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REVIEW ARTICLE

The climate change, conflict and migration nexus: A holistic view

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Abstract

Current discourse relating to climate change, conflict, migration (CCM), and the causal links thereof, is polarized. It is widely acknowledged that climate change will have a detrimental effect on quality of life, and that this impact will not be homogeneous across the globe. However, proposed causal links among CCM remain contentious. This paper argues that to better grasp the implications of climate change on global society and security, it is vital to develop a more systemic understanding of the interplay among CCM. Although this nexus is already recognized, studies to date have tended to be qualitative and statistical evidence of multivariate causality has been lacking, where quantitative analysis is present, it has typically been limited to two components at a time; few studies have addressed the nexus holistically, making research conclusions sometimes difficult to reconcile. Hence, by reviewing literature from a broad range of sources, this paper suggests a suite of systemic and quantitative approaches with which to address the CCM nexus. This review critically assesses the existing research approaches employed across a range of examples and suggests how leveraging the power of 'big data' and modelling the nexus as a complex system encapsulating both human and environmental drivers could offer new insights, especially for those looking to explore the increasing number of 'what if' scenarios relating to climate and human dynamics.

KEYWORDS
climate change, complex systems, conflict, migration

1 | INTRODUCTION

There is much academic debate over the complex links among climate change, conflict and migration (CCM), and a need for new approaches to deepen collective understanding and help reconcile disparate positions (Solow, 2013). These links can be referred to as a nexus, where each component is linked to each of the others both separately and together. Although there are excellent qualitative and mixed-method studies on each aspect of the nexus individually (Conte et al., 2019; Nelson et al., 2020; Warner et al., 2013) and, indeed, several that reference all three topics (Abel et al., 2019; Reuveny, 2007b; Reuveny, 2007a), there is a distinct lack of quantitative literature addressing the issue as a whole. This represents a significant research gap, which will only become more pressing as the impacts of climate change increase in severity.

Many early predictions and assessments of the links among CCM predicted that large numbers of people would inevitably be displaced. This had the effect of sensationalizing the issue: This fear of 'large numbers of people "flooding" the United States and Western Europe' has played a central role in the securitization of migration, especially in the context of climate change (Brzoska, 2016). However, the theoretical foundation and empirical support for this conclusion are, currently, thin (de Haas, 2020; Selby et al., 2017). This is not to say that the 'mass migration' hypothesis is irrelevant or inconceivable; many studies have shown that under ongoing high-end climate change (e.g. representative concentration pathway 8.5), large swathes of the globe could become almost inhospitable (Brzoska, 2016; Werz & Conley, 2012; Xu et al., 2020).

A major driver of work in this field is the desire to gain a deeper understanding of how climate – and, more specifically, climatic change – will impact human populations. However, this is not straightforward. The Earth is, inherently, a complex system, as are human societies. Adding to that, the two are inextricably linked in a multitude of ways. There is no 'easy answer', nor one superior way of approaching the question.

Some researchers have expressed a level of concern that the literature in this domain is, to an extent, largely self-referencing in a way that risks the entrenchment of bias (Selby et al., 2017). Many policy documents discuss the threats of the looming security crisis, driven by mass migration, without compelling empirical evidence. Some believe that the perpetuation of this narrative is not being challenged as it provides justification for the ongoing use of public funding to further 'securitise' borders (Boas et al., 2019).

The connection between climate change and migration – with or without conflict as a causal mediator – is by no means deterministic. Rather, it depends on a wide range of factors relating to considerations such as the vulnerability of the people and the region in question (Perch-Nielson et al., 2008). It is also vital to stress that the influx of migrants into a country is not inherently negative – in most cases, migrant populations strengthen the economy and collective well-being in the host country (d'Albis et al., 2018; Gaskell, 2019). It is therefore important to develop a fuller and more joined-up picture of how the three factors interact, with the aim of identifying how more quantitative approaches can help move towards a more forward-looking and proactive, rather than reactive, approach to climate migration. There is increasing demand in policy-making circles for 'what-if' scenarios based on alternative futures (e.g. high/low climate impacts, pop projections and open/closed borders) to formulate appropriate policy interventions. As it is not possible for the research community to undertake a 'real world' experiment, the design and development of a representative modelling solution will be of significant benefit.

First, this paper will provide an overview of the current understanding of the CCM nexus using insights derived via both qualitative and quantitative methods. This forms a springboard from which to discuss a range of quantitative approaches currently used in tackling different aspects of the CCM nexus. This is achieved in the form of an integrative literature review of applicable modelling methodologies. This form of review was chosen for its applicability to 'topics that generate a growing body of literature that may include contradictions or a discrepancy between the literature and observations about the issue' (i.e. the ongoing debate revolving around the significance of climate signals in the CCM, and therefore the robustness of the CCM itself, as expanded on in Section 2) (Torraco, 2016; Hajro et al., 2019).

The paper concludes by setting out the argument for taking a complex systems approach in future analyses in order to take advantage of the full gamut of 'big data' available on the topic. In summary, it is argued that it is vital for future modelling strategies to be reflective of the realities of a complex system so that they can provide insightful and robust guidance to policymakers. This can only be achieved through greater interdisciplinary collaboration, especially between those with environmental, social and computational backgrounds.

2 | CONTEXT TO THE CLIMATE CHANGE, CONFLICT AND MIGRATION NEXUS

Migration has long been an active area of academic interest. Defined as 'the movement of groups and individuals from one place to another, involving a change of usual residence', migration is typically distinguished from general mobility via the inclusion of a spatio-temporal aspect (i.e. the move is long-term, permanent and/or traverses a significant distance or border crossing). By general convention, travel must involve the traversal of an international boundary for an 'actual or intended period' of at least 1 year in order to be considered international migration (Castree et al., 2013). Within this report, an environmental migrant is defined, per International Organisation for Migration (IOM), as 'persons or groups of people who, for compelling reasons of sudden or progressive change in the environment that adversely affects their lives or living conditions, are obliged to leave their habitual homes, or choose to do so, either temporarily or permanently, and who move either within their country or abroad' (UN, 2015). Conflict, for the purposes of this paper, is defined as sustained violence between armed groups.

Other important avenues for movement include internal migration – often as an initial response to lack of resources or a natural disaster (Berlemann et al., 2020; Mastrorillo et al., 2016) – and established seasonal/cyclic mobilities (Adeyode, 2019; Butt, 2010; Larsson et al., 2020). It is important to note that these are not mutually exclusive; seasonal/cyclic mobility can be cross border, and under certain circumstances, internal migration can form part of a stepwise pattern towards international movement (Engbersen et al., 2013; Hugo, 2016). Though these topics will be touched upon, due to its current prominence in international discourse, the focus of this literature review will be on direct international migration without an established pattern of return.

Despite the long pedigree of migration studies and its related disciplines, there is still plenty to uncover and dissect. At the time of writing, there is a sense that we are living through a period of considerable uncertainty – politically, economically and environmentally. In this context, there is a growing body of evidence to demonstrate that migration – and its interpretation in the broader context of society – is deeply interconnected with broader global policy decisions (Geiger et al., 2010; Triandafyllidou, 2018). Indeed, there is plenty of international discussion on the topic. Both separately and collectively, the 2016 Sustainable Development Goals (SDG), the 1992 UN Framework Convention on Climate Change (UNFCCC) and the 2018 UN Global Compact for Safe, Orderly and Regular Migration (The Global Compacts) provide policy-making tools to guide the governance of migration flows (McLeman, 2019).

In the 1990s, early assessments of the links among CCM predicted that large numbers of people would be displaced, resulting in a series of 'mass migrations'. Recurring waves of alarmism surrounding mass international displacement gained much attention among policy circles (Bettini, 2017). This interpretation has since guided the majority of Western migration policy and it forms the backbone of the so-called securitization of migration (Brzoska, 2016). Although The Global Compacts endeavour to improve outcomes for migrants and displaced people, it is a non-binding agreement and, to date, few countries have shown interest in following the guidance it sets out (McLeman, 2019). Indeed, many Western countries have stated that they will not ratify The Global Compacts as they feel that it will 'erode national sovereignty' and prevent the implementation of border controls (McLeman, 2019; Reiffel, 2018).

Due to the ongoing polarization of attitudes around migration, governments are making fewer distinctions among immigration management, border enforcement and state security (McLeman, 2019). This stance is, at least partially, fuelled by the fear that climate change will increasingly result in conflict. In turn, it is assumed that this conflict will result in uncontrolled migration and potentially drive further conflict in the receiving countries (Brzoska, 2016). Conflict in the receiving country is likely to be on a smaller scale (e.g. interpersonal violence and hate crimes rather than armed violence) (Rüegger, 2019). The securitization of migration makes it important to develop a more in-depth and nuanced impression of the drivers behind, and the potential scale of, this predicted migration. Although securitization does not necessarily rest on correct data and hard facts, it is vital that policy makers are equipped with accurate and appropriate data with which to make decisions, especially if those decisions are likely to have far-reaching impacts. Although improved modelling is unlikely to change the overall political landscape or counteract the impact of broader societal discourse (especially in relation to polarising topics such as xenophobia, populism and right-wing propaganda), it is hoped that it could form a part of a more informed and open dialogue among policy professionals and experts across the many interdisciplinary fields this topic overlaps.

There are plenty of drivers for both conflict and migration that are not climate related, as discussed by Collier & Hoeffler, (2004) and Castelli (2018), but in-depth discussion of these is out of scope for this paper. As implied by the corresponding nature of links within a nexus, it should also be noted that conflict has been recognized as a major contributor to global greenhouse gas emissions (Crawford, 2019; Reisch & Kretzmann, 2008). The US Department of Defense, for example, has consistently been responsible for the consumption of between 77% and 80% of the entire US government's energy budget, and concerns have also been raised about the environmental impact of conflicts such as the Iraq war and the ongoing Russo-Ukrainian conflict (Reisch & Kretzmann, 2008; Crawford, 2019; Pereira et al., 2022). However, although important to acknowledge their existence in relation to the CCM nexus, this paper will not specifically draw out and consider conflict-driven emissions. Rather, this paper considers anthropogenic climate change more generally.

As stated elsewhere, 'the relationship between environmental factors and migration is not deterministic' (Hoffmann et al., 2020, p.12). Therefore, gaining a more thorough understanding of the underlying drivers is imperative. Unfortunately, without seismic political and social change, the development of data-driven policy and successful mitigation strategies will likely remain subject to the cherry-picking of data that best supports a given moral or political stance. Due to the nature of climate-driven phenomena, this is not entirely unexpected (Selby et al., 2017). However, that does not mean that policymakers should not be equipped with the knowledge and tools with which to make informed decisions. The relationship between climate and other drivers of migration such as resource availability, demographics, the economy and general social context is rarely – if ever – linear. They are complex and spatially diverse. It has also been shown that environmental conditions can have immediate effects on both health and productivity, both of which can spur migration (Hoffmann et al., 2020). The picture is often further complicated by factors such as the implementation of governmental policies which can both reduce and exacerbate climatic issues (Abel et al., 2019; Kelley et al., 2015; Gerber et al., 2017; Holden et al., 2004; Hermans-Neumann et al., 2017; Tou'meh, 2014). Climate change has been increasingly highlighted as a potential security threat (Foresight, 2011), and most policy in this area is increasingly based on the assumption that future climate-induced migration flows will be overwhelming and are to be prevented, as far as is possible (Boas et al., 2019). Hence the primary focus of this paper will be to examine how anthropogenic climate change can act as a driver of conflict and/or migration rather than scrutinise all possible pathways to those outcomes.

The interconnectivity of these three topics is summarized as the CCM nexus. Within this, there are links between each of the topics, though these are often via intermediary factors which could provide alternate pathways to the outcome. As an example, a drought could cause widespread crop failures, resulting in resource scarcity (Comolli, 2017). Bereft of their livelihoods, the rural population may be forced to migrate, many choosing urban destinations (Kelley et al., 2015; Selby et al., 2017). The resultant urban population boom could then place increasing strain on local infrastructure, which, if already lacking, is likely to exacerbate any existing tensions among the population, government and the recent immigrants (Abel et al., 2019). In this situation, there is the distinct possibility that this instability could flare into a conflict (e.g. riots, anti-government protesting and sectarian violence) (UNHCR, 2021). It has also been hypothesized that depending on the surrounding political and social situation, the lack of resources could directly trigger conflict (Abel et al., 2019; Fjelde & von Uexkull, 2012; Griffin, 2020; Vestby, 2019). This is then likely to lead to increased migration, depending on its severity (Carius, 2017; Comolli, 2017; Lipp, 2017; Schon, 2018; Seven, 2020). In some cases, this migration has been linked to the outbreak of conflict in the migrant receiving countries (Rüegger, 2019). However, these instances are edge cases and only arise under very specific circumstances. The arrival of immigrants – refugees or otherwise – is deeply unlikely to result in conflict if the groundwork has not already been laid (Bajoria, 2009; Brzoska, 2016; Reuveny, 2007b; Rüegger, 2019; Salehyan et al., 2006).

The most appropriate way to examine these interlocking variables and the potential implications of climate change is to address the nexus as a whole. Thus far, most quantitative analysis has typically focussed on the various pairwise relationships among the three variables. This leaves a compelling research niche to fill.

3 | MODELLING METHODOLOGIES

'Any model is a metaphor (the equations are interpreted as being like the world in some respects)' Smith (2020).

There is a lack of a strong theoretical framework and conclusive evidence for climate driven migration leading to conflict and climate driven conflict leading to migration. Additionally, there is a lack of quantitative literature examining the nexus of the three issues (Brzoska, 2016). Although building a 'perfect' model is currently impossible – as the use of assumption generates flaws without exception – it is still beneficial to explore the different quantitative methodologies available for analysis of the CCM nexus. If a model is well validated and representative, it can act as a powerful tool to generate greater collective understanding of the mechanisms and drivers behind the CCM. Hopefully, this will enable better and more effective responses and appropriate mitigative action where practical. This can provide a valuable addition to qualitative studies, which have set the precedent for migration, conflict and development research over many decades (Levitt et al., 2007; Thomson, 1999). Qualitative approaches cannot utilize the full scale and volume of data currently available, and this is where quantitative approaches can add value. Although it is rare for a modelling approach to provide an exact and definite answer to a question, modelling can provide a valuable – and often alternative – 'voice' in the overall discussion. This can represent the views of many, otherwise excluded, voices and/or demographics.

Data, and the presence, absence and volume thereof, plays a key role in all forms of modelling. This is especially true of predictive modelling, as expanded on in the following sections. Here, 'big data' refers to 'extremely large datasets that may be analysed computationally to reveal patterns, trends and associations' (Oxford Languages, 2022). Big data is often described using the '3Vs': volume, velocity and variety. Recently, some have expanded this to include two further Vs: value and veracity. Depending on the data available and the task at hand, the exact nature of the 3Vs can differ. As an example, the volume of data considered 'big' by Google or Twitter would dwarf the amount considered 'big' by most NGOs. Predictably, the relevance and veracity of the conclusions drawn by each of the modelling approaches discussed in this section relies on the quality of their underlying datasets, something that is inextricable from the 3Vs.

3.1 | Differential equations

At their most basic, models based on differential equations tend to describe the path over time, t, of an independent variable, x, in relation to a dependent variable, a (Smith, 2020). Equations (1) and (2) show the Richardson model, a set of differential equations which describes the path over time, t, of the level of arms, x and y, of two countries, A and B.

$$\frac{dx}{dt} = ky - ax + g \tag{1}$$

$$\frac{dy}{dt} = lx - by + h \tag{2}$$

As described by Imkeller et al. (2001); Keane et al. (2017) and Palmer (2019), differential equations have a long pedigree within the field of climate modelling. In the context of the CCM nexus, modelling one or more of the pairwise elements with differential equations is relatively commonplace and has been for many years. Indeed, one of the earliest examples of work in this area was undertaken by Lewis F Richardson, a physicist and pacifist, who used mathematics to better understand how conflict is precipitated in the 1960s (Equation 1) (Richardson et al., 1962; Scheffran, 2018; Smith, 2020). To some extent, ongoing work in this field – especially that involving differential equations – can trace the roots of its methodology to Richardson's original theories.

More recently, Maxwell & Reuveny (2000) and Reuveny & Maxwell (2001) used differential equations to model the interaction between renewable resource and population, featuring the possibility of per capita resource scarcity triggering conflict Maxwell & Reuveny (2000; Reuveny & Maxwell, 2001). Similarly, Prieur & Schumacher (2016) utilized a series of differential equations to investigate the roles that both internal and external conflict play in the context of optimal climate and immigration policy Prieur & Schumacher (2016). However, modelling in this manner is not limited to conflict-related themes. For example, Maurel et al. (2016) used differential equations to illustrate the conceptual framework behind the indirect link between climate variability and international migration via the climate-induced increase in urbanization Maurel et al. (2016).

Despite their widespread appeal and practicality, it is also important to note that in a realm not governed by fundamental physical laws (e.g. fluid dynamics), the use of differential equations as a modelling approach tends to require a careful balance of assumption and caveating, thereby limiting the applicability of their results to 'real-world' scenarios. Although an explicit explanation of assumptions is valuable regarding deriving empirical conclusions, it must also be acknowledged that the more defined and specific the parameters, especially if tailored to a specific case study or area, the less transferrable the model and its results. This also increases the likelihood of overfitting. Despite Prieur & Schumacher (2016) discussing the ability of climate change to induce conflict, the authors assume that the probability of conflict in a country is endogenous to the number of potential migrants (originating from that country) who are not admitted into the receiving country (i.e. conflict is caused by those who potentially want to immigrate but are obstructed from doing so) Prieur & Schumacher (2016). This is valid, but from the perspective of the CCM nexus it is oversimplified, as conflict can arise independently of migration as a function of resource scarcity. Indeed, it can oftentimes be conflict that precedes the migration decision. There is also the inescapable lack of empirical data/evidence, and little capacity for nuance, which could limit the degree to which complex human behavioural drivers are incorporated (Maurel et al., 2016; Smith et al., 2000; Scheffran, 2018; Smith, 2020). Although differential equations allow for optimized decision-making, actors do not take future consequences into account. This can be seen in the studies carried out by Maxwell & Reuveny (2000) and Prieur & Schumacher (2016), where although the impact of migrants on the receiving environment was factored into the model, the agent was unable to consider this as part of their 'decision'.

Although differential equations may be too blunt an instrument to tackle the entire nexus in a sensitive and nuanced manner, they remain a powerful tool with which to assess correlation and causal relationships between factors (though, of course, one does not equal the other). Differential equations underpin many of the current 'state of the art' approaches to integrated assessment models (IAMs) (Nordhaus, 2017) (e.g. the Integrated Model to Assess the Global Environment [IMAGE]) (Beek et al., 2020). However, the methodology underpinning IAM-based approaches have been subject to criticism. Recently, Asefi-Najafabady et al. (2020) stated that although IAMs give the impression of being rooted in data, thereby giving the impression of validity, they are deeply unrealistic in their representation of the interplay between the Earth and human systems. Through the use of a 'representative agent' which homogenizes human behaviour and narrowly focuses on economic optimization, it is argued that IAMs impose unrealistic assumptions about behaviour and therefore represent the wrong system

(Asefi-Najafabady et al., 2020). This is a more general criticism of mainstream academic economics – not just specific to IAMs. Of course, anther pitfall of statistical modelling is overfitting. Whenever multiple variables are introduced, the risk of overfitting is raised. This can skew modelling outcomes and produce misleading results. Asefi-Najafabady et al. (2020) posited that to generate a genuinely representative model of human–Earth interactions, alterations to existing IAMs will be insufficient and suggest a radical overhaul of the modelling approach. Due to the significance of heterogeneous behaviour, any future approach must be able to represent agents with limited knowledge and diverse information, interests and motivations.

3.2 | Gravity models

Gravity models have their roots in economics and the prediction of bilateral trade flows and, as such, approaches using this method tend to take a more econometric approach to the CCM. As is implied by their name, gravity models are used in the social sciences to describe behaviours that mimic Newton's description of gravitational interaction. It follows that these models invariably incorporate some element of 'mass' and distance, which can then be used to estimate the volume of flows between two or more locations. Although this type of modelling cannot predict flows, it can instead act as a measure by which observed values can be compared (Ramos, 2016).

The usage of gravity models has increased exponentially since the mid 1990s (Ramos, 2016). A common use of gravity equations is to model the bilateral migration flows among an origin, i, a destination, j, at time, t, as a function of push and pull factors. These push and pull factors can vary depending on the modelling question. In terms of the analysis questions posed by the CCM nexus, Maurel et al. (2016) model of climate instability in urbanization and international migration take climate-induced urbanization as the push factor and income differential as the pull. On the other hand, Conte et al. 2019 used intensity of conflict and geographical distance between capital cities to model the role of conflict in forced migration. This demonstrates the versatility of the modelling technique and its applicability to multiple aspects of the CCM nexus.

One of the higher profile applications of gravity modelling to an aspect of the CCM nexus is the recent Groundswell report (Clement et al., 2021; Rigaud et al., 2021). In this, the authors attempt to model future migration patterns in response to the changing climate by aggregating human behaviour in response to various 'push' and 'pull' factors. Although they acknowledge that gravity modelling is unable to shed light on individual motives, they argue that it remains the most representative technique for modelling migration dynamics at scale, something that most other methodologies, such as Agent-based model (ABM), cannot achieve to the same level at scale (Rigaud et al., 2021).

Despite similarities in the fundamental composition of most gravity models, their predictions are rarely congruent. This can be ascribed to many factors, including scale, granularity of sample data and range of socioeconomic variables, to name a few. One strength of gravity models is the ability to incorporate numerous diverse push and pull factors. In the context of the CCM, this helps to capture a degree of the nuance involved in human decision-making by including variables, such as population size, median per capita income and employment-to-population ratio, political freedom and state fragility (Gori Maia & Schons, 2020; Wesselbaum, 2020).

Despite their plasticity and widespread application to migration-related research problems, it is comparatively rare for gravity models to be applied to the overall CCM in any depth. Although Wesselbaum (2020) did acknowledge the potential role of conflict by including a time-variable dummy to proxy for the presence of civil conflict, this is taken as a control rather than a key independent variable. This means that the overall conclusions cannot be used to elucidate potential mechanisms behind the CCM nexus (Wesselbaum, 2020). There is growing evidence and discussion of the ability of climate to precipitate conflict under certain conditions (Abel et al., 2019; Detges, 2017; Burke et al., 2015; Prieur & Schumacher, 2016;). Therefore, further qualitative analysis of the role of conflict in relation to climate, especially with consideration of migration, would be prudent.

Although gravity models can provide an intuitive framework with which to understand population flows, a drawback to this approach is the implicit assumption that flows between locations are directly proportionate to their size and inversely proportional to the physical distance between them. Gravity models also require detailed data pertaining to the relevant location pairings; this is not always easy to obtain, and issues can arise when datasets include negative or zero values (Ramos, 2016). It is for these reasons that gravity models may not be best suited to investigate the presence of multivariate causal links within the CCM. It has also been suggested that, due to the inherent failure of most gravity models to capture temporal dynamics, they are fundamentally unsuited to the prediction of international migration dynamics over time (Beyer et al., 2022). Nevertheless, they may prove useful in elucidating specific, well-defined relationships within the nexus under certain conditions. Indeed, Beyer et al. (2022) proposed that the inclusion of country-pair-specific timeseries data could provide a valuable source of information by partially surmounting the tendency of gravity models to overlook temporal trends.

Like the differential equations discussed previously, the use of gravity models relies on a fine balance of assumptions and caveating. They are also subject to the same issues of wider applicability once they are tailored to a specific case study or set of data points. Unfortunately, these are somewhat universal themes within mathematical modelling and something that is unlikely to be easily surmounted without advances in both computing and data availability.

3.3 | Machine learning

Increasingly, techniques such as machine learning (ML) are being used to quantify and predict the interactions between different aspects of the CCM nexus. As the volume of data available for exploitation grows, so does the need for more sophisticated data mining techniques. This is an area in which data science approaches, such as ML, can provide useful insights. Described as the use of statistical models to analyse and draw inferences from patterns in data, ML-based approaches have been applied to CCM nexus related problems, such as the monitoring of conflict-related migration and the prediction of climate-driven asylum migration, with success (Hao et al., 2022; IBM., 2020; Niva et al., 2021; Schutte et al., 2021; Unver, 2022). Indeed, conclusions drawn from studies based on random forests (RFs) have consistently reflected those taken from other approaches described in this paper, with studies further illustrating that there is a non-linear relationship between climatic impacts and both conflict and migration (Hao et al., 2022; Schutte et al., 2021). However, as with the other approaches discussed within this paper, these analyses tend to focus on pairwise interactions.

The most common ML approach within this field is the RF. In ML terms, an RF is an ensemble learning method typically used for classification and/or regression tasks. It achieves this through the construction of multiple 'decision trees' during training. When solving a classification task, the mode of all the tree outputs is taken as the result. For regression, the mean prediction of the trees is taken (Ho, 1995). For tasks related to the elucidation of the CM nexus, regression-based approaches are by far the most common.

When undertaking a regression task, RFs use an ensemble of multiple bootstrapped sample predictions (decision trees) to produce a consensus regression fit. The inclusion of bootstrapping enables the identification and ranking of endogenous explanatory factors underlying decisions (e.g. the decision to migrate). This is because the method randomly splits the data into multiple samples, each containing only a subset of variables. Potentially correlated variables are not represented in all decision trees, meaning that the importance of each variable to the overall result describes the increase in prediction error when the values of that variable are randomly permuted (Niva et al., 2021). This is the functionality most useful for the prediction of human behavioural dynamics in response to either climatic- or conflict-driven stressors.

RFs are valuable in this context due to their explicit consideration of multivariate interactions between predictors. They are also able to incorporate a range of different data types, lending themselves to the analysis of highly complex interactions. This enables them to account for the theorized relationships among climatic, economic and political factors (Schutte et al., 2021). This is an improvement over previous 'traditional' reduced-form regression analyses, as described in Section 3.2.

Like the majority of ML-based methodologies, RFs cannot be used to estimate causal effects. Instead, they serve to test observable implications of relevant theories and to evaluate the veracity of empirical models (Schutte et al., 2021). However, due to their ability to describe the relative importance of each variable within a modelling scenario, it has been argued that the application of RFs could enhance the results of differential equation-based modelling approaches such as IAMs by improving their representation of migration drivers. Although IAMs are useful for shedding light on the potential causal effects of a variable of interest, the accuracy of their inferences depends on the correct specification and representation of the multivariate factors which shape their outcome. For this reason, their casual nature is often explicitly caveated away (Maurel et al., 2016; Schutte et al., 2021). By optimizing these factors using ML, their results may become more reflective of reality.

It is important to take in as many decision-influencing factors as possible when designing a model. This is an area where ML approaches such as RFs can be advantageous. However, in terms of ML-based analyses, studies that include both environmental and socioeconomic factors tend to be regional in scope (Niva et al., 2021). ML models are also subject to the same data limitations as the other methodologies described in this paper in terms of the data variety and, to some extent, its velocity. However, ML methodologies are explicitly designed to cope with, and indeed perform better with, extraordinarily large data volumes. Therefore, any results are inevitably prone to some degree of uncertainty. It should also be noted that, as with other techniques, studying a complex phenomenon using purely quantitative methods cannot capture more granular decision-making processes or emergent properties (Niva et al., 2021).

3.4 | Agent-based models

ABM are a form of simulation modelling technique which utilizes a collection of autonomous decision-making entities, named agents, to characterize the behaviour of a complex system. Each agent can individually assess the situation and make a decision based on a set of rules. It is these interactions between the agents, each other and their environment which enables ABMs to explore dynamics outside the reach of most conventional modelling methodologies. Indeed, even the simplest ABM can exhibit complex behaviour patterns and emergent properties (Bonabeau, 2002). ABM is often considered more of a concept/approach than an explicit technology.

In comparison to differential equations and gravity models, ABMs are better placed to interrogate any potential indirect relationships between variables. Due to the nature of their mathematical underpinning, gravity models can be somewhat limited in scope when considering complex networks of interactions. When considering the impact of individual stress thresholds on climate migration, although gravity models provide a valuable method of explaining, and to some degree, predicting migration, they are only capable of telling half the story (Adams et al., 2019). As human motivations are driven by many cultural, psycho-social and emotional factors, many of which do not present external logic, it can be challenging to incorporate them into predictive models. ABMs can, to a certain extent, bridge this gap between external drivers (e.g. climate, economics and conflict) and the complexities of human behaviour and decision-making. This combination of micro and macro influences makes it a powerful modelling tool.

It is also beneficial that conceptually, many of the initial ABMs were developed with social dynamics in mind (Schelling, 1971). As has been shown by Hébert et al. (2018); Kniveton et al. (2012) and Entwisle et al. (2016), it is possible to use ABM to successfully model the migration response to both climate shocks and conflict scenarios. ABMs configuration can also capture a range of narratives to include demographic futures, governance decisions and openness of borders which influence migration decisions by agents (Speelman et al., 2021). However, to date, most models have tended to either over-generalize or be overly specific. It appears that there is an opportunity to combine these approaches to generate a more wide-ranging model, encompassing some of the more nuanced aspects of the individual case studies, in order to gain a deeper understanding of the movements of individuals after a crisis (Piguet, 2022). It has also proved challenging to find literature which uses ABM to address the CCM nexus within one model. Hence the use of ABM could be a valuable next step. By addressing the three variables within the context of complex systems modelling, it may be possible to identify emergent properties of the system – meaning phenomena which result from the interactions of system parts, which cannot be reduced to properties of the parts (Bonabeau, 2002).

That said, it is also important to note that ABMs cannot be considered a 'silver bullet'. Properly calibrating the agents and environment to be representative necessitates a significant amount of both data and prior understanding of system dynamics. ABMs can also be challenging to scale. As the number of agents increases, as does the associated compute. This limits the scale to which ABMs can be used to provide a representative model. For example, the scarcity of data on the extent to which a range of political factors, including conflict, influence migration decisions at the individual level partly remain underrepresented in ABMs (Thober et al., 2018).

There is an absence of quantitative literature which examines the nexus of all three issues in tandem (Brzoska, 2016). Due to the complex interplay of factors, it seems prudent to take a complex systems approach in order to model as much of the system as possible and attempt to capture any emergent properties. The ability of ABMs to explicitly model the micro-level dynamics of demographic behaviour based on both theory and empirical evidence is a significant strength, if there is sufficient data. However, this can limit the spatial resolution of the system making larger scale conclusions difficult to reach (Rigaud et al., 2021). As with all modelling approaches, an ABM is only as good as its underpinning assumptions (Adams et al., 2019). In the context of the CCM and the relative paucity of pertinent data, it is likely that several large-scale assumptions would have to be made to generate an ABM relevant to the problem.

4 | MODELLING THE CCM NEXUS

Literature quantitatively addressing the CCM nexus in its entirety is challenging to find. This echoes the lack of a strong theoretical framework and is likely attributable to the lack of granular empirical data and the complexity of the system. Indeed, both Maurel et al. (2016) and Prieur & Schumacher (2016) explicitly reference the inherent difficulty of conducting quantitative analysis in this area, citing the multitude of variables at play (e.g. floods and global warming) along with other intervening variables (e.g. migrant selectivity and socioeconomic status) and the overarching lack of consistent and reliable data. This suggests that taking incremental steps to develop a systems-based modelling solution, such as an ABM, could provide a more robust, quantitative solution, well suited to complexity. This approach would gain applicability as a predictive tool as and when more consistent data becomes available. However, although this will be both significant and useful, it is important to note that modelling can be used for both prediction and understanding. Even without predictive data, the use of ABMs is likely to increase general system understanding and therefore improve the assumptions underpinning the development of other modelling methodologies. It is under this reasoning that the use of ABM is recommended for future research endeavours in this field.

There are already several examples of ABM providing insight into potential migration pathways (Hébert et al., 2018; Suleimenova et al., 2017; Speelman et al., 2021). The use of autonomous agents within the simulation allows the incorporation of different demographics, influences and drivers, all of which can combine to provide a more reflective image of the potential post-disaster response (Searle et al., 2021). By allowing a heterogeneous mix of agents to act and interact autonomously, it is also more likely that any emergent properties of the system will be observed.

An ABM approach to the CCM nexus may help clarify the ways in which people could decide to move if the decision to migrate was taken. Having a larger volume of empirical evidence in this area can only be beneficial, as currently most international migration and climate policy assumes that anthropogenic climate change is – and will continue to be – a driver of mass migration. If the effort is expended to attempt to model the entire complex system, it may be possible to forecast where climate-related conflicts are likely to spark (Guo et al., 2018). By representing populations as 'agents' with a bounded 'free' will, it follows that it will be possible to estimate where the resultant migrants are likely to be displaced to (Willekens, 2019). That way, it will be easier to equip for the future and ensure that resources and support are offered pre-emptively to potentially vulnerable areas. This is counter to the current popular securitized approach to migration, which is likely to be detrimental to all parties.

It is also interesting to note that despite the explicit causality of both differential equations and gravity models, many studies referencing conflict or climate as a driver of migration, and/or climate as a driver of conflict, either do not mention causality or include an explicit caveat stating that their results should be viewed as purely correlational (Bertoli et al., 2017; Maurel et al., 2016). It is possible that this could be ascribed to ongoing academic debate and critique of prior broad-brush assumptions about the presence of a causal link between climate change and migration. Although the inherent sensitivity and overt political interest in the topic requires a level of caution when reporting potential links, this appears to have led to a degree of hesitancy around the reporting of causality-linked conclusions. This is of note as, due to the pressing nature of the rapidly unfolding climate crisis, it is important to understand the ways in which the elements of the CCM nexus interact. It will also be beneficial to have the ability to generate some form of 'effects forecast', and a level of confidence in it, as there is increasing interest in this from both human and national security angles, and this is unlikely to abate. As described in Section 3.3, there is potential for the application of ML techniques, such as RFs, to improve these causal techniques by providing greater certainty around the relative significance of variables. The integration of these methods into a predictive pipeline could be a valuable addition to the CCM literature corpus.

ABMs are able to provide a 'bottom-up' perspective of social phenomena decoupled from linear effects (Bonabeau, 2002). Although many researchers are proponents of the ABM approach due to its ability to imbue each agent with a degree of 'choice' to better reflect the dynamics of an operational system (Willekens, 2019), this is by no means the only way to approach the task. There is equal merit in further exploration of more traditional statistical methods of causal inference – beyond correlation. There have also been exploratory studies conducted to forecast climate-induced migration using a combination of longitudinal surveys and satellite data (Mueller et al., 2014). Other computational modelling methods, such as Bayesian networks, have also been applied with some success (Azose et al., 2015). As with ABM, these methods are yet to be applied to the CCM nexus in its entirety.

Indeed, in cases such as this, more imaginative and innovative approaches are often met with success. An example of this is Bohme et al. (2020), where they use geo-referenced online search data as a proxy for the intent to migrate. A similar approach was taken by Carammia et al. (2020), who used a combination of search-engine derived data alongside official data channels to develop a machine-driven forecasting model to predict migration flows (Carammia et al., 2020). If expanded to interrogate the entire climate-conflict-migration nexus, further application of ML techniques to the problem could prove both fascinating and insightful. These approaches have become increasingly accessible over recent years due to the advent and uptake of Cloud computing services.

It is therefore suggested that further research in this area should address the nexus holistically, preferably modelling the interactions as a complex system as far as is possible and practicable. Here, the concept of 'holism' is taken in its philosophical sense, in that each part of the whole (i.e. the CCM nexus) are in intimate interconnection. That is, they

TABLE 1 An overview of the modelling approaches discussed in Section 3, accompanied by their relevance to each related discipline

Modelling type	Use case	Policy perspectives	Environmental science perspectives	Data and computational considerations
Differential equations	Able to describe the dynamic aspects of a system and have a long pedigree in both climate and conflict modelling. Theoretically able to ascribe causality but tends to be underpinned by a balance of assumption and caveating	Offers casual dynamical perspectives, and, due to long term and common use, there is widespread pre-existing understanding across disciplines	Strong pedigree of prior use in other environmental science contexts, such as crop production and water availability. This expertise can be drawn upon and, to some degree, transferred	Relatively easy to compute, though they rely on large numbers of assumptions. They also lend themselves to conceptual modelling rather than the more granular details of 'real world' scenarios
Gravity models	Provide an econometric approach, estimates the 'flow' of an entity governed by 'push' and 'pull' factors. Theoretically able to ascribe causality but cannot predict flows. These models tend to act as a measure by which observed values can be compared	Potential to project flows to meet needs for planning and adaptation purposes (e.g. where to send aid after the redistribution of populations after a natural disaster etc.)	Offers a way to model climate impacts on variables such as crop production and water availability as well as changes to ecosystems and their impact on populations	Limitations associated with slow onset sectoral changes and eventual low spatial resolution of exposed areas
Machine learning	Able to ascribe relative importance to variables with comparatively high confidence. Cannot be used to estimate casual effects	Able to produce and test multiple hypotheses to assess different outcomes. Easy and flexible to use. However, explainability tends to decline with complexity, leading to the 'black box' problem	Widespread application of RF models to derive correlations (e.g. large-scale vegetation). Possible to expand beyond RFs to gain further insights	Proven methodology for finding patterns in massive datasets. Capable of processing both structured and unstructured data to great effect
Agent-based	Able to exhibit complex behaviour patterns and emergent properties to characterize complex systems. Provides a 'bottom-up' approach	Potential to explore agent behaviour under different circumstances. Powerful tool with which to stress-test and/or develop new policies	Offers a way to model how social systems are impacted by the environment and vice versa	Due to computational constraints, the spatial resolution of these models can be limited

Abbreviation: RF, random forest.

cannot be fully understood without reference to the whole. For example, the discontinuities that are likely to arise because of political events and upheavals that can heavily influence migration behaviour. Such holistic approach may help understand armed conflicts' non-linear links to climate variability and change. Computational models are generally not yet sophisticated enough to forecast the changing nature of conflict or the context in which state failure occurs, which may lead to further armed conflict with precision.

Wider exploration of ground-breaking ML-based methodologies could also prove insightful, where appropriate data is available for training and validation, as demonstrated by Schutte et al. (2021), Niva et al. (2021) and Hao et al. (2022). However, the most practical modelling approach for the near future is likely to be underpinned by ABMs. Despite their limitations of scale, they are powerful tools capable of deriving both temporal and spatial causal inferences. Their ability to model heterogenous agents surmounts the limitation of gravity models, as described by Beyer et al. (2022), and enables them to capture both feedback dynamics and emergent properties within the complex system.

As this is a fundamentally interdisciplinary problem, it is highly recommended that any future modelling attempts in this area utilize the expertise of multiple practitioners from within different fields. As such, Table 1 aims to provide an overview of each modelling methodology discussed as it pertains to three key disciplines working on the CCM. After all, in the words of Helen Keller, 'alone we can do so little, together we can do so much'.

5 | CONCLUSION

This paper outlines the current state of analysis around the interactions among CCM. Currently, much of the debate – both academic and political – around these topics and the proposed causal linkages between them is both polarized and largely defined by qualitative and/or anecdotal evidence. Although these qualitative studies are valuable, they are unable to utilize the scale of new data now available (e.g. remote sensing, telephone networks and social media sites in addition to more traditional governmental statistics). This review shows the extent of the dissonance underlying this research area and underlines the lack of a cohesive theoretical framework within the discipline.

To get a representative idea of the causal interactions among CCM, they must be modelled as a nexus. It is proposed that future analyses on this topic consider the interdisciplinary and dynamical nature of the problem and aim to represent the vagaries of human behaviour into their modelling methodologies as far as is possible and practical. ABMs are uniquely placed to provide insight in this regard. In order to proceed, more novel datasets (e.g. social media and remote sensing) must be sought to counteract the lack of 'traditional' ground truth. This paper is intended as part of the slow drift towards using more systems thinking to tackle the increasingly systemic problems faced by governments. Through this, it may be possible to begin dispelling some of the harmful myths that underlie the securitization of migration and facilitate the development of better grounded climate and migration policies.

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