Dynamic Model of Displacement
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Introduction

Displacement is as old as history itself. From the expulsion of Adam and Eve to the flights of Moses, Jesus and Mohammed, the Judeo-Christian-Muslim religious tradition is replete with examples of displacement. Other religions are founded on similar examples of flight. In recent years, the global population of people forcibly displaced by conflict and persecution has reached levels unprecedented since World War II, reaching a recorded high of 80 million in mid 2020 (UNHCR, 2019). This total number masks variations in displacement. About 26 million persons are refugees or in refugee-like situations, having crossed an international border to escape the effects of conflict, persecution and repression. Most are under the direct mandate of the UN High Commissioner for Refugees. The number includes, however, more than five million Palestinian refugees under the mandate of the UN Relief and Works Administration for Refugees from Palestine who live in Jordan, Lebanon, Syria, or the West Bank and Gaza. The largest number—some 45.7 million—were internally displaced persons (IDPs) who had fled within their home countries from the same factors that cause refugees to flee. And, about 4.2 million were asylum seekers who have not yet been granted refugee status (all statistics are from UNHCR, 2021).

Displaced persons are not evenly distributed throughout the world. Two-thirds of refugees and internationally displaced persons are from five countries—Syria, Venezuela, Afghanistan, South Sudan, and Myanmar (UNHCR, 2021). Overall, about 85 percent of refugees and displaced persons were in low- and mid-income countries, with the vast majority of these living in neighboring countries to their own. The vast majority of IDPs are also in developing countries. The top five destination countries for refugees are Turkey, Colombia, Pakistan, Uganda and Germany; only Germany is a high income country. The majority of refugees are living in urban areas, especially in poorer slums, but camps are still the fate of millions of other refugees and internally displaced persons.

Conflict and repression are not the only contexts in which displacement takes place. Large-scale movement also occurs in the context of acute natural hazards. The number of new disaster-displaced IDPs averaged 24 million each year from 2008 to 2018 (IDMC, 2019). East Asia had the largest number of new disaster displacements since 2008 and the middle East the smallest (IDMC, 2019). Floods and storms accounted for the largest numbers of IDPs (IDMC, 2019). In many cases, both human-made and natural factors are the context in which large-scale displacement takes place, as witnessed by recurrent famines in Somalia caused by the confluence of drought, conflict, and political instability that impede access to food relief. Climate change, which is expected to increase the frequency and severity of acute natural disasters as well as produce slow onset effects such as increased drought and rising sea levels, is likely to be a contributing factor to still more displacement in the years ahead.

In recent decades, early warning systems alert the international community as well as national and local actors of impending humanitarian crises. Tsunami and famine early warning systems

monitor and analyze data relevant in anticipating acute and slow onset crises, respectively, relying on scientific, technological, economic, social and other indicators (See FEWS Net (2021) and NOAA National Tsunami Warning Center (2021)). Predicting crises in other domains, such as conflict and violence, has proven more difficult but organizations such as ACLED, the Armed Conflict Location and Event Dataset (2021), provide essential information by coding the actions of rebels, governments, and militias within unstable states, specifying the exact location and date of battle events, transfers of military control, headquarter establishment, civilian violence, and rioting.

Forecasting displacement during these situations, particularly when a complex mix of drivers are at work, as seen in places facing prolonged drought and conflict, has proven more elusive. A number of problems must be solved to improve early warning, particularly as they apply to displacement: 1) identifying and collecting masses of timely, reliable data on the complex factors that affect flight; 2) developing analytic capability to discover indicators of movement—specifically, leading indicators that displacement will occur rather than trailing indicators that confirm that movement has already taken place; 3) instituting mechanisms to allow policymakers and practitioners to test out scenarios to determine if actions will have positive or negative consequences in averting displacement or providing better assistance and protection; and 4) building the political will to act on the warnings. New technologies and analytic tools make it more likely that the first three problems can be tackled. The fourth problem is, of course, more difficult to solve but more effective early warning tools might challenge political leaders to act, at least in implementing more timely emergency relief operations.

This paper focuses on an important pre-condition for effective forecasting—a theoretical model that captures the full range of drivers that are implicated in decisions to move from one location to another. The paper first reviews the academic literature on the drivers of displacement. It also discusses the corollary of displacement—immobility that may be forced or voluntary. The heart of the article is the model of displacement that we have developed. We describe the process through which we developed the model and then explain its components. We conclude with a discussion of potential approaches that could be used to test the model.

Literature Review: Existing Causal Models of Displacement

The earliest causal models of migration tended to focus on voluntary movements. They assumed that there were ‘push’ and ‘pull’ factors that determined whether people migrate. The push factors were largely economic (in the case of men) and social/marital (in the case of women); similarly, the pull factors related to economic and social opportunities in the destination country. Faced with these people decided whether to migrate based on a rational assessment of the costs and benefits to themselves and their families. In economic terms, this often meant evaluating differences in earning potential in source and destination countries. In social terms, the networks that facilitate movement often determine where people go. This framework is decidedly simple in its approach but remains one of the most manageable ways to explain why people move from one location to another.

Theories about the causes of displacement were much less developed. Generally, they focused on push factors such as conflict and persecution, with little attention to or consideration of what

might pull someone to a specific location even in the context of such driving forces. Whereas, the migrant in these frameworks has considerable agency with regard to the decision to migrate, the displaced person has little choice but to leave home. In extreme cases, the displaced person is expelled, trafficked or otherwise forced to relocate.

A surge of research in the early 1990's led to some of the first attempts to go beyond simple push and pulls and understand how the drivers of population movement relate to one another (Massey et al, 1994). In a review synthesizing literature on the causes of economic migration, Massey and colleagues illuminate how differences in markets and earning potential are only one piece of the calculation made by families when deciding whether to move. Movement can be explained as a risk mitigation strategy rather than just a reaction to current disparities. Families move in response to *expected variability* in earning potential, and relative deprivation. Households leave or send family members away to diversify their family income in the face of uncertainty about their livelihoods, especially when their ability to earn money is dependent on weather patterns (Afifi et al., 2014; Martin et al. 2014; Hunter et al., 2015;). They also move when costs to movement are low, such as when social networks and diasporic connection (Massey et al., 1994; van Hear, 2014) and colonial ties (Moore & Shellman, 2007, provide financial and logistical support at possible destinations. In addition, changes in policy and the hardening of borders (Massey, 2016), as well as geographical barriers (Clark, 1989), affect the nature and flow of migrants. Importantly, these processes occur within a more global context in which segmented labor markets, the demands of globalization and capitalism, growth of metropolises, colonial relationships, demographic shifts, and other such drivers create the environment in which movements take place (Massey et al., 1994).

The push to understand the multi-causality of movement was mirrored in the study of displacement. Early models, pioneered by Schmeidl, focused on comparing structural factors to compare the effect of root causes (1997) and their predictive power in an early warning system (Schmeidl & Jenkins, 1996; Schmeidl & Adelman, 1998). Schmeidl's model focused primarily on structural factors such as the onset of war, oppression, and economic conditions, providing the groundwork for the primacy of violence as a factor in forced migration. Clark (1989) made the additional contribution of contrasting structural factors or root causes, that affect both stayers and movers, and proximate on more immediate causes and intervening factors that may create conditions for certain communities and households that make flight a necessity.

In the early 2000s, scholars sought to disaggregate the factors influencing displacement. Rather than theorizing at the structural level, Moore and colleagues considered how these structural factors influenced individuals making decisions about whether to flee (Moore & Shellman, 2004; Davenport et al., 2003), and where to go (Moore & Shellman, 2006; Moore & Shellman, 2007), for both causal inference and early warning (Rubin & Moore, 2007; Martineau, 2010). Similar to Schmeidl, these studies aggregated theories from the literature to compare the effect of different factors. These models acknowledged that the push factors that might drive a family to leave may be different from the factors that attract them to a particular destination (Moore & Shellman, 2004), also finding that violence threatening an individual's personal integrity at home is of primary importance (Adhikari, 2013; Davenport et al., 2003; Steele, 2009; Balcells & Steele, 2016). Others have found that distance, colonial ties, and level of civil liberties in the destination country are important determinants of preferred destinations (Böcker & Havinga, 1998;

Neumayer, 2004; Robinson et al., 2002; Echevarria & Gardeazabal, 2016). These models further highlighted the importance of temporal effects in predicting forced migration: once movement has started it is more likely to continue, possibly in part because of the diaspora networks that form (Rubin & Moore, 2007).

The literature on the impact of conflict on displacement is particularly relevant to our endeavor as we are attempting to explain variations seen in the movement of refugees and internally displaced persons. Following Schmeidel's pioneering work have been other studies focusing specifically on conflict. Naude (2010) looked more broadly at patterns of international migration in Sub-Saharan Africa and found that violent conflict and GDP growth differentials have the largest impacts on international migration in the region. He concluded that international migration from sub-Saharan Africa is both an adapting and mitigating strategy in the face of conflicts and economic stagnation (Naude, 2010, p.350). Moore and Shellman (2004) find that the magnitude of genocide and politicide significantly increase both the likelihood and magnitude of forced migration. They also suggest that past movements generate new ones either by providing a network that reduces the cost of moving for subsequent persons or by increasing the costs of staying by its disruptive effect on the society from which people flee (2004, p. 132). Melander and Oberg (2007) found that the intensity of armed conflict is not significantly related to the number of forced migrants. Rather they suggest that "the threat perceived by potential forced migrants is more related to where the fighting is taking place, than to the overall intensity of the fighting" (2007, p.157). Salehyan and Gleditsch (2006) find that the probability of violent conflict is more than three times higher in source countries than in receiving ones.

The timing and practicability of flight is a further determinant of whether and how it occurs. Schmeidl and Jenkins (1996) discuss some of the problems of timing where long-term or root causes may occur years before the exodus while medium-term (or proximate) causes may occur only months beforehand. They argue that "[t]riggering events are the most difficult to place. Theoretically, they would occur almost simultaneously with, or only days before, flight but most conventional methods are unable to evaluate the close timing of triggering events" (Schmeidl & Jenkins, 1996, p.6). Clark (1989) identified five intervening factors that may affect refugee outflows, including the existence of alternatives to international flight within the country, obstacles to international flight, expected reception in the asylum countries, patterns of decision-making among potential refugee groups, and seasonal factors.

Displacement also varies by geography and means of transport. Even members of the same household may go to different locations, sometimes because they are separated in flight and sometimes because they want to hedge their bets in the hopes that some will survive. Most displacement is internal, with a smaller number of people crossing borders. The majority of those who do cross borders go to neighboring or other near-by countries; a minority go to distant locations. The decision of where to go is not necessarily by choice—many go only as far as their resources will take them. Those lucky enough to have a choice may be influenced by social networks (e.g., family or friends who might help them); economic or educational opportunities in wealthier countries or urban areas of their own; or, even, what smugglers tell them would be best (Day & White, 2002, Spinks, 2013). This does not mean that those who choose their destinations are any less affected by the conflict, repression or disasters that compel people to leave. It just reflects the complexity of the causal factors at work.

On the whole, these models are significant in disaggregating push and pull factors, and problematizing the decisions made by individuals and families. Many models continued to rely on country-year level data, but others took additional steps to understand individual and family decision by using surveys to compare major economic, geographical, social and violence factors (Adhikari, 2013), exploiting temporal variation in a country to compare the effect of violence, economic conditions, and foreign interventions (Shellman & Stewart, 2007) or within-country variation to explore the effect of minority-majority status (Balcells & Steele, 2016).

While many of these disaggregated models compare causal factors, few problematize how these factors interact with one another in the decision-making process of the individual. Push and pull factors can be substitutable (de Haas, 2011), and many of the factors that may lead some families to flee may be compensated for in other contexts. For example, families with more diverse income sources may be more resilient and able to stay in the face of livelihood destruction than those without (Warner & Afifi, 2014; Hunter et al., 2013). At the same time, they may have more resources that can be devoted to migrating out of harm's way if that is the only option.

While many studies have focused on the individual or household, others have kept an eye on how to model movement at the structural level, such as developing a network model of migration flows between countries (Schon & Johnson, 2021). Highlighting the importance of structural factors, Schon has also shown that although structural factors cannot theoretically determine *when* a family will flee, they often provide greater leverage in explaining variation in movement (Schon, 2015). Combined with (Rubin & Moore, 2007), this suggests that structural and temporal factors are critical in understanding dynamic movement patterns even as we continue to disaggregate individual decisions.

Physics-based models, including gravity models (Beine et al., 2016; Ravenstein, 1885; Ravenstein, 1889; Saldarriaga, 2019; Lozano-Gracia et al., 2010; Rigaud et al., 2018), spatial and change-point models (Schon, 2015), have the potential to integrate both push and pull factors and to test theories that better integrate factors. Early gravity models highlighted the importance of spatial dynamics such as distance (Ravenstein, 1885; Ravenstein, 1889), but have since been adapted to consider other important structural and micro-level conditions, such as economic conditions at the origin and potential destinations (Lozano-Gracia et al., 2010), distance (Lozano-Gracia et al., 2010), the availability of labor, social networks, and political conditions (Fitzgerald, Leblang & Teets, 2014) and impact of climate change on internal migration (Rigaud et al., 2018). While gravity and diffusion gradient models are an effective way to model space, and changepoint models present an effective way to model time, while also linking between structural and micro-level factors, neither provides a framework for considering the iterative decision-making process made by potential migrants, nor do they consider the myriad of possible options available to would-be movers.

Nor do they take into account the psychological or emotional dimension of displacement. What is commonly referred to as dread threat theory (Starr, 1969; Slovic, 1987; Slovic, 2000; Slovic, et al., 2000b; Slovic et al., 2000a) identifies a heterogeneous list of “fright factors,” to measure people’s responses to safety questions. Because forced migration often occurs in situations of persistent threat, we add a dynamic element to dread threat theory – the menacing context that

emerges when a dread threat persists and requires a community to reorganize its life to mitigate consequences of threat. The concept of menacing context has evident value in analyzing the determinants of forced migration because it links situational factors to decision-making as well as macro, meso and micro levels of analysis through local perceptions of, and responses to dread threat (Collmann et al., 2016).

A major weakness in existing models is that some people do not move on their own or become displaced even when others believe it is imperative to leave. Carling's typology includes four boxes useful in understanding this issue: one encompasses voluntary immobility, the second is involuntary immobility, the third is voluntary mobility and the fourth is involuntary mobility. Whether mobility is voluntary or not is often a function of the social, financial and human capital an individual or family may have. It is a truism that the most needy-- that is, those who would benefit the most from migration—are usually the least able to move. Older, poorer, and more infirm persons become the involuntarily immobile, or trapped in place, as described in the Foresight report on environmental migration (Office of Science, 2011). The voluntarily immobile—or those who choose to remain in place even if they have the resources to move—include persons who either do not believe the events precipitating displacement will occur or believe they will be able to survive those events without moving.

Black and his colleagues at the Foresight Project attempted to address this problem in their causal model of environmental migration/non-migration (Black et al., 2011). They conceptualized the drivers of the decision to migrate or stay in three principal ways: First are the macro-level drivers, including broad environmental, political, social, economic and demographic factors. Second are the meso-level drivers that are facilitators or barriers to movement; they include geographic and logistical barriers, policies and receptiveness of destination communities/countries, availability of smugglers, labor recruiters or others to get you to a destination, and other similar factors. Third are micro-level, including the socio-economic and demographic characteristics of those who must make a decision to migrate or stay.

A final relevant issue raised in the literature focuses on the extent to which the entire concept of forced versus voluntary movements holds in assessing the causes of displacement. The forced/voluntary dichotomy has been criticized for at least two decades. In 1993, Richmond put forward the continuum of 'proactive' (voluntary) and 'reactive' (involuntary) migration (Richmond, 1993). Since then, numerous scholars have referenced this continuum, arguing that the categories of 'voluntary' and 'forced' are unsatisfactory and may be misleading. 'Mixed migration' or the 'migration-displacement nexus' are terms that represent the growing realization of the difficulties inherent in cleanly demarcating between forced and voluntary movement, and further still, theorizing and analyzing movement across a linear continuum with forced movement at one end and voluntary at the other. In deconstructing the so-called nexus, Martin and Koser (2011) posit six different manifestations: (1) mixed motivations (i.e. political, social and/or economic); (2) mixed flows, or migrants with different motivations utilizing the same routes to enter transit and destination countries (such as those arriving off the coast of southern Europe); (3) mixed strategies, in which different types of migrants adopt similar coping mechanisms (such as Somalis and Ethiopians arriving in Yemen); (4) mixed categories, when migrants change status or category intentionally or unintentionally (i.e. Afghans in protracted refugee situations who become labor migrants in Iran); (5) intersection of categories, when

migrants simultaneously fit two or more pre-existing categories (such as internally displaced non-citizens in Libya); and finally, (6) single categories or ‘labels’ that encapsulate people moving for a range of different motivations and who may have very different levels of vulnerability and need (as is found in refugee flows).

While initial movement may be forced, precipitated by persecution, armed conflict or some other life-threatening circumstances, subsequent movement, including the choice of determination of the destination, may also be shaped by economic livelihood, betterment, or other life-chance considerations. Betts (2010) delineated two groups of ‘vulnerable irregular migrants’ who fall outside international refugee law: those with protection needs resulting from conditions in the country of origin that are unrelated to conflict or political persecution (those fleeing severe economic and social distress such as state collapse, environmental change or natural disaster) and those who have protection needs arising as a result of movement.

Oliver Bakewell (2011) develops this idea in his analysis of the migration-displacement nexus for the sake of greater clarity in practice. He makes the distinction between categories, condition and process: “While it may be correct to say that refugees are not migrants (categories), this does not mean refugees cannot become migrants (as a condition), or that displacement cannot be usefully analyzed as a form of migration (as a process).” He argues that in many cases, experiences and strategies of those who fall outside categories addressing displacement tend to disappear from view. This leads to neglect or worse, diminishing widespread problems of displacement. Thus, a more nuanced understanding of the complex processes of migration, the shifting conditions of displacement and their relationship with the categories that frame policy, is useful in understanding why people move.

Developing a New Theoretical Model

Our impetus to rethink the theoretical models was a project on early warning of displacement. Developing an effective early warning system of population displacement requires collaboration and shared learning between subject matter experts who understand the factors that contribute to displacement and technical experts who understand how to collect, store, mine and analyze masses of data derived from international, national and local sources. It also requires a close working relationship between these academic experts and practitioners who understand the intricacies of implementing an early warning system in the real-world context of mass displacement. In 2013, we began assembling such a team with funding from the National Science Foundation (NSF) in the United States. The team grew with additional funding from the Canadian Social Sciences and Humanities Research Council (SSHRC). It has included scholars renowned in their respective fields, from Georgetown (US), York (Canada), Fairfield (US), Fordham (US) Kultur (Turkey), Sussex (UK) Universities, University of Toronto (Canada), and Lawrence Livermore National Laboratory (US). We have drawn on the advice of practitioners from the Jesuit Relief Services, Refugees International, Women’s Refugee Commission, the Brookings-LSE Project on Internal Displacement, CARE Canada, Médecins Sans Frontières Canada, and the UN High Commissioner for Refugees (UNHCR).

The interdisciplinary approach exposed social scientists to new modeling approaches for analyzing their subject matter. At the same time, computer scientists have benefited from domain expertise in the social sciences, enhancing the intellectual merit of our project. This expertise has

provided insight for the development of beyond state-of-the-art data mining and machine learning of very large, incomplete and potentially biased open source databases for topic modeling, event detection, sequential mining, change detection, sentiment analysis and dynamic graph mining to name a few. Attempting to explain the drivers of forced migration to the computer scientists who were attempting to model flows has also demonstrated the necessity of improving the theoretical models explaining displacement, as well as a need to collect the empirical data that can test these models. Most theoretical work on migration has focused on labor movements and, to a lesser degree, conflict or environmental migration; relatively little has been done in building theoretical frameworks for understanding complex displacement driven by multiple factors.

Our work on early warning focuses on displacement in the context of humanitarian crises, that is, any situation in which there is a widespread threat to life, physical safety, health or basic subsistence that is beyond the coping capacity of individuals and the communities in which they reside (Martin et al., 2014). We chose two principal case studies to use in testing our theoretical framework: Somalia (2006-2007) and Iraq/Syria (2011-2015). These cases were chosen because of the complexity of forces underway in displacing people from their homes, as well as the familiarity of the study team with the drivers and their consequences for displacement. They also allowed the team to examine one retrospective though still pertinent case—Somalia—and at the time of our study, one escalating and, rapidly unfolding case—Iraq and Syria.

The Dynamic Model of Displacement

The Dynamic Model of Displacement (DMD) presented in Figure 1 builds most directly on the Foresight model described above. The DMD model focuses on the decision-making process and the factors that impact it. It captures high level factors, grouping them based on factors previously identified in the literature and on driver type (macro, intervening, micro, and menacing context). These high-level factors, both push and pull factors, are then connected to a decision-making process. Together, these factors capture the context of the situation and the feasibility of movement.

Displacement occurs when there are macro-level drivers that affect entire communities and societies (that is, conflict, violence, political instability, disease, economic crises, human rights violations, acute- and slow-onset natural disasters, etc.). These define the environment or context in which decisions are made about moving. We have added a further dimension to the drivers to capture the extent to which the macro-level drivers present a menacing context that will persist or a more temporary impact from which people can readily recover. In effect, people assess threats to themselves and their communities as these macro-drivers manifest themselves.

Figure 1
Dynamic Model of Forced Migration

Because our interest is displacement in the context of conflict and acute hazards, we give special attention to political and environmental drivers of movement. With regard to political drivers, the model includes longer term factors affecting political security as well as more immediate political triggers that can affect people's decisions to move. Within these broad areas are multiple subsets. Conflict, for example, can be international or internal. It can involve states, insurgencies, communities or even households. The level of violence and how targeted or indiscriminate will vary. Conflicts can be acute with ongoing attacks by one or more parties or be frozen with all parties refraining from attacking the others but not agreeing to a peaceful conclusion of hostilities.

Repression also takes many forms. The definition of a refugee refers specifically to persecution, a particularly serious harm, based on race, religion, nationality, membership in a particular social group or political opinion. Genocide is an especially extreme form of persecution. Other human rights violations are also forms of repression, even if they do not rise to the level of persecution. Examples may be discrimination that is not of a serious enough form or is not for reasons other than one of the protected grounds cited in the refugee definition. Poor governance may repress the rights of certain populations because governments are unable or unwilling to protect all vulnerable people.

Natural disasters can be understood to combine two elements—natural hazards and the efficacy of the response. The natural hazards may include acute events, such as earthquakes, tsunamis, cyclones, and floods, or slow-onset processes, such as drought or sea level rise. In and of themselves these events and processes do not necessarily result in a disaster. When governments are unable or unwilling, because of poor governance or the sheer scale of the hazard, to protect

the affected population, then a disaster may be forthcoming. Failure to respond adequately can lead to famine, spread of infectious disease and other calamities that become disaster in and of themselves.

The model also recognizes that these macro-level drivers interact with each other. An example would be Somalia, in which conflict, political instability and terrorism combined to prevent food from reaching starving populations, thereby magnifying the impact of an environmental driver—drought. Long-term drought in Syria intensified opposition to the government, contributing to the advent of civil war that led to mass displacement. The interplay between economic and political factors was captured by the Inter-American Commission on Human Rights when highlighting the complex macro-level drivers of displacement from Venezuela: “massive violations of human rights, as well as the serious crisis that Venezuela has been facing as a result of the shortage of food and medicines, has led to the exponential growth of hundreds of thousands of Venezuelan people who have been forced to migrate to other countries in the region in recent years as a survival strategy that allows them and their families to preserve rights such as life, personal integrity, personal liberty, health, and food, among others” (Inter-American Commission on Human Rights, 2018).

As in the Foresight model, the DMD takes into account micro-level drivers (that is, socio-economic characteristics, sex-, age- and health-related vulnerabilities and resiliencies) as well. These are factors that can play out at the community, household and individual level. For example, poverty may make certain people more vulnerable to conflict, repression and disasters. It may also make them less likely to be able to flee from these conditions. Social and human capital may increase resilience and allow people to cope with worsening conditions or relocate in safety and dignity. The opposite is true. People with few social networks and/or skills may not know where or how to depart. Demography plays a role as well. The elderly, for example, are often trapped in place because of health or cognition problems, especially when they do not have younger family members to help them escape harm. They may refuse to leave in fear that they will slow down the flight of others.

The DMD also includes intervening factors beyond the personal that facilitate or retard movement (that is, geological barriers such as mountains or seas, admission policies in potential destinations, availability of transport, etc.). These together often determine the feasibility of migration versus other strategies to escape threat. That helps set preferences for one option over another. It further takes into account the perception of threat—or menacing context—in which decisions on displacement take place. Of particular concern in our analysis is perceived physical, food and health insecurity but other perceptions of persistent and severe threat could also drive displacement (Collmann et al., 2016).

Finally, the model assumes that typically there are multiple responses to the same drivers, only some of which include movement from the origin community. Displacement, after all, is only one response to deteriorating conditions at home. In our case study of Somalia during the 2006 drought and conflict, we identified several non-exclusive responses to the worsening situation: accepting the status quo, even if it means eventual death; joining militias for self-protection; testing the viability of new markets for selling and buying needed items; migration of some family members to increase remittances; and displacement of entire families to new locations.

Prior knowledge and experience with different options, including flight, then feed back into the decision-making process. Prior migration or displacement is an important element in making decisions about displacement. Displacement is seldom a one-time occurrence. People are often repeatedly displaced as conflict shifts from one area of a country to another or natural hazards recur in either the place of origin or subsequent places of displacement. Internal displacement may lead to cross border movements as people find it difficult to find safety within the country. The reverse occurs as well. Refugees and disaster-displaced repatriating to their home countries may become internally displaced if they are unable to return to their original communities (which may have been destroyed by conflict or disasters). Incorporating the potential for multiple movements is important because there is empirical evidence that prior migration experience correlates strongly with the decision to migrate again. It is also important because the decision to stay or go is not a linear one. Rather it takes into account changing circumstances and may vary from day to day or week to week as the decision-making process assesses the risks and benefits of staying and those of leaving.

Measuring Factors

The presented factor model is general enough to be applied to displacement from different conflicts and other humanitarian crises around the world. What varies are the specific variables that map to the factors and the importance of each driver given the differences in geographic, temporal and contextual dynamics. In other words, the causal relationships and the importance of the variables themselves can differ substantially depending on the time period, the location, and the local dynamics of the situation. The DMD model is designed with this variation in mind. Each factor in the model affects and is affected by migration and each other, creating new dynamics as the drivers of movement interact with each other.

One challenge associated with using this factor model for early warning is determining how to measure each factor. Data that adequately represent the changing dynamics of each factor are not always readily available, and when they are available, they are inconsistent with respect to quality and quantity. Consider a simple example focusing on the macro-factor *Political*. When translating that factor to a set of relevant variables, a few of the variables that can be used to represent the factor include variations in extremist/political violence level, attitudes toward different political leaders, parties, and policy, violent death counts, and key political events, such as elections, demonstrations, legislative actions, and judicial opinions. With these types of variables, we can model their increases or decreases in different locations (cities, states, governorates) through time to determine their possible importance as factors of movement.

Unfortunately, it is unlikely that we will have access to all the variables of interest at the same temporal and spatial resolution. For some variables representing the *Political* factor, we will have data at the district or city level, while for others the data will only be available at the country level. It will also be the case that certain variables within a factor will be captured monthly, while others are available at a daily or weekly resolution. An even larger challenge is that many of the factors are hard to obtain, particularly in areas of conflict. Surveys are one traditional approach for obtaining these forms of data. However, they are costly, (especially if done longitudinally), are not always timely, may be difficult to get reasonable samples in conflict areas, and pose significant ethical issues (Wood, 2006; Romano, 2006; Rudloff & Vinson, 2021). Satellite imagery (Chen & Mueller, 2018; Chen et al., 2017; Gray & Wise, 2016), mobile data

(Bengtsson et al., 2010; Bengtsson et al., 2011; Lu et al., 2012; Lu et al., 2016; Wilson et al., 2016), and social media data (Singh et al., 2019; Messias et al., 2016; Zagheni et al., 2014) are all new forms of organic data that can be used to identify forced movement.

Satellite imagery and mobile data can be valuable for physically seeing movement, but its usage is uneven because there is no consistent available source that researchers can use. Plus, this type of source is more of an “in-time” indicator of movement as opposed to an early indicator of movement. It is most valuable for current situational awareness and retrospective analyses. People also discuss movement on social media. These data are unfiltered, highly accessible, timely, and regionally specific. A recent study uses geotagged Twitter data to measure flows in and out of Venezuela (Mazzoli et al., 2020). Another way to use social media data is to monitor movement of people directly by looking at individual location information from sites like LinkedIn (Jacobs, 2021) or considering aggregate population information using the advertising platforms from sites like Facebook (Fatehkia et al., 2020; Rama et al., 2020). Again, while looking directly at movement variables from social media is a fruitful direction, social media has other information that can be used to provide important context. Therefore, to improve early warning capability, it is also important to think about different proxies or indirect indicators that may be more readily available and provide needed context to use to represent the variables of interest.

One approach that has been suggested by Martin and Singh (2018) is to make use of publicly available social media data to look at the changing dynamics of conversation associated with the factors presented in our factor model. Social media data give insight into conversations and discussions that are hard to access in other ways. For example, conversation buzz about political events in a region can be a proxy for a political instability variable. Or tone of discussion about closing shops can be an indirect indicator for an economic sentiment variable within the set of variables representing the economics factor.

We suggest constructing three types of temporal/spatial variables from organic data sources, e.g. newspapers and social media, for each factor in the model: conversation buzz, targeted event count, and perception (Martin & Singh, 2018). Conversation buzz represents the amount of conversation related to a particular factor at a particular location. Event count is number of events that occurred in a specific location for each factor, e.g. a bombing, an election, or a drought. When the volume of events associated with a factor rises, e.g. political events or environmental events increase in a particular week, that may also serve as an indirect signal of changing conditions in a location. Finally, perception measures how people perceive local conditions, e.g. perception of the economy, perception of disease, etc. Some ways to measure perception include creating a daily sentiment or tone score based on the posts associated with each factor or using emotion of the post or the poster to determine if emotions like fear, anger, and happiness are rising or falling. A large number of algorithms have been developed that use social media, newspaper, and other text to identify events, conversation buzz, sentiment, and emotion (Wei et al. 2016; Hockett et al. 2018; Zagheni et al., 2014; Wei & Singh, 2017; Zhao et al., 2017). These can be foundational for constructing variables from more timely text posts on social media and newspaper articles.

Tables 1 and 2 list different possible variables and potential data sources. Table 1 maps to macro level drivers of displacement; Table 2 focuses on the intervening, micro and menacing context factors influencing displacement in the DMD model. The tables are not exhaustive, but rather are

representative of the different types of variables that can be used directly or indirectly to measure forced migration and potential sources for collecting data on each.

Irrespective of how the variables are captured, they need to be put into a mathematical framework. Along with the theoretical strengths of the factor model, the model also lends itself to straightforward translation to different mathematical frameworks. While a number of options exist, agent-based models and Bayesian models are two good options. Agent-based modeling (ABM) has become a preferred and effective methodology for modeling complex socio-environmental systems in recent years (National Science Foundation, 2013). ABM in the context of forced migration allows for a detailed simulation of forced migration by including dynamic actions and interactions of different agents that are involved in the migration and its humanitarian response management. A number of projects related to movement and migration have been modeled using ABMs (Collins & Frydenlund, 2016; Groen, 2016; Hassani-Mahmooei & Parris, 2012; Hébert 2018). Bayesian models can be viewed as a probabilistic framework for a dynamic systems model. Some Bayesian models, like the Hierarchical Bayesian Model, are designed to allow for multiple levels of heterogeneity and has the ability to extract more “signal” from noisy data than traditional point-estimate statistical models. Some examples of using a Bayesian methodology for modeling movement also exist (Bijak 2010; Singh et al., 2019). Given the availability of large-scale compute infrastructure and the availability of new data sources and data exchanges, we are now at a point where blending these different forms of data for understanding displacement is possible.

Conclusion

As discussed earlier in this paper, the authors’ own interest in understanding causality stems from our work on early warning of displacement. With earlier and more accurate warning, steps could be taken to address the precipitating causes and avert what are often dangerous journeys to safety. International organizations, governments and nongovernmental aid groups would be able to do a better job of pre-positioning supplies and otherwise planning for arrivals when prevention does not work. Of course, as discussed below, the danger of early warning is that governments will use it to prevent the movements themselves and leave people trapped in even more dangerous situations so a cautious approach to early warning is necessary.

In studying how to improve early warning, we were struck by the inadequacy of existing theories and frameworks for elucidating the causes of forced migration. In particular, existing theories seemed too linear to account for shifting patterns of displacement and unable to predict when, where and how displacement would take place. This is not surprising since modeling displacement is complicated. Capturing all of the intersecting drivers of displacement requires an analysis at the macro-, intervening, and micro-levels but such an analysis is inadequate for determining who among those affected by these drivers will actually be displaced. This is partly because perception of threats can be as important in driving displacement as the reality of those factors. But, it is also because displacement is seldom the first option that people choose. They often try alternatives—for example, setting up militias of their own when the threat is conflict or selling or slaughtering livestock when the threat is famine. Understanding the alternatives and when these coping strategies no longer work is as necessary to understand the causes of displacement as are the underlying drivers. Moreover, displacement may itself lead to secondary, tertiary and beyond movements as conflicts shift in location or intensity, opportunities for greater security open elsewhere, or public policies necessitate relocation.

Given the complexities of displacement, we present a theoretical model that captures the interplay amongst the complex factors that drive displacement and is capable of considering changing contexts, events, and perceptions as well as the feedback from prior experiences in trying to cope with threats. The Dynamic Model of Displacement factors in the traditional macro-, micro and intervening drivers while including perceptions to these drivers (menacing contexts) and feedback loops to account for the experiences people have in testing different options for survival, including previous movements.

A strength of DMD is that it lends itself well to mathematical models of analysis. Two models discussed in the paper—Agent Based Models and Hierarchical Bayesian Models—show particular promise. ABM allows for analysis of complex socio-environmental systems while HBM supports analysis of multiple levels of heterogeneity. We also argue for the use of big data to feed into these models. Finding information on all of the drivers of displacement, as shown in the DMD, is near impossible using standard sources of data. The task is even more difficult when the aim is to identify the triggers of movement, which are often related to people's perception as much as to the reality of the situation. As the intent is to forecast dynamic situations such as displacement from conflicts and disasters, the data must be granular and timely enough to capture what are often quickly changing events and the evolving perception of these events in real time. We recommend use of social media, satellite imagery, mobile phone data and other sources that can be captured in real time and location.

The forecasting of displacement is still in its infancy. Many practical and ethical issues must be addressed before more progress will be made. We understand that early warning of displacement, which may be feasible with the theoretical model and data sources discussed herein, can be used towards good or bad ends. Certainly, with more timely and accurate information about potential displacement, humanitarian actors may be better prepared to assist and protect those in need. Yet, governments that want to close borders or restrict internal movements may also be better prepared and without alternative options for those in fear for their lives. Scrutiny of the use of early warning will be essential to ensure that displaced persons are helped, not harmed, by initiatives such as ours to improve both the theoretical understanding of the drivers of displacement and life-saving responses to these movements of people.

Table 1: Macro Factors and Data Sources

Macro Factor	Variable Examples	Data Source
Environmental	Historical climate data	Global Historical Climatology Network at NOAA
	Environmental Changes	NOAA Satellite Maps , USGS Earth Explorer , NASA Earthdata , Copernicus Open Access Hub , DigitalGlobe Open Data Program
	Drought	World Meteorological Organization – severe weather data
	Flooding	World Meteorological Organization – severe weather data
	Salination	National Snow and Ice Data Center
	Deforestation	The Global Forest Watch
	Air quality	World Air Quality Index
Political	Leaders	Rochester University – Archigos database
	Freedom scores	Democracy Barometer , V-Dem
	Political parties	Comparative Political Data Set & www.politicalparty.org
	Political leader hashtags	Twitter
	Minority protections	Minorities At Risk
	Conflict Events	ACLED
	Violent Deaths	ACLED
	Gender Rights	V-Dem
Social	Movements and Protests	NAVCO , Mass Mobilization Project
	Community organizations	V-Dem
	School Attendance	UNESCO
	Intention to Migrate	Gallup Polls
	Social Networks	Surveys, social media friendship networks, mobile device calling/texting networks.
Health	Infectious Diseases	World Health Organization (WHO) , Government public health offices
	Public Health Travel restrictions	WHO , national health ministries, International Organization for Migration
	Health Outcomes	The Global Health Observatory , WHO
	Access to Health Care	WHO , national health ministries

Table 1 cont.: Macro Factors and Data Sources

Macro Factor	Variable Examples	Data Source
Economic	GDP	World Bank
	GDP Per Capita	World Bank
	Poverty Rates: Child, Household	World Bank , UN Development Program
	Labor Market Participation, Unemployment, Underemployment	Country governments, World Bank
	Remittances	World Bank
	Corruption	Corruption Perceptions Index , Global Corruption Barometer (Transparency International)
	Food Availability and Prices	Food and Agriculture Organization & www.foodsecurityportal.org/
Demographic	Age Distribution	Country statistical offices, UN Population Division
	Gender Statistics	Country statistical offices, UN Population Division
	Mortality Rates	Country statistical offices, UN Population Division
	Fertility Rates	Country statistical offices, UN Population Division
	Population Growth Projections	Country statistical offices, UN Population Division
	International Emigration and Immigration	UN Population Division, World Bank , International Organization for Migration
	Internal Emigration and In-migration	Country statistical offices, Census, Registries, Surveys
	Religious composition	World Religion Database (Boston University) , Pew Research Center
	Ethnic composition	Ethnic Composition Data , PRIO

Table 2: Intervening, Micro and Menacing Context Factors and Data Sources

Intervening Variables	Variable Examples	Data Sources
Relief	Accessibility, Type, Duration, Cost	Office for the Coordination of Humanitarian Assistance (OCHA) , UNHCR , IOM , OECD
Infrastructure	Roads, Bridges, Ports	Satellite imagery, OpenStreetMap , Google Maps
	Hospitals and health clinics	WHO
	Primary and Secondary Schools	UNESCO
Terrain	Mountains, rivers, lakes, other potential barriers or facilitators	Satellite imagery
Laws and Policies	Internal Displacement and Migration	Government offices, Internal Displacement Monitoring Center , regional organizations such as the African Union or Organization of American States
	Refugee, Internationally Displaced Persons and International Migrants	Government offices, UN Population Division , IOM , RefWorld , other UN agencies
	Human Rights	United Nations (e.g., ratification of human rights conventions, reports of human rights rapporteurs and treaty bodies)
Micro Variables	Demographics (age, sex, household composition), Human Capital (education, skills), Social Capital (networks), Financial Capital (income, assets) of populations at risk of displacement	Household surveys, social media
	Household Attitudes	Surveys, social media
Perceptions (Menacing Context)	Physical, Food, Health Insecurity	Surveys, social media, newspaper articles and opinion pieces and television transcripts

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