeler and Excel (Cousins, 2022a).

Scenarios

FCMs uses an inference process to simulate a system's changes over time (Nápoles et al., 2018). The process evaluates the AV of each component based on its relationships at each discrete time step (iteration), leading to three different behaviours, equilibrium, a cyclical state, or total chaotic behaviour (Harmati et al., 2021). FCM software enables exploration of the system dynamics, pattern recognition, and "what-if" scenarios for decision processes and policy assessment (Liu et al., 2018; Alipour et al., 2019; Harmati et al., 2021). Scenario analyses involved altering the AV of components, reflecting a certain scenario (an intervention), performing an inference process in FCM Expert (Mcculloch and Pitts, 1990), and calculating percentage change between the AVs for the indicator components (Table 1) at steady state (equilibrium) and the AV from the baseline scenario (inference process conducted with the initial AV of all components). The indicator components were chosen by the research team because they covered many areas important to assessing impacts of interventions to combat AMR and on the broader system from a One Health lens. Therefore, the indicators cover the range of sectors in the One Health spectrum (human, animal, and environment), include important human and animal health indicators (illness in humans, illness in food-producing animals), are important indicators for assessing AMR (AMU and antimicrobial-resistant organisms (AROs) within the various sectors), and were of special interest to the research team (impacts on healthcare costs, cost of food, food security, and trade). Eighteen scenarios were assessed to determine the impact on the AMR system when certain interventions were implemented (outlined in Supplementary Materials). Each scenario was assessed at three intensities: low; medium; and high. These represent the strength of the intervention, and relates to the magnitude of the change in activation value implemented in the model. The different intensities of the scenarios are described in the following naming conventions: low (X.1); medium (X.2); and high (X.3). Therefore, Scenario 10 at the low intensity would be 10.1.

A priori *scenarios*

Nine scenarios were initially explored representing three interventions under current conditions and a climate change scenario (Table 2). A description of the *a priori* interventions and the reason for assessing them are outlined in Table 2. Climate change was also implemented into the model to determine how it may impact AMR and the other indicator components as well as to assess the sustainability of the interventions. The *a priori* scenarios were implemented into the model by altering the AVs of select components and running an inference process. For example, Scenario 1 represented the intervention of increased infection prevention and control. Therefore the AVs for *Non-antimicrobial disease prevention and control in health and social care* and *Non-antimicrobial disease prevention and control in food-producing animal agriculture* were increased, and an inference process was performed. The impact of the scenarios were assessed by comparing the AVs of the indicator components at equilibrium to the baseline scenario. A more detailed description of the rationale for the four *a priori* interventions and climate change are outlined in Supplementary Materials, and details on how they were implemented into the model can be found in Supplementary Materials, Table S1.

A posteriori *scenarios*

It was found that altering the AVs of components and performing an inference process alone were unable to significantly change the system. A significant impact was determined by a difference of greater than 1.0% in the AV of a component at equilibrium from the baseline compared to the scenario being tested. This was done for the *a priori* interventions and two additional scenarios that altered the AVs of highly impactful nodes; 10 components with the highest centrality, and the components with the highest outdegree, not including indicator components (see Supplementary Materials 2, Table S2). However, the sensitivity analysis (see section 4.3.3), which altered the weights of the relationships, was able to cause significant impacts and therefore new interventions were created aimed at altering the relationships. The experts (Lambrakiet al., 2022a,2022b) stressed the importance of attending to the underlying causes (e.g., poverty, inequality) and achieving the sustainable development goals (SDG; Søgaard Jørgensen et al., 2016, 2020; United Nations Department of Economic and Social Affairs, 2022) as fundamentally critical. Thus, by using the experts' suggestions (Lambrakiet al., 2022a,2022b), and further evidence from other research in AMR (Søgaard Jørgensen et al., 2016, 2020), four interventions addressing various aspects of the SDGs, were tested under current and climate change conditions (Table 2). These interventions were found to be ineffective at reducing AMR, thus, a final intervention (the "Hail Mary" scenario), which combined all *a posteriori* interventions was assessed. The details for

https://doi.org/10.1017/one.2024.2 Published online by Cambridge University Press

Table 1. List of components (referred to as indicator components) in the fuzzy cognitive map of the emergence and transmission of antimicrobial resistance in a Swedish One Health system used to assess the impacts of various scenarios on the system

Component	Name of component	Assigned level (activation value[1])	Level at equilibrium (activation value[1])	Description of component
AMa	Antimicrobial use in aquaculture	Low (0.25)	Medium-low (0.33)	The level used to describe the amount of use of antimicrobials in aquatic food-producing animals for all purposes (treatment, prevention, control)
AMh	Antimicrobial use in humans	Low (0.25)	Medium-high (0.58)	The level used to describe the amount of antimicrobial use in humans for all purposes (treatment, prevention, control)
AMp	Antimicrobial use in plant agriculture	Low (0.25)	Very low (0.21)	The level used to describe the amount use of antimicrobials in agricultural plants for all purposes (preventative, control, and treatment)
Amt	Antimicrobial use in terrestrial food-producing animals	Low (0.25)	Medium-low (0.28)	The level used to describe the amount use of antimicrobials in terrestrial food-producing animals for all purposes (preventative, control, and treatment)
ARe	Resistance in the environment	Low (0.25)	Highest (0.99)	The level used to describe the number of resistant organisms and genes in the surrounding environment (soil, water, plants)
ARh	Antimicrobial-resistant organisms in humans	Low (0.25)	Highest (0.99)	The level used to describe the number of resistant organisms in all humans
ARi	Exposure to antimicrobial-resistant organisms from imported food products	Medium (0.5)	High (0.75)	The level used to describe the number of resistant organisms in imported food products
ARm	Antimicrobial-resistant organisms in food-producing animals	Low (0.25)	Highest (0.89)	The level used to describe the number of resistant organisms in all food-producing animals
ARp	Antimicrobial-resistant organisms in plant agriculture	Low (0.25)	Highest (0.92)	The level used to describe the number of resistant organisms in all plant crops
DIT	Domestic and international trade regulations	High (0.75)	Very high (0.76)	The level used to describe the strength or amount of trade regulations for international and domestic trade of food products
FS	Food security	High (0.75)	Very high (0.78)	The level used to describe the amount of people with reliable access to enough affordable, nutritious food and clean, potable water from domestic production only
HC	Healthcare costs	Medium (0.5)	Very high (0.88)	The level used to describe the actual costs of providing services related to the delivery of health care, including the costs of procedures, therapies, and medications
Ih	Illness in humans	Low (0.25)	Very low (0.13)	The level of infectious disease in the human population
Im	Illness in food-producing animals	Low (0.25)	None (0.05)	The level of diseases in all animals (incl. poultry, livestock, aquatic animals) raised in agriculture
IP	Amount of imported product	High (0.75)	Medium-high (0.62)	The level used to describe the total amount of food products available for sale that have been imported from a different country
Ip	Disease in plant agriculture	Low (0.25)	High (0.65)	The level of disease in all plants used for agriculture
RC	Retail cost of food	High (0.75)	Very high (0.83)	The level used to describe the relative cost of food in retail stores

[1]Activation values represents the level at which the different drivers (components) of AMR in the Swedish One Health system context exist and were informed by expert opinion and a literature review, and a description of the component. The activation value can take on a value between [0,1] and was divided into eight categories to represent the different levels with the following cut-off values: none (0), very low (0.13), low (0.25), medium-low (0.38), medium (0.5), medium-high (0.63), high (0.75), very high (0.88).

the rationale for the four *a posteriori* interventions are outlined in Supplementary Materials and how they were implemented into the model can be found in Supplementary Materials, Table S3.

Sensitivity analysis

Formal sensitivity analyses are not common-place in fuzzy cognitive mapping as the models are typically expert-driven and created through discussion (Lavin and Giabbanelli, 2017). However, because there were many assumptions made for the weight values (Cousins, 2022a), an adjusted sensitivity analysis was performed to determine the influence of a subset of the relationships on the system. The outward relationships of the five components with the highest centrality (components with the most incoming and outgoing relationships (Kosko, 1986); that were assigned "medium" as an assumption were chosen for the sensitivity analysis because these components have the most influence within the system. To determine the sensitivity of a set of components of interest (further referred to as indicator components, Table 1) to the selected relationships, the weights of the relationships were adjusted to the 0 and 1 or −1

Table 2. Description of interventions assessed in a fuzzy cognitive map of the emergence and transmission of antimicrobial resistance in a Swedish One Health system and the reason for including them in the analysis

A priori interventions				
Intervention Name	Description of intervention	Reason for inclusion	Under current conditions	Under climate change conditions
Baseline			Baseline scenario	Scenario 5
Increased biosecurity and infection prevention and control measures	Aimed to increase (provide better) infection prevention and control, both on-farm (e.g., biosecurity) and in health and social care settings	Successful intervention in the scenario planning workshops (Lambraki, Cousins, Graells, Léger, et al., 2022ab), wanted to determine if successful in model.	Scenario 1	Scenario 6
Educational campaign	Aimed to increase knowledge about AMs and proper AMU through educational campaigns targeted to the public and prescribers	Identified as a potential high-leverage intervention during the participatory modelling workshops (Lambrakiet al., 2022ab), wanted to determine if successful in model.	Scenario 2	Scenario 7
Antimicrobial stewardship	Combination of Increased biosecurity and infection prevention and control measures and Educational campaign	Interested in the combined impact of interventions in the model to determine if multiplicative.	Scenario 3	Scenario 8
Increased trade regulations	Aimed to increase trade regulations for antimicrobial use on farm (representing a reduction in use of antimicrobials for growth promotion).	Based on the European Union's decision to ban the importation of all animal-based food products from animals that have received growth promoters (Agence Europe, 2022), wanted to determine if would be successful in model.	Scenario 4	Scenario 9
High centrality	Five components with the highest centrality value (the greatest number of incoming and outgoing relationships)	Interested in the ability of the components that were the most connected in the system to impact the system.		
High out degree	Five components with the highest out degree value (most outgoing relationships)	Interested in the ability of the components with the most outward influence on the system to impact the system.		
A posteriori interventions				
Intervention Name	Description of intervention	Reason for inclusion (SDG addressed)	Under current conditions	Under climate change conditions
Cost as a barrier	Aimed to increase access to nutritious and sustainable food through subsidies to reduce costs to farmers and consumers for food from alternative production systems (e.g., organic, animal welfare friendly).	Identified as a barrier to addressing antimicrobial resistance during scenario planning workshops (Lambraki et al., 2022ab). Addresses the second SDG (Zero hunger), and the twelfth SDG (Responsible consumption and production; United Nations, 2022).	Scenario 10	Scenario 14
Trade regulations	Aimed to increase the influence that trade regulations have on antimicrobial use in agricultural and antimicrobial-resistant organisms in imported food.	Similar to *a prioiri* intervention Increased trade intervention but more targeted at implementation and enforcement, which was identified as a barrier in the participatory modelling workshops (Lambraki et al., 2022ab). Addresses the seventeenth SDG (Partnerships for the goals; United Nations, 2022).	Scenario 11	Scenario 15
Technological advancements	Aimed to reflect an enhancement to rapid diagnostic technology and alternatives to antimicrobials.	Identified as potential success factor during the scenario planning workshop (Lambraki et al., 2022a,2022b). Address the ninth SDG (Industry, innovation, and infrastructure)	Scenario 12	Scenario 16
Addressing population vulnerabilities	Aimed to reduce the negative impacts that vulnerable populations endure (e.g., increase access to healthcare and nutritious food) through increasing social supports.	Identified as a major driver of illness, antimicrobial use and antimicrobial resistance in the scenario planning workshops (Lambraki et al., 2022ab). Addresses the first SDG (No poverty) and the tenth SDG (Reduced inequalities; United Nations, 2022).	Scenario 13	Scenario 17
"Hail Mary" scenario	Combination of previous four *a posteriori* interventions resistance.	Interested to determine if together they could reduce antimicrobial resistance in the system.		

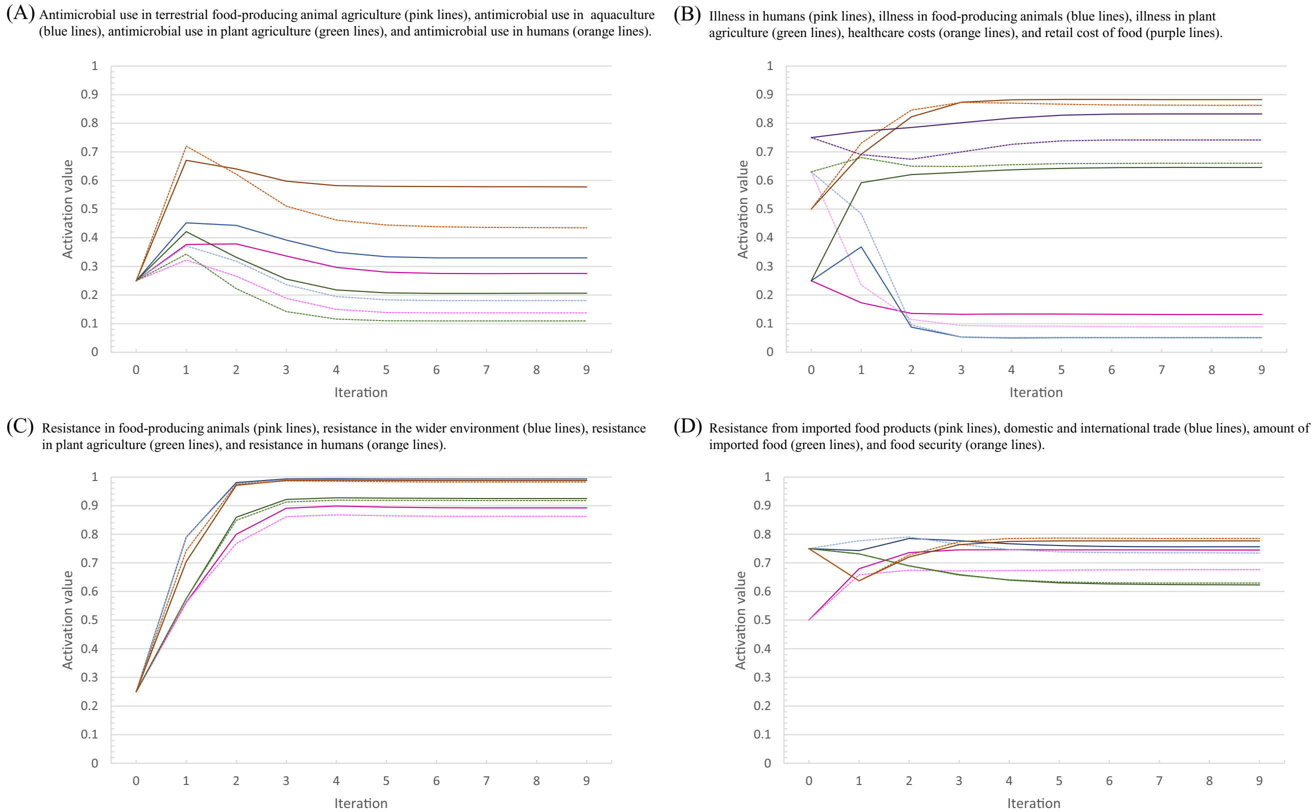


Figure 2. Results of the sensitivity analysis performed on a fuzzy cognitive map of the drivers of antimicrobial resistance in the Swedish One Health system context. The activation values for the indicator variables over the nine iterations of the inference process for the sensitivity analysis with the relationships tested at the lowest possible value (dotted lines) and highest possible value (light solid lines) compared to the baseline (dark solid lines). **(a)** The activation values for: antimicrobial use in terrestrial food-producing animal agriculture (pink lines), antimicrobial use in aquaculture (blue lines), antimicrobial use in plant agriculture (green lines), and antimicrobial use in humans (orange lines). **(b)** The activation values for illness in humans (pink lines), illness in food-producing animals (blue lines), illness in plant agriculture (green lines), healthcare costs (orange lines), and retail cost of food (purple lines). **(c)** The activation values for: resistance in food-producing animals (pink lines), resistance in the wider environment (blue lines), resistance in plant agriculture (green lines), and resistance in humans (orange lines). **(d)** The activation values for: resistance from imported food products (pink lines), domestic and international trade (blue lines), amount of imported food (green lines), and food security (orange lines).

(see Supplementary Materials, Table S4), and the percentage change for each indicator component was calculated (Figure 2).

Results

The final FCM consisted of 90 components with 491 relationships. The components with the highest indegree (number of incoming relationships, ID), outdegree (number of outgoing relationships, OD), and centrality are outlined in Table 3. All network metrics for the FCM are reported in Cousins, 2022a. The model reached equilibrium (as opposed to cyclical or chaotic behaviour) and therefore could be used for scenario analysis (Cousins, 2022a).

Scenarios

The AVs for each component during the inference processes during each iteration of the 18 scenarios were published on Borealis (Cousins, 2022b). Visual representations of the AVs for the 17 indicator components during the scenario analyses can be found in Supplementary Materials; includes the eight interventions (Figures S1–17), the high centrality and high outdegree test scenario (Figure S18), the “Hail Mary” scenario (Figure S19), and the sensitivity analysis (Figure 2). The results for the scenarios are described by percentage change in the AV of the given component after an inference process for a scenario compared to the baseline. This change does not represent a numerical value but a way to compare the scenario to the baseline (e.g., a larger percentage change implies a larger impact on the component). To qualitatively describe the magnitude of the relative changes, the following terms were used: significant (any difference >1.0%); slight/minor (>3.0% difference); moderate (3.1%–7.0% difference); large/a lot/greatly (>7.1% difference). The changes in AV are also described in terms of the change in level (e.g., went from “high” to “medium”) based on the cut-off points that were assigned during model building (Figure 1) and these levels must be taken with caution.

Base scenario

The AVs for the 17 indicator components are listed in Table 1 and shown in Figure 2. The AVs for AMU (except for *AMU in plant agriculture*), AMR, *disease in plant agriculture, healthcare costs, retail cost of food, domestic and international trade, food security* all reached equilibrium at higher levels than the initial AVs assigned (Table 1). *Illness in humans, illness in food-producing agriculture*, and *amount of imported product* had lower levels at equilibrium. In general, if the system was to continue in its current state, then although disease (and thus AMU) will remain very low, there may still be a large increase in AMR to a very high level, which may have trade implications (increase in trade regulations) and economic impacts (increased healthcare costs and cost of food).

Table 3. The nodes with the five highest indegree,[1] outdegree[2] andcentrality[3] from a fuzzy cognitive map of antimicrobial resistance in a Swedish One Health system context, originally created by Cousins, 2022a

Node	Indegree[1]	Outdegree[2]	Centrality[3]
Antimicrobial-resistant organisms in food-producing animals	8.13	4.50	12.63
Antimicrobial-resistant organisms in humans	10.85	4.88	15.73
Development of alternatives to AMs	3.88	6.50	10.38
Domestic and international trade	2.50	6.00	8.50
Illness in food-producing animals	9.00	6.00	15.00
Illness in humans	8.38	4.38	12.76
Resistance in wider environment	7.63	2.75	10.38
Type of production systems	1.00	9.02	10.02
Understanding and awareness	3.63	7.51	11.14

[1]Indegree: the number of incoming relationships (+).
[2]Outdegree: the number of outgoing relationships (–).
[3]Centrality: the absolute value of either: (a) overall influence in the model (all positive (+) and negative (–) relationships indicated, for entire model); or (b) influence of individual concepts as indicated by positive (+) or negative (–) values placed on connections between components.

A priori *interventions, climate change conditions, high centrality, and high outdegree scenarios*

The interventions that were created *a priori* (Supplementary Materials, Figures S1–4,6–9), the climate change scenario (Supplementary Materials, Figures S5), and the high centrality and high outdegree scenarios (Supplementary Materials, Figures S18) had very little impact on the system, with a difference of less than 1.0% in the 17 indicator components at all levels of the intervention.

A posteriori *interventions*

The relative changes in AV at equilibrium for the indicator components between the baseline scenario and each *a posteriori* scenario at the highest intensity are depicted in Figure 3. For further detail, the AVs for the indicator components at each time step of the inference processes for the three intensities of each *a posteriori* scenario are depicted in Supplementary Materials, Figure S10–19.

Reducing the cost barrier by a small amount (Scenario 10.1) significantly reduced *illness in humans, illness in food-producing animals, and retail cost of food.* When the cost barrier was reduced further (Scenario 10.3), there was a significant change in six of the indicator components, causing a reduction in *retail cost of food, illness in food-producing animals, illness in humans, AMU in terrestrial animals, AMU in aquaculture,* and increase in *food security* (Figure 3(A)). The largest impact was in *retail cost of food*, with a reduction from the very high to the high level (16.5% reduction). A moderate reduction in *illness in food-producing animals* (5.7% reduction) and *illness in humans* (3.9% reduction) were noticed but did not cause a change to the level at equilibrium.

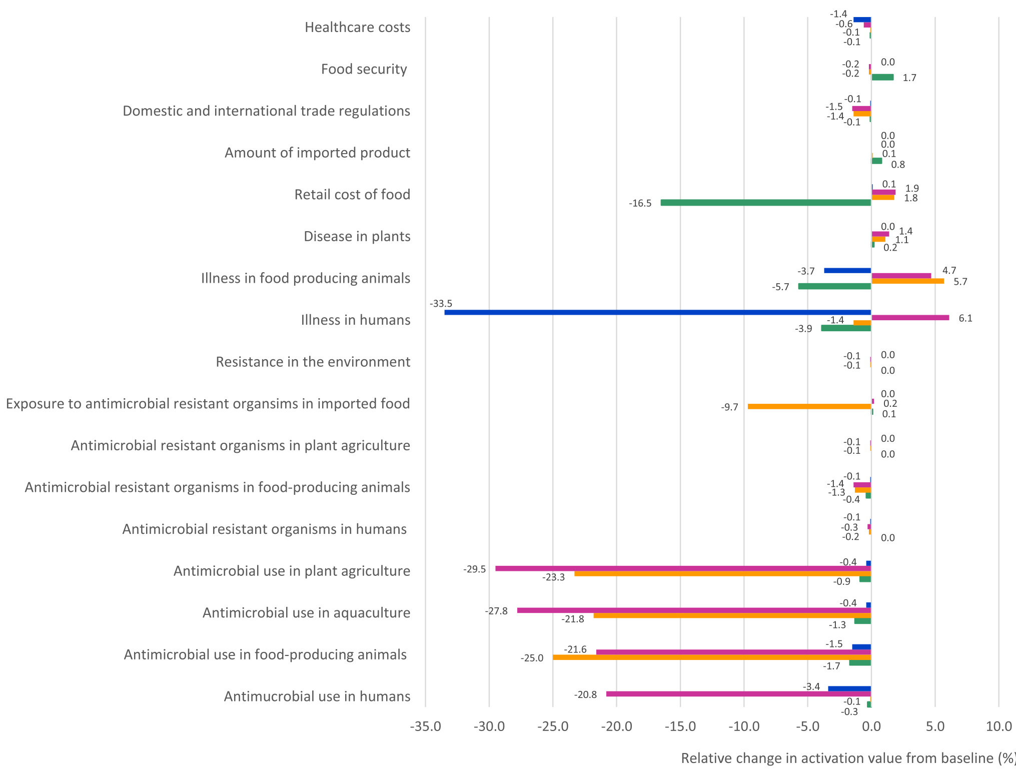
Increasing trade regulations slightly (Scenario 11.1) significantly reduced *AMU in terrestrial food-producing animals, AMU in aquaculture, AMU in plant agriculture,* and *exposure to AROs from imported food,* and a slight increase in *illness in food-producing animals*. When trade regulations was strengthened further (Scenario 11.3), there were significant changes in ten of the indicator components, causing a reduction in *AMU in terrestrial food-producing animals, AMU in plant agriculture, AMU in aquaculture, exposure to AROs from imported food, illness in humans, domestic and international trade regulations, and AROs in food-producing animals*, and increases in *illness in food-producing animals, retail cost of food,* and *disease in plant agriculture* (Figure 3(A)). The largest impacts were in AMU in agriculture, specifically in *AMU in terrestrial food-producing animals* (25.0% reduction), *AMU in plants* (23.3% reduction), and *AMU in aquaculture* (21.8% reduction). This caused *AMU in terrestrial food-producing animals* to fall from the medium-low level to the low level. *AROs from imported food* significantly improved (9.7% reduction) but remained in the high level. A moderate increase to *illness in food-producing animals* were noticed (5.7% increase), remaining in the very low level.

A small increase in technological advancements (Scenario 12.1) caused a significant reduction in AMU in all sectors (*AMU in humans, AMU in terrestrial food-producing animals, AMU in aquaculture, and AMU in plant agriculture),* but caused slight increases in *illness in humans* and *illness in food-producing animals*. With even more effective technological advancements (Scenario 12.3), significant changes occurred in ten of the indicator components, including reductions in AMU (*AMU in humans, AMU in terrestrial food-producing animals, AMU in aquaculture, and AMU in plant agriculture*), *AROs in food-producing animals,* and *domestic and international trade regulations*, and increases in *illness in humans, illness in food-producing animals, disease in plants,* and *retail cost of food* (Figure 3(A)). The largest impacts were seen in AMU in all sectors, with large reductions in *AMU in plant agriculture* (29.5% reduction), *AMU in aquaculture* (27.8% reduction), *AMU in terrestrial food-producing animals* (21.6% reduction), and *AMU in humans* (20.8% reduction). These reductions caused *AMU in aquaculture* and *AMU in terrestrial food-producing animals* to move from a level of medium-low to low, and *AMU in humans* to move from medium-high to medium. *AMU in plant agriculture* remained in the low level. There were moderate increases to *illness in humans* (6.1% increase), moving from the very low to the low level, and *illness in food-producing animals* (4.7% increase), remaining in the very low level.

Slightly improving social inequalities and poverty (Scenario 13.1) only slightly improved the system through the reduction of *AMU in humans, illness in humans,* and *illness in food-producing animals.* However, through further improvements to addressing social inequalities and poverty (Scenario 11.3), greater reductions occurred in not only *AMU in humans, illness in humans,* and *illness in food-producing animals*, but reductions were also found in *AMU in terrestrial food-producing animals,* and *healthcare costs* (Figure 3(A)). Improving vulnerable populations access to healthcare, social supports, and nutritious food, caused a significant reduction to *illness in humans* (33.5% reduction). Additional moderate reductions were found in *AMU in humans* (3.4% reduction) and *illness in food-producing animals* (3.7% reduction).

The impact of the four interventions at the highest intensity under climate change conditions (Scenario 14.3, 15.3, 16.3, and 17.3) on the 17 indicator components are depicted in Figure 3(B). Overall, climate change conditions did not significantly change how the interventions impacted the system, except for technological advancements and innovation (Scenario 16). At the highest

(A) *a priori* interventions under current conditions (Scenarios 10-13) at the highest intensity



(B) *a posteriori* interventions under climate change conditions (Scenarios 14-17) at the highest intensity

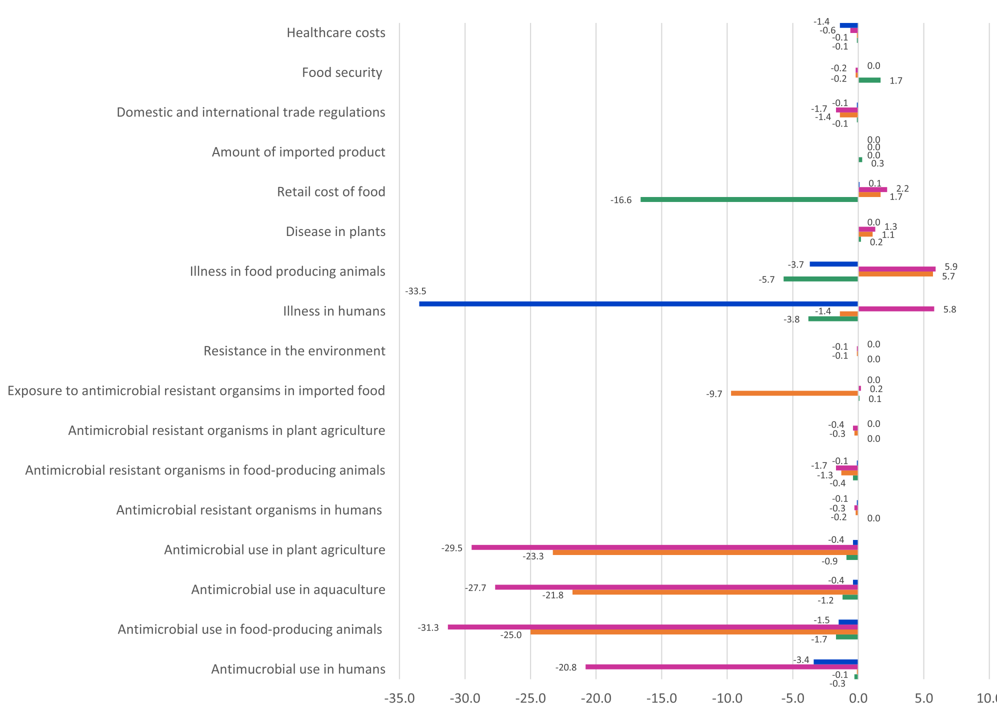


Figure 3. The relative reduction in the activation value of the indicator components at equilibrium from Scenarios 10 to 13 (A), Scenarios 14 to 17 (B), and Scenario 18 (C). (A) Scenarios 1013 at the highest intensity: Scenario 10 represents a reduction in barrier as a cost for nutritious food and sustainable production practices under current conditions (blue), Scenario 11 represents increased international trade regulations and implantation under current conditions (pink), Scenario 12 represents technological advancement and innovation under current conditions (orange), and Scenario 13 represents addressing poverty and social inequalities under current conditions (r green). (B) Scenarios 1417 at the highest intensity: Scenario 14 represents a reduction in barrier as a cost for nutritious food and sustainable production practices under climate change conditions (blue), Scenario 15 represents increased international trade regulations and implantation under climate change conditions (pink), Scenario 16 represents technological advancement and innovation under climate change conditions (orange), Scenario 17 represents addressing poverty and social inequalities under climate change conditions (green). (C) Scenario 18 represents scenarios 10–13 in combination at the highest intensity.

https://doi.org/10.1017/one.2024.2 Published online by Cambridge University Press

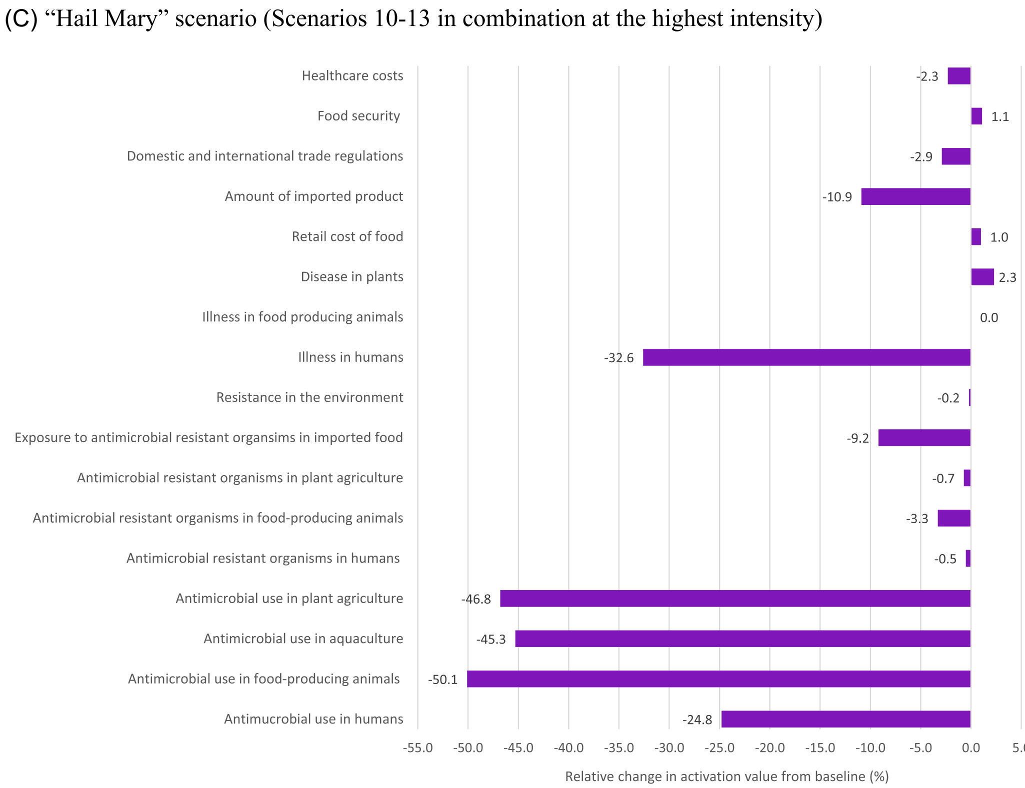


Figure 3. (Continued).

intensity of the intervention (Scenario 16.3), technological advancements and innovation decreased *AMU in terrestrial animals* by 10% more under climate change than under current conditions (Scenario 12.3) and led to a larger increase in *illness in food-producing animals* compared to a under current conditions (5.9% increase compared to a 4.7% increase).

The "Hail Mary" Scenario assessed all *a posteriori* interventions together, under current conditions (Scenarios 10–13). These interventions in combination were able to significantly reduce AMU in all sectors, with the largest reduction seen in *AMU in food-producing animals* (50.1% reduction, Figure 3(C)), moving from the medium-low to the low level. They were also able to greatly reduce *illness in humans* (32.6% reduction, Figure 3(C)). However, these interventions were unable to significantly impact most resistant outcomes, aside from *AROs from imported foods* (9.2% reduction, Figure 3(C)) and *AROs in food-producing animals* (3.3% reduction, Figure 3(C)). The reduction in *AROs in food-producing animals* was able to shift the level from highest to the very high, but the reduction did not have an impact on the level of *AROs from imported foods*, remaining in the high level.

Sensitivity analysis

The sensitivity analysis showed that altering the 10 relationships (Supplementary Materials, Table S4) had varying results on the system, with some components being relatively unaffected (*amount of imported food, AROs in imported food, resistance in the environment, food security,* and *healthcare costs)* and some being significantly affected (*AMU in terrestrial food-producing animals, AMU in aquaculture, AMU in plant agricultural,* and *retail cost of food*). The results of the inference process for the sensitivity analysis are depicted in Figure 2.

Discussion

This study presents an innovative way to analyse the system of drivers for AMR and uses a systems thinking approach to analyse the effects of interventions to address AMR within the One Health system, including under a climate change scenario. The FCM highlighted the ability of components to influence and be influenced by the system, thus identifying high-leverage factors that when altered, could have great impact on changing the system (Meadows, 1999). High centrality indicates components that are the most interconnected and thus these important factors within the system may be of particular interest when choosing where in the system to act. Many of the components with the highest centrality were expected (such as illness in food-producing animals and illness in humans) as they are typically the target of current intervention strategies (for example increased biosecurity (Niewiadomska et al., 2019; Pinto et al., 2020; Smith et al., 2003), hand washing (Smith et al., 2003; Niewiadomska et al., 2019), or vaccination (Smith et al., 2003; Niewiadomska et al., 2019; Pinto et al., 2020). Similarly, interventions that aim to increase understanding and awareness (another highly connected node) in consumers to reduce the demand for AMs (Wutzke et al., 2007; Azevedo et al., 2013; Price et al., 2018). However, animal welfare, the component with the fourth highest centrality, is not typically the target of intervention The experts from the participatory modelling workshop (Lambrakiet al., 2022a) and the ReAct Group, an international network to provide education on AMR (ReAct, 2020), have identified farming systems that enable high levels of animal welfare as a key factor in reducing the need for AMs and may be an important factor missing in current interventions. Components with high ODs are also of interest as these factors have a lot of outward influence on the system.

The proportion of alternative production systems (e.g., organic, and antimicrobial free farming), and good farm practices were two components with a lot of outward influence. Alternative production systems may have practices that promote high animal welfare (Carlsson-Kanyama and Lindén, 2001; Mie et al., 2017; The European Food Information Council, 2013), and therefore may also have a large influence on the system.

Scenarios

Baseline model

When the FCM was simulated with the initial AVs, all AMR and many AMU indicators at final equilibrium were much higher than the initial values, especially in humans and the environment. However, it is well documented that AMR in all sectors is quite low in Sweden, especially compared to other countries (Axén et al., 2019; European Food Safety Authority, & European Centre for Disease Prevention and Control, 2020; Nulty et al., 2016; The Centre for Disease Dynamics & Economics & Policy, n.d.), and has not been increasing rapidly or in some cases has been decreasing in recent years (Nulty et al., 2016; Axén et al., 2019; The Centre for Disease Dynamics & Economics & Policy, n.d.). Therefore, it was concerning that the model predicted rapid and large increases in AMR. This could indicate that some balancing factors may be missing from the system, or that relationships that increase AMR may be too strong, or those that decrease AMR are too weak. One hypothesis is that the workshop aimed to identify and analyse the drivers of AMR (Lambraki et al., 2022a). Therefore, many of the factors identified aimed to drive (increase) AMR, but fewer may have been identified to reduce AMR. Overall, the over-estimated AMR levels and potential missing relationships and feedback loops would greatly impact the system behaviour and limit the ability to accurately interpret intervention impacts.

A priori *interventions, climate change, high centrality, and high outdegree scenarios*

The *a priori* interventions (including the high centrality and high outdegree scenarios) demonstrated that a change in the AV of a few components were unable to cause system-wide changes. The low system density (Cousins, 2022a) may limit an intervention's reach within the system due to poor connectivity (Eden et al., 1993; gray et al., 2013). Smaller FCMs (8–42 components) prove that AV changes can impact low-density systems (Giles et al., 2007; gray et al., 2013). However, large numbers of components may limit an intervention's reach the outer edges of the system. Experts in the scenario planning workshops (Lambrakiet al., 2022b) agreed that simple interventions like taxing AMs alone would not be enough to alter the system. They recommend multi-pronged interventions to address underlying causes of AMR (e.g., poverty, social inequalities, basic hygiene, and access to resources), and a shift in worldviews of the population (e.g., reducing capitalism, prioritizing public health) were essential in reducing AMR (Lambraki et al., 2022b).

The way in which climate change was modelled in the FCM, by only altering AVs, caused no significant changes in the system. However, it is hypothesized that climate change will impact AMR and the One Health system that drives AMR in multiple ways, including but not limited to: increasing and emerging diseases in humans, animals, and the environment causing greater transmission, a loss of food production, and a greater need for AMs (World Health Organization, 2017; Rodríguez-Verdugo et al., 2020; Carlson et al., 2022); increased migration leading to overcrowding causing poor living conditions (Parry et al., 2005; Semenza and Ebi, 2019; Abirham, 2020); increased chronic illnesses and heat stress leading to reduced immunity and increased susceptibility to infectious diseases in humans and animals (World Health Organization, 2017; Rodríguez-Verdugo et al., 2020; Carlson et al., 2022). Due to these changes, AMR is predicted to increase under climate change conditions (World Health Organization, 2017; Fouladkhah et al., 2020; Burnham, 2021; Pepi and Focardi, 2021). Therefore, this may indicate issues in the FCM (described above) or that it was modelled too simplistically (e.g., climate change may impact relationships as well as AVs). Further research is required to assess the model structure and dynamics as well as to further develop the climate change scenario both with research and with experts to more accurately capture the changes to the system and how they should be inputted into the model.

A posteriori *interventions*

Reducing cost as a barrier to sustainable food production systems had most impact on reducing illness in food-producing animals. This was most likely due to the impacts of increased animal welfare both directly (through animal-welfare friendly practices) and indirectly (through organic production systems which are more likely to have more animal-welfare friendly practices). There was a correlation between poor animal welfare conditions and stressed animals and a reduction in immunity in these animals (Ashenafi et al., 2018; Gunnarsson and Cerenius, 2004; Lambrakiet al., 2022a). A potential explanation for how reducing the cost barrier could improve animal welfare and reduce disease in animals based on the relationships that exist in the FCM could be as follows: reducing the cost barrier early in the chain (e.g., reducing the cost of production through subsidies to farmers) could enable farmers to prioritize health interests of their animals, rather than on their practical economic constraints affecting health decisions where these two considerations come into conflict (e.g., the farmer cannot afford to use the best medication and has to choose a more affordable one which might have less efficacy or where antibiotic treatment is cheaper than vaccination). Two positive unintended consequences found through the FCM were a reduction in human illness (due to increased access to nutritious foods) and an increase food security (due to increased yield).

Enhanced diagnostic technology and development of better alternatives to AMs was most effective at reducing AMU in humans, animals, and plants. These interventions specifically targeted AMU, either through better prescribing from enhanced diagnostics or better alternatives. Increasing access to diagnostics has improved prescribing behaviour (Engström et al., 2004; Llor et al., 2014; O'Neill, 2015). Therefore, if diagnostics were more widely available and more specific (better at determining organisms), this could greatly improve prescribing and reduce AMU. The development and accessibility of alternatives to AMs (e.g., vaccines, phage therapy) compounded this by also reducing traditional AMU. Vaccines are the most researched alternative to AMs and have been associated with reductions in animals and human AMU (Buckley et al., 2019; Doherty et al., 2020).

Increased trade regulations and enforcement of trade regulations was effective at reducing AMU in agriculture and the only intervention to significantly reduce the importation of AROs through food, as restrictions included food with trace AROs or AM residues. This was under the assumption that Sweden would conform to the trade restrictions and reduce their on-farm AMU to remain trading partners with other countries in the European

Union. A scenario analysis in the United States of America (USA) from 2011 assessed the trade and economic implications of the USA conforming, or not conforming, to the restrictions on the use of certain AMs in feed for growth promotion and other AM practices (e.g., antimicrobial rinses) some of their largest trading partners (e.g., South Korea and Russia) put in place (Johnson, 2011). This analysis estimated great economic losses if the USA were to conform because the current competitive advantages they hold (low cost of their products) would be reduced (due to increased costs of production), and thus decrease exports (Johnson, 2011). The assumption that Sweden would conform to these regulations is valid as Sweden is less likely to be impacted by these trade regulations compared to the USA due to their existing strict AMU policies (Wierup, 2001; Wierup et al., 2021), the production systems they have in place (Lambraki et al., 2022a, 2022b; Wierup et al., 2021), and their weak reliance on income from exports (World Integrated Trade Solutions, 2022; Lambraki et al., 2022a).

Technological advancements and increased trade regulations, however, both caused an increase to the cost of food. The reduction in AMU on-farm could increase production costs through the need for better farm practices and animal welfare (Lambraki et al., 2022a). However, when Sweden and Denmark banned AMU for growth promotion, there were limited economic consequences to farmers (Wierup, 2001), and thus may not be as impacted within this context. If cost of food were to increase, however, could cause other negative impacts throughout the system such as inaccessibility to nutritious foods, especially to vulnerable populations, thus impacting health outcomes in these populations (Lambraki et al., 2022a). Other negative unintended consequences due to AMU reductions were an increase in illness in animals (from increasing trade regulations and technological advancements) and in humans (from enhanced technological advancements). AMs are necessary for life-saving treatment, and therefore accessibility is required (Government of Canada, 2017).

Reducing negative impacts to vulnerable populations was most effective at reducing human illness and AMU. Vulnerable populations are at higher risk of negative health outcomes and AMR (Elisabeth et al., 2021; Planta, 2007), and addressing poverty and social inequalities was identified as integral to combatting AMR by experts from within the system (Lambraki et al., 2022a, 2022b). This intervention was successful at reducing illness and AMU in humans but was the least impactful on broader factors within the system. Some possible explanations for this phenomena could be: 1) the factors and relationships associated with population vulnerabilities and social inequalities were not fully developed; 2) the level of population vulnerabilities, human illness, and human AMU are already so low in Sweden (Cousins et al., 2024) and may cause major issues within the system that reducing these further would not provide large changes to the system; or 3) human-centred interventions may not be enough to shift the system and multi-faceted approaches are required. One positive unintended consequence was a moderate reduction in illness in food-producing animals, most likely due to the relationship between farmers and their ability to care for their animals; healthy farmers (both physically and mentally) provide better care to their animals, thus improving animal welfare and reducing animal illness (Lambraki et al., 2022a).

Overall, no intervention had significant impacts on resistance in any sector (humans, animals, or environment). This is an important and not overly surprising result due to the complexity of the system. A study on interventions of climate change, another extremely complex system, found that current interventions to tackle climate change are not quick or deep enough to slow climate change and that "radical" interventions are needed to combat this complex challenge (Morrison et al., 2022). Further research is needed to brainstorm and assess such "radical" interventions to combat AMR.

The only intervention to reduce AMR greatly in the FCM was enhanced trade regulations, with a reduction in the exposure to AROs from imported food. However, this did not cause a reduction in AROs in humans, meaning this may not be a significant source of resistance in humans in this FCM. Literature is scarce on the relative contribution of imported food to overall resistance in humans (Jung et al., 2022) and further research is required to validate this result.

Increasing trade regulations and technological advancements had the largest impacts on AMR in the FCM. Both caused small reductions to resistance in food-producing animals and technological advancements also had minor impacts on resistance in humans and plant agriculture. However, the modelled outcomes showed that large reductions in AMU lead to minimal changes in AMR, and thus AMU is not a major driver of resistance in this FCM of the Sweden context. One potential explanation for this could be there is already very low AMU and AMR in Sweden (Cousins et al., 2024) and therefore reducing AMU further may not have much impact in this context. This is similar to the minimal impacts that reducing human illness and the level of population vulnerability had on AMR, as these are also very low in this context. However, reducing AMU in different contexts, with differing AMU and AMR levels, may result in larger impacts to AMR. However, in Sweden, interventions aimed to reduce AMU may not be the best place to target action, and focusing on upstream drivers (e.g., improving animal welfare and good farming practices) may provide larger impacts within the system.

Sensitivity analysis

The sensitivity analysis revealed two interesting behaviours of the system. Firstly, by removing or setting to the highest possible value the 10 selected relationships that were highly influential to the system, there was not significant changes in the AMU and AMR components as expected. Therefore, these relationships may have influence in the system but not on AMR or there are other relationships that are more important or "take over" when others are removed.

Secondly, the final activation values were different than the baseline when the relationship weights were altered and thus, to change the final activation values of the components at equilibrium and provide sustainable change over time, the weights of the relationships must be altered, not just the AVs of the components. Therefore, the relationships are important drivers of the system and future work is needed to better define the weights of the relationships through further engagement of stakeholders and a formal scoping review of these associations.

Strengths & limitations

This study highlighted the benefits of FCM in a Swedish One Health system, including socio-ecological drivers from multiple sectors, to assess interventions. Current quantitative models of AMR are limited by data availability, have difficulties capturing real-world behaviour, and may overlook important factors like political forces or human decision-making (Birkegård et al., 2018; Ramsay et al., 2018; Cousins, 2022a; Trochim et al., 2006).

https://doi.org/10.1017/one.2024.2 Published online by Cambridge University Press

Thus, models currently used to assess interventions for AMR are limited in scope and do not include drivers from sectors across the One Health system (e.g., not accounting for potential unintended consequences in the broader system), and contain much uncertainty, thus limiting the ability to adequately assess interventions in the real world. This FCM brings together factors in the human, animal, and environment, and therefore, provided a tool assess multiple scenarios and analyse unintended consequences and unforeseen interactions across sectors under potential climate change conditions (Gray et al., 2013; Sypher, 2017; Nápoles et al., 2018).

This FCM has limitations inherent to fuzzy cognitive mapping, the way in which the FCM was created (outlined by Cousins, 2022a), and in use for scenario analysis. One limitation was related to the uncertainty in the data used to inform relationships, requiring further engagement with stakeholders (Cousins, 2022a). Exclusive to this study, there are challenges of interpreting intervention outcomes due to the arbitrary time steps and the relative nature of AVs; although AVs are numerical, they do not have an absolute meaning but rather relative ordinal interpretations (Bueno and Salmeron, 2009; Mpelogianni and Groumpos, 2016; Vassiliki Mpelogianni and Groumpos, 2018). Therefore, intervention impacts cannot be quantified (e.g., an intervention reduces the average cost of food from \$10 per day to \$8 per day) but can be used to compare interventions (e.g., one intervention reduces cost of food more than another). Despite these limitations, fuzzy cognitive mapping provided invaluable insight into system dynamics, identified impactful factors, and allowed comparison of interventions under climate change from a systems perspective.

Conclusion

The use of fuzzy cognitive mapping allowed us to evaluate eight interventions under climate change conditions, of which none of the initial interventions had any impact on the system and no intervention was able to reduce AMR in the system, thus highlighting the complexity of the system that drives AMR. Network analysis of the FCM allowed us to identify influential components for potential future interventions. This study highlighted the need for multi-faceted interventions that target the underlying system, but more work is needed to adequately assess how interventions will impact AMR within the complex system. Finally, this work advocates for further participatory and mixed methods in the exploration of AMR and the complex One Health system that drives it.

Supplementary materials. The supplementary material for this article can be found at https://doi.org/10.1017/one.2024.2.

Data availability statement. The data that support the findings of this study are openly available at the following:

Cousins, M. (2022). *Mapping out a One Health model in the context of the Swedish food system using a modified scoping review methodology: Scoping Review Database*. Borealis. https://doi.org/10.5683/SP3/UQZJMB

Cousins, M. (2022). *Using expert knowledge and experience to parameterize a simulation model of AMR emergence and transmission in a Swedish food system context: Framework Matrices*. Borealis, V1. https://doi.org/10.5683/SP3/WUXL5F

Cousins, M. (2022). *A One Health and fuzzy cognitive map-based approach to assess interventions to reduce antimicrobial resistance in a Swedish food system context under potential climate change conditions: Decision matrix and Scenario results*. Borealis, V2. https://doi.org/10.5683/SP3/Z2IJTE

Acknowledgements. We would like to thank Stephan Harbarth and Max Troell for their involvement on the AMResilience team and inputs into the broader research project for which this is a part of.

Author contributions. Conceptualization: MC, SEM, IAL, EJP, CAC. Data analysis: MC. Visualization: MC. Validation: MC, SEM, EJP, CAC. Funding acquisition: DW, PSJ, SEM. Project administration: IAL, JEP, PSJ, DW, SEM. Supervision: IAL, SEM. Writing of main manuscript: MC. Editorial comments: EJP, ALG, EN, IAL, TG, AL, PJGH, DW, PSJ, CAC, SEM.

Financial support. This study is funded through an operating grant of the 5th Joint Programming Initiative on Antimicrobial Resistance (JPIAMR 2017). Funding was provided by an operating grant from the Canadian Institutes for Health Research (Institute of Infection and Immunity, Institute of Population and Public Health, grant number 155210, PI SEM), a Swedish Research Council grant (grant number 2017-05981, PI and Project Coordinator PSJ); and an operating grant from the Swiss National Science Foundation (grant number 40AR40_180189, PI DW). The funders had no role in the design analysis or writing of this article.

Competing interests. Melanie Cousins and Irene A. Lambraki are employed at the Public Health Agency of Canada. E. Jane Parmley is engaged in research funded by the Canadian Institutes for Health Research, Natural Sciences and Engineering Research Council, Ontario Ministry of Agriculture, Food and Rural Affairs, the Public Health Agency of Canada, and the Canadian Safety and Security Program. She is currently President of the Board of Directors of the Centre for Coastal Health, president of the Canadian Association of Veterinary Epidemiology and Preventive Medicine, member of the Board of Directors of the McEachran Institute, member of the Advisory Council for Research Directions: One Health, and a member of the Royal Society of Canada One Health Working Group. Prior to February 2019, she was employed by the Public Health Agency of Canada. Peter Søgaard Jørgensen was funded via an ERC starting grant: INFLUX, grant number 101039376. He holds/has held grants as principal or co-investigator, from the following agencies and foundations all related to the topics of social-ecological systems and/or AMR: Swedish Research Council FORMAS, Wallenberg Foundations, IKEA Foundation, Erling Persson Family Foundation. Carolee A. Carson is employed by the Public Health Agency of Canada. In that role she has been a subject matter expert for the World Organisation for Animal Health and the World Health Organization (WHO). She is a member of the advisory committee for Animal Health Canada. She has previously been engaged in research funded by the Canadian Institutes for Health Research, Ontario Ministry of Agriculture, Food and Rural Affairs, and the Canadian Safety and Security Program. Patrik JG Henriksson is partially funded by FORMAS Inequality and the Biosphere Project (2020-00454) and partially by CGIAR Trust Fund. Amy L. Greer, Elena Neiterman, Tiscar Graells, Anaïs Léger, Didier Wernli, and Shannon E. Majowicz declare no competing interests.

Ethics statement. This study received ethics clearance from the University of Waterloo's Research Ethics Committee (ORE# 40,519).

Connections references. Keune, H. (2023). How can One Health approaches be operationalized in order to enable action to reduce or prevent AMR? *Research Directions: One Health, 1*, E6. https://doi.org/10.1017/one.2022.7

References

Abirham W (2020) Impact of climate change on animal production and expansion of animal disease: a review on Ethiopia perspective. *American Journal of Pure and Applied Biosciences* **June**, 64–76. https://doi.org/10.34104/ajpab.020.064076.

Agence Europe (2022) *France Bans Import of Meat From Farms Using Growth-Promoting Antibiotics*. Agence Europe.

Alipour M, Hafezi R, Papageorgiou E, Hafezi M and Alipour M (2019) Characteristics and scenarios of solar energy development in Iran: fuzzy cognitive map-based approach. *Renewable and Sustainable Energy Reviews* **116**, 9, 109410. https://doi.org/10.1016/j.rser.2019.109410.

Alividza V, Mariano V, Ahmad R, Charani E, Rawson TM, Holmes AH and Castro-Sánchez E (2018) Investigating the impact of poverty on colonization and infection with drug-resistant organisms in humans: a systematic review. *Infectious Diseases of Poverty* **7**, 1, 1–11. https://doi.org/10.1186/s40249-018-0459-7.

Ashenafi D, Yidersal E, Hussen E, Solomon T and Desiye M (2018) The effect of long distance transportation stress on cattle: a review. *Biomedical Journal of Scientific & Technical Research* **3**, 3, 3304–3308. https://doi.org/10.26717/BJSTR.2018.03.000908.

Azevedo MM, Pinheiro C, Yaphe J and Baltazar F (2013) Assessing the impact of a school intervention to promote students' knowledge and practices on correct antibiotic use. *International Journal of Environmental Research and Public Health* **10**, 7, 2920–2931. https://doi.org/10.3390/ijerph10072920.

Birkegård AC, Halasa T, Toft N, Folkesson A and Græsbøll K (2018) Send more data: a systematic review of mathematical models of antimicrobial resistance. *Antimicrobial Resistance & Infection Control* **7**, 1, 1–12. https://doi.org/10.1186/s13756-018-0406-1.

Buckley BS, Henschke N, Bergman H, Skidmore B, Klemm EJ, Villanueva G, Garritty C, Paul M (2019) Impact of vaccination on antibiotic usage: a systematic review and meta-analysis. *Clinical Microbiology and Infection* **25**, 10, 1213–1225. https://doi.org/10.1016/j.cmi.2019.06.030.

Bueno S and Salmeron JL (2009) Benchmarking main activation functions in fuzzy cognitive maps. *Expert Systems with Applications* **36**, 3, 5221–5229. https://doi.org/10.1016/j.eswa.2008.06.072.

Burnham JP (2021) Climate change and antibiotic resistance: a deadly combination. *Therapeutic Advances in Infectious Disease* **8**, 1–7. https://doi.org/10.1177/2049936121991374.

Carlson C J, Albery G F, Merow C, Trisos C H, Zipfel C M, Eskew E A, Olival K J, Ross N, Bansal S (2022) Climate change increases cross-species viral transmission risk. *Nature* **607**, 7919, 555–562. https://doi.org/10.1038/s41586-022-04788-w.

Carlsson-Kanyama A and Lindén AL (2001) Trends in food production and consumption: Swedish experiences from environmental and cultural impacts. *International Journal of Sustainable Development* **4**, 4, 392–406. https://doi.org/10.1504/IJSD.2001.001558.

Cousins M (2022a) *Exploring the Ddrivers of, and Ppotential Iinterventions to Rreduce, Aantimicrobial Rresistance in the European Ffood Ssystem Ccontext (University of Waterloo)*, University of Waterloo. http://hdl.handle.net/10012/18478.

Cousins M (2022b). *A One Health and fuzzy cognitive map-based approach to assess interventions to reduce antimicrobial resistance in a Swedish food system context under potential climate change conditions: decision matrix and Scenario results*, University of Waterloo. https://doi.org/10.5683/SP3/Z2IJTE.

Cousins M, Parmley EJ, Greer AL, Neiterman E, Lambraki IA, Vanderheyden MN, Wernli D, Jorgensen PS, Carson CA, Majowicz SE (2024) Mapping out a One Health model of antimicrobial resistance in the context of the Swedish food system: a literature scan. *Research Directions: One Health* **2**, 1–43. https://doi.org/10.1017/one.2023.15.

Doherty TM, Hausdorff WP and Kristinsson KG (2020) Effect of vaccination on the use of antimicrobial agents: a systematic literature review. *Annals of Medicine* **52**, 6, 283–299. https://doi.org/10.1080/07853890.2020.1782460.

Dorokhov O, Dorokhova L, Delibasic M and Streimikis J (2017) Consumer behavior modeling: fuzzy logic model for air purifiers choosing. *Montenegrin Journal of Economics* **13**, 4, 61–77. https://doi.org/10.14254/1800-5845/2017.13-4.5.

Eden C, Ackermann F and Cropper S (1993) The analysis of cause maps. *Journal of Management Studies* **29**, 3, 309–324.

EFSA (European Food Safety Authority), Control, A., & ECDC (European Centre for Disease Prevention and Control), The European Union Summary Report on Antimicrobial Resistance in zoonotic and indicator bacteria from humans, animals and food in 2017/2018. *EFSA Journal* **18**, 3, 6007. https://doi.org/10.2903/j.efsa.2020.6007.

Elisabeth M, Maneesh PS, Katarina SF, Slobodan Z and Michael S (2021) Antimicrobial resistance & migrants in Sweden: poor living conditions enforced by migration control policies as a risk factor for optimal public health management. *Frontiers in Public Health* **9**, July, 1–5. https://doi.org/10.3389/fpubh.2021.642983.

Engström S, Mölstad S, Lindström K, Nilsson G and Borgquist L (2004) Excessive use of rapid tests in respiratory tract infections in Swedish primary health care. *Scandinavian Journal of Infectious Diseases* **36**, 3, 213–218. https://doi.org/10.1080/00365540310018842.

Fouladkhah AC, Thompson B and Camp JS (2020) The threat of antibiotic resistance in changing climate. *Microorganisms* **8**, 5, 8–10. https://doi.org/10.3390/microorganisms8050748.

Frost I, Van Boeckel TP, Pires J, Craig J and Laxminarayan R (2019) Global geographic trends in antimicrobial resistance: the role of international travel. *Journal of Travel Medicine* **26**, 8, taz036. https://doi.org/10.1093/jtm/taz036.

Giles BG, Findlay CS, Haas G, LaFrance B, Laughing W and Pembleton S (2007) Integrating conventional science and aboriginal perspectives on diabetes using fuzzy cognitive maps. *Social Science and Medicine* **64**, 3, 562–576. https://doi.org/10.1016/j.socscimed.2006.09.007.

Government of Canada (2017) Tackling antimicrobial resistance and antimicrobial use: a Pan-Canadian framework for action. Available at https://www.canada.ca/en/health-canada/services/publications/drugs-health-products/tackling-antimicrobial-resistance-use-pan-canadian-framework-action.html.

Gray J and Rumpe B (2016) Models in simulation. *Software and Systems Modeling* **15**, 3, 605–607. https://doi.org/10.1007/s10270-016-0544-y.

Gray SA, Gray S, Cox LJ and Henly-Shepard S (2013) Mental Modeler: a fuzzy-logic cognitive mapping modeling tool for adaptive environmental management. *Proceedings of the Annual Hawaii International Conference on System Sciences* **January**, 965–973. https://doi.org/10.1109/HICSS.2013.399.

Gunnarsson S and Cerenius F (2004) *Animal Health and Welfare in Free Range Cattle: A Survey of Farms in western Sweden*. International Society for Animal Hygiène, pp. 419–492.

Harmati I, Hatwágner MF and Kóczy LT (2021) Global stability of fuzzy cognitive maps. *Neural Computing and Applications* **9**, i, 7283–7295. https://doi.org/10.1007/s00521-021-06742-9.

Hoffmann I (2010) Impacts of climate change on livestock sector and Kenya's preparednes. *World Conference on Genetics Applied to Livestock Production*. https://doi.org/10.13140/2.1.2891.8405.

Holmes AH, Moore LSP, Sundsfjord A, Steinbakk M, Regmi S, Karkey A, Guerin P J, Piddock L J V (2016) Understanding the mechanisms and drivers of antimicrobial resistance. *The Lancet* **387**, 10014, 176–187. https://doi.org/10.1016/S0140-6736(15)00473-0.

Johnson R (2011) CRS report for congress potential trade implications of restrictions on antimicrobial use in animal production.

Jung D, Morrison BJ and Rubin JE (2022) A review of antimicrobial resistance in imported foods. *Canadian Journal of Microbiology* **68**, 1, 1–15. https://doi.org/10.1139/cjm-2021-0234.

Kokkinos K, Lakioti E, Papageorgiou E, Moustakas K and Karayannis V (2018) Fuzzy cognitive map-based modeling of social acceptance to overcome uncertainties in establishing waste biorefinery facilities. *Frontiers in Energy Research* **6**, OCT, 1–17. https://doi.org/10.3389/fenrg.2018.00112.

Kosko B (1986) Fuzzy cognitive maps. *International Journal of Man-Machine Studies* **24**, 1, 65–75. https://doi.org/10.1016/S0020-7373(86)80040-2.

Koulouriotis D, Diakoulakis I and Emiris D (2001) A fuzzy cognitive map-based stock market model: synthesis, analysis and experimental results. In *10th IEEE International Conference on Fuzzy Systems*, pp. 465–468. https://doi.org/10.1109/FUZZ.2001.1007349.

Lacetera N (2019) Impact of climate change on animal health and welfare. *Animal Frontiers* **9**, 1, 26–31. https://doi.org/10.1093/af/vfy030.

Lambraki I A, Cousins M, Graells T, Léger A F;s, Abdelrahman S, Desbois A P, Gallagher R, Staaf Larsson B, Mattson B, Henriksson P, Troell M, Søgaard Jørgensen P, Wernli D, Carson C A, Parmley E J, Majowicz S E (2022b) Governing Antimicrobial Resistance (AMR) in a changing climate: a participatory scenario planning approach applied to Sweden in 2050. *Frontiers in Public Health* **10**, July, 1–17. https://doi.org/10.3389/fpubh.2022.831097.

Lambraki IA, Cousins M, Graells T, Léger AF, Henriksson P, Harbarth S, Troell M, Wernli D, Søgaard Jørgensen P, Desbois AP, Carson CA, Parmley EJ, Majowicz SE, Islam MT (2022a) Factors influencing antimicrobial resistance in the European food system and potential leverage points for intervention: a participatory, One Health study. *PLoS ONE* **17**, 2, 1–19. https://doi.org/10.1371/journal.pone.0263914.

Lavin EA and Giabbanelli PJ (2017) Analyzing and simplifying model uncertainty in fuzzy cognitive maps. In *Proceedings - Winter Simulation Conference, (December 2017)*, pp. 1868–1879. https://doi.org/10.1109/WSC.2017.8247923.

Lavrakas PJ (2008) *Encyclopedia of Survey Research Methods (Vol. 1-0)*. Thousand Oaks, CA: Sage Publications, Inc, https://doi.org/10.4135/9781412963947.

Liu S, Triantis KP, Zhao L and Wang Y (2018) Capturing multi-stage fuzzy uncertainties in hybrid system dynamics and agent-based models for enhancing policy implementation in health systems research. *PLoS ONE* **13**, 4, e0194687. https://doi.org/10.1371/journal.pone.0194687.

Llor C, Bjerrum L, Munck A, Cots JM, Hernández S and Moragas A (2014) Access to point-of-care tests reduces the prescription of antibiotics among antibiotic-requesting subjects with respiratory tract infections. *Respiratory Care* **59**, 12, 1918–1923. https://doi.org/10.4187/respcare.03275.

Mcculloch WS and Pitts W (1990) A logical calculus nervous activity. *Bulletin of Mathematical Biology* **52**, l, 99–115. https://doi.org/10.1016/S0092-8240(05)80006-0.

McEwen SA and Collignon PJ (2017) Antimicrobial resistance: a one health perspective. *Microbiology Spectrum* **6**, 2, 1–26. https://doi.org/10.1128/microbiolspec.ARBA-0009-2017.Correspondence.

Meadows D (1999) *Leverage points: places to intervene in a system*. Hartland, VT, The Sustainability Institute. Available at https://donellameadows.org/wp-content/userfiles/Leverage_Points.pdf.

Meehl GA, Stocker TF, Collins WD, Friedlingstein P, Gaye AT, Gregory JM, Noda A, *et al.* (2007) Global climate projections. In M. T, Solomon HLM, D.Qin S, Manning M, Chen Z, Marquis M and Averyt KB (eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK & New York, NY: Cambridge University Press.

Mie A, Andersen H R, Gunnarsson S, Kahl J, Kesse-Guyot E, Rembiałkowska E, Quaglio G, Grandjean P (2017) Human health implications of organic food and organic agriculture: a comprehensive review. *Environmental Health: A Global Access Science Source* **16**, 1, 1–22. https://doi.org/10.1186/s12940-017-0315-4.

Morrison TH, Adger WN, Agrawal A, Brown K, Hornsey MJ, Hughes TP, Jain M, Lemos MC, McHugh LH, O'Neill S, Van Berkel D (2022) Radical interventions for climate-impacted systems. *Nature Climate Change* **12**, 12, 1100–1106. https://doi.org/10.1038/s41558-022-01542-y.

Morse SS (1995) Factors in the emergence of infectious diseases. *Emerging Infectious Diseases* **1**, 1, 7–15. https://doi.org/10.3201/eid0101.950102.

Mpelogianni V and Groumpos PP (2016) Towards a new approach of fuzzy cognitive maps. In *7th International Conference on Information, Intelligence, Systems & Applications (IISA)*, Chalkidiki, Greece.

Mpelogianni Vassiliki and Groumpos PP (2018) Re-approaching fuzzy cognitive maps to increase the knowledge of a system. *AI and Society* **33**, 2, 175–188. https://doi.org/10.1007/s00146-018-0813-0.

Murray C J L, Ikuta K S, Sharara F, Swetschinski L, Robles Aguilar G, Gray A, Han C, Bisignano C, Rao P, Wool E, Johnson S C, Browne A J, Chipeta M G, Fell F, Hackett S, Haines-Woodhouse G, Kashef Hamadani B H, Kumaran E A P, McManigal B, Achalapong S, Agarwal R, Akech S, Albertson S, Amuasi J, Andrews J, Aravkin A, Ashley E, Babin Fçois-X, Bailey F, Baker S, Basnyat B, Bekker A, Bender R, Berkley J A, Bethou A, Bielicki J, Boonkasidecha S, Bukosia J, Carvalheiro C, Castañeda-Orjuela C, Chansamouth V, Chaurasia S, Chiurchiù S, Chowdhury F, Clotaire Donatien R, Cook A J, Cooper B, Cressey T R, Criollo-Mora E, Cunningham M, Darboe S, Day N P J, De Luca M, Dokova K, Dramowski A, Dunachie S J, Duong Bich T, Eckmanns T, Eibach D, Emami A, Feasey N, Fisher-Pearson N, Forrest K, Garcia C, Garrett D, Gastmeier P, Giref A Z, Greer R C, Gupta V, Haller S, Haselbeck A, Hay S I, Holm M, Hopkins S, Hsia Y, Iregbu K C, Jacobs J, Jarovsky D, Javanmardi F, Jenney A W J, Khorana M, Khusuwan S, Kissoon N, Kobeissi E, Kostyanev T, Krapp F, Krumkamp R, Kumar A, Kyu H H, Lim C, Lim K, Limmathurotsakul D, Loftus M J, Lunn M, Ma J, Manoharan A, Marks F, May J C;rgen, Mayxay M, Mturi N, Munera-Huertas T, Musicha P, Musila L A, Mussi-Pinhata M M, Naidu R N, Nakamura T, Nanavati R, Nangia S, Newton P, Ngoun C, Novotney A, Nwakanma D, Obiero C W, Ochoa T J, Olivas-Martinez A, Olliaro P, Ooko E, Ortiz-Brizuela E, Ounchanum P, Pak G D, Paredes J L, Peleg A Y, Perrone C, Phe T, Phommasone K, Plakkal N, Ponce-de-Leon A, Raad M, Ramdin T, Rattanavong S, Riddell A, Roberts T, Robotham J V, Roca A, Rosenthal V D, Rudd K E, Russell N, Sader H S, Saengchan W, Schnall J, Scott J A G, Seekaew S, Sharland M, Shivamallappa M, Sifuentes-Osornio J, Simpson A J, Steenkeste N, Stewardson A J, Stoeva T, Tasak N, Thaiprakong A, Thwaites G, Tigoi C, Turner C, Turner P, van Doorn H R, Velaphi S, Vongpradith A, Vongsouvath M, Vu H, Walsh T, Walson J L, Waner S, Wangrangsimakul T, Wannapinij P, Wozniak T, Young Sharma T E M W, Yu K C, Zheng P, Sartorius B, Lopez A D, Stergachis A, Moore C, Dolecek C, Naghavi M (2022) Global burden of bacterial antimicrobial resistance in 2019: a systematic analysis. *The Lancet* **399**, 10325, 629–655. https://doi.org/10.1016/S0140-6736(21)02724-0.

National Veterinary Institute (SVA) (2019) Surveillance of infectious diseases in animals and humans in Sweden 2019. Uppsala, Sweden: National Veterinary Institute (SVA). SVA:s rapportserie 64, 1654–7098. Available at https://www.sva.se/media/8d93c82701fd794/surveillance-of-infectious-diseases-in-animals-and-humans-in-sweden-2019.pdf.

Nápoles G, Espinosa ML, Grau I and Vanhoof K (2018) FCM expert: software tool for scenario analysis and pattern classification based on fuzzy cognitive maps. *International Journal on Artificial Intelligence Tools* **27**, 07, 1860010. https://doi.org/10.1142/S0218213018600102.

Niewiadomska AM, Jayabalasingham B, Seidman JC, Willem L, Grenfell B, Spiro D and Viboud C (2019) Population-level mathematical modeling of antimicrobial resistance: a systematic review. *BMC Medicine* **17**, 1, 1–20. https://doi.org/10.1186/s12916-019-1314-9.

Ntarlas O and Groumpos P (2015) Unsupervised learning methods for foreign investment using fuzzy cognitive maps. In *Information, Intelligence, Systems and Applications (IISA), 2015 6th International Conference*, pp. 1–5.

Nulty KM, Soon JM, Wallace CA and Nastasijevic I (2016) Antimicrobial resistance monitoring and surveillance in the meat chain: a report from five countries in the European Union and European Economic Area. *Trends in Food Science and Technology* **58**, 1–13. https://doi.org/10.1016/j.tifs.2016.09.010.

O'Neill J (2015) *Rapid diagnostics: stopping unnecessary use of antibiotics*. London, UK: Review on Antimicrobial Resistance.

O'Neill J (2016) Tackling drug-resistant infections globally: final report and recommendations. Available at https://amr-review.org/sites/default/files/160518_Final paper_with cover.pdf.

Parry M, Rosenzweig C and Livermore M (2005) Climate change, global food supply and risk of hunger. *Philosophical Transactions of the Royal Society B: Biological Sciences* **360**, 1463, 2125–2138. https://doi.org/10.1098/rstb.2005.1751.

Pepi M and Focardi S (2021) Antibiotic-resistant bacteria in aquaculture and climate change: a challenge for health in the mediterranean area. *International Journal of Environmental Research and Public Health* **18**, 11, 5723. https://doi.org/10.3390/ijerph18115723.

Pinto JC, Keestra S, Tandon P and CHandler C I R (2020) *WASH and biosecurity interventions for reducing burdens of infection, antibiotic use and antimicrobial resistance in animal agricultural settings: a One Health mixed methods systematic review*. London, UK: London School of Hygiene & Tropical Medicine. https://doi.org/10.17037/PUBS.04658914.

Planta MB (2007) The role of poverty in antimicrobial resistance. *Journal of the American Board of Family Medicine* **20**, 6, 533–539. https://doi.org/10.3122/jabfm.2007.06.070019.

Poomagal S, Sujatha R, Kumar PS and Vo DVN (2021) A fuzzy cognitive map approach to predict the hazardous effects of malathion to environment (air, water and soil). *Chemosphere* **263**, 127926. https://doi.org/10.1016/j.chemosphere.2020.127926.

Price L, Gozdzielewska L, Young M, Smith F, MacDonald J, McParland J, Williams L, Langdridge D, Davis M, Flowers P (2018) Effectiveness of interventions to improve the public's antimicrobial resistance awareness and behaviours associated with prudent use of antimicrobials: a systematic review. *Journal of Antimicrobial Chemotherapy* **73**, 6, 1464–1478. https://doi.org/10.1093/jac/dky076.

Ramsay DE, Invik J, Checkley SL, Gow SP, Osgood ND and Waldner CL (2018) Application of dynamic modelling techniques to the problem of antibacterial use and resistance: a scoping review. *Epidemiology and Infection* **146**, 16, 2014–2027. https://doi.org/10.1017/S0950268818002091.

ReAct (2020) *Animal welfare and antibiotic resistance in food animals*. Uppsala, Sweden: React Group.

Reverter M, Sarter S, Caruso D, Avarre J-C, Combe M, Pepey E, Pouyaud L, Vega-Heredía S, de Verdal H, Gozlan R E (2020) Aquaculture at the crossroads of global warming and antimicrobial resistance. *Nature Communications* **11**, 1, 1–8. https://doi.org/10.1038/s41467-020-15735-6.

Robinson TP, Bu DP, Carrique-Mas J, Fèvre EM, Gilbert M, Grace D, Hay SI, Jiwakanon J, Kakkar M, Kariuki S, Laxminarayan R, Lubroth J, Magnusson U, Thi Ngoc P, Van Boeckel TP, Woolhouse MEJ (2016) Antibiotic resistance is the quintessential One Health issue. *Transactions of The Royal Society of Tropical Medicine and Hygiene* **110**, 7, 377–380. https://doi.org/10.1093/trstmh/trw048.

Rodríguez-Verdugo A, Lozano-Huntelman N, Cruz-Loya M, Savage V and Yeh P (2020) Compounding effects of climate warming and antibiotic resistance. *iScience* **23**, 4, 1–16. https://doi.org/10.1016/j.isci.2020.101024.

Semenza JC and Ebi KL (2019) Climate change impact on migration, travel, travel destinations and the tourism industry. *Journal of Travel Medicine* **26**, 5, 1–13. https://doi.org/10.1093/jtm/taz026.

Shomaker S (2014) OneHealth: a paradigm for interdisciplinary collaboration. *Academic Medicine: Journal of the Association of American Medical Colleges* **90**, 7, 997. https://doi.org/10.1097/ACM.0000000000000441.

Smith R, Coast J, Millar M, Wilton P and Karcher A-M (2003) *Interventions against antimicrobial resistance: a review of the literature and exploration of modelling cost-effectiveness*. Institute of Medicine (US) Forum on Emerging Infections.

Søgaard Jørgensen P, Folke C, Henriksson PJG, Malmros K, Troell M and Zorzet A (2020) Coevolutionary governance of antibiotic and pesticide resistance. *Trends in Ecology and Evolution* **35**, 6, 484–494. https://doi.org/10.1016/j.tree.2020.01.011.

Søgaard Jørgensen P, Wernli D, Carroll S, *et al.* (2016) Use antimicrobials wisely. *Nature* **537**, 159–161. https://doi.org/10.1038/537159a.

Sypher S (2017) *Fuzzy Cognitive Maps: A Design Research Tool to Address Systems of Scaled Complexity*, ProQuest Dissertations and Theses, 45. Available at https://www.proquest.com/docview/1998853457?accountid=26642%0Ahttp://link.periodicos.capes.gov.br/sfxlcl41?url_ver=Z39.88-2004&rft_val_fmt=info:.

The Centre for Disease Dynamics, & Economics & Policy (n.d.) *ResistanceMap: Antibiotic use*. Available at https://resistancemap.onehealthtrust.org/AntibioticUse.php.

The European Commission (2018) *AMR: a major European and Global challenge*. The European Commission. Available at https://health.ec.europa.eu/system/files/2020-01/amr_2017_factsheet_0.pdf.

The European Food Information Council (EUFIC). Organic food and farming: Scientific facts and consumer perceptions (2013), Available at https://www.eufic.org/en/food-production/article/organic-food-and-farming-scientific-facts-and-consumer-perceptions.

Trochim WM, Cabrera DA, Milstein B, Gallagher RS and Leischow SJ (2006) Practical challenges of systems thinking and modeling in public health. *American Journal of Public Health* **96**, 3, 538–546. https://doi.org/10.2105/AJPH.2005.066001.

United Nations (2022) The sustainable development goals report. Available at https://unstats.un.org/sdgs/report/2022/The-Sustainable-Development-Goals-Report-2022.pdf.

United Nations Department of Economic and Social Affairs (2022) The 17 goals. Available at https://sdgs.un.org/goals.

Van Dijk J, Sargison ND, Kenyon F and Skuce PJ (2010) Climate change and infectious disease: helminthological challenges to farmed ruminants in temperate regions. *Animal* **4**, 3, 377–392. https://doi.org/10.1017/S1751731109990991.

van Helden PD, van Helden LS and Hoal EG (2013) One world, one health. *European Molecular Biology Organization* **14**, 6, 497–501. Available at http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3674448/pdf/embor201361a.pdf.

Wegner GI, Murray KA, Springmann M, Muller A, Sokolow SH, Saylors K and Morens DM (2022) Averting wildlife-borne infectious disease epidemics requires a focus on socio-ecological drivers and a redesign of the global food system. *EClinicalMedicine* **47**, 101386. https://doi.org/10.1016/j.eclinm.2022.101386.

Wernli D, Jørgensen PS, Harbarth S, Carroll SP, Laxminarayan R, Levrat N, Pittet D, *et al.* (2017) Antimicrobial resistance: the complex challenge of measurement to inform policy and the public. *PLOS Medicine* **14**, 8, e1002378. https://doi.org/10.1371/journal.pmed.1002378.

WHO Regional office for Europe. The burden of food borne diseases in the WHO European region (2017) Retrieved from The Regional Office for Europe of the World Health Organization website: https://www.euro.who.int/__data/assets/pdf_file/0005/402989/50607-WHO-Food-Safety-publicationV4_Web.pdf.

WHO (World Health Organization) (2018) Antibiotic resistance. Available at https://www.who.int/news-room/fact-sheets/detail/antimicrobial-resistance.

Wierup M (2001) The Swedish experience of the 1986 year ban of antimicrobial growth promoters, with special reference to animal health, disease prevention, productivity, and usage of antimicrobials. *Microbial Drug Resistance* **7**, 2, 183–190. https://doi.org/10.1089/10766290152045066.

Wierup M, Wahlström H and Bengtsson B (2021) Successful prevention of antimicrobial resistance in animals—a retrospective country case study of Sweden. *Antibiotics* **10**, 2, 1–24. https://doi.org/10.3390/antibiotics10020129.

World Health Organization (2017) A global health guardian: climate change, air pollution, and antimicrobial resistance. In *Ten Years Public health 2007-2017*

World Integrated Trade Solutions (2022) Sweden.

Wutzke SE, Artist MA, Kehoe LA, Fletcher M, Mackson JM and Weekes LM (2007) Evaluation of a national programme to reduce inappropriate use of antibiotics for upper respiratory tract infections: effects on consumer awareness, beliefs, attitudes and behaviour in Australia. *Health Promotion International* **22**, 1, 53–64. https://doi.org/10.1093/heapro/dal034.

Zadeh LA (1990) The birth and evolution of fuzzy logic. *International Journal of General Systems* **17**, 2-3, 95–105. https://doi.org/10.1080/03081079008935510.

https://doi.org/10.1017/one.2024.2 Published online by Cambridge University Press