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Modeling climate migration: dead ends and new avenues

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Understanding and forecasting human mobility in response to climatic and environmental changes has become a subject of substantial political, societal, and academic interest. Quantitative models exploring the relationship between climatic factors and migration patterns have been developed since the early 2000s; however, different models have produced results that are not always consistent with one another or robust enough to provide actionable insights into future dynamics. Here we examine weaknesses of classical methods and identify next-generation approaches with the potential to close existing knowledge gaps. We propose six priorities for the future of climate mobility modeling: (i) the use of non-linear machine-learning rather than linear methods, (ii) the prioritization of explaining the observed data rather than testing statistical significance of predictors, (iii) the consideration of relevant climate impacts rather than temperature- and precipitation-based metrics, (iv) the examination of heterogeneities, including across space and demographic groups rather than aggregated measures, (v) the investigation of temporal migration dynamics rather than essentially spatial patterns, (vi) the use of better calibration data, including disaggregated and within-country flows. Improving both methods and data to accommodate the high complexity and context-specificity of climate mobility will be crucial for establishing the scientific consensus on historical trends and future projections that has eluded the discipline thus far.

KEYWORDS
migration modeling, climate mobility, gravity models, machine-learning, data disaggregation, migration forecasting, climate change

1. Introduction

Whilst the details of how climate change will affect worldwide mobility remain subject to high uncertainties, there is consensus that sudden- and slow-onset climate hazards will lead to significant spatial redistributions of populations in many parts of the world. The socio-economic challenges associated with this process can benefit strongly from evidence-based insight and foresight that can enable anticipatory action by decision makers and other stakeholders. Quantitative models of climate mobility aim to fill this knowledge gap and facilitate concrete action to avert and minimize the adverse effects of climate change impacts on human mobility.

A first series of quantitative predictions of the potential magnitude of future climatic and environmental migration published between 1995 and 2010 (Myers and Kent, 1995; Myers, 2002; Christian Aid, 2007; Stern and Stern, 2007; Biermann and Boas, 2010) was heavily challenged, citing lack of methodological transparency and scientific rigor

(Gemenne, 2011; Jakobeit and Methmann, 2012). To improve the quantitative evidence base on climate mobility, numerous models aiming to establish statistical relationships between historical migration flows and environmental—in addition to demographic, economic, social, and other—variables have appeared in the scholarly literature since the late 2000s. These models are complementary to approaches that statistically analyze, and extrapolate, migration flow time series data without linking them to any exogenous drivers (Bijak, 2006). The compilation and curation of global migration datasets (Özden et al., 2011; Abel, 2018; Abel and Cohen, 2019, 2022) have played a critical role in the rapid increase in the number of models. Models used to project future migration dynamics in response to expected climatic changes are still few but are increasing steadily, responding to a strong high-level demand for forecasts.

Quantitative models of climate mobility are based on a range of different methods, often depending on the spatial and temporal scale of the exercise. Agent-based models (Thober et al., 2018) are typically used at small scales where detailed data, e.g., household surveys, exist to parameterize context-specific behavioral rules. Other approaches, including econometric gravity models (Poot et al., 2016), radiation models (Simini et al., 2012), and spatially explicit models of net migration (Niva et al., 2021), seek to describe spatial and temporal interactions and patterns of migration at larger scales. In some instances, these are embedded into Integrated Assessment Models (Benveniste et al., 2020), complex global modeling frameworks simulating major global environmental, economic, and social dynamics (Parson and Fisher-Vanden, 1997). Although parts of our analysis and recommendations equally apply to small-scale models, here, our main focus are models operating at the multinational, intra- and interregional, or global level.

At these large spatial scales, econometric methods have been the basis of the large majority of quantitative models of migration in the context of climatic and environmental changes (Hoffmann et al., 2021), and their use has increased sharply over time (Ramos, 2016). These approaches typically assess whether some climate-related variable in the areas of origin or destination has a statistically significant effect on flows, based on historical observations covering large sets of countries and migration corridors. Econometric models have produced a wide range of results that are not always consistent, or even comparable, with one another. Literature reviews and quantitative meta-analyses have highlighted the divergence of the effects of sudden- and slow-onset environmental factors on internal and international human mobility estimated by different econometric studies (Obokata et al., 2014; Berlemann and Steinhardt, 2017; Hoffmann et al., 2020; Kaczan and Orgill-Meyer, 2020). Whilst some general qualitative statements are supported by a majority of studies—for example that adverse environmental conditions tend to have stronger effects on internal than international migration—, there is no consensus on the quantitative strength of effects. In some cases, model coefficients associated with environmental drivers differ by orders of magnitude across studies (Wesselbaum and Aburn, 2019), suggesting a small degree of robustness in the estimates. In other cases, even the sign of the effect is unclear (Table 1). A recent prominent example, the Groundswell model (Clement et al., 2021) forecast increased climate mobility in African countries under increased global warming, while the follow-up Africa Climate Mobility Model (Amakrane et al., 2023), based on a similar methodology, forecast the opposite. In summary, at present, there is no consensus on the effects of climate-related factors on internal and international migration (Beine and Parsons, 2017; Berlemann and Steinhardt, 2017; Niva et al., 2021).

TABLE 1 Examples of contrary results from econometric models on climate mobility.

Hypothesis	Significant effect	No significant or significant opposite effect
Higher temperatures increase international migration	Cai et al., 2016; Wesselbaum and Aburn, 2019	Beine and Parsons, 2015; Drabo and Mbaye, 2015; Nawrotzki and Bakhtsiyarava, 2017
Less rainfall increases international migration	Beine and Parsons, 2015	Cai et al., 2016; Wesselbaum and Aburn, 2019
Disasters increase international migration	Reuveny and Moore, 2009; Coniglio and Pesce, 2015; Drabo and Mbaye, 2015; Wesselbaum and Aburn, 2019	Naudé, 2010; Beine and Parsons, 2015; Cattaneo and Peri, 2016
Higher temperatures increase internal migration	Mueller et al., 2014	Beine and Parsons, 2015
Less rainfall increases internal migration	Barrios et al., 2006; Gray and Mueller, 2012	Mueller et al., 2014; Beine and Parsons, 2015
Disasters increase internal migration	Saldaña-Zorrilla and Sandberg, 2009; Beine and Parsons, 2015	Bohra-Mishra et al., 2014; Ruyssen and Rayp, 2014

Whilst the use of different migration data and different climatic and non-climatic variables considered in models account for some of the discrepancies (Beine and Parsons, 2017; Abel et al., 2019; Helbling et al., 2023), several other fundamental issues are present in the large majority of models introduced to date that limit what such models can contribute to our understanding of historical trends and our ability project future trajectories of climate mobility both within borders, where most of it is likely to take place (Pörtner et al., 2022), and across. Here we discuss ways to overcome these issues and highlight recent innovative approaches with the potential to replace classical methods and introduce a new generation of climate mobility models.

When assessing migration models, it is important to bear in mind that the definition of migration in modeling exercises is context-specific. Models examining international migration rely on migration data collected by national statistical offices that can cover a range of definitions developed to meet policy demands of individual countries. These typically count migrants as those who have changed their usual country of residence; however, the definition of when a person is taking up a new residence varies. In countries where persons are defined as migrants after registering in their new country will have comparatively more migrants enumerated than if it were to wait for individuals to reside in the country for 12 months, as recommended by the

United Nations. Models describing annual net migration at the grid cell level account for any type of movement in and out of a location between successive years, while models considering acute displacement may focus on persons that do, or do not, return home within a certain time period. Considering these differences is important when interpreting results. Climate mobility in particular faces an additional challenge of attributability. It is typically very difficult to quantify the extent to which climate has impacted an individual person's decision or need to migrate (Obokata et al., 2014; Boas et al., 2019). Large-scale models can circumvent this problem by conducting simulations with and without accounting for climate change, which allows them to formally define the number of migrants attributed to climate change as the difference between the climate-change and the counterfactual simulations. Recent examples of this approach include the works of Benveniste et al. (2020, 2022) and Clement et al. (2021).

2. Moving beyond linear models

The large majority of econometric models describes logarithmized migration flows as a linear function of demographic, economic, social, political, environmental, and other factors (Hoffmann et al., 2020; Moore and Wesselbaum, 2022). Qualitative studies have demonstrated, however, that migration decisions and outcomes are the result of complex interactions of these factors, operating across multiple scales (Black et al., 2011). Linear approximations of these highly non-linear relationships inevitably fail to capture important, often even very basic, patterns in migration dynamics. For example, migration rates from poor countries tend to increase with increasing per-capita income (as people gain the economic ability to migrate) before they decrease as income moves beyond a certain threshold (as people lose the economic incentive to migrate), a pattern described as the "migration hump" (Clemens, 2014; Dao et al., 2018). Assuming a linear response of mobility to income cannot accommodate this pattern.

The relationship between migration and agricultural yields provides a climate-related example of the limitations of linear approaches. In agriculture-dependent countries, climate-induced yield losses may decrease migration in low-income contexts, increase it in medium/high-income contexts, and have no measurable effect in countries that are weakly dependent on agriculture or in which farmers can readily shift to alternative economic sectors. Some econometric models have attempted to account for this context-specificity by introducing categorical variables that encode whether countries are agriculture-dependent and/or have high income levels (Cai et al., 2016; Cattaneo and Peri, 2016; Beine and Parsons, 2017); however, given that both agricultural dependency and income are continuous variables, these approaches are, by design, limited in how complete a picture they can provide.

Some econometric analyses have introduced quadratic terms to account for non-linear effects of selected variables on migration flows (Bohra-Mishra et al., 2014; Cattaneo and Peri, 2016; Gray and Wise, 2016); however, the assumed shape of the function may still be too constraining. Generalized additive models—which describe the predictand in terms of the sum of functions of one or two predictor variables, where each function can in principle take an arbitrary shape—would alleviate this issue to some extent, whilst retaining model interpretability in terms the ability to visualize the one- or two-dimensional summands of the regression function; however, the fact that standard implementations are limited to capturing at most pairwise interactions of predictor variables may once again be too simplistic.

More complex non-linear machine-learning approaches, such as random forests and neural networks, represent promising solutions to the above-described issues of econometric models. In principle, these approaches can describe arbitrarily complex interactions between the various demographic, economic, social, political, and environmental drivers and thus accommodate the high context-specificity of how migration responds to these variables. Care needs to be taken to avoid issues like overfitting; however, standard software packages nowadays allow users to solve these challenges in computationally efficient ways. Valuable examples of advanced machine-learning methods in modeling complex dynamics in the context of climate mobility include the works of Best et al. (2021, 2022), Niva et al. (2021), and Schutte et al. (2021). Given their high-dimensional and non-linear nature, regression functions estimated from methods like random forests and neural networks cannot be readily visualized or verbally summarized analogous to statements like "a 1° increase in temperature increases migration by x%", which have enjoyed popularity in linear econometric analyses (Barrios et al., 2006; Bohra-Mishra et al., 2014; Coniglio and Pesce, 2015; Cai et al., 2016; Cattaneo and Peri, 2016; Beine and Parsons, 2017; Peri and Sasahara, 2019; Wesselbaum and Aburn, 2019). Loosing this intuitive, though, likely too simplistic, interpretability of linear models may be unavoidable for accommodating the complexity of migration dynamics. Partial dependences of migration flows on single predictor variables or pairwise interactions can still be plotted for high-dimensional non-linear models, providing useful information about the average effect of specific drivers. In addition, feature importance ranking provides insights into the relative weights of individual drivers in influencing migration.

Whilst non-linear regression methods like random forests or artificial neural networks can be very effective in quantitatively modeling climate mobility, they may not always be the best tool for advancing conceptual understanding of economic, social, and other processes that affect migration, due to the at-times 'black box' nature of these methods. Alongside advancing purely statistical models of climate mobility, it remains important to develop mechanistic models that translate causal theories of migration into mathematical language. Systematic assessments of models representing alternative theories would make an important contribution toward establishing a comprehensive conceptual framework of the mechanisms of climate mobility that holds across large scales, which continues to be an open problem (De Sherbinin et al., 2022). Solving it will require ways to represent the multicausal and non-linear relationships inherent to climate mobility without sacrificing mathematical tractability. Beyond their value for advancing conceptual understanding, mechanistic models can have the advantage of being able to generate robust predictions even with relatively little training data, given that the qualitative shape of the regression function is predefined (Baker et al., 2018). In contrast, non-parametric statistical models like the aforementioned random forests and neural networks, which make no prior assumptions about the relationships between relevant driver variables and the resulting mobility outcome but derive these relationships entirely from the training data, require a large number of observations.

Models that predict future migration based only on historical migration patterns (i.e., without incorporating exogenous drivers) have established excellent standards for quantifying uncertainties in forecasts (Bijak, 2010; Azose and Raftery, 2015; Azose et al., 2016; Welch and Raftery, 2022). In contrast, models focused on how the interaction of different drivers results in a migration outcome, including the ones discussed here, lag behind these developments (Bijak, 2006). For example, the uncertainty intervals in the projections of the Groundswell model (Clement et al., 2021) are based only on the uncertainty in one input variable (out of several) and do not account for the estimated confidence ranges of model parameters and the model's goodness of fit. Rigorous and transparent quantification of uncertainties in climate mobility models will be crucial if model results and forecasts are to inform decision makers.

3. Moving beyond significance testing

Most econometric models of climate mobility to date have focused on estimating whether the effect of certain climatic or environmental variables on migration is statistically significant or not. In a number of cases when a variable is estimated to be statistically significant, models including and excluding the variable barely differ in terms of their R^2 values (the proportion of the variation in the observed migration data that they explain) (Beine and Parsons, 2015, 2017; Coniglio and Pesce, 2015; Drabo and Mbaye, 2015; Cai et al., 2016). This shows that establishing statistical significance does not equate to improving the ability to quantitatively explain migration patterns. Indeed, in a number of studies that provide R^2 measures, models explained only a small proportion of the migration data (Drabo and Mbaye, 2015; Beine and Parsons, 2017; Cattaneo and Bosetti, 2017; Wesselbaum and Aburn, 2019; Benveniste et al., 2020, 2022; Adger et al., 2021). Focusing on the question of statistical significance of predictor variables in terms of p-values (ignoring their broader issues (Wasserstein and Lazar, 2016)) limits progress not only with regard to understanding historical migration patterns, but also, importantly, in the context of forecasting future migration dynamics, for which high model R^2 values are essential.

At the same time, it is easy to obtain misleadingly high R^2 values by overfitting. Time-invariant origin-destination fixed effects, used in a number of econometric models of bilateral migration (Coniglio and Pesce, 2015; Cai et al., 2016; Wesselbaum and Aburn, 2019; Beyer et al., 2022) suffice to explain $R^2 > 90\%$ of the variation in the observed flow data without explaining any causal mechanisms (Beyer et al., 2022). Overfitting can be avoided by incorporating model selection methods, e.g., based on Akaike or Bayesian information criteria (Dziak et al., 2020). These can be used to determine whether the inclusion of a given predictor variable provides a strong enough improvement of the model in relation to the cost of the additional degree(s) of parameter freedom, and thus to rank the quality of alternative models based on different sets of predictors. Thus far, information criteria-based model selection has received little attention in migration modeling but will likely become important for identifying relevant predictors and building robust models that can extrapolate migration dynamics into the future.

4. Moving beyond temperature and precipitation

Over three quarters of empirical studies on climate mobility consider the effect of some measure of temperature or precipitation on migration (Hoffmann et al., 2021). This is surprising given that temperature and precipitation are very rarely direct drivers of migration, in that people are unlikely to move *just* because it rains marginally more or less or because it is marginally warmer or colder (unless physiologically critical thresholds are crossed (Im et al., 2017; Xu et al., 2020). Instead, temperature and precipitation averages, variations, and anomalies typically act upon mobility via changes in flood risk, water stress, salinization and other land degradation, agricultural productivity, and other impacts that can compromise human wellbeing and socio-economic welfare depending on local vulnerability and resilience.

In most econometric models of climate mobility, temperature or precipitation enter the regression equation linearly or at most quadratically. This tacitly assumes that the relationship between the climatic variables and the more directly relevant environmental impacts (floods, yield losses, etc.) combined with the relationship between these impacts and the eventual migration outcome can be reasonably approximated by a linear or quadratic function. The complex non-linear equations describing flood occurrences, water stress, crop yields, and other impacts as a function of climatic conditions in state-of-the-art simulation models in these disciplines (Schewe et al., 2019; Lange et al., 2020) demonstrate how problematic even only the first part of this assumption is. For example, the effect of temperature and precipitation on agricultural yields is strongly contingent upon crop, location, technology, and management (Jägermeyr and Frieler, 2018). Higher temperatures may decrease yields of some crops in warm countries but have the opposite effect in cold countries. Rainfall deficits decrease yields but so does excess rainfall. Models assuming a linear response of migration to temperature or precipitation disregard these and many other important mechanisms, leading to conflated results.

The strong focus on temperature and precipitation as predictors of climate mobility in existing models is not an unavoidable necessity. Global observational datasets of floods (Tellman et al., 2021), droughts (Vicente-Serrano et al., 2022), storms (Geiger et al., 2018), wildfires (Artés et al., 2019), and crop yields (Kim et al., 2021; FAOSTAT, 2022) have become available at high quality. In addition, model-based historical reconstructions of these and other variables are available from model intercomparison initiatives such as ISIMIP (Warszawski et al., 2014). These provide comprehensive spatio-temporal coverage and allow users to assess the effects of climate change, simulated by the models, in isolation. The above data can be readily incorporated into migration models to avoid oversimplifying (oftentimes well-understood) complex relationships between climatic conditions on the one hand and relevant environmental hazards on the other hand.

Future projections of these sudden- and slow-onset impacts under different emission pathways have also become available (Frieler et al., 2017; Lange et al., 2020) and can be readily incorporated into models projecting future climate mobility, while accounting for uncertainties through the use of multi-model ensemble data. For example, Clement et al. (2021) used future crop yield, water stress, and sea level rise projections to forecast climate-induced internal migration.

5. Moving beyond aggregated analyses

Climate mobility is characterized by a number of heterogeneities that are often not accounted for in existing models but are likely too important to ignore. Recent progress in four exemplary areas in which disaggregation has enabled deeper analyses illustrates the potential of this strategy for modeling.

5.1. Space

Climate-related impacts relevant for human mobility are highly heterogeneous across space, even within countries (Pörtner et al., 2022). Sea level rise and river floods directly affect only coastal and riverine populations, respectively, while extreme temperatures, water stress, and agricultural productivity can increase in some areas of a country and decrease in others. Likewise, socio-economic conditions often differ considerably within countries, even between different rural areas and between different urban centers. Many high-quality gridded socio-economic (De Sherbinin et al., 2015; Leyk et al., 2019; Smits and Permanyer, 2019) and environmental (see previous section) global datasets have appeared in recent years, enabling migration models to account for spatial heterogeneities in ways that nationally aggregated data cannot. Such models are not limited to explaining past migration dynamics, thanks to gridded projections of relevant variables, available for different future socio-economic (Hurtt et al., 2011; Jones and O'Neill, 2016; Murakami et al., 2021; Wang and Sun, 2022) and climatic scenarios (Frieler et al., 2017; Lange et al., 2020) that can be incorporated into models forecasting future migration.

Gridded maps of population densities over time, combined with birth and death rates, allow for the estimation of local net migration rates in grid cells (De Sherbinin et al., 2015). Linking these to local socio-economic and environmental conditions can reveal important relationships between the latter and observed mobility patterns. Given that each spatial grid cell corresponds to one data point per point in time, gridded approaches feature a large quantity of data available for model calibration, allowing for the study of effects that may be too subtle for spatially aggregated country-level approaches. Recent years have seen several very promising examples of spatially explicit models of climate mobility, revealing complex sub-national patterns between mobility drivers and outcomes (Neumann et al., 2015; Clement et al., 2021; Niva et al., 2021; Burzyński et al., 2022; Amakrane et al., 2023).

5.2. Income

Across countries, income levels strongly influence the ability and incentive to migrate. The same is true within countries, yet most country-level models do not account for this due to lack of empirical migrant data disaggregated by economic background. Until such data become available, indirect methods of accounting for national income heterogeneities will likely play an important role. Using historical and projected future income heterogeneities measured in terms of the Gini coefficient, Benveniste et al. (2022) considered bilateral migration flows disaggregated by income quintiles at origin and destination countries. This allowed the authors to model the trade-off between a higher destination-origin income gradient incentivizing migration and a lower income level at the origin hampering migration due to resource constraints. The approach can generate complex model behavior, e.g., when socio-economic or environmental changes simultaneous increase migration for some income groups in the origin and decrease it for others, a mechanism that aggregated models cannot simulate.

5.3. Age

Migration rate is typically a multimodal function of age, peaking at the pre-labor force stage (children of young migrating parents), early labor force stage (young adults migrating for education and employment), and post-labor force stage (retirement migration) (Rogers and Castro, 1981; Plane, 1993), while also being strongly context-specific. With age structures differing substantially between countries, accounting for age could improve models of climate mobility substantially. Whilst migration flow estimates do not yet exist for different age groups, national migrant stock data through time are available by age (United Nations, 2020), which, combined with birth and death data, would allow for statistically deriving a first-order approximation of age-disaggregated flows. Fertig and Schmidt (2005) provided a notable example of such an approach.

5.4. Sex

Sex-based socio-economic differences imply that migration responses to climatic hazards can differ considerably between females and males. In many contexts, lower access of females to financial and natural resources, education, health, and other services leads to higher vulnerability to adverse environmental changes (Chindarkar, 2012), while sex differences in legal, social, and security aspects relevant for migration often affect the ability of females and males to move easily and safely (Jolly et al., 2005). International migration flow estimates are now available for females and males (Abel and Cohen, 2022), and highlight important differences in flow rates across both countries and time. Explicitly accounting for male and female migrants in climate mobility models would help to accommodate these heterogeneities.

6. Moving beyond spatial patterns

Econometric models of migration are based on the assumption that relationships between migration and relevant predictors coincide at the spatial and the temporal scale (Beine and Parsons, 2015). For example, a strong positive relationship across countries between national population size and national out-migration levels would be used to infer that, for any given country, an increase in population size over time will result in an increase in out-migration; however, migration data available to date have not allowed to confirm this latter temporal relationship (Beyer et al., 2022). At present, it cannot be concluded with certainty whether this apparent discrepancy between spatial and temporal patterns of migration is an artifact linked to potential noise in the empirical flow time series or whether indeed spatial and temporal patterns follow different statistical rules. Summary statistics conventionally used to validate econometric models have been shown to assess merely whether models capture spatial patterns, without providing insights into whether models correctly describe temporal migration dynamics (Beyer et al., 2022). This is because migration flows across countries vary over several orders of magnitude, whereas flows to or from a given country over time typically do not. A model may thus reproduce the order of magnitude of the observed flow well but fail to correctly describe the changes in flow over time—a deficit that cannot be inferred from standard R^2 values of modeled vs. observed logarithmized flows across all corridors (Beyer et al., 2022). Explaining how migration flows change over time in response to changes in driver variables represents a key prerequisite both for explaining historical trends and for forecasting future trajectories. Models therefore need to be evaluated based on metrics specifically designed to isolate the temporal signal, enabling assessments of how well corridor-specific modeled and observed flow time series agree.

7. Moving beyond current data

Global-scale estimates of international migration have only recently approached a level of quality suitable for in-depth analyses on migration in the context of climate and beyond, thanks to curated stock data and improved flow estimation methods (Abel and Cohen, 2019, 2022). Previous datasets, used for early models of climate mobility, are subject to important issues. Those datasets include the stock data compiled by Özden et al. (2011), available only in 10-year intervals, which contain a number of implausible data points (Abel, 2013) that have not been revised. In migration models, these data have most often been used to derive flows via stock differencing methods, which produce estimates that are more weakly correlated to available migration flow statistics than with other methods (Abel and Cohen, 2019). More sophisticated methods are also subject to uncertainties. Demographic accounting approaches rely on population, birth and death data that are susceptible to inaccuracies that will impact estimated flows. The Pseudo-Bayesian demographic accounting approach of Azose and Raftery (2019) uses a weight within its calculation based on comparisons to migration flows within Europe, where international migration is relatively easy due to freedom of movement regulations, and hence the resulting flow estimates are pushed toward an upper end of a viable limit on the volume of global migration flows.

A weak point in current available data is the lack of confidence intervals around the estimated flows. Those would make it possible to weigh individual observations during model calibration according to their uncertainties, which are likely not uniform across migration corridors and time. Whilst uncertainties in the demographic estimation methods used to infer flow from stock data (Abel and Cohen, 2019) could in principle be quantified using methods such as those proposed by Little and Wu (1991) and Lang (2004), the stock data themselves are published without any uncertainty measures, which prevents a comprehensive estimation of the uncertainties in the derived flow. Incorporating independent flow datasets compiled by national, supranational, and intergovernmental bodies (e.g., OECD, 2019; Eurostat, 2020) for selected migration corridors may provide further insights into uncertainties in available global datasets.

Most large-scale modeling studies on climatic effects on human mobility have focused on international migration, even though movement related to climatic and environmental changes thus far has taken place mostly within countries (McLeman, 2013). Lack or inaccessibility of internal flow data, especially with large spatial coverage, has strongly contributed to this. Whilst in a number of countries, such data have been gathered either directly by local registration offices or through censuses and surveys, or would be inferable from records collected by internal revenue, health, other centralized administrative systems, suitably anonymized versions are rarely available to researchers. The IMAGE project provides internal migration data from a number of countries (Bell et al., 2020) but has yet to be fully explored by the research community. The IPUMS International data repository contains a number of variables related to migration from census data from over 60 countries (Ruggles et al., 2003) that have begun to be utilized for studying internal migration patterns in relation to climate events (Thiede et al., 2016; Mueller et al., 2020; Abel et al., 2021). Improved access to internal flow data would provide an extremely valuable resource for future climate mobility modeling.

Digital data, including social media traffic and search engine queries, are an emerging resource that has proven useful for tracking mobility at a high spatial and temporal resolution both within and across national borders (Tjaden, 2021). Whilst in some contexts, these data can lack representativeness due to spatially heterogeneous internet access and social media penetration (Sohst et al., 2020), they can provide important information allowing researchers to address questions for which traditional data may be unsuitable, including fine-grained, and high-frequency, and real-time movement patterns. Examples in which such digital data have been used to study mobility include the works of Blumenstock (2012), Lu et al. (2016), and Lai et al. (2019a), Lai et al. (2019b).

8. Conclusion

Global human mobility in response to climatic changes and associated environmental hazards is as much a geopolitically significant topic as an exceptionally complex challenge for quantitative modeling and forecasting. Literature reviews and meta-analyses have highlighted the diverging findings of existing approaches in the field, which are in part likely a result of the high complexity and context-specificity of migration, which classical methods are not always able to accommodate. Here, we proposed six priorities for elevating models of climate mobility to a level where scientific consensus on future shifts in the spatial distributions of populations worldwide under different climatic and socio-economic scenarios could be more likely achievable, and where models can generate reliable and actionable outputs for decision makers and other stakeholders. Our recommendations are

- The use of non-linear machine-learning techniques, rather than linear methods that have proven too simplistic for climate mobility dynamics.
- The prioritization of explaining the observed data and systematically selecting meaningful driver variables, rather than testing statistical significance.
- The consideration of sudden- and slow-onset climate impacts with immediate relevance for humans, such as floods and crop failure, rather than more abstract temperature- and precipitation-based variables.
- The examination of heterogeneities through approaches that are spatially explicit and account for socio-economic factors, including age, sex, and income, rather than aggregated measures.
- The investigation of temporal migration dynamics by means of appropriate new summary statistics beyond standard model evaluation metrics that mostly assess spatial patterns.
- The use of better calibration data, including disaggregated and within-country flows, that are more suitable for identifying subtle and complex dynamics.

Effective adaptation measures in regions where climate change is likely to have adverse impacts on human mobility are dependent on reliable analytics and scenario-based forecasting. Several contributions in recent years have provided valuable examples of a new generation of models based on methods and data that are fit for the purpose of yielding operationalizable results. Building on these approaches while continually refining modeling methodologies as well as data collection and curation efforts at small and large scales will be vital toward improving the evidence base on the effects of a changing climate on global human mobility.

Climate impact research has greatly benefited from standardized simulation protocols (O'Neill et al., 2016) and scenarios of future greenhouse gas concentration (RCP) (Van Vuuren et al., 2011) and socio-economic conditions (SSPs) (Riahi et al., 2017) that have been developed collaboratively by the research community. These have enabled consistent comparisons of the results generated by alternative models, allowing for a rigorous separation of robust signals and inter-model uncertainty. While future projections of climate mobility are already largely embedded in the RCP-SSP framework (but would benefit from additional quantified scenarios, e.g., of border policy), the questions addressed by different models thus far have been too different to allow for meaningful comparative assessments, for example, of how climate change is going to alter the spatial distribution of populations worldwide through migration in the coming years and decades under different RCP-SSP scenarios. Developing standardized simulation protocols for climate mobility modeling would be a major step toward identifying knowledge bottlenecks and building much-needed scientific consensus.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

RB conceived the study. RB, JS, and GA wrote the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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