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The need for a complex systems approach in rural health research

Adam Hulme*[1], Jason Thompson[2], Geoff Argus[1,3]

*Corresponding author

[1]Southern Queensland Rural Health

Faculty of Health and Behavioural Sciences

The University of Queensland

Baillie Henderson Hospital campus

Corner Hogg and Tor Streets, Toowoomba QLD 4350

PO Box 24, Harlaxton QLD 4350

P +61 07 4633 9789

M (+61) 488 225 006

E a.hulme@uq.edu.au

[2]Department of Rural Health

Faculty of Medicine

The University of Melbourne

Parkville, Victoria, 3010

Australia

[3]School of Psychology and Wellbeing

Faculty of Health, Engineering and Sciences

University of Southern Queensland

Toowoomba, Queensland, 4530

Australia

Abstract

On a global scale, many major rural health issues have persisted for decades despite the introduction of new health interventions and public health policies. Although research efforts have generated valuable new knowledge about the aetiology of health, disease and health inequities in rural communities, rural health systems remain to be some of the most deprived and challenged in the developed world. Whilst the reasons for this are many, a significant factor contributing to the current state of play is the pressing need for methodological innovation and new scientific approaches that have the capacity to support the translation of novel solutions into 'real world' rural contexts. Fortunately, complex systems approaches, which are yet to be applied to rural health systems, could provide answers to some of the most resilient rural health problems in recent times. The purpose of this article is to promote the value and utility of a complex systems approach in rural health research. We explain the benefits of a complex systems approach and provide a background to the complexity sciences, including the main characteristics of complex systems. Two popular computational methods are described. The next step for rural health research involves exploring how a complex systems approach can help with the identification and evaluation of new and existing solutions to policy-resistant rural health issues. This includes generating awareness around the analytical trade-offs that occur between the use of traditional scientific methods and complex systems approaches.

Strengths and limitations

- We argue that the field of rural health research would benefit greatly from a complementary systems thinking perspective and complexity science paradigm.
- Modelling rural health systems prior to the implementation of new health interventions and/or policies could potentially save time, effort and resources. We propose a number of methods that could be used for this purpose moving forwards.
- The next step for rural health researchers is to become familiar with the complex systems approaches suggested. Doing so will open up new lines of research and possibilities for enhancing the health and well-being of our global rural communities.

1.0 Introduction

The field of complexity science engenders its own lexicon, theories, and concepts. We have therefore provided the following key definitions and explanations to assist the reader with an understanding of the material forthcoming.

1.1 Terms and definitions

Complex systems are found across the micro (e.g., biological), meso (e.g., individual) and macro (e.g., social) levels of the physical and natural world. Complex systems include biological systems, the earth's atmosphere and climate, ant colonies, diseases, political entities, the stock market, rainforests, organisations and corporations, and pertinent to this article, rural health systems. A complex system is:

> "…made up of many heterogenous elements; these elements interact with each other; the interactions produce an emergent effect that is different from the effects of the individual elements; and this effect persists over time and adapts to changing circumstances".
>
> ~Luke and Stamatakis, p.2 (1)

In attempting to map and understand complex systems, systems modellers and analysts often attempt to identify *leverage points*. Leverage points are key places within a complex system where a small intervention can produce a large (positive) effect on the system's outcome. Leverage points are frequently counterintuitive, meaning that change is often required to be enacted in the opposite direction to produce the intended outcome. The points of greatest leverage within a system may not always be obvious at first glance or may even exist beyond initial conceptualisations of a system.

> "The silver bullet, the miracle cure, the secret passage, the magic password, the single hero who turns the tide of history. We not only want to believe that there are leverage points, but we also want to know where they are and how to get our hands on them. Leverage points are points of power".
>
> ~Meadows, p.145 (2)

1.2 Background and purpose

The purpose of this article is twofold. First, to encourage new ways of thinking about how rural health issues and health inequalities are created, maintained and prevented through a systems research lens; and second, to promote the value and utility of a complex systems approach in this space. Although the article is written with the rural health researcher in mind, the content may also be interesting to a wider *BMJ Open* readership, including clinicians, service providers, stakeholders and policy-makers tackling the results of failed and/or troubled healthcare systems.

1.3 Why rural health?

Rural health is a multidisciplinary area of study within the field of public health that has largely been neglected from a funding and research perspective (3). Whilst specialist research groups and university departments around the world – Australia, Canada, United States, New Zealand, United Kingdom and Europe – are producing excellent (traditional) work in the area of rural health (e.g., 4, 5), the disparities in health outcomes and health inequalities between urban and rural communities continue to persist in the face of new health interventions and policies (6-8). Whilst the reasons for this are many, including factors related to geography, healthcare access, service provision, workforce retention, cultural sensitivities and wider political systems (9), it is these authors' opinion that the rural health research field is also in drastic need of scientific innovation if it is to seriously tackle the complex global challenges that it faces. The answers we seek, and the change that is desired for rural communities by way of research and advances in knowledge, may lie in the field of complexity science and its many diverse approaches, methods and models.

2.0 Traditional methods in a complex world

Against a backdrop of increasing global interconnectedness, a growing number of researchers have questioned whether clinical and epidemiological methods can alone identify effective solutions to the most resilient public health problems in recent times (10-15). Arguments have centred around the fact that Randomised Controlled Trials (RCTs) and experimental study designs, considered to be *the* 'gold standard' approaches for assessing causality, are only able to quantify the efficacy of a targeted individual-level health intervention (11-13, 16). Attempts to 'scale-up' evidence-based clinical and behavioural interventions and deliver them into complex, uncontrolled, real-world settings without consideration of the broader socio-political context is known to erode their fidelity, adoption, maintenance and effectiveness (17, 18).

Whilst the traditional Person, Intervention, Comparison, Outcome (PICO) framework has been met with considerable success and should continue to be applied to address well-defined causal research questions, the very act of controlling for background noise; the collapsing down of complexity; the reliance on data at the expense of theory; and desire to increasingly sharpen the effect of individual-level health interventions is not optimal for all health problems, social contexts and circumstances (12, 14-16, 19, 20). The occurrence of health and disease across populations, including rural communities, can also be viewed as a product of the complex interactions that occur among biological, behavioural, societal, environmental and political determinants (10, 19, 21). This line of thinking encourages debate around what exactly constitutes 'a cause' from a scientific perspective, and where within 'the system' the most appropriate leverage point may be (10, 11).

Analytical reductionism can only deliver on so much if the goal of research is to either: (i) ask questions about the effectiveness of upstream interventions that exert their effect on downstream factors and health outcomes over an extended timescale; or (ii) ask questions about how new or existing solutions can be supported or degraded in context of the wider health system (10, 12, 17, 18, 22). Complementary research approaches are required to explore the intermediate and distal pathways that shape population health, and by definition rural health, from a broad perspective.

2.1 From reductionism to complexity

In response to the need for system level evaluations of health interventions, there has been a recent groundswell of interest in epidemiology and public health around the use of *complex systems approaches* from the field of complexity science (16, 21-27). Complex systems approaches are used to study discontinuous relations, complex forms of non-linear feedback between factors across multiple levels, networks between people, groups and their environment, and processes of exchange between individual actors in systems that give rise to emergent macro-level system behaviours (1, 10, 21, 23-26, 28-32). There is mounting evidence to suggest that a complex systems approach can be of practical assistance in both explaining mechanisms driving adverse health outcomes and system behaviour and also determining where and how to intervene (18, 23-25, 27).

Despite growing momentum around complex systems approaches, their specific application to issues contained within rural health has received a lack of attention. Complex systems approaches may help to identify new rural health solutions, identify solutions to workforce issues, support cost-benefit decision-making, and contribute to the evaluation of existing strategies given competing priorities and the balancing of limited resources.

3.0 What is complexity science?

Complexity science is a discipline that attempts to understand and respond to problems that are dynamic and unpredictable, multi-dimensional, and comprise various interrelated actors and components (33). Researchers who study complexity, and by extension complex problems, focus on the *interactions* among various elements within a complex system, rather than on the role and contribution of those elements in *isolation* (28, 34).

Where appropriate, complexity science proponents will advocate for a systems thinking perspective over a reductionist one, as doing so is to consider the whole system, and multiple interacting elements of it, as the primary unit of analysis (28, 34). This affords insight into how the constituent elements of a complex system converge in context of a much greater whole, which is useful when attempting to make sense of resilient, persistent and policy resistant problems (12).

3.1 Mapping the complexity sciences

Complexity science incorporates multiple traditions, disciplines, methods, techniques and analytical tools. The *Map of the Complexity Sciences* (35) (Figure 1) shows the historical progression of five major intellectual traditions over several decades. There is no single, unified understanding of what complexity science is when it is subjected to formal investigation and analysis (34). Which complex systems approach to adopt depends on many factors, including available resources, individual expertise and the type of problem to be examined.

<Insert Figure 1 about here>

4.0 Characteristics of complex systems

There are discernible characteristics that are universal to all complex systems. Type 2 Diabetes Mellitus (T2DM), a significant issue in the Australian rural health sector, is selected to elucidate the key concepts. This section elaborates in greater detail on the definition of a complex system provided at the opening of the communication (1).

Table 1: Complex systems characteristics. The characteristics and descriptions appear in Hulme et al. 2019 (30) and 2020 (34); however, the examples reflect the occurrence of Type 2 Diabetes Mellitus (T2DM) within the Australian context.

Characteristic	**Description**	**T2DM example**
Multiple system levels, scalable	Complex systems vary in type, size, and scale, from the micro (e.g., molecular, cellular), through to the meso (e.g., individual) and macro (e.g., socioeconomic, political) levels.	• The occurrence of T2DM can be conceptualised and studied at the cellular (e.g., insulin secretion by pancreatic β-cells), individual (e.g., behavioural), societal (e.g., employment security, living conditions) or policy (e.g., provision of state and Commonwealth funding) levels. • The T2DM system is composed of, and is a component within, other complex systems (i.e., complex systems are nested). • Focussing on individual behaviour change alone, such as physical inactivity or diet, will not be effective at preventing the occurrence of T2DM in rural communities. Biological factors, individual behaviours, and personal motivations should be explored, understood and contextualised within a broader context.
Diverse range of agents (i.e., people and organisations), and	Complex systems contain many fundamentally different agents and factors that interact, both within and across	The occurrence of T2DM is influenced by a multitude of agents and factors: • Biological predisposition (e.g., familial history, genetics) • Physiology (e.g., blood lipid levels, weight)

factors	multiple system levels.	• Demographics (e.g., age, sex, race, ethnicity) • Psychology (e.g., risk perception, individualism) • Individual behaviours (e.g., dietary habits, physical activity) • Social determinants (e.g., education, health literacy, community groups) • Culture (e.g., religion, spirituality, beliefs) • Physical environment (e.g., infrastructure, space, food outlets) • Natural conditions (e.g., climate, temperature) • Geography and location (e.g., isolation, remoteness, food security) • Work/employment responsibilities • Media, social media, websites/information • Healthcare providers (GPs, Allied Health, clinical educators) • Private medical and health insurance companies • Universities (e.g., Departments/Schools of Rural Health) • Sporting and recreational facilities (e.g., clubs, gymnasiums) • Local councils (e.g., community events, 'get moving' initiatives) • Online health services (e.g., Nurse & Midwife Support) • Food distributors and suppliers

- Primary Health Networks (PHNs)
- Hospital and Health Services (HHS)
- Peak bodies (e.g., Australian Rural Health Education Network; ARHEN)
- Australian Diabetes organisations and societies
- State Departments of Health
- Department of Health (DOH) portfolio agencies
- Services Australia (e.g., Medicare)

The above list is by no means comprehensive, and many categories can be further expanded. However, the question remains: if decisions and actions at higher levels of the T2DM system influence and exert their effect on proximate individual behaviours and biology, then is it not reasonable to consider distal determinants as part of the broader set of causes to which T2DM emerges? If new Government legislation increased the number of Continuing Professional Development (CPD) credits that Allied Health Professionals were required to undertake annually, and hypothetically this reduced the occurrence of T2DM in the aggregate, then it can be concluded that the legislation change was indeed a causal factor, and perhaps an important leverage point. Any unintended and counterintuitive effects that result

		from this decision would need to be examined using a complex systems approach that has the capacity to model, simulate and forecast causal feedback within systems.
Open boundaries	Complex systems are ‘open systems’ with permeable boundaries. They continually learn and reconfigure in response to internal perturbation and external influence and intervention.	• Boundary definitions in complex systems are related to the concept of autopoiesis (i.e., replication and self-organisation of living entities). A complex system can maintain its bounded identity if processes are regenerated between its elements at a defined level of causal determination. It is thus more difficult to identify system boundaries as the level of system entropy and disorder increases. Systems exhibit greater levels of randomness at scale. • Depending on the research purpose and aims, the boundary of the T2DM system can be defined at a micro (e.g., biological), meso (e.g., individual) or macro (e.g., socio-political) level. • People living in rural and remote communities do not operate within a sociocultural or political vacuum. If upstream factors shape and regulate individual behaviours and biology, then it may be acceptable to establish the T2DM system boundary at the macroscopic level in order to guide

		prevention initiatives across populations.
Adaptive & self-organising	Complex systems continually shift towards and away from acceptable boundaries of safety and performance. Abrupt transitions without adequate adaptation to maintain equilibrium can result in a tipping point, or system failure.	• People living in rural and remote communities continuously navigate through a changing set of everyday circumstances to maintain health and well-being, and to minimise the risk of disease and ill-health. • Complex rural health systems migrate towards, and shift away from, acceptable boundaries of health and disease. • The release of a new T2DM health policy; the 'boom and bust' economic cycles that can occur in rural locations; workforce shortages/fluctuations; temporary service provisions; seasonal variations that dictate food quality and availability; emerging pandemics and natural disasters in already under resourced settings; new state-level programs and initiatives to increase physical activity; sporting events; and the influence of peer groups, community members and social pressures on the expression of individual behaviours can collectively 'pull' the rural health system in different directions. • There is no hierarchy of command or identifiable controller of events, only a rural health system that is forced to readjust to systemic change with

		individuals and communities attempting to respond accordingly.
Complex behaviours and relationships	Complex systems exhibit non-linear behaviours and feedback among its many agents and factors. This means that small causes can have large effects and vice versa.	• The cost and availability of healthy food in the environment (or lack thereof) can increase the purchasing of unhealthy food, which in turn, can affect the health of rural populations thereby reducing the desire to improve health status. This effect is *reinforced* and is *cyclical* within tightly-coupled, interconnected rural communities. The resulting perceived value of healthier foods is further diminished, and due to income inequality, a greater number of individuals make poor food choices which feeds directly back into the health of rural communities. Knowledge of nutrition and health, education status, geographic isolation, food marketing; and, higher up the chain, food policies, tax systems and government mandates exert their effect at the coal face. • Gradually over time, the incidence rate of T2DM in rural communities increases, and medical/public health researchers are left asking: *what is the cause of T2DM in rural communities, and how can it be reduced/prevented?* • The 'inputs' and 'outputs' of complex systems are difficult to identify,

		however it is possible to interrogate and understand causal feedback and non-linear system behaviours with static and computational modelling approaches. Section 5.0 of this article proposes the use of two suitable computational methods.
Emergent properties	Complex systems give rise to emergence. Emergence is defined as difficult-to-predict, higher-level patterns, behaviours and/or outputs.	• T2DM is an emergent phenomenon that results from the complex interactions that occur among a range of heterogenous agents and factors within the rural health system. • The occurrence of T2DM can be viewed as a product of the above system characteristics coming together as a whole.

5.0 Two complex systems approaches

In the health sciences, two complex systems approaches, Agent-Based Modelling (ABM) and System Dynamics (SD) modelling, are gaining popularity due to their capacity to capture and communicate the behaviours and dynamics of complex systems (23, 36-38) (Table 1). Rural health researchers are encouraged to explore how ABM and SD modelling may help with the identification, implementation and evaluation of new and existing strategies within complex rural health systems.

5.1 Agent-Based Modelling (ABM)

ABM is a form of microsimulation whereby interactions between synthetic populations of individual *agents* (e.g., molecules, cells, healthcare professionals, patients) can be observed within a computational environment (31, 32). Ideally, these interactions at the individual-level produce various macro-level patterns and complex behaviours that can grow, reflect or explain real-world phenomena (32). Agents can learn, adapt and respond to change based on the programming of demographic, lifestyle and environmental characteristics (29). Empirical data and/or expert theories can be used to instantiate ABMs depending on the modelling purpose (e.g., prediction, description, explanation) (36, 37, 39).

Methodologically, ABM can be performed hundreds or even thousands of times and the modelled outputs compared under different hypothetical scenarios (1, 20). ABM is an in-silico laboratory that has the capacity to evaluate the potential effectiveness of health policies over time (36, 37). For example, ABM could be used to estimate the incidence rate of T2DM within a virtual rural community following the implementation of various hypothetical health interventions and policies under changing environmental conditions.

A search for the term(s) '((agent-based model[Title/Abstract]) AND (rural health[Title/Abstract]))' in the National Library of Medicine PubMed.gov database (June 2022) produced no articles, pointing to a gap in the rural health literature. The reader is referred to several comprehensive resources covering the origins, purpose and use of ABM (1, 20, 29-32, 36, 37), including issues pertaining to the development, verification and validation of simulations (39, 40).

5.2 Systems Dynamics (SD) modelling

The first phase of SD modelling usually involves the development of a Causal Loop Diagram (CLD) (41-43). A CLD is a model that describes the conceptual, causal relationships between variables that comprise a complex system. There are two types of causal loops in a CLD: *reinforcing loops* and *balancing loops* (41-43). Reinforcing loops (labelled 'R' in models) produce exponential growth patterns, whereas balancing loops (labelled 'B' in models) produce exponential collapse. The joint effect of two or more of loops in a CLD can create either equilibrium or polarity within a complex system, the latter of which can trigger rapid oscillation and other chaotic, unpredictable behaviours. Conceptual behaviour over time (BOT) graphs can visualise such patterns (Figure 2) (44).

<Insert Figure 2 about here>

A CLD is a useful standalone method for visualising complexity, including how the various parts of a system (e.g., agents, factors, processes) interact to create a problem (43). Causal loops are, however, static system representations and conceptual errors are often only realised when they are translated into a dynamic format, such as SD modelling.

SD modelling is computational method that can be used to explore the structure and dynamics of both simple and complex systems (38, 41, 45). The method is capable of simulating non-linear behaviours of complex systems over time, primarily using differential equations and related mathematical formulae (30, 31, 45). SD modelling incorporates the same features from a CLD, such as variables, feedback loops and time delays; however, *stocks* and *flows* are also included in the representation to allow for the accumulation and depletion of key elements over time (38) (e.g., inventory, money, assets, employees – the rural health workforce). SD modelling has the capacity to reveal the complex processes and pathways that give rise to emergent system behaviours at a macro-level. It is a useful tool for understanding counterintuitive behaviours within complex systems as a basis to identify potential leverage points for health-related interventions and policies.

A recent systematic review of SD modelling in health and medicine provides a comprehensive overview of the method and its background and reports on 301 different applications (38). Despite this growth, a search for the term(s) '((system dynamics[Title/Abstract]) AND (rural health[Title/Abstract]))' in the PubMed.gov database (June 2022) produced no eligible articles. The research opportunities in rural health are apparent.

6.0 Methods that are fit for purpose

Complex systems approaches are not intended to act as a replacement for traditional scientific methods well-suited to simpler problems (e.g., PICO problems) in the health sciences. The analytical trade-offs associated with both reductionist and complex systems approaches must be acknowledged. To describe these, we refer to the desiderata *precision*, *fit*, *generality*, and *realism* (46).

Clinical and epidemiological methods have the advantage of being able to score relatively highly across statistical dimensions of precision and fit, albeit they equally score lower in measures of generality and realism. The inverse is generally true for complex systems approaches which tend to place a greater reliance on theory relative to data (20). Examples are shown in Figure 3.

Precision and fit can be thought of as the capacity of a model to produce precise numerical outputs, and to make quantitative predictions based on historical data, respectively (46). Realism on the other hand, explains the accuracy to which a systems model has face validity, describes the world qualitatively, and agrees with expert mental models. Generality is the extent to which a model has external validity across domains (46).

<Insert Figure 3 about here>

6.1 An example multi-method complex systems approach

The main point conveyed by Figure 3 is that there is a trade-off with respect to all four analytical desiderata (46). Satisfying all four concurrently is not possible via a single application, the outcome of which depends on the research question(s), project goal, use of data and approach. Fortunately, a multi-method complex systems approach could provide a promising way forward in rural health research.

To illustrate, sacrificing precision and fit for generality and realism is not necessarily a detriment if the first phase of a research program involves mapping all agents and factors from across the 'rural health system' that contribute to a health or health system outcome. In this regard, static systems modelling, such as CLDs or socioecological models, could be a useful starting point to explain and highlight the key agents, factors, processes and potential leverage points as a means to direct subsequent analyses. The next step in the research program might involve the use of a 'top down' computational method, such as SD modelling, to reveal how non-linear system dynamics and behaviours drive change and shape health outcomes, thereby increasing quantitative precision. The third and final phase may drill down further into key parts of the rural health system via the use of an ABM, to understand the complex processes that give rise to health or health system outcomes, albeit from a 'ground up' perspective that appreciates individual exchanges of information, labour and skill between health professionals and health system managers. This three-step progression from CLD to SD to ABM may act as a simple framework by which rural health researchers can become comfortable and familiar with systems modelling approaches into the future.

6.2 The many uses of complex systems approaches

From the above it is concluded that unlike traditional clinical and epidemiological methods, which are used exclusively to test well-defined and falsifiable *a priori* causal hypotheses, there are many different reasons to use a complex systems approach.

Static complex systems methods, such as CLDs and socioecological models (2, 27, 30, 34, 42, 43, 46), can be used to:

i. Synthesise large amounts of evidence and/or information
ii. Offer a 'big picture' perspective to e.g., support analysis and intervention design
iii. Illustrate complex causal feedback, theorise system dynamics, and identify possible leverage

iv. Generate new hypotheses and identify gaps in knowledge
v. Inform an understanding of the range of factors that contribute to an outcome
vi. Gain an understanding of the problem 'envelope' or system boundary
vii. Facilitate participatory and group model-building initiatives

Computational complex systems methods, such as ABM and SD modelling (1, 20, 29, 32, 36-41, 45, 46), can be used to:

i. Explain, predict and forecast the emergence of various patterns and phenomena (e.g., survival rates, impact of health policies, direction of effect of interventions)
ii. Understand the mechanisms that drive the behaviour of complex systems
iii. Simulate the dynamics of a problem to observe how factors, structures and systems behave over time
iv. Conduct multiple in-silico 'what if' experiments that otherwise would not be possible in situ

7.0 Towards a complex systems approach in rural health

Adopting a complex systems approach in rural health research would recognise that real, long-term change within rural communities is only created when systems and processes are redesigned and reconfigured, and not necessarily when a single 'fix' or individual-level health intervention is implemented (12, 22). The role of subject matter expertise and causal theories explaining health generation in rural settings would play a greater role in complexity science applications relative to a traditional scientific approach (10, 20). The triangulation of various sources of data across multiple system levels and from the perspective of various stakeholders would feed into the development of models to enrich understanding of where to intervene in rural health systems (18, 25). Involving rural health communities, consumers, service providers, stakeholders and policy-makers in the development of conceptual systems models would provide a sense of ownership and transparency of the model-construction process to ensure that the resulting solutions are endorsed long-term (38).

Under a complexity framework, rural health researchers would ask not whether a specific intervention *works*; but rather, *how* new or existing solutions could be supported or degraded by the wider system

(17, 24). When rural health systems are mapped, modelled and understood, it is possible to identify where key leverage points may be and how to best to manipulate them through a multidisciplinary effort (2, 18). These points of leverage may be found across all levels of the complex rural health system; however, further interrogation of the outputs would expose optimal targets for interventions and solutions given limited resources and competing priorities. To achieve this, the use of static and computational methods from the complexity sciences, such as CLD (43), SD modelling (23, 38) and ABM (32, 36, 37) can be used to conceptualise and simulate the non-linear behaviours of complex rural health systems. Doing so will offer original data and evidence to complement traditional forms of scientific inquiry to translate effective new rural health interventions and policies.

The field of implementation science has become important in marrying the outcomes of complex systems thinking and real-world objectives for better health outcomes (18, 24, 25). Implementation science, which is increasingly integrating realist evaluation theories (24), has seen a tremendous uptake in the application of complex systems approaches as it allows a better understanding of what *works*, for *whom*, *when*, and *why* (17, 18, 25). The integration of complexity science, implementation science and realist evaluation frameworks is an encouraging future direction for rural health research.

8.0 Closing remarks

Rural health researchers are encouraged to consider how adopting systems approaches could provide a new spark in a field that arguably needs scientific innovation and complementary methods. By taking a systems thinking perspective, rural health researchers can begin to explore, model and understand the myriad of factors and interactions that contribute to health outcomes and health system issues at scale, both within and between different rural communities. The present authors welcome this challenge and embrace the possibilities that are derived from adopting new ways of thinking about, and scientifically approaching, rural health issues.

Contributorship statement

All authors contributed to the content in accordance with the ICMJE guidelines for authorship. AH: Conceptualisation, writing – initial draft; reviewing and editing. JT: Writing, reviewing and editing. GA: Writing, reviewing and editing.

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Data sharing statement

No data are available.

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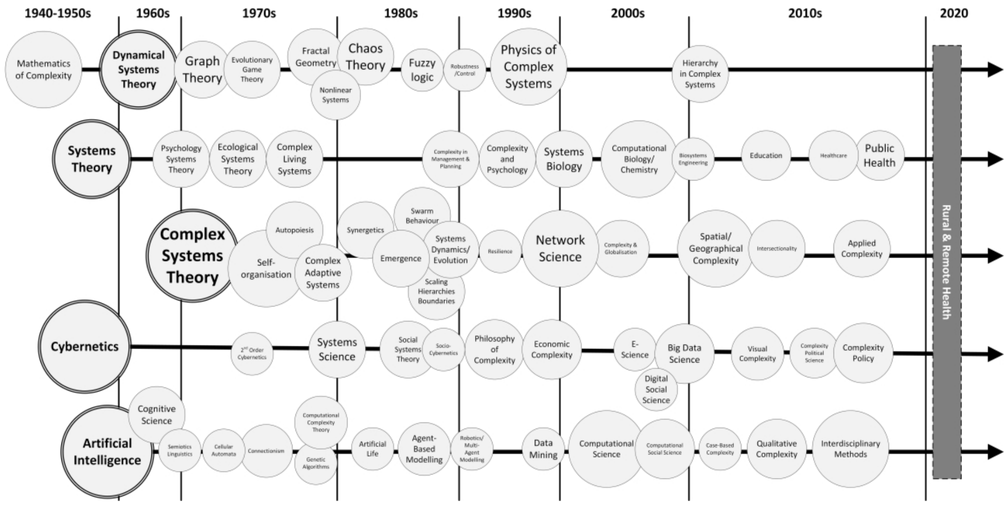
Figure legend/captions

Figure 1: Map of the complexity sciences. Redrawn and modified from Castellani and Gerrits (35). The full colour depiction with associated scholars in the corresponding fields can be viewed at: https://www.art-sciencefactory.com/complexity-map_feb09.html. The five traditions are: (i) dynamical systems theory; (ii) systems theory; (iii) complex systems theory; (iv) cybernetics; and (v) artificial intelligence. Rural health is indicated from ~2022 onwards leaving open the possibility of applying complex systems approaches to contemporary issues in this space.

Figure 2: A simple Causal Loop Diagram (CLD) (far left) that theoretically explains the behaviour of the rural health workforce. Polarity indicators, positive (+) and negative (-), indicate reinforcing and balancing loops linking variables. If recruitment rate is the same as the departure rate, as shown here, then the behaviour of the workforce over time (in this case 24 months) will result in dynamic equilibrium as shown by the conceptual behaviour over time (BOT) graph (far right). BOT graphs are useful to facilitate group model-building activities; they articulate and synthesise individual mental models and can generate a shared understanding of a problem. CLDs can quickly grow in size and complexity, making it impossible to understand system behaviour. At that point researchers should consider using the CLD as a basis to develop a computational System Dynamics (SD) model.

Figure 3: The trade-off between the analytical desiderata of precision, fit, realism and generality. The article by Ip and colleagues (45) provides an overview of key terms and concepts. Panel A: Linear regression analysis/Randomised Controlled Trial (RCT); Panel B: Agent-Based Model (ABM) of estimated disease incidence; Panel C: System Dynamics (SD) model of health service costs to health service utilisation; Panel D: Causal Loop Diagram (CLD) or a socioecological model of a health system. We note that whilst four simple examples are shown, there are many different traditional statistical approaches and complex systems approaches, including multiple variations *within* them, that would produce different results across the four dimensions.



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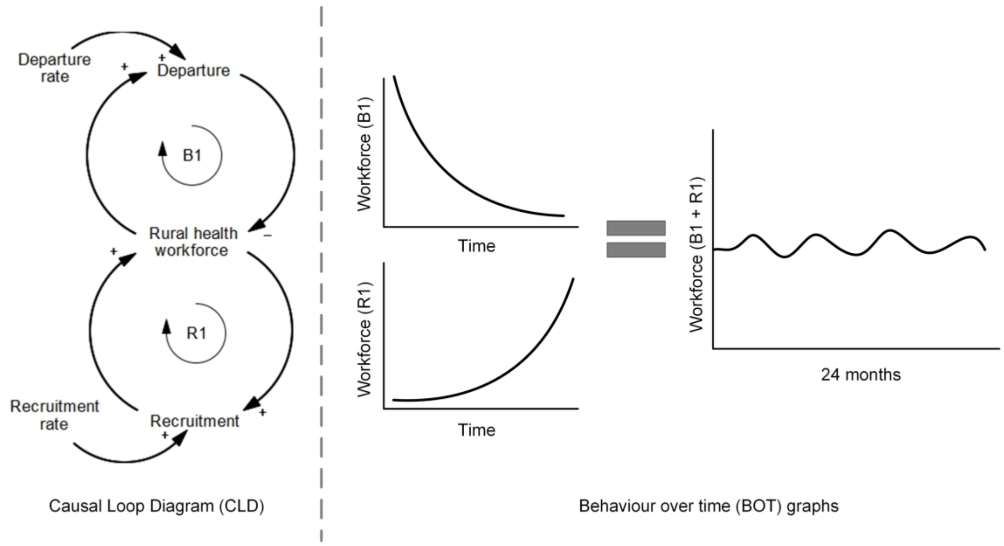

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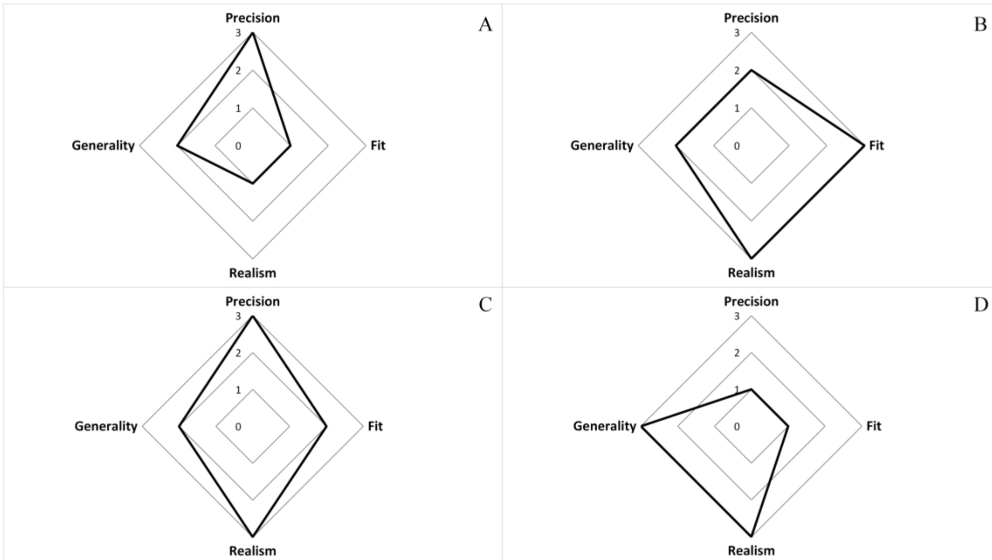

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The need for a complex systems approach in rural health research

Adam Hulme*[1], Jason Thompson[2], Andrew D. Brown[3], Geoff Argus[1,4]

*Corresponding author

[1]Southern Queensland Rural Health

Faculty of Health and Behavioural Sciences

The University of Queensland

Baillie Henderson Hospital campus

Corner Hogg and Tor Streets, Toowoomba QLD 4350

PO Box 24, Harlaxton QLD 4350

P +61 07 4633 9789

M (+61) 488 225 006

E a.hulme@uq.edu.au

[2]Department of Rural Health

Faculty of Medicine

The University of Melbourne

Parkville, Victoria, 3010

Australia

[3]Institute for Health Transformation

Global Centre for Preventive Health and Nutrition

Deakin University

Geelong, Victoria 3220

Australia

[4]School of Psychology and Wellbeing

Faculty of Health, Engineering and Sciences

University of Southern Queensland

Toowoomba, Queensland, 4530

Australia

Abstract

On a global scale, many major rural health issues have persisted for decades despite the introduction of new health interventions and public health policies. Although research efforts have generated valuable new knowledge about the aetiology of health, disease and health inequities in rural communities, rural health systems remain to be some of the most deprived and challenged in both the developing and developed world. Whilst the reasons for this are many, a significant factor contributing to the current state of play is the pressing need for methodological innovation and relevant scientific approaches that have the capacity to support the translation of novel solutions into 'real world' rural contexts. Fortunately, complex systems approaches, which have seen an increase in popularity in the wider public health literature, could provide answers to some of the most resilient rural health problems in recent times. The purpose of this article is to promote the value and utility of a complex systems approach in rural health research. We explain the benefits of a complex systems approach and provide a background to the complexity sciences, including the main characteristics of complex systems. Two popular computational methods are described. The next step for rural health research involves exploring how a complex systems approach can help with the identification and evaluation of new and existing solutions to policy-resistant rural health issues. This includes generating awareness around the analytical trade-offs that occur between the use of traditional scientific methods and complex systems approaches.

1.0 Introduction

The field of complexity science engenders its own lexicon, theories and concepts. We have therefore provided the following key definitions and explanations to assist the reader with an understanding of the material forthcoming.

1.1 Terms and definitions

Complex systems are found across the micro (e.g., biological), meso (e.g., individual) and macro (e.g., social) levels of the physical and natural world. Complex systems include biological systems, the earth's atmosphere and climate, ant colonies, diseases, political entities, the stock market, rainforests, organisations and corporations, and pertinent to this article, rural health systems. A complex system is:

> "…made up of many heterogenous elements; these elements interact with each other; the interactions produce an emergent effect that is different from the effects of the individual elements; and this effect persists over time and adapts to changing circumstances".
>
> ~Luke and Stamatakis, p.2 (1)

In attempting to map and understand complex systems, systems modellers and analysts often attempt to identify *leverage points*. Leverage points are key places within a complex system where a small intervention can produce a large (positive) effect on the system's outcome. Leverage points are frequently counterintuitive, meaning that change is often required to be enacted in the opposite direction to produce the intended outcome. The points of greatest leverage within a system may not necessarily be obvious at first glance or may even exist beyond initial conceptualisations of a system.

> "The silver bullet, the miracle cure, the secret passage, the magic password, the single hero who turns the tide of history. We not only want to believe that there are leverage points, but we also want to know where they are and how to get our hands on them. Leverage points are points of power".
>
> ~Meadows, p.145 (2)

1.2 Background and purpose

The purpose of this article is twofold. First, to encourage new ways of thinking about how rural health issues and health inequalities are created, maintained and prevented through a systems research lens; and second, to promote the value and utility of a complex systems approach in this space. Although the article is written with the rural health researcher in mind, the content may also be interesting to a wider *BMJ Open* readership, including clinicians, service providers, stakeholders and policy-makers tackling the results of failed and/or troubled healthcare systems.

1.3 Why rural health?

Rural health is a multidisciplinary area of study within the field of public health that has largely been neglected from a funding and research perspective (3). Whilst specialist research groups and university departments around the world – Australia, Canada, United States, New Zealand, United Kingdom and Europe – are producing excellent (traditional) work in the area of rural health (e.g., 4, 5), the disparities in health outcomes and health inequalities between urban and rural communities continue to persist in the face of new health interventions and policies (6-8). Whilst the reasons for this are many, including factors related to geography, healthcare access, service provision, workforce retention, cultural sensitivities and wider political systems (9), it is these authors' opinion that the rural health research field is also in drastic need of scientific innovation if it is to seriously tackle the complex global challenges that it faces. The answers we seek, and the change that is desired for rural communities by way of research and advances in knowledge, may lie in the field of systems research and complexity science and its many diverse approaches, methods and models.

2.0 Traditional methods in a complex world

Against a backdrop of increasing global interconnectedness, a growing number of researchers have questioned whether clinical and epidemiological methods can alone identify effective solutions to the most resilient public health problems in recent times (10-15). Arguments have centred around the fact that Randomised Controlled Trials (RCTs) and experimental study designs, considered to be *the* 'gold standard' approaches for assessing causality, are only able to quantify the efficacy of a targeted individual-level health intervention (11-13, 16). Attempts to 'scale-up' evidence-based clinical and behavioural interventions and deliver them into complex, uncontrolled, real-world settings without consideration of the broader socio-political context is known to erode their fidelity, adoption, maintenance and effectiveness (17, 18).

Whilst the traditional Person, Intervention, Comparison, Outcome (PICO) framework has been met with considerable success and should continue to be applied to address well-defined causal research questions, the very act of controlling for background noise; the collapsing down of complexity; the reliance on data at the expense of theory; and desire to increasingly sharpen the effect of individual-level health interventions is not optimal for all health problems, social contexts and circumstances (12, 14-16, 19, 20). The occurrence of health and disease across populations, including rural communities, can also be viewed as a product of the complex interactions that occur among biological, behavioural, societal, environmental and political determinants (10, 19, 21). This line of thinking encourages debate around what exactly constitutes 'a cause' from a scientific perspective, and where within 'the system' the most appropriate leverage point may be (10, 11).

Analytical reductionism can only deliver on so much if the goal of research is to: (i) ask questions about the effectiveness of upstream interventions that exert their effect on downstream factors and health outcomes over an extended timescale; and/or (ii) ask questions about how new or existing solutions can be supported or degraded in context of the wider health system and its behaviour (10, 12, 17, 18, 22). Complementary research approaches are required to explore the intermediate and distal pathways that shape population health, and by definition rural health, from a broad perspective.

2.1 From reductionism to complexity

In response to the need for system level evaluations of health interventions, there has been a recent groundswell of interest in epidemiology and public health around the use of *complex systems approaches* from the field of complexity science (16, 21-27). Complex systems approaches are used to study discontinuous relations, complex forms of non-linear feedback between factors across multiple levels, networks between people, groups and their environment, and processes of exchange between individual actors in systems that give rise to emergent macro-level system behaviours (1, 10, 21, 23-26, 28-32). There is mounting evidence to suggest that a complex systems approach can be of practical assistance in both explaining mechanisms driving adverse health outcomes and system behaviour and also determining *where* and *how* to intervene through optimal leverage to achieve positive population health outcomes (18, 23-25, 27).

Despite growing momentum around complex systems approaches, their specific application to issues contained within rural health has received a lack of attention aside from a few notable exceptions, including systems mapping (33-35) and dynamic modelling (36) studies. Complex systems approaches may help to identify new rural health solutions, identify key leverage points to address workforce issues such as provider maldistribution and shortage (e.g., 37), support cost-benefit decision-making, and contribute to the evaluation of existing strategies given competing priorities and the balancing of limited resources. Whilst the use of a complex systems approach may not necessarily differ methodologically between urban, semi-urban and rural health contexts, the contribution of systems research in rural health specifically lies in the generation of new evidence and knowledge to complement traditional scientific inquiry.

3.0 What is complexity science?

Complexity science is a discipline that attempts to understand and respond to problems that are dynamic and unpredictable, multi-dimensional, and comprise various interrelated actors and components (38). Researchers who study complexity, and by extension complex problems, focus on the *interactions* among various elements within a complex system, rather than on the role and contribution of those elements in *isolation* (28, 39).

Where appropriate, complexity science proponents will advocate for a systems thinking perspective over a reductionist one, as doing so is to consider the whole system, and multiple interacting elements of it, as the primary unit of analysis (28, 33, 35, 39). This affords insight into how the constituent elements of a complex system converge in context of a much greater whole, which is useful when attempting to make sense of resilient, persistent and policy resistant problems (12).

3.1 Mapping the complexity sciences

Complexity science incorporates multiple traditions, disciplines, methods, techniques and analytical tools. The *Map of the Complexity Sciences* (40) (Figure 1) shows the historical progression of five major intellectual traditions over several decades. The 'map' shows that there is no single, unified understanding of what complexity science is when it is subjected to formal investigation and analysis (39). Which complex systems approach to adopt depends on many factors, including available resources, individual expertise and the type of problem to be examined.

<Insert Figure 1 about here>

4.0 Characteristics of complex systems

There are discernible characteristics that are universal to all complex systems. Type 2 Diabetes Mellitus (T2DM), a significant issue in the Australian rural health sector, is selected to elucidate the key concepts (Table 1). This section elaborates in greater detail on the definition of a complex system provided at the opening of the Communication (1).

Table 1: Complex systems characteristics. The characteristics and descriptions appear in Hulme et al. 2019 (30) and 2020 (39); however, the examples reflect the occurrence of Type 2 Diabetes Mellitus (T2DM) within the Australian context.

Characteristic	**Description**	**T2DM example**
Multiple system levels, scalable	Complex systems vary in type, size, and scale, from the micro (e.g., molecular, cellular), through to the meso (e.g., individual) and macro (e.g., socioeconomic, political) levels.	• The occurrence of T2DM can be conceptualised and studied at the cellular (e.g., insulin secretion by pancreatic β-cells), individual (e.g., behavioural), societal (e.g., employment security, living conditions) or policy (e.g., provision of state and Commonwealth funding) levels. • The T2DM system is composed of, and is a component within, other complex systems (i.e., complex systems are nested). • Focussing on individual behaviour change alone, such as physical inactivity or diet, will not be effective at preventing the occurrence of T2DM in rural communities. Biological factors, individual behaviours, and personal motivations should be explored, understood and contextualised within a broader context.
Diverse range of agents (i.e., people and organisations), and	Complex systems contain many fundamentally different agents and factors that interact, both within and across	The occurrence of T2DM is influenced by a multitude of agents and factors: • Biological predisposition (e.g., familial history, genetics) • Physiology (e.g., blood lipid levels, weight)

factors	multiple system levels.	• Demographics (e.g., age, sex, race, ethnicity) • Psychology (e.g., risk perception, individualism) • Individual behaviours (e.g., dietary habits, physical activity) • Social determinants (e.g., education, health literacy, community groups) • Culture (e.g., religion, spirituality, beliefs) • Physical environment (e.g., infrastructure, space, food outlets) • Natural conditions (e.g., climate, temperature) • Geography and location (e.g., isolation, remoteness, food security) • Work/employment responsibilities • Media, social media, websites/information • Healthcare providers (GPs, Allied Health, clinical educators) • Private medical and health insurance companies • Universities (e.g., Departments/Schools of Rural Health) • Sporting and recreational facilities (e.g., clubs, gymnasiums) • Local councils (e.g., community events, ‘get moving’ initiatives) • Online health services (e.g., Nurse & Midwife Support) • Food distributors and suppliers

- Primary Health Networks (PHNs)
- Hospital and Health Services (HHS)
- Peak bodies (e.g., Australian Rural Health Education Network; ARHEN)
- Australian Diabetes organisations and societies
- State Departments of Health
- Department of Health (DOH) portfolio agencies
- Services Australia (e.g., Medicare)

The above list is by no means comprehensive, and many categories can be further expanded. However, the question remains: if decisions and actions at higher levels of the T2DM system influence and exert their effect on proximate individual behaviours and biology, then is it not reasonable to consider distal determinants as part of the broader set of causes to which T2DM emerges? If new Government legislation increased the number of Continuing Professional Development (CPD) credits that Allied Health Professionals were required to undertake annually, and hypothetically this reduced the occurrence of T2DM in the aggregate, then it can be concluded that the legislation change was indeed a causal factor, and perhaps an important leverage point. Any unintended and counterintuitive effects that result

		from this decision would need to be examined using a complex systems approach that has the capacity to model, simulate and forecast causal feedback within systems.
Open boundaries	Complex systems are 'open systems' with permeable boundaries. They continually learn and reconfigure in response to internal perturbation and external influence and intervention.	• Boundary definitions in complex systems are related to the concept of autopoiesis (i.e., replication and self-organisation of living entities). A complex system can maintain its bounded identity if processes are regenerated between its elements at a defined level of causal determination. It is thus more difficult to identify system boundaries as the level of system entropy and disorder increases. Systems exhibit greater levels of randomness at scale. • Depending on the research purpose and aims, the boundary of the T2DM system can be defined at a micro (e.g., biological), meso (e.g., individual) or macro (e.g., socio-political) level. • People living in rural and remote communities do not operate within a sociocultural or political vacuum. If upstream factors shape and regulate individual behaviours and biology, then it may be acceptable to establish the T2DM system boundary at the macroscopic level in order to guide

		prevention initiatives across populations. • The most impactful solution to T2DM may equally reside *outside* of the immediate health system in other global and political systems. Exogenous influences, such as global conflicts, climate change and food insecurity, may impact endogenous system dynamics. Complex systems approaches may begin to examine the effects of global dynamics on internal behaviours.
Adaptive & self-organising	Complex systems continually shift towards and away from acceptable boundaries of safety and performance. Abrupt transitions without adequate adaptation to maintain equilibrium can result in a tipping point, or system failure.	• People living in rural and remote communities continuously navigate through a changing set of everyday circumstances to maintain health and well-being, and to minimise the risk of disease and ill-health. • Complex rural health systems migrate towards, and shift away from, acceptable boundaries of health and disease. • The release of a new T2DM health policy; the 'boom and bust' economic cycles that can occur in rural locations; workforce shortages/fluctuations; temporary service provisions; seasonal variations that dictate food quality and availability; emerging pandemics and natural disasters in already under resourced settings; new state-level programs and initiatives to increase

		physical activity; sporting events; and the influence of peer groups, community members and social pressures on the expression of individual behaviours can collectively 'pull' the rural health system in *different directions*. • There is no hierarchy of command or identifiable controller of events, only a rural health system that is forced to readjust to systemic change with individuals and communities attempting to respond accordingly in the best way possible according to their needs.
Complex behaviours and relationships	Complex systems exhibit non-linear behaviours and feedback among its many agents and factors. This means that small causes can have large effects and vice versa.	• The cost and availability of healthy food in the environment (or lack thereof) can increase the purchasing of unhealthy food, which in turn, can affect the health of rural populations thereby reducing the desire to improve health status. This effect is *reinforced* and is *cyclical* within tightly-coupled, interconnected rural communities. The resulting perceived value of healthier foods is further diminished, and due to income inequality, a greater number of individuals make poor food choices which feeds directly back into the health of rural communities. Knowledge of nutrition and health, education status, geographic isolation, food

		marketing; and, higher up the chain, food policies, tax systems and government mandates exert their effect at the coal face. • Gradually over time, the incidence rate of T2DM in rural communities increases, and medical/public health researchers are left asking: *what is the cause of T2DM in rural communities, and how can it be appropriately treated and managed?* • The 'inputs' and 'outputs' of complex systems are difficult to identify, however it is possible to interrogate and understand causal feedback and non-linear system behaviours with static and computational modelling approaches. Section 5.0 of this article proposes the use of two suitable computational methods.
Emergent properties	Complex systems give rise to emergence. Emergence is defined as difficult-to-predict, higher-level patterns, behaviours and/or outputs.	• T2DM is an emergent phenomenon that results from the complex interactions that occur among a range of heterogenous agents and factors within the rural health system. • The occurrence of T2DM can be viewed as a product of the above system characteristics coming together as a whole.

5.0 Two complex systems approaches

In the health sciences, two complex systems approaches, Agent-Based Modelling (ABM) and System Dynamics (SD) modelling, are gaining popularity due to their capacity to capture and communicate the behaviours and dynamics of complex systems (23, 41-43) (Table 1). Rural health researchers are encouraged to explore how ABM and SD modelling may help with the identification, implementation and evaluation of new and existing strategies within complex rural health systems.

5.1 Agent-Based Modelling (ABM)

ABM is a type of microsimulation whereby interactions between synthetic populations of individual *agents* (e.g., molecules, cells, healthcare professionals, patients) can be observed within a computational environment (31, 32). Ideally, these interactions at the individual-level produce various macro-level patterns and complex behaviours that can grow, reflect or explain real-world phenomena (32). Agents can learn, adapt and respond to change based on the programming of demographic, lifestyle and environmental characteristics (29). Empirical data and/or expert theories can be used to instantiate ABMs depending on the modelling purpose (e.g., prediction, description, explanation) (41, 42, 44).

Methodologically, ABM can be performed hundreds or even thousands of times and the modelled outputs compared under different hypothetical scenarios (1, 20). ABM is an in-silico laboratory that has the capacity to evaluate the potential effectiveness of health policies over time (41, 42). For example, ABM could be used to estimate the incidence rate of T2DM within a virtual rural community following the implementation of various hypothetical health interventions and policies under changing environmental conditions. The reader is referred to several comprehensive resources covering the origins, purpose and use of ABM (1, 20, 29-32, 41, 42), including issues pertaining to the development, verification and validation of simulations (44, 45).

5.2 Systems Dynamics (SD) modelling

The first phase of SD modelling may involve the development of a Causal Loop Diagram (CLD) (33-35, 46-48). A CLD is a qualitative model that describes the conceptual, causal relationships between variables that comprise a complex system. There are two types of causal loops in a CLD: *reinforcing loops* and *balancing loops* (46-48). Reinforcing loops (labelled ‘R’ in models) produce exponential growth and decay patterns, whereas balancing loops (labelled ‘B’ in models) act to stabilise the system (i.e., balancing loops are referred to as ‘goal-seeking’ loops). The combined effect of two or more loops in a CLD can create either stable or unstable equilibrium within a complex system. Time delays between system elements can further trigger oscillation and other unpredictable behaviours. Conceptual behaviour over time (BOT) graphs can visualise such patterns (49). Figure 2 presents a ‘fixes that fails’ system archetype structure (50) and the associated behaviour over time graph applied to the rural health workforce shortage problem.

<Insert Figure 2 about here>

A CLD is a useful standalone tool for visualising complexity and conceptualising relatively simple behaviours, including how the various parts of a system (e.g., agents, factors, processes) interact to explain or create a problem (48). There are very few examples of CLDs applied specifically in rural contexts (e.g., 33-35), and further applications are warranted. Despite their holistic point of reference, CLDs are still only static representations and conceptual errors and complex behaviours are often only realised when models are translated into a dynamic format, such as SD modelling.

SD modelling is computational method that can be used to explore the structure and dynamics of both simple and complex systems (43, 46, 51). The method is capable of simulating non-linear behaviours of complex systems over time, primarily using differential equations and related mathematical formulae (30, 31, 51). SD modelling incorporates the same features from a CLD, such as variables, feedback loops and time delays; however, *stocks* and *flows* are also included in the representation to allow for the accumulation and depletion of key elements over time (43) (e.g., inventory, money, assets, employees – the rural health workforce). SD modelling has the capacity to reveal the complex processes and pathways that give rise to emergent system behaviours at a macro-level. It is a useful complex systems approach for understanding counterintuitive behaviours within complex systems as a basis to identify potential leverage points for health-related interventions and policies. As with ABM, a range of existing data sources can be used to paramterise and calibrate simulations. For example, in terms of Australian rural health, there is a huge research opportunity around using the readily available and comprehensive National Health Workforce Data Tool (52), along with other data sources, to instantiate models and forecast various rural health system behaviours. The reader is directed to two papers using SD modelling, one examining the implementation of clean cooking interventions in rural India (36), and another that compared the demand and supply of Australian radiologists over 40 years under various scenarios (though not exclusively rural focussed) (37).

Figure 3 presents a reformulation of the fixes that fail workforce CLD (Figure 2), this time as a Stock and Flow Diagram (SFD) to allow for quantitative simulation (Vensim PLE Version 9.3.0 x64). Figure 3 demonstrates that it is far better to work on identifying and implementing the fundamental solution to the workforce problem than it is to invest in quick fixes to correct the shortage, even if this initially comes at a greater cost to time, expenses and resources. Vensim code provided in Supplementary Material.

<Insert Figure 3 about here>

6.0 Methods that are fit for purpose

Complex systems approaches are not intended to act as a replacement for traditional scientific methods well-suited to simpler problems (e.g., PICO problems) in the health sciences. The analytical trade-offs associated with both reductionist and complex systems approaches must be acknowledged. To describe these, we refer to the desiderata *precision*, *fit*, *generality*, and *realism* as reported by Ip et al (53).

Clinical and epidemiological methods have the advantage of being able to score relatively highly across statistical dimensions of precision and fit, albeit they equally score lower in measures of generality and realism. The inverse is generally true for complex systems approaches which tend to place a greater reliance on theory relative to data (20). Examples are shown in Figure 4.

Precision and fit can be thought of as the capacity of a model to produce precise numerical outputs, and to make quantitative predictions based on historical data, respectively (53). Realism on the other hand, explains the accuracy to which a systems model has face validity, describes the world qualitatively, and agrees with expert mental models. Generality is the extent to which a model has external validity across domains (53).

<Insert Figure 4 about here>

6.1 An example multi-method complex systems approach

The main point conveyed by Figure 4 is that there is a trade-off with respect to all four analytical desiderata (53). Satisfying all four concurrently is not possible via a single application, the outcome of which depends on the research question(s), project goal, use of data and approach. Fortunately, a multi-method complex systems approach could provide a promising way forward in rural health research.

To illustrate, sacrificing precision and fit for generality and realism is not necessarily a detriment if the first phase of a research program involves mapping all agents and factors from across the 'rural health system' that contribute to a health or health system outcome. In this regard, static systems modelling, such as CLDs or socioecological models, could be a useful starting point to conceptualise complexity and generate a rich picture of the problem and the key agents and factors involved as a means to direct subsequent analyses (e.g., 33-35). The next step in the research program might involve the use of a 'top down' computational method, such as SD modelling, to reveal how non-linear system dynamics and behaviours drive change and shape health outcomes, thereby increasing quantitative precision. The third and final phase may drill down further into key parts of the rural health system via the use of an ABM, to understand the complex processes that give rise to health or health system outcomes, albeit from a 'ground up' perspective that appreciates individual exchanges of information, labour and skill between health professionals and health system managers. This three-step progression from CLD to SD to ABM may act as a simple framework by which rural health researchers can become comfortable and familiar with systems modelling approaches into the future.

6.2 The many uses of complex systems approaches

From the above it is concluded that unlike traditional clinical and epidemiological methods, which are used exclusively to test well-defined and falsifiable *a priori* causal hypotheses, there are many different reasons to use a complex systems approach.

Static complex systems methods, such as CLDs and socioecological models (2, 27, 30, 33-35, 39, 47, 48, 53), can be used to:

i. Synthesise large amounts of evidence and/or information
ii. Offer a 'big picture' perspective to e.g., support analysis and intervention design
iii. Illustrate complex causal feedback, theorise system dynamics, and identify possible leverage
iv. Generate new hypotheses and identify gaps in knowledge
v. Inform an understanding of the range of factors that contribute to an outcome
vi. Gain an understanding of the problem 'envelope' or system boundary
vii. Facilitate co-design, participatory and group model-building initiatives

Computational complex systems methods, such as ABM and SD modelling (1, 20, 29, 32, 36, 37, 41-46, 51, 53), can be used to:

i. Explain and forecast the emergence of various patterns and systems phenomena (e.g., survival rates, impact of health policies, direction of effect of interventions)
ii. Understand the mechanisms that drive the behaviour of complex systems

iii. Simulate the dynamics of a problem to observe how factors, structures and systems behave over time

iv. Conduct multiple in-silico 'what if' experiments that otherwise would not be possible in situ (i.e., policy comparative analyses)

7.0 Towards a complex systems approach in rural health

Adopting a complex systems approach in rural health research would recognise that real, long-term change within rural communities is only created when systems and processes are redesigned and reconfigured, and not necessarily when a single 'fix' or individual-level health intervention is implemented (12, 22). The role of subject matter expertise and causal theories explaining health generation in rural settings would play a greater role in complexity science applications relative to a traditional scientific approach (10, 20). The triangulation of various sources of data across multiple system levels and from the perspective of various stakeholders would feed into the development of models to enrich understanding of where to intervene in rural health systems (18, 25). Involving rural health communities, consumers, service providers, stakeholders and policy-makers in the development of conceptual systems models would provide a sense of ownership and transparency of the model-construction process to ensure that the resulting solutions are endorsed long-term (43).

Under a complexity framework, rural health researchers would ask not whether a specific intervention *works*; but rather, *how* new or existing solutions could be supported or degraded by the wider system (17, 24). When rural health systems are mapped, modelled and understood, it is possible to identify where key leverage points may be and how to best to manipulate them through a multidisciplinary effort (2, 18). These points of leverage may be found across all levels of the complex rural health system; however, further interrogation of the outputs would expose optimal targets for interventions and solutions given limited resources and competing priorities. To achieve this, the use of static and computational methods from the complexity sciences, such as CLD (35, 48), SD modelling (23, 43) and ABM (32, 41, 42) can be used to conceptualise and simulate the non-linear behaviours of complex rural health systems. Doing so will offer original data and evidence to complement traditional forms of scientific inquiry to translate effective new rural health interventions and policies.

Indeed, a particularly important issue in rural health that systems methods could be applied to includes the widespread maldistribution and shortage of medical and allied health professionals (8, 9). Understanding the complex interrelationships between various system wide factors that are driving this problem with the aim of identifying optimal systemic leverage given the presence of counterintuitive behaviour is a major future research opportunity for the systems-based (computational) modelling community.

The field of implementation science has become important in marrying the outcomes of complex systems thinking and real-world objectives for better health outcomes (18, 24, 25). Implementation science, which is increasingly integrating realist evaluation theories (24), has seen a tremendous uptake in the application of complex systems approaches as it allows a better understanding of what *works*, for *whom*, *when*, and *why* (17, 18, 25). The integration of complexity science, implementation science and realist evaluation frameworks is also an encouraging future direction for rural health research.

8.0 Closing remarks

Rural health researchers are encouraged to consider how adopting a complex systems approach could provide a new spark in a field that arguably needs scientific innovation and complementary methods. By taking a systems thinking perspective, rural health researchers can begin to explore, model and understand the myriad of factors and interactions that contribute to health outcomes and health system issues at scale, both within and between different rural communities. The qualitative and quantitative systems modelling methods described in this article will be highly useful should they find their way into the rural health researcher's methodological and analytical toolkit – though the appropriate training and learning elements are to precede novel applications to ensure best practice principles are adhered to. The present authors welcome this challenge and embrace the possibilities that are derived from adopting new ways of thinking about, and scientifically approaching, rural health issues.

Contributorship statement

All authors contributed to the content in accordance with the ICMJE guidelines for authorship. AH: Conceptualisation, writing – initial draft; reviewing and editing. JT/AB/GA: Writing, reviewing, editing and refining figures and models.

Competing interests

None declared.

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Data sharing statement

No data are available.

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Figure legend/captions

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Figure 2: A Causal Loop Diagram (CLD) (left) that theoretically explains the behaviour of the rural health workforce over time (right) framed through the lens of a 'fixes that fails' systems archetype (50). Polarity indicators, positive (+) and negative (-), indicate that variables *move in the same direction* or *move in opposite direction*, respectively. Reinforcing loops and balancing loops are represented with the notation (R) and (B), respectively. Time delays are shown by two dashed lines. The fixes that fail system archetype in Figure 2 explains that the immediate problem of a rural workforce shortage is giving rise to short-term hiring solutions. For example, under a return of service obligation scheme, health professionals may be required to spend a set numbers of years working in rural locations following government/state supported training. Whilst the short-term intervention appears to improve the situation under a narrow time horizon, over the long run, the solution is equally increasing turnover rate within the rural health service sector, making the shortage worse. Political cycles and/or changes to governments may explain the archetypal fixes that fail system structure. Researchers should consider transforming the CLD into a Stock and Flow Diagram (SFD) as a basis to simulate more complex system behaviours using System Dynamics (SD) modelling.

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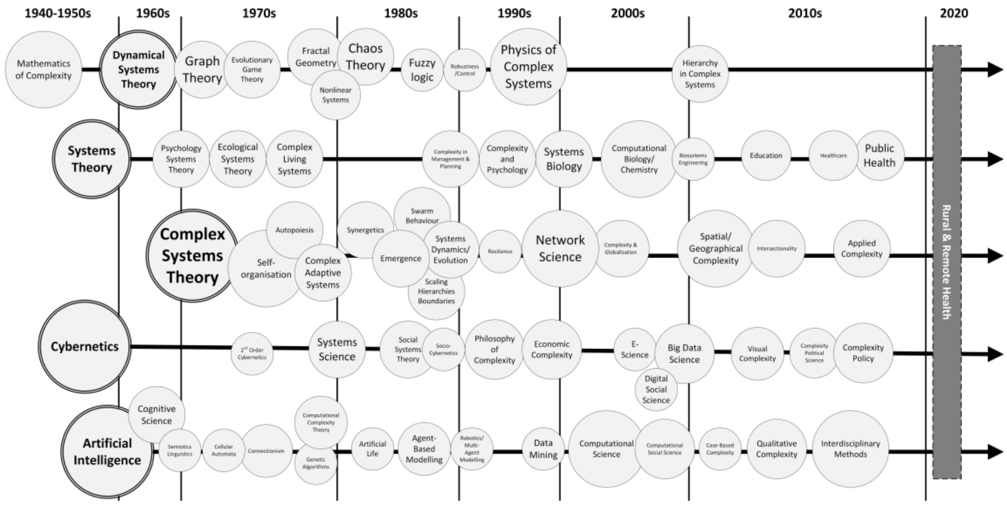

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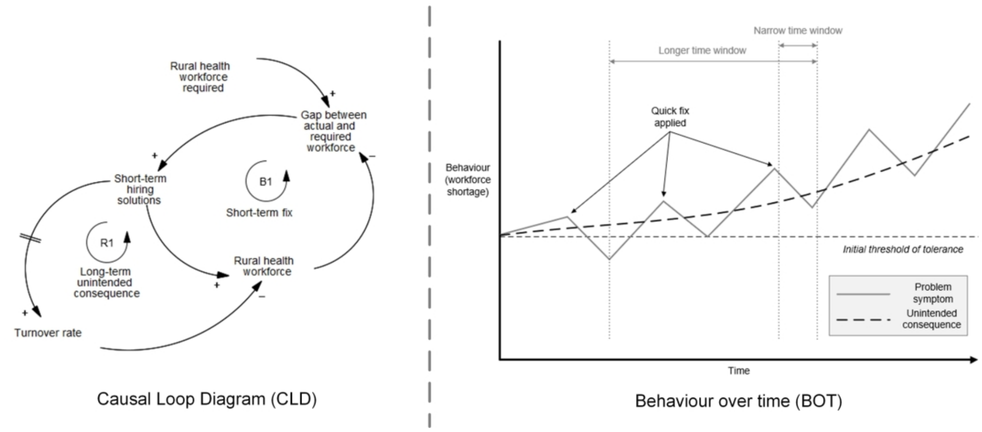

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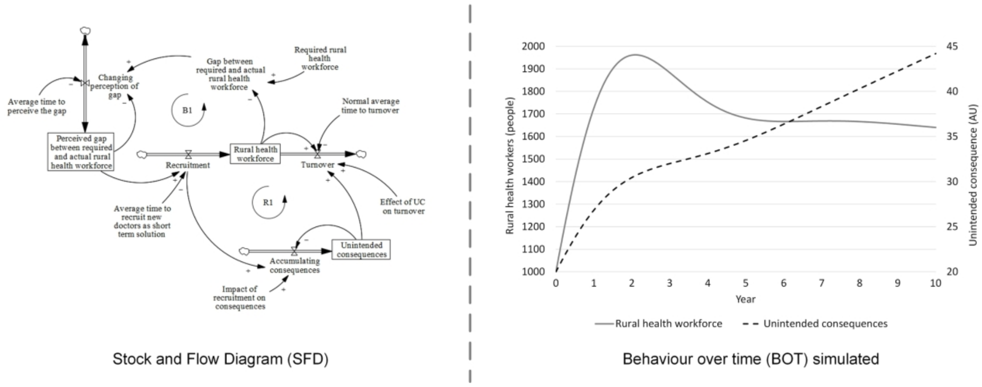

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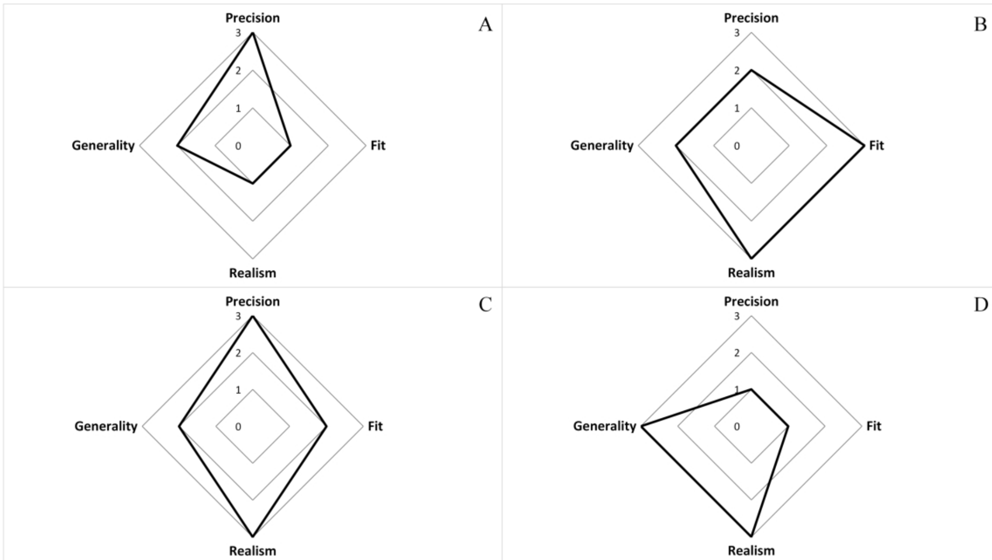

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278x156mm (300 x 300 DPI)

(01) Accumulating consequences=

Impact of recruitment on consequences*Recruitment*(Maximum UC-Unintended consequences)/Maximum UC

Units: consequences/Year

(02) Average time to perceive the gap=

1

Units: Year

(03) Average time to recruit new doctors as short term solution=

1

Units: Year

(04) Changing perception of gap=

(Gap between required and actual rural health workforce-Perceived gap between required and actual rural health workforce)/Average time to perceive the gap

Units: people/Year

(05) Effect of UC on turnover(

[(0,0)-(10,10)],(0,0),(0.2,1),(1,5))

Units: dmnl

(06) FINAL TIME = 10

Units: Year

The final time for the simulation.

(07) Gap between required and actual rural health workforce=

Required rural health workforce-Rural health workforce

Units: people

(08) Impact of recruitment on consequences=

0.01

Units: consequences/people

(09) INITIAL TIME = 0

Units: Year

The initial time for the simulation.

(10) Maximum UC=

100

Units: consequences

(11) Normal average time to turnover=

10

Units: Year

(12) Perceived gap between required and actual rural health workforce= INTEG

(

Changing perception of gap,

1000)

Units: people

(13) Recruitment=

Perceived gap between required and actual rural health workforce/Average time to recruit new doctors as short term solution

Units: people/Year

(14) Required rural health workforce=

2000

Units: people

(15) Rural health workforce= INTEG (

Recruitment-Turnover,

1000)

Units: people

(16) SAVEPER =

TIME STEP

Units: Year [0,?]

The frequency with which output is stored.

(17) TIME STEP = 0.01

Units: Year [0,?]

The time step for the simulation.

(18) Turnover=

(Rural health workforce/Normal average time to turnover)*Effect of UC on turnover

(Unintended consequences/Maximum UC)

Units: people/Year

(19) Unintended consequences= INTEG (

Accumulating consequences,

20)

Units: consequences