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Improving the evidence base: A methodological review of the quantitative climate migration literature

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ABSTRACT

The question whether and how climatic factors influence human migration has gained both academic and public interest in the past years. Based on two meta-analyses, this paper systematically reviews the quantitative empirical literature on climate-related migration from a methodological perspective. In total, information from 127 original micro- and macro-level studies is analyzed to assess how different concepts, research designs, and analytical methods shape our understanding of climate migration. We provide an overview of common methodological approaches and present evidence on their potential implications for the estimation of climatic impacts. We identify five key challenges, which relate to the i) measurement of migration and ii) climatic events, iii) the integration and aggregation of data, iv) the identification of causal relationships, and v) the exploration of contextual influences and mechanisms. Advances in research and modelling are discussed together with best practice cases to provide guidance to researchers studying the climate-migration nexus. We recommend for future empirical studies to employ approaches that are of relevance for and reflect local contexts, ensuring high levels of comparability and transparency.

1. Introduction

The past decade has seen a steady increase in the number of quantitative empirical studies exploring how climatic and other environmental drivers influence migration. These range from case studies in highly localized settings to macro studies considering global migration flows. While the majority of studies agree that climatic conditions are important for migration, their results vary substantially, making it difficult to establish when and under which conditions climate migration occurs (Cattaneo et al., 2019; Hunter et al., 2015; Obokata et al., 2014; Piguet, 2010; Warner and Afifi, 2014). One reason for the heterogeneity of the findings are differences in the empirical approaches employed in the analyses.

This study provides a systematic methodological review of the quantitative climate migration literature and discusses how our understanding of the climate-migration nexus is influenced by methodological choices. Our review is based on two recent meta-analyses led by two of the authors (Hoffmann et al., 2020; Šedová et al., 2021), which synthesized the evidence of 127 original micro- and macro-level studies on climate migration worldwide estimating 4962 separate relationship coefficients (supplement Table S1). The first meta-analysis focused on macro studies at the country level (hereafter meta-analysis M1), the second one considered both micro- and macro-level studies (hereafter meta-analysis M2). To be included in the meta-analyses, the original studies had to report statistical model estimates on the relationship between a climatic factor and migration. In addition to the estimates of the relationships, detailed information about the used data sources (including both primary and secondary data), measurements, and analytical techniques were collected. Both meta-analyses took peer-reviewed articles and grey literature (reports and working papers) into account (see supplement B for detailed information about procedures).

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Our review complements previous methodological reviews (Auffhammer et al., 2013; Berlemann and Steinhardt, 2017; Dell et al., 2014; Fussell et al., 2014b; Gemenne, 2011; McLeman, 2013; Piguet, 2010; Warner, 2011) by adding a distinctive meta-analytical perspective. Our approach builds on a systematic screening and selection of studies, which comprehensively reflects the scope and diversity of the quantitative literature on the topic. The meta-data collected as part of the two meta-analyses allows us to thoroughly describe and compare the statistical results of multiple studies and their characteristics to understand how differences in approaches can influence research outcomes, providing unique insights into challenges and gaps that exist when it comes to studying and modeling climate migration. Beyond methodological questions, our paper also contributes to recent substantive literature reviews on climate migration by providing key insights derived from the meta-analyses (Cattaneo et al., 2019; Hunter et al., 2015; Millock, 2015).

Every methodological approach comes with certain trade-offs and there is no universally best way for studying climate migration. Depending on the research questions and contexts at hand, different methods can be suitable, including both quantitative, qualitative, and mixed methods. While this review is primarily focused on the quantitative literature, also other, more qualitative approaches form an integral part of the study of the climate-migration nexus (see Gemenne, 2018 for an overview). Here, we highlight advantages, potential challenges and pitfalls, and implications of the use of certain quantitative methods and raise a number of relevant questions researchers working in the field should address. Our review shall help to better recognize and understand inter-dependencies and complexities in the modeling of climate migration and provide researchers with an overview of state of the art methodical tools and data sources that can help them to address some of the pertinent challenges.

In section 2, we first provide a descriptive overview of conceptual frameworks, data types, and research strategies used based on the collected meta-data. Here, we also show how certain methodological choices can influence results and their interpretation based on some of the key findings from our meta-analyses. Implications of these are discussed in section 3, where we highlight challenges typical for the analysis of the climate-migration relationship and how to overcome them. Section 4 provides an overview of recent advancements in the field and Section 5 concludes with key recommendations. This text is accompanied by supplementary materials providing an overview of the reviewed studies (A), the procedures employed in the meta-analyses (B), and common data sources used in the literature (C).

2. Approaches in the quantitative climate migration literature

2.1. Diverse schools of thought

The academic literature on climate migration has emerged from diverse schools of thought that conceptualize migration through different lenses. Scholars from the natural, social, and legal sciences have contributed to the development of the field using both quantitative and qualitative approaches (Gemenne and Blocher, 2017; Warner and Afifi, 2014; Warner and Van Der Geest, 2013). Piguet (2010) provided a first overview of the different methods used for analyzing climate migration. Since then, the portfolio of empirical approaches has grown, including interview-based methods, participatory approaches, comparative analyses, agent-based models, and large scale spatial and longitudinal analyses. Scientists have investigated the entire cycle of migration, from intentions, the decision to migrate, the journey itself to the consequences of climate migration.

Here, we focus on quantitative empirical work studying the first part of the migration cycle, the relationship between climatic impacts, underlying conditions, and migration. This focus already has effects on the disciplinary representation of authors (Fig. 1, Panel A-C), as political scientists, moral philosophers, sociologists, and legal and development scholars focus on different aspects of climate migration, such as the adaptive capacity of migrants, international protection frameworks, the role of climate-related displacement in conflicts, infringement of basic human and civil rights, or normative considerations of climate justice. While these are important parts of the wider climate migration field, they have already been mapped by other scholars (Piguet et al., 2018).

From the 1970s, researchers have theoretically conceptualized climatic impacts in migration models. The seminal Harris and Todaro model, for example, explains rural–urban movements through expected wage differences between sending and destination areas (Harris and Todaro, 1970). Even though the model does not consider environmental factors explicitly, it provides a framework for understanding rural–urban migration in response to climatic events, which can lead to deteriorating conditions in the origin regions with long-term effects on

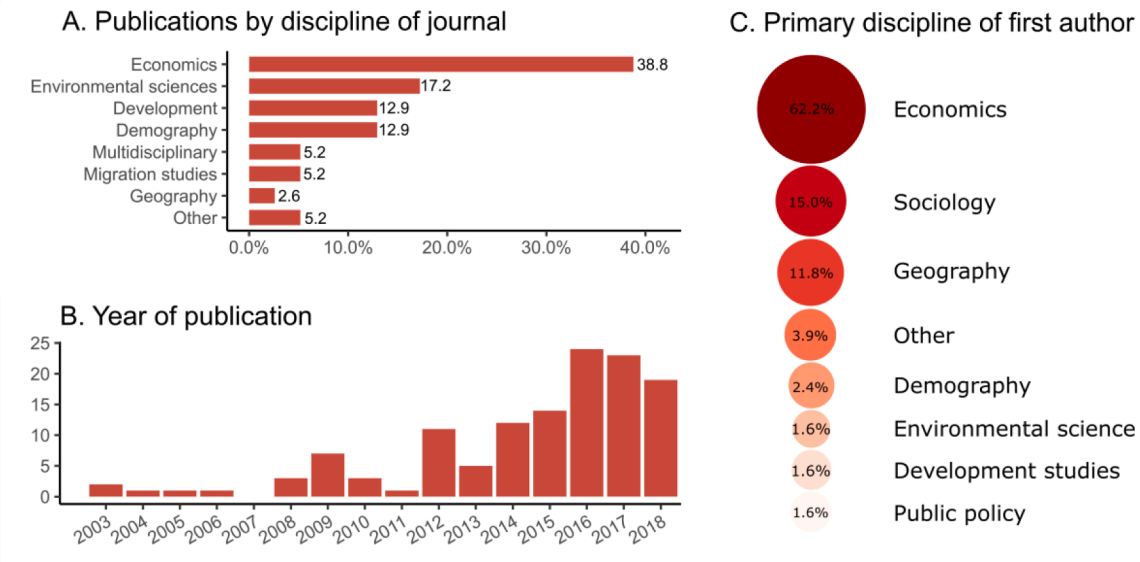

Fig. 1. Schools of thought and publication characteristics of 127 micro- and macro-level studies on climate migration between 2003 and 2018. Panel A shows the distribution of publications by journal discipline (grey literature excluded), Panel B shows the distribution of papers by year of publication (grey literature included), and Panel C shows the primary disciplines of the first authors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

wages and employment.

Building on these contributions, recent studies use extensions of the Roy-Borjas model (Borjas, 1987; Roy, 1951) to analyze the effects of slow-onset climatic impacts on migration also accounting for migration costs (Cattaneo and Peri, 2016; Šedová and Kalkuhl, 2020; Benonnier et al., 2019). In this setting, liquidity constraints imposed by adverse climatic events reduce the likelihood of emigration for poor segments of the populations and drive outmigration only for those who can afford it (see also the migration hump theory by Martin and Taylor, 1996). In line with this reasoning, both meta-analyses find a non-linear relationship between socio-economic status and migration with middle-income groups being most likely to migrate in response to climatic stress.

"The new economics of labor migration" (NELM) by Stark and Bloom (1985) goes a step beyond the individual's motivation for migration and considers entire households as decision-making entities. According to NELM, households engage in risk diversification by sending family members to areas unaffected by climatic impacts. Here, migration and remittance systems form an integral part of livelihoods and risk mitigation *ex-ante* adverse shocks. In addition to conceptualizing migration as a preventive investment, Kleemans (2015) suggests that migration also serves as an *ex-post* risk coping strategy after sudden events and income shocks, when alternative risk coping strategies fail (e.g., reducing savings, selling assets).

Beyond economic incentives, it is widely accepted that other factors also influence migration. Migrants do not only seek to increase economic opportunities and maximize profits, but rather weigh a variety of aspects in their decision making process (Hunter et al., 2015). As is the case with all human behavior, the decision to migrate is generally multi-causal and may evolve over different time scales. The same is true for the interactions of climatic impacts, which occur in varying levels of magnitude and can materialize suddenly or over long periods of time, leading to migration or (forced) immobility.

Recent theoretical contributions have emphasized the importance of not only understanding whether but also how climate-related events affect migration (see Black et al. (2011) for a conceptual overview). These events can either directly influence migration decisions, e.g., by posing an immediate threat to health and well-being (Muttarak and Dimitrova, 2019) or indirectly by affecting other migration drivers such as economic (Marchiori et al., 2017, 2012; Maurel and Tuccio, 2016) and socio-political conditions (Abel et al., 2019; Hsiang et al., 2013). In addition, also subjective factors, like perceptions, well-being or place-attachment, are significant when trying to understand why some people stay and others leave in the face of adverse climatic events (Khanian et al., 2019; Koubi et al., 2016b). The complexity to decipher these interactions between quantifiable and non-quantifiable factors is reflected in the multitude of data sources and methods used in the studies that were captured by the two meta-analyses.

2.2. Data

Empirical climate migration studies can be broadly categorized into micro studies, which focus mostly on individual and household migration, and macro studies, which consider migration at the regional or national level. Depending on the level of analysis, different forms of research designs and data are used, ranging from highly localized case studies using surveys for data collection, to global comparisons based on country level data derived from administrative records. Whereas the former type of approaches allows researchers to gain a deeper understanding of processes and mechanisms on the ground, higher levels of aggregation enable to obtain a bigger picture via comparisons of different contexts. The choice of the level of analysis can affect the findings, as meta-analysis M2 suggests, which shows that estimated migration patterns in response to increasing temperatures or droughts can differ for micro- and macro-level studies.

Existing studies are primarily focused on migration within or from low- and middle-income countries, with the US as a notable exception (e.g., Fussell et al., 2014a; Thiede and Brown, 2013). Fig. 2 shows the representation of countries in the samples used by the original studies. Countries in darker red colors were found to be included in a larger number of samples. The representation of countries in the meta-data mirrors well the evidence on the distribution of climate migration studies reported by Piguet et al. (2018). Based on the CliMig bibliographic database (Piguet et al. 2019), which provides a comprehensive list of literature on migration, the environment and climate change, the authors identify a hemispheric asymmetry in research on climate migration with the majority of studies being conducted in developing countries and emerging economies by researchers from high-income countries. A particular research focus is placed on countries in West and East Africa, South Asia, and selected countries in Latin America and the Caribbean.

Studies typically consider the migration impacts of short-term, temporal variations in weather rather than long-term climate changes, which manifest over decades. Considering short-term fluctuations has advantages for the analysis and the identification of effects due to the better availability of and greater variation in the data, but has implications for the transferability of the results. Yet, an increasing literature shows how short-term events, such as storms, and medium-term events, such as droughts, are linked to anthropogenic climate change (Lehmann et al., 2018; Otto, 2017; Stott et al., 2016) and can also be used for the estimation of longer-term climatic impacts (Hsiang, 2016). In our meta-analyses, we considered broadly climatic impacts on migration, including extreme events and gradual changes that are in line with the observed and projected climate trends. Generally, the temporal dimension is critical for the measurement and modelling of climatic impacts. As shown in meta-analysis M1, broader timeframes of measurement (five or ten years compared to one) are associated with an estimation of overall lower climatic effects on migration. Moreover, as shown in M2, the longer the time periods since the occurrence of an adverse event, the lower the likelihood of finding evidence of climate migration.

2.3. Measurement

Typically, studies distinguish between sudden events that emerge quickly or unexpectedly, such as extreme storms or floods, and slow-onset events, such as desertification or sea level rise, which emerge gradually and may appear less destructive at first (UNISDR, 2015). The boundaries between the two types are highly fluid with hazards typically ranging on a continuum from immediate to delayed threats, which has implications for their conceptualization and measurement Fig. 3, Panel A). Distinguishing by types of hazards, most studies focus on changes in the level and variability of precipitation and temperature as two factors commonly linked to climate change (Fig. 3, Panel B). The majority of studies consider slow-onset (76.5%) as compared to sudden events (23.5%).

Studies use a myriad of approaches to measure climatic hazards. Sudden events are typically captured either by binary variables indicating whether a region or a country was exposed to an event, or count or share variables measuring the number or proportion of the affected population. In addition to simply reflecting the occurrence of an event, measurements of the latter type also capture the event's intensity and the vulnerability of the affected populations. The way how these events are conceptualized and measured matters, as the results of both meta-analyses suggest. For example, M2 shows that studies measuring drought intensity, as compared to their mere occurrence, are more likely to find evidence of climate migration. Also, self-reported, subjective measurements tend to produce different results as compared to analyses based on objective climate data.

As regards slow-onset hazards, studies primarily consider the influence of changes in precipitation (40.2%) and temperature (35.1%) (Fig. 3B). Here, the broad set of measures can be divided into measures focusing on level changes, e.g., effects of increasing temperatures, and those focusing on variability changes and anomalies, such as irregular

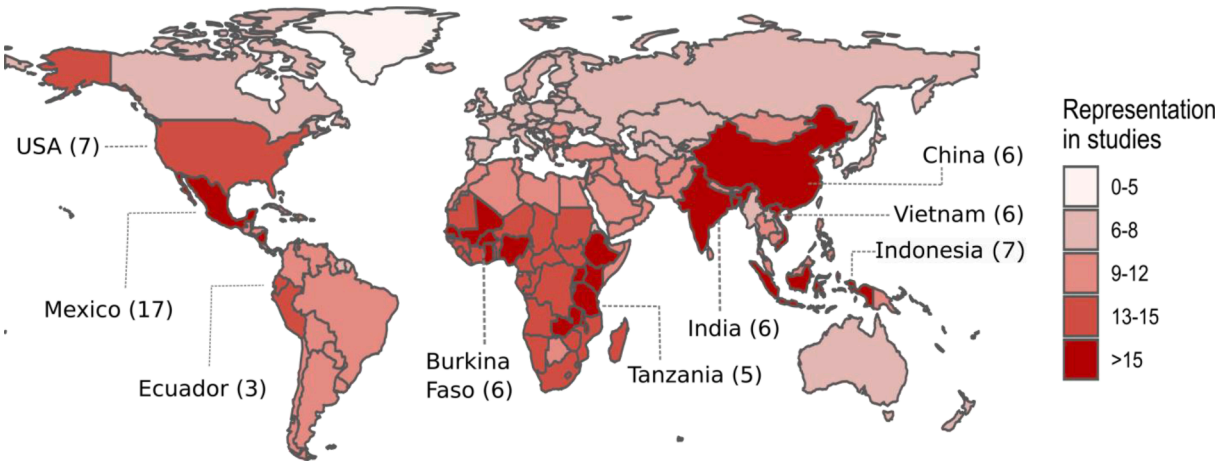

Fig. 2. Representation of countries in samples of 127 micro- and macro-level studies on climate migration. Darker shades of red indicate a higher frequency meaning that the respective countries were included in a larger number of study samples. Macro studies, which considered several countries at the same time, were counted by half in contrast to micro studies with a focus on only one country. Highlighted are those countries, which are represented in a large number of micro-level studies (in parentheses), e.g., there are 17 micro-level studies considering climate migration in Mexico and 3 in Ecuador.

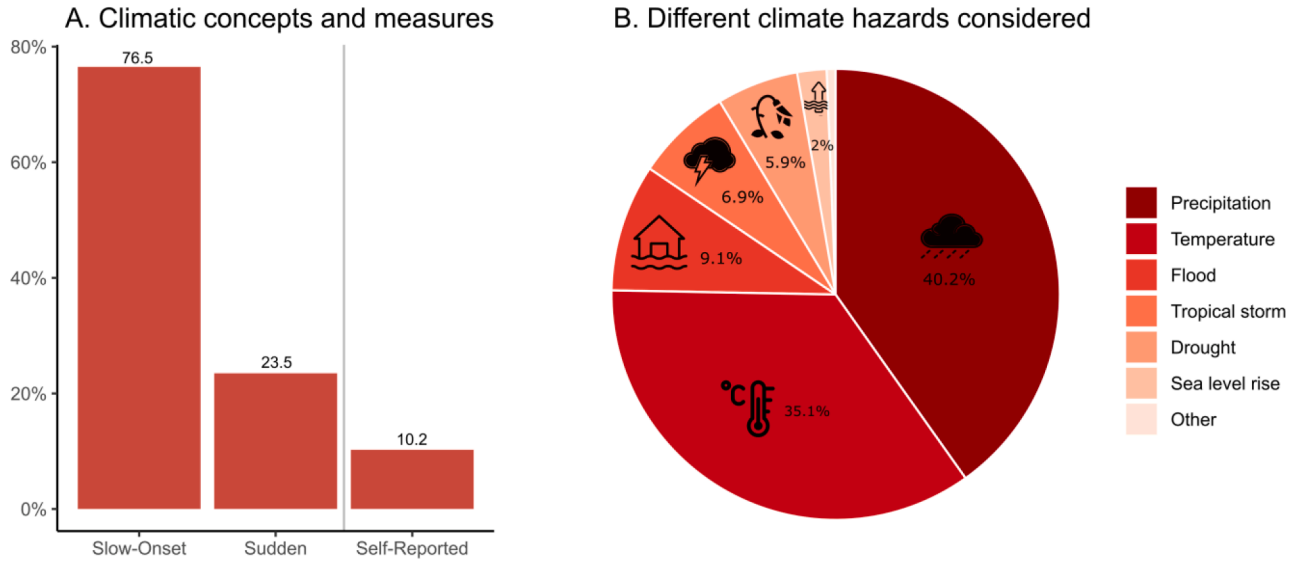

Fig. 3. Climatic concepts and measures in 127 micro and macro-level studies on climate migration. Panel A shows the percentage of studies focusing on slow-onset and sudden climatic events; and the percentage of studies using self-reported subjective climatic measures. Slow-onset events refer to climatic events that manifest over a longer period, whereas sudden refers to abrupt events, such as heavy storms, extreme rainfall, or flooding. Self-reported refers to climatic events that were reported by respondents in a survey. Panel B shows the distribution of studies by different types of climatic hazards considered.

precipitation patterns or deviations from a location-specific long-term mean. Others take intermediary environmental outcomes and impacts of climatic processes into account, such as changes in soil quality or land degradation.

Migration can take very different forms: It can be over a short- or long-term, circular or linear, over a short- or a long-distance, within national borders or international, and forced or voluntary. Like with climatic hazards, studies consider migration as ranging along a continuum between these different poles. Scholars have developed a broad range of methods to collect and analyze migration data, which have been used in the climate migration literature. Unlike for other demographic events, such as birth or death, migration data is typically not recorded by administrations in form of official statistics, but has to be collected either in censuses or surveys (Fussell et al., 2014b). Within these, migration measures can be based on stated intentions, actually observed processes, indirect measures, or retrospective information.

The results of studies are sensitive to the conceptualization and measurement of migration, as both meta-analyses show (see also Beine & Jeusette 2019). The meta-analyses suggest that climatic events are more likely to lead to internal rather than international migration. M2 further considers the characteristics of climate migrants. The analysis shows that climate migration serves as an important livelihood and adaptation strategy, particularly in rural areas, likely driving urbanization patterns. Further, men are often found to be more likely than women to change their migration behavior in response to slow-onset climatic events (see also Ayeb-Karlsson, 2020).

2.4. Statistical designs and models

To analyse the effects of a changing climate, researchers have applied different statistical designs to create a hypothetical counterfactual (Fig. 4A). The pioneering cross-sectional Ricardian approach was developed by Mendelsohn, Nordhaus, and Shaw (1994). In this framework, the identification of impacts comes from the spatial variation in

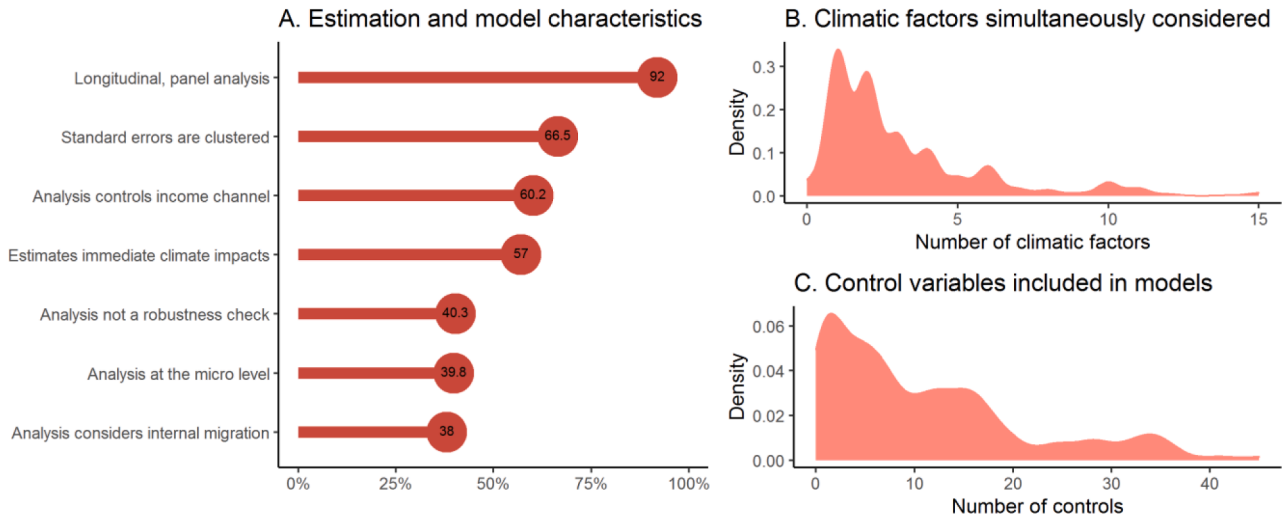

Fig. 4. Different modelling and estimation approaches used in the literature based on 127 micro- and macro-level studies on climate migration. Figure A. captures the percentage of i) estimates derived from panel-data analyses, ii) models using clustered standard errors, iii) models controlling for (potentially mediating) income-related variables, iv) models estimating immediate (as opposed to lagged) climatic effects, v) main models as opposed to robustness tests, vi) models estimated at the micro as opposed to the macro-level, and vii) models considering internal as opposed to international migration as main outcome. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the long-run climatic conditions. Further covariates typically cover variables that may be correlated with the climatic variables (e.g., elevation, distance to coast, or soil composition) and may affect the outcome of interest (see, e.g., Bhattacharya and Innes 2008, Nawrotzki, Schlak, and Kugler 2016, or Šedová and Kalkuhl, 2020).

Another approach commonly used in the climate migration literature is the analysis of longitudinal panel or time series data (Chen and Mueller, 2019; Deschênes and Greenstone, 2007; Gray and Mueller, 2012; Marchiori et al., 2012). In this setting, response coefficients are derived from temporal (mostly annual or decadal) variation of the climatic and outcome variables. Typically, longitudinal studies control for observation-specific intercepts and common time trends via fixed effects, comparing a given entity under different climatic conditions (Fig. 4A). The fixed effects absorb the influence of time-invariant factors and trends and thus allow the researcher to control for unobserved heterogeneity (e.g., Cai et al. 2016; Chen and Mueller 2019; Missirian and Schlenker 2017). Findings from our meta-analyses illustrate how accounting for unobservable heterogeneity and time trends can systematically affect the estimation of climatic impacts on migration.

In terms of analytical approaches, studies use a broad variety of methods to estimate the climate-migration relationship. When considering bilateral international migration, studies often employ a variation of the gravity model. These models explain migration by the population size of and the distance between countries of origin and destination. If the migration outcome has few zero observations, Ordinary Least Square (OLS) estimation can be applied. If the outcome is zero-inflated (e.g., for count data), studies typically employ Poisson regression or negative binomial models accounting for over-dispersion (Wooldridge 2007). Micro studies at the individual or household level typically measure migration as a binary variable, capturing whether or not an individual or a household migrated. For this type of outcome, binary dependent variable models, such as logit, probit or linear probability models, are often applied. In more detailed settings, when different destinations can be distinguished, multinomial models are used (Berlemann and Steinhardt, 2017).

Studies typically include a number of climatic variables in their models, which are either considered iteratively in multiple or simultaneously in one model (Fig. 4 B) (Auffhammer et al., 2013). Both meta-analyses find that results are sensitive not only to the type and measurement of the climatic factors considered but also to whether or not other influences are simultaneously accounted for in a model, suggesting correlations between the different factors. For example, if similar climatic signals are considered in the same model, effects are estimated to be smaller. Effects also change if different types of climatic variables are included: Effects of precipitation changes are found to be weaker if temperature changes are controlled for, whereas temperature effects are estimated larger if precipitation changes are controlled for, as shown by M1. Besides including different climatic factors, studies often control for a range of other factors that might be direct outcomes of climatic inputs considered (Fig. 4 C). As we discuss in detail in the next section, the inclusion of further variables as controls can be problematic as these additional variables may represent 'bad controls', potentially biasing the estimation of migration impacts (Angrist and Pischke, 2008).

3. Common challenges and how to address them

This section discusses challenges in the analysis of climatic impacts on migration as identified in our review as well as corresponding best practices and solutions (Fig. 5). The aim is to highlight a set of pertinent methodological questions that researchers working in the field of climate migration should be aware of and address. References to complementary literature sources, which discuss the considered issues in greater detail, are provided throughout the text.

3.1. *Accurately measuring climate migration*

Migration is by its nature a dynamic and multifaceted process challenging the empirical conceptualization and measurement of the phenomenon (for comprehensive overviews, see Bilsborrow 2016; Vargas-Silva 2012). It encompasses the spatial movement of a person or a household as a change in the habitual place of residence, typically over a longer time horizon, within the borders of a country or internationally (IOM, 2019). A first challenge arises with the empirical identification of migrants. Given the rich diversity and inherent complexity of human movements, it is instrumental for empirical research to clearly define who is considered to be a climate migrant and to highlight which forms of migration are covered by the respective research design and which are not (e.g., individual vs. household or long-term vs. short-term migration). How migration is conceptualized and measured can have important implications for the findings, which should be thoroughly reflected and discussed (Bilsborrow et al., 2012; Fussell et al., 2014b).

Certain types of migration affected by climatic impacts may be

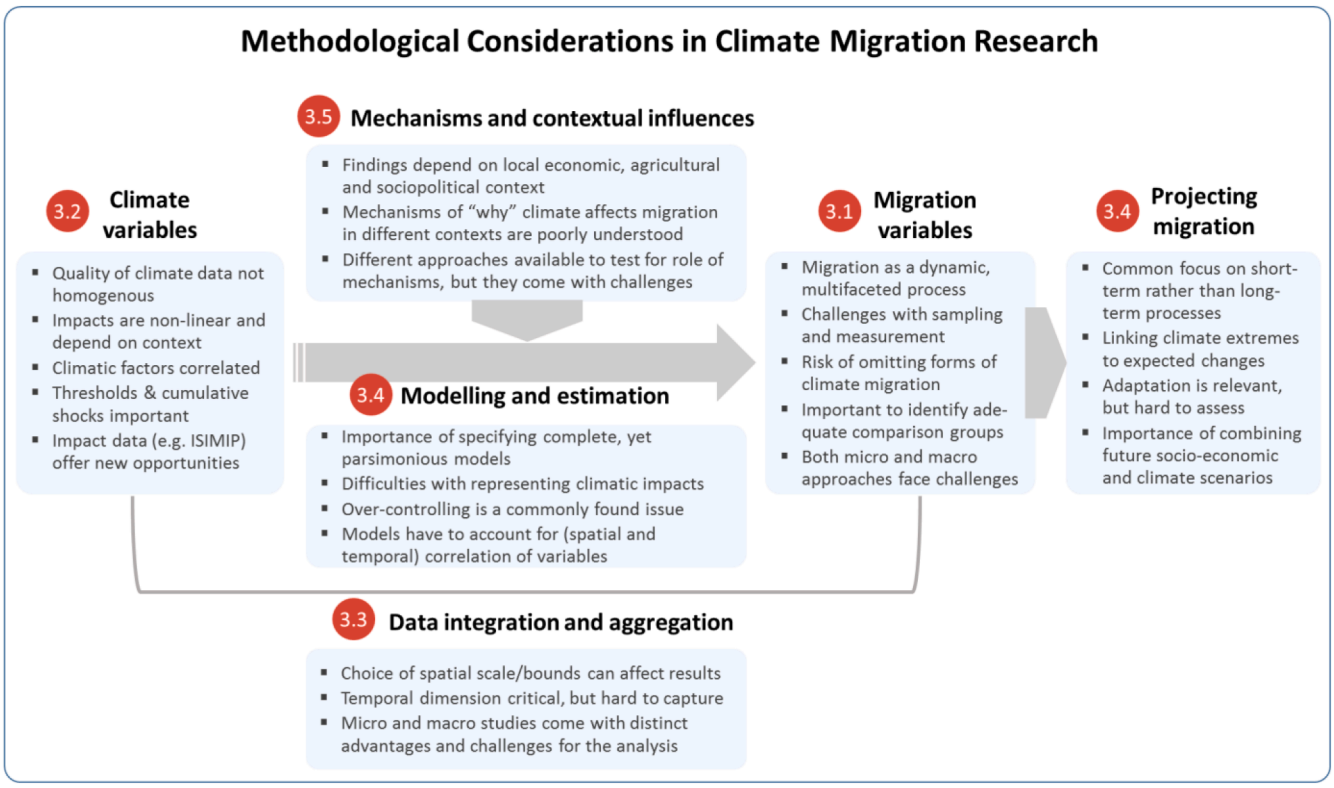

Fig. 5. Key messages from section 3: Methodological considerations in climate migration research. The numbers in the red circles refer to the sub-section numbering. The arrows indicate the line of reasoning: Migration variables (3.1) and climatic variables (3.2) are combined in a joint data set (3.3) and regressed on each other in quantitative models (3.4), which also form the basis of projections. Models also allow to test for the role of mechanisms and contextual influences (3.5) mediating and moderating the relationship between the climatic variables and migration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

systematically omitted from the data. National censuses, for example, are only completed once every several years or decade, potentially missing short-term and short-distance movements or displacement which often range below the covered geographical and temporal scales (e.g., within states or districts and below 6 months of absence). Also in other publicly administered migration data sources, such as population registries, certain forms of migration, commonly related to climatic impacts, are not well represented and may hence remain undocumented. These include moves from rural areas to informal urban settlements, where many inhabitants are not registered with local or national authorities resulting in differences between the *de facto* and *de jure* place of residence (Massey and Capoferro, 2018; Vinke and Hoffmann, 2020).

Surveys offer a well-suited tool to study migration but can be prone to sampling and measurement errors. Especially the sampling of migrants is challenged by the unavailability of appropriate sampling frames, difficulties in identifying and tracing migrants, and issues with choosing an appropriate sample size to cover a sufficiently large number of migrants as *rare elements* in the population (Bilsborrow, 2016; Reichel and Morales, 2017). On the other hand, micro-level surveys can provide data on a wide range of variables related to the migration process, including detailed information on the determinants, circumstances, and consequences of migration. They are typically carried out either in the destination area using retrospective questions about past movements, or in the origin area by collecting indirect information about migrants from household members or other proxy respondents, such as neighbors.

Both forms of data collection can be prone to certain biases (Bilsborrow et al., 2012). Retrospective questions may only deliver imprecise information about the migration drivers and circumstances when the migration occurred, especially if the migration has occurred far back in time and if a person or household has migrated not only once but several times in a given time period. Using indirect information about absent household members in origin areas can equally suffer from inaccuracies, if respondents cannot recall the migration process well or if there is confusion of who is a member of the household and who is not. Also, if it is not an individual, but an entire household who migrated, then there is often no one left to reliably report on the household's situation before departure, the migration drivers, and the household's whereabouts. This represents an inherent limitation of all migration research carried out only in areas of origin, which may lead to an underrepresentation and undercounting of migrants in the sample (Bilsborrow, 2016).

Temporal aspects and timing play an important role for migration, but are particularly hard to grasp. They can be studied using longitudinal forms of data, which can also help overcoming some of the challenges associated with retrospective and indirect forms of data collection outlined above (Duncan and Kalton, 1987; Rindfuss et al., 2007). However, the collection of longitudinal panel or time series data typically requires considerable time and effort, especially if it involves the tracking of migrants in a larger country or internationally. The dearth of data makes it difficult to capture linked migration moves and trajectories, and to effectively compare the outcomes of the migration process to the conditions faced by individuals and households prior to the migration. Despite these difficulties, longitudinal data offer a range of important advantages, especially for the study of climate migration. With information over several periods, researchers can assess how environmental conditions change over time, how they affect household characteristics, and ultimately the decision to migrate or not. Also, the timing of migration as well as seasonality effects can be better understood. Attrition represents an inherent challenge in longitudinal data, but can be reduced through careful tracing efforts (Thomas et al., 2001, 2012). If researchers have no resources for a primary data collection, they can revert to various sources of secondary longitudinal data from several countries providing detailed information on migration drivers,

processes and consequences (see Section 4.1).

A key issue in climate migration research is the identification of suitable comparison groups that allow studying the role climatic factors play for human mobility. This is particularly challenging if information on migration was collected retrospectively, making it difficult to connect the provided information about the migration to the situation in origin areas of both migrants and non-migrants prior to the migration. In this case, data should ideally contain information from a sample of migrants and non-migrants, which can be used to make comparisons about the conditions faced by the groups. This requires a coordinated, multi-location/country study, covering both areas of origin and destination (Bilsborrow, 2016). The groups can then be compared through means of matching, difference-in-difference estimation, and multivariate modelling. Also here, longitudinal data provides useful advantages as they allow studying changes in the climatic conditions, migration, and the consequences over time. Here, migrants and non-migrants can effectively serve as their own comparison groups by observing changes in their characteristics and behaviors over time prior and after a climatic event (see Section 3.4).

Abstracting from the micro level, macro studies capture migration at a more aggregated level, typically considering migration rates or counts between regions or countries. Also this approach comes with certain limitations that are important for the interpretation of the results (Cattaneo et al., 2019). Special difficulties arise when it comes to measuring international migration. Currently available data sources, such as the World Bank Global Bilateral Migration Database or the OECD Migration Database (supplement Table S2), are based on migration stock data as opposed to flows, although this is the concept researchers are most commonly interested in. Also, most international migration measures heavily rely on administrative sources, which can be prone to reporting and measurement biases, potentially missing undocumented forms of migration. By not considering internal migration patterns, studies focusing exclusively on international migration may also not accurately capture the full scope of climate migration and displacement in an area. Measuring urbanization at the national level, which is often used as a proxy for internal migration, comes with further specific challenges, which have been discussed elsewhere (Henderson et al., 2017; Storeygard et al., 2014).

3.2. Conceptualizing and representing climatic events and hazards

Climate data products that researchers typically use come with advantages and disadvantages (for a detailed discussion see Auffhammer et al. 2013; Dell et al. 2014). Weather station data, for example, can be affected by the entry and exit of stations. Also, lower-income and sparsely populated regions have far fewer weather stations and less continuous high quality data. Gridded data, which are based on interpolations between weather stations, offer an alternative, but also suffer from the unequal distribution of stations across the globe and measurements may differ depending on the interpolation approach used. Data assimilation methods, producing reanalysis data, are another way to address missing observations. This approach combines observational data from weather stations and remote sensing with a physics-based model. Reanalysis data allows tackling the endogeneity problem resulting from the station placement as well as issues with variations in data quality producing a consistent best estimate of atmospheric parameters over time and space (Auffhammer et al., 2013; Donaldson and Storeygard, 2016). Researchers are advised to consult different sources of climatic data and to conduct robustness checks, which can help identifying and mitigating data problems.

In many cases, what constitutes a climatic hazard needs to take local conditions and potential inter-dependencies into account. When modeling climatic events, we often operate with broad categories and averages lacking information about how a particular change has affected local livelihoods (Dinar et al., 2008; Karl and Easterling, 1999). As our meta-analyses show, climatic influences are not independent, but may be correlated with each other. Models are commonly specified by either accounting only for one or few factors, or by including the broadest possible range of climatic factors in kitchen sink models. If correlated climatic variables are not simultaneously considered, this may lead to omitted variable biases (Auffhammer et al. 2013; Berlemann and Steinhardt 2017; Hsiang 2016). On the other hand, including a broad range of variables capturing the same type of climatic hazard or event may come at the cost of losing interpretive value of the models.

A streetlight effect is visible in the selection of climatic indicators. Given the data availability, researchers most commonly analyze the impacts of temperature and precipitation changes and to a lesser extent those of sudden events or gradual deterioration caused by desertification, land degradation, or sea level rise. We recommend a refined approach, which focusses on the accurate representation of climatic events of relevance for the respective context and which takes interdependencies between different climatic influences into account, without over-specifying the model. Given recent data advances (see section 4.1) researchers can now choose from a wide array of environmental and climate data products.

Climatic impacts are highly non-linear and context-dependent (Bohra-Mishra et al., 2014; Burke et al., 2015a; Lenton et al., 2008; McLeman, 2017). Their marginal effect on livelihoods and ultimately migration depends to a large extent on the climatic conditions in a region, the respective season as well as other contextual factors (see section 3.5). Climatic factors often become relevant only once their impact exceeds a certain threshold beyond which a system can no longer sustain or adapt. For instance, M2 finds that extreme rather than moderate changes in temperature and precipitation are linked to migration. However, it has not yet been well conceptualized under which conditions and impact levels households decide to migrate. Also, current studies in the field are often focused on modelling the impact of a singular climatic factor over time, such as an idiosyncratic shock, but do not consider the impact of the accumulation of shocks over time (both climatic and non-climatic) and how these affect households and migration decisions.

Researchers have also emphasized the role of perceptions in understanding climate-related migration (Koubi et al., 2016a, 2016b). The use of objective and subjective measures may produce very different results and may strongly be influenced by cultural contexts and local perceptions (Bertrand and Mullainathan, 2001). For illustration, M2 shows that using self-reported climatic data produces systematically different evidence on climate migration compared to when more objective data is applied. Such potential differences between measured and perceived changes have further been documented, among others, by Shukla et al. (2019), Brüssow et al. (2019), and De Longueville et al. (2020) in different social and geographic settings. The link between measured changes in weather and climate, perceptions of these processes, and migration is an important area for further research. Psychological drivers – such as fear – can also be potent factors in determining whether people move, which has not been fully captured in previous empirical research on climate migration (Collmann et al., 2016).

3.3. Data integration and aggregation

Given the increasing availability of climatic and migration data from various sources, the question of how to best integrate and combine different types of data is of increasing importance (Devogele et al., 1998). In a first step, researchers have to decide how narrow they want to define the spatial measurement frame. The available spatial scale of migration data, which is often defined by political or other arbitrary boundaries, such as census tracts, may not correspond to the scale of the climate variables (Fussell et al., 2014b). Researchers thus have to choose how to best aggregate differently scaled data to find a common denominator for the analysis. This so called “modifiable areal unit problem” has important implications for the analysis and may be a source of statistical bias in the estimation of climatic impacts on migration. For

example, the calculation of summary values, such as migration rates or the total number of households affected by a climatic event, can be influenced by both the shape and scale of the spatial aggregation unit (Montello, 2015).

The spatial frame also plays a role for the question of how far reaching climatic impacts are across locations. For example, a climate-induced conflict may spill-over to neighboring regions influencing areas that have not been directly, but only indirectly affected by the climatic hazard. A broader scaling in the climatic measure may thus result in differently estimated effects. It is recommendable to explore different spatial scales and to document how these affect the analytical outcomes, as such differences may matter for the interpretation of the results. Spatial models, which take influences of neighboring regions into account, offer a possibility to directly test for indirect influences (Saldaña-Zorrilla and Sandberg, 2009). However, these models are rarely used in the empirical climate migration literature.

The temporal dimension is critical for climate migration research. Besides choosing the right spatial aggregation approach, researchers have to make choices about how to measure and model temporal processes in their analysis. Understanding what role time plays for migration decisions requires high-frequency longitudinal data, which either might not be available or may only provide restricted information about migrants. Retrospective data offers an alternative, but is limited in the extent of information available and prone to measurement errors. Despite these challenges, considering the role of time is important as it might largely affect the way climatic hazards influence migration. With few exceptions (Fussell, 2012; Kleemans, 2015) there is little conceptual and empirical work that explicitly considers temporal aspects of climate migration, including those that affect household decision making, such as strategic waiting or inertia.

Climatic shocks may only have an impact on migration after a certain period, requiring researchers to consider temporal lags in their models. Distinguishing by seasons is another important factor as climate and weather variations may only play a role at certain points in time, for instance during the harvesting season. Broader time frames (e.g., 5 or 10 years compared to 1 year) allow to capture climate migration at a more coarse temporal scale accounting for adaptation, but may miss important (seasonal) dynamics and circular migration patterns. Like with the spatial dimension, the aggregation chosen to model influences over time should be inspired by the local context and the research questions at hand. Additional checks using different conceptualizations and specifications, e.g., by choosing a different measurement timeframe or by including additional lags in the models, can help to identify interesting patterns that would have not been visible otherwise.

Commonly, the distinction is made between micro studies, using survey or small-scale administrative data, and macro studies conducted at a more aggregated level, analyzing migration between regions or countries. Depending on the particular research question, both micro and macro approaches have advantages and disadvantages. A higher level of aggregation may allow to capture general patterns of relationships and to effectively compare different contexts with each other. Yet, it may come at the loss of contextualization, for example, in the measurement of climatic influences. Whereas macro-level studies have to choose more generic approaches in their modeling, micro-level studies can more accurately represent influences of relevance for local contexts. In some cases, on the other hand, it is better to aggregate up, for example if data quality is low or not representative for lower levels of spatial aggregation. Importantly, the questions discussed above of how to best aggregate over spatial and temporal scales affect micro and macro studies alike. In both cases, researchers should clearly define how and why they chose certain spatial and temporal scales and conduct robustness checks to test for the reliability of their findings.

Many new data sources, such as IPUMS Terra, offer researchers ready-made, integrated solutions, providing both climatic and migration data in one source. While this development has clearly made the study of the climate-migration relationship easier, it comes with the risk of not critically reflecting and questioning the provided climatic data. Interdependencies and the accumulation of uncertainties and measurement errors is also often not properly taken into account in the modelling and there is limited knowledge how these uncertainties may affect the estimation. The wide range of data sources and complexity of the measures makes inter- and cross-disciplinary collaborations more relevant. Despite their importance, disciplinary boundaries prevail in the climate migration field and collaboration across disciplines is rather the exception than the rule, as also our meta-analyses show (see also Heberlein, 1988; Lowe, Phillipson, & Wilkinson, 2013).

3.4. Modeling and the identification of causal effects

There are different analytical approaches to estimate the causal impact of climatic events and changes on migration. Since climatic variables are exogenously determined in the short run, reverse causality is typically not an issue, even in cross-sectional analyses. However, cross-sectional analyses may suffer from omitted variable bias. This bias arises if a variable, which is correlated with both the climate signal and migration, is omitted from the model, which then attributes the effect of the missing variable to the ones included. For example, characteristics of a region, such as its location or topography, may influence both its climate and observable migration patterns (Auffhammer, 2018; Burke and Emerick, 2016; Dell et al., 2014). To address omitted variable issues, it is recommendable to use longitudinal panel data analysis and to control for unobserved heterogeneity through the use of fixed effects (Cai et al., 2016; Chen and Mueller, 2018). Under certain assumptions, this allows for a causal interpretation of the model response coefficients.

A variety of further issues related to the specification of models can result in biased estimates. First, because climatic events are correlated, the estimated effects might plausibly pick up the effect of other not-included, but correlated climatic events, which would result in an omitted variable bias (Auffhammer et al., 2013). At the same time, controlling for a broad range of factors measuring the same climatic concepts could reduce the interpretive value of the models as suggested in section 3.2. We recommend an accurate, context-specific modelling of climatic events, which accounts for interdependencies between different climatic influences, without over-specifying the model. A good starting point is to compare how effects differ when climatic variables are included separately and simultaneously in the model to understand the extent of their correlation and how they affect the model results.

A second essential specification issue, which can be commonly found in the literature, is the inclusion of potentially mediating control variables in models. These variables are themselves influenced by the climatic event and have at the same time a causal impact on migration. For example, economic or sociopolitical variables such as income, conflict, or institutional quality are likely to be influenced by climatic conditions and affect migration. If a model controls for these factors, it would no longer estimate the relevant total climatic impact on migration, but only the partial impact net of the effect that runs through the controlled mediating channel (Burke et al., 2015b; Berlemann and Steinhardt, 2017). This is referred to as “over-controlling” (Dell et al., 2014) or “bad control” problem (Angrist and Pischke, 2008). While having some models control for mediating factors can provide important information about mechanisms and channels at work (section 3.5), such models do not allow deriving conclusions about the total climatic effect on migration. Here, we encourage authors to choose controls depending on the specific research question in focus and to exclude problematic controls, such as income, from the analysis. It is recommendable to always present one well-specified parsimonious model, i.e., a model, which focuses primarily on the causal estimation of the respective climatic impacts, as a baseline for model comparisons (Berlemann and Steinhardt, 2017). This also facilitates the synthesizing of coefficients across models in future meta-analyses.

Spatial and temporal autocorrelation are of high relevance for modelling and not accounting for the correlation of climatic and other

variables might produce biased error estimates (Auffhammer et al., 2013). Generally, there are four ways to address autocorrelation: i) application of spatial weights, which is an efficient approach if the weighting matrix is known (Saldaña-Zorrilla and Sandberg, 2009); ii) application of clustered standard errors that allow for spatial and temporal correlation within the clusters, or application of clustering that allows the correlation to decrease with spatial or temporal distance (Conley, 1999); iii) usage of a grouped bootstrapping method where years are resampled and replaced (Auffhammer et al., 2013), and iv) spatial models, which explicitly model spatial interdependencies (Angrist and Pischke, 2008; Wooldridge, 2007).

A final question is to what extent model findings are generalizable and can be used for projections. Typically estimates are derived from observations of short-term weather variations rather than long-term changes and are thus not necessarily representative for population responses to a changing climate in the longer run, e.g., due to possible adaptation. Derived conclusions hence only have limited temporal external validity. Another issue are the highly non-linear dynamics of climate change, which could significantly alter migration patterns. For example, non-analogue events, such as the complete melting of the glaciers in the Andes, are without precedent in human civilization and existing studies can therefore not fully capture their effect on migration (Bergmann et al., 2021).

Recently, new approaches were developed to consider the impacts of longer-term changes on migration, such as the "long-differences" (Hsiang, 2016), "Ricardo meets panels" (Auffhammer, 2018) or the "partitioning variation" methods (Bento et al., 2020; Kolstad and Moore, 2020), addressing shortcomings of both cross-sectional and panel data analyses. The "long-differences" approach utilizes changes in long-run averages of the outcome and climate variable at two points in time at a given location to estimate the long-run effect of a changing climate. The "Ricardo meets panels" approach studies how short-run responses to weather events derived from a panel analysis change as a function of a long-run change in climatic conditions (Ricardian approach). New applications of the "partitioning variation" method consider both long- and short-term variations in the climatic conditions enabling an estimation of both long- and short-run effects in a panel setting. These methods have thus-far only been used to a limited extent in the climate migration literature, but offer a promising way forward in the estimation of climatic impacts on migration. They require long time-series of both climatic and migration variables which get increasingly available with new data products (see Section 4.1).

3.5. *Exploring mechanisms and context effects*

The growing consensus among researchers is that climatic events indeed affect human migration, yet the prevailing questions are under which circumstances, how and why (Cattaneo et al., 2019). Understanding what the contextual factors and mechanisms of influence are is especially critical for policy interventions aimed at protecting vulnerable populations.

There is an increasing acknowledgment that the character of climate migration is strongly determined by contextual factors, such as the political or socioeconomic conditions in a region, which affect households' access to alternative in-situ adaptation options, resources to bear the costs of migration, and the existence of migration networks (Black et al., 2011). At the macro-level, studies have, for example, empirically shown how income and agricultural dependence shape the relationships (Cai et al., 2016; Marchiori et al., 2017, 2012). At the micro-level, the existing literature has highlighted the role of gender, (agricultural) income, networks and age as important factors (Mueller et al., 2020; Šedová and Kalkuhl, 2020; Chen and Mueller, 2018).

There are several empirical approaches that researchers can apply to analyze heterogeneities and differential responses to climatic events. Studies can draw on interaction or sub-sample analyses to understand how climatic effects differ conditional on socioeconomic and political conditions. These approaches allow to test for heterogeneous implications of climatic events for different sub-groups in a population. For example, Cattaneo and Peri (2016) employ interaction terms and subsamples to analyze the effect of warming trends across countries on the probability of migrating in dependence of wealth. Their study shows the presence of stricter liquidity constraints for poorer economies inhibiting migration as an adaptation strategy to climatic changes.

Moreover, there are different mechanisms at play determining whether or not climatic impacts result in migration, for instance of an economic (e.g., income differentials between origin and destination) or a socio-political character (e.g., conflicts). As noted in the previous section, extending a baseline model by adding further mediating factors provides an indirect way to study the role of different mechanisms in a mediation analysis (MacKinnon et al., 2007). If an included factor actually represents a mechanism explaining the relationship between a climatic event and migration, then we would expect the estimated model coefficients of the climatic variable to change in a model that controls for the mediator compared to a baseline model that does not. The larger the difference between the coefficients, the more important the mediating factor (Hoffmann and Lutz, 2019; Hoffmann and Muttarak, 2017). Researchers can test for the strength of mediation using the Durbin-Wu-Hausman-Test (Hausman, 1978) or the KHB method for the comparison of linear and non-linear model coefficients (Breen et al., 2013).

Instrumental variable methods are another commonly used approach to examine underlying mechanisms explaining climatic effects on migration (e.g., Marchiori et al., 2017, 2012). Here, the focus is on obtaining unbiased estimates of the effects of a mediating channel, such as agricultural income, on migration. Climatic events are used as (plausibly) exogenous variables, so called instruments, to predict the mediators in a first stage to obtain an unbiased estimate of the effect of the mediating channel in a second stage. The method has strong assumptions. First, it is required that the instrument is strongly correlated with the mediator (relevance) and second, it should not influence the migration outcome through any other channel than the considered mediator (exclusion restriction). As pointed out by Burke et al. (2015b) and Koubi (2019), especially the exclusion restriction can be easily violated as there is typically more than one channel through which climatic events affect migration. Therefore, we generally recommend to only use this approach if researchers can plausibly argue that climatic variables affect migration only via their effect on the instrumented mediating variable.

The existing literature emphasizes the important role of different mechanisms for climate migration, such as the (agricultural) income channel (Cai et al., 2016; Chen and Mueller, 2018; Gray and Mueller, 2012). Likewise, urbanization and internal migration due to climatic stress can result in increased pressures on the labor market at the destination and trigger further outmigration, which can result in migration cascades (Marchiori et al., 2017, 2012; Maurel and Tuccio, 2016). Also, conflicts can play an important role and more research is needed to understand their implications for climate-related mobility. For example, climatic changes can contribute to conflict under certain conditions and conflicts can exacerbate climatic effects on migration (Abel et al., 2019; Burke et al., 2015b; Cattaneo and Bosetti, 2017; Ghimire et al., 2015; Hsiang et al., 2013). Impacts on health and productivity may further contribute to higher outmigration from a region, especially if the impacts constitute an existential threat (Deschênes and Greenstone, 2011; Dimitrova et al., 2020; Zivin and Neidell, 2013; Burgess et al., 2017).

4. Advances in research and modeling

In recent years, there has been a number of methodological advances in the climate migration field, providing researchers with new data, measures, and analytical methods. These allow to address some of the challenges outlined in the previous section and to contribute to a further advancement of the field.

4.1. Data and measurement

First, more detailed, georeferenced micro-level migration data over longer time horizons have become available. To adequately assess climate-related migration, high time and spatial resolution are needed. Large-scale geo-referenced survey data, such as the Demographic and Health Surveys (DHS), the Multiple Indicator Cluster Surveys (MICS), and different Labor Force Surveys (LFS) have started collecting data on migration, providing comparative and longitudinal data for a large number of countries worldwide. In addition, numerous countries now carry out large-scale panel surveys with detailed information on migration, which can be combined with climatic data. Examples include the Indonesian Family Life Survey (IFLS), the China Family Panel Study, the Tanzanian National Panel Study, the Brazil National Household Sample Survey, the Peru National Household Survey (ENAHO) and the Mexican Family Life Survey (MFLS). Increased attention is also devoted to tracking and re-interviewing migrants, for example in the IFLS and the MFLS.

Migration data are increasingly comparable thanks to global data collection and harmonization efforts. Censuses are an important source of information for migration modelling. IPUMS International provides researchers with a unique collection of censuses and surveys, offering harmonized information across various countries. For example, the IPUMS microdata was used to model internal migration flows (Garcia et al., 2015) or to determine migration intensities in different parts of the world (Bell et al., 2015; Bell and Muhidin, 2009). Further internal migration data at a high resolution can be retrieved from the census-based Global Estimated Net Migration Grids By Decade Database (de Sherbinin et al., 2015), which provides estimated net-migration flows per 1 km^2 grid cell, or from the Gridded Population of the World (GPW) database (CIESIN, 2016). Comparable international migration data are now available for a wide range of countries, e.g., in the World Bank Global Bilateral Migration Database. In addition, projects such as the Migrations between Africa and Europe Project (https://mafeproject.site.ined.fr/en/) or the Latin American Migration Project (https://lamp.opr.princeton.edu/) have collected data on international migration connecting information from origin and destination areas.

New forms of migration data provide novel insights. Efforts have been undertaken to collect migration data using digital technologies, machine learning, and big data. In particular, digital trace data has become a fruitful source for migration researchers in the past years with a large untapped potential for climate migration research (Sîrbu et al. 2020; Stier et al. 2019; see IOM Data Innovation Directory for a comprehensive overview, https://migrationdataportal.org/data-innovation). Digital traces are records of activity, which can be collected from a multitude of technical systems and communication devices, such as websites, search engines, social media platforms, smartphone apps, or sensors (Böhme et al., 2020; Cesare et al., 2018; Stier et al., 2019). Anonymized cellphone data, for example, have successfully been used in different contexts to identify migrants and to learn about their trajectories and destinations (Bengtsson et al., 2011; Lu et al., 2016b). At the same time, social media, such as Facebook or Twitter, provide innovative ways to learn about migration pathways and the profiles of migrants (see e.g., Blumenstock 2012; Chi et al. 2020; Spyratos et al. 2019; Zagheni et al. 2014). They also offer a range of useful complementary information that can be accessed via text mining and content analytical tools. Posts on Facebook or Tweets, for example, can provide information about the emotional well-being of migrants (Guntuku et al., 2019; Park et al., 2015) and thus serve as an indicator for migration outcomes.

Climate data are also increasingly available and accessible. Data about the earth's climate, local anomalies and extremes, and disasters are now gathered at an increasing rate facilitating the conceptualization and representation of climatic events (see supplement C Table S2 for a comprehensive overview of data sources). Numerous platforms make data publicly available and accessible for researchers and other stakeholders, including policy-makers and businesses. The EU Copernicus Climate Data Store (https://cds.climate.copernicus.eu/#!/home), for example, provides an overview of a range of available climate data sources; and the NASA's Application for Extracting and Exploring Analysis Ready Samples (AppEEARS) platform provides users a simple way to perform data access and transformation processes, including the download of relevant data for pre-defined geo locations (https://lpdaac.usgs.gov/tools/appeears/). Ready-made and easily usable data products are provided by the Climatic Research Unit of the University of East Anglia (Harris et al., 2020) or the ERA5 reanalysis group (Hersbach et al., 2020). Thanks to the increased availability of georeferenced locations (e.g., through GPS, spatial polygons, or administrative regions) in social science and population data, the integration of climatic data has become increasingly feasible along spatial and temporal scales.

Also, information on locally relevant climatic impacts is increasingly becoming available. The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) developed by the Potsdam Institute for Climate Impact Research (PIK) and the International Institute for Applied Systems Analysis (IIASA) explicitly models climatic impacts across affected sectors and spatial scales (Warszawski et al., 2014). Beyond historical impacts, ISIMIP provides a consistent picture under different future climatechange scenarios. It also has potential for climate migration research, yet thus far it has only been applied to a limited extent, e.g., in the Groundswell Report (Rigaud et al., 2018). Accessible platforms, such as IIASA's Global Hotspots Explorer (https://hotspots-explorer.org/) or PIK's Climate Impacts Online (https://www.climateimpactsonline.com/) illustrate for a broad audience the potential of climate impacts under different scenarios.

Better climate and migration data can certainly improve our understanding of migratory movements. Yet, they come with various ethical challenges. The collection and analysis of certain forms of migration data, such as digital trace data, for example, can have problematic implications for data protection and privacy (Bengtsson et al., 2011; Lu et al., 2016a). While researchers call for better data, it has to be considered that misuse such as the personalized monitoring or the persecution of certain groups could ensue. Therefore, a carefully balanced approach between the protection of privacy and the advancements of data collection is required.

4.2. Analytical methods and modeling

An increasing number of studies use longitudinal empirical approaches in their analyses controlling for unobserved heterogeneity and common time trends via fixed effects (Dell et al., 2014). The availability of longer panels and time series allows for a better approximation of long-term climate change impacts, which only manifest over decades. A stronger focus on space in modeling, for example, in form of spatial models that explicitly account for spatial inter-dependencies, could be a fruitful direction for further empirical research. Machine learning is another approach, which could provide useful insights in data-heavy applications for which more traditional statistical approaches might not be suitable, such as medium- to long-term forecasts of climate migration trends (see Schutte et al., 2021).

Better modelling can help improve future migration projections. Typically, to derive end-of-century, out-of-sample projections, researchers combine estimated coefficients of climatic variables on migration with future climate predictions. Currently, the best practices to estimate climatic responses are those, which focus on long-run, causal climate change impacts and take adaptation processes into account. Nevertheless, also these methods do not overcome the issue that response coefficients are derived from historical climatic changes that are smaller in magnitudes compared to expected future changes and thus the responses might be understated. At the same time, if unprecedented adaptation takes place in the future, these predictions might overstate the effects.

An important element of recent projection exercises is the attribution

of currently observed changes to long-term trends to derive predictions about how environmental conditions will change with global warming in the future (Otto, 2017; Stott et al., 2016). Taken together, the goal is to combine knowledge about currently observed responses to climatic extremes with different scenarios for future climate change (van Vuuren et al., 2011) and socio-economic development (O'Neill et al., 2014, 2017). In the application there are data-related challenges. For climate projections, researchers typically employ data from one of the spatially explicit physics-based models of the global climate referred to as General Circulation Models (GCMs). However, the choice of a GCM significantly affects the estimated future impacts, since for some of the indicators (e.g., precipitation), predictions vary heavily across models (Christensen et al., 2013). Thus, it is recommended either i) to average the impacts across models and indicate their variability, or ii) to report outcomes for a number of models. Another issue related to the use of GCMs is the geographical and/or temporal aggregation bias, which affects the estimations of future impacts. There are several ways how to address and minimize these aggregation biases, which vary on case to case basis (for a detailed discussion, see Auffhammer et al. (2013), or Fowler, Blenkinsop, and Tebaldi (2007).

Gaining a better understanding about how individuals, households, and communities respond to climate variability is important to translate empirical findings into projections (Gemenne, 2011). Here, also further theoretical and conceptual contributions are needed to extend our theoretical knowledge on the topic. Increasingly, migration models explicitly take climatic factors into account when modeling migration decisions (Barrios et al., 2006; Marchiori et al., 2012). Micro-founded simulations, such as agent-based models, offer possibilities to analyze complex decision-making processes and to study how migration may change in the future under different scenarios. These approaches also increasingly include climatic factors as a migration driver (Entwisle et al., 2016; Hassani-Mahmooei and Parris, 2012; Klabunde and Willekens, 2016). A stronger integration of the different perspectives and approaches across disciplines could prove very beneficial for the development of the climate migration field in the future.

5. Conclusions

Based on two recent meta-analyses, this paper systematically reviews methodological approaches used in the quantitative climate migration literature, outlines major challenges, and discusses possible solutions how to address them. As we show, methodological choices can have far-reaching implications: Issues related to the conceptualization and measurement of key indicators, the integration and aggregation of data, and the modeling of relationships can play an important role. Complementing previous studies, we provide a comprehensive overview of the literature covering 127 micro and macro studies estimating 4962 separable coefficients of the climate-migration relationship, providing novel insights on how different concepts, research designs, and analytical methods shape our understanding of climate migration.

While our meta-analysis approach has certain strengths, it also comes with weaknesses which are important for the interpretation of our results. Meta-analyses provide a powerful tool to synthesize large amounts of evidence and to analyze underlying mechanisms. At the same time, they can only provide a descriptive overview of existing research, leaving some uncertainty about the usefulness of considered approaches in different settings. Meta-analyses and related systematic reviews like ours also come with a degree of abstraction necessary to harmonize results and to make them comparable across studies. As highlighted above, methodological choices should always be informed and guided by the research questions and the local study context. Here, we conclude with three central recommendations for future research.

First, future quantitative studies of climate migration should strive to draw on climatic and migration data and fit models that reflect and are of relevance for the situation on the ground. This entails considerations of relevant climatic impacts and corresponding migration forms, and their correct representation with respect to functional forms, or temporal and geographical scales. Available data sources and their advantages and disadvantages should be thoroughly considered and the choice should be determined by their quality and the research questions at hand. Ideally, researchers should draw on different climatic and migration data to verify the derived conclusions. Innovative approaches, e.g., the use of digital trace data or machine learning, are a promising way forward, for instance in contexts when conventional data is not available, e.g., for analyzing undocumented or short-distance migration.

Second, whenever possible, researchers should employ longitudinal models controlling for spatial heterogeneity and time trends to allow for a causal interpretation of climatic impacts. Uncertainty estimates, such as standard errors, should be adjusted to account for spatial and temporal clustering and auto-correlation. With improved data availability and longer time series, the observation and analysis of long-term climatic changes becomes possible. The presented "long difference", "Ricardo meets panels" or "partitioning variation" approaches produce response coefficients, which allow for a causal interpretation of long-run climatic changes, also accounting for adaptation. The results of these models can be effectively employed for projections using future climate and socio-economic scenarios.

Third, while considering all of the above, future studies on climate migration should employ parsimonious and comparable models capturing total climatic impacts on migration without over-controlling for mediating factors. This would also facilitate future meta-analyses on the topic aimed at quantifying total climatic impacts on migration, such as the impact of increasing temperature levels. Such evidence is not only important to accurately assess the magnitude of climate migration in different parts of the world, it can also inform future projections and migration scenarios under climate change improving our abilities to respond to and mitigate related adverse consequences for affected populations. In this regard, adequate and complete documentation of all research steps and methodological choices is key to ensure full reproducability and transparency of the results.

By providing a comrehensive overview of approaches and tools available in the field, our review has also important implications for policy-makers and practitioners working on climate migration. By highlighting the manifold challenges that exist, we warn users of too simplistic interpretations of findings as well as deterministic conclusions. The relationships underlying the climate-migration nexus are complex and – as our meta-analyses show – driven by a range of contextual factors. There is a need for users to understand the underlying causes of the uncertainty and context-denpendeny of the analyses. As the threats of climate change to local livelihoods are getting increasingly severe, more solution and policy-oriented research is neeeded, involving different stakeholders, including researchers from the Global South and representatives of communities directly affected by climate change. Advancing the field also requires more exchanges bridging disciplines and methodological approaches, including a stronger integration of quantitative and qualitative research. This would not only allow to bring in new perspectives, but also to tap into new opportunities to improve the evidence base on climate migration.

CRediT authorship contribution statement

Roman Hoffmann: Conceptualization, Resources, Software, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing, Visualization. **Barbora Sedova:** Conceptualization, Resources, Software, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing. **Kira Vinke:** Conceptualization, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2021.102367.

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