AI for Social Risk Forecasting and Explanation:
The Power of Machine Learning–Based Social Risk Models

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Efforts to measure the consequences of concurrent and compounding global and local crises (a "polycrisis") lack coherence and verified forecasting accuracy and hence do not support reliable responses.[1] The World Bank's Social Policy practice is exploring how machine learning can complement and improve forecasting and explanation of social phenomena. By drawing on large data sets machine learning observes billions of relationships and patterns, predicting change and identifying the factors most associated with it.

Emerging sources and methods, including satellite imagery, image recognition software, and natural language processing, are making available large quantities of data representing previously unquantified phenomena. Methods that measure these data at scale render the information useful for machine learning models that identify complex dynamic patterns. To mitigate the risk that bias undermines the findings, diverse context-specific expertise and lived experience must inform data selection, curation, and modeling. Combining these methods with existing analytic approaches can transform the specificity and impact of policy and operations through improved monitoring, forecasting, and analysis of a range of risks at country and global levels.

The World Bank has developed three proof-of-concept models to demonstrate the efficacy of social science–informed AI approaches for understanding social phenomena, with the intention to operationalize the models to support ongoing programs. Significant potential exists to complement, inform, and enhance current analytic methods and development policy for greater impact.

In the Democratic Republic of Congo, the model predicts change in violence, and the World Bank's Stabilization and Recovery in Eastern DRC project anticipates using the model's output to inform strategy and decision-making. In the Horn of Africa, the model predicts change in population between cities and across country borders, and the World Bank DRIVE (De-risking, Inclusion and Value Enhancement of Pastoral Economies in the Horn of Africa) project is leveraging this information to better understand the drivers of migration and the impact of climate events. In a Small Island Developing State (SIDS), the model predicts change in crime; it is being used by the World Bank Country Office and has informed the indicators within the Country Policy and Institutional Assessment.

1. Some advances have been made in forecasting change in social phenomena—such as demographics, poverty levels, or levels of violence. See (among others) Meng and Srihari (2019); Parmigiani et al. (2022).

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Introduction

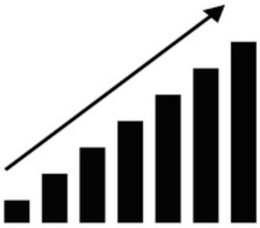
Conventional approaches for understanding the drivers of social risks, such as war, social unrest, violence, and poverty, tend to underperform given the complex and poorly understood interactions of a high number of real and perceived factors in varying contexts (i.e., the natural, built, and social worlds). Index-based approaches have increasingly been adopted to measure social sustainability (Cuesta, Madrigal Correa, and Pecorari 2022). Increased data availability provides an opportunity to test new modeling methods for understanding and forecasting complex and dynamic social risks, so that preparedness and response mechanisms can better foster social sustainability.

Development institutions now routinely face compounding crises, as increasing numbers of countries experience a combination of climatic shocks, displacement, and social unrest. Over the past five years alone, World Bank client countries have had to manage the impact of the COVID-19 pandemic, the Russia-Ukraine War, inflationary pressures, climatic shocks, and food insecurity. Social risks, including poverty, social group–specific discontent, human displacement, and different forms of social unrest and violence, compound in poorly understood ways, placing livelihoods, development, and economic growth at risk.

Responding to this increasingly complex landscape, World Bank management has endorsed Independent Evaluation Group recommended use of AI-enabled tools to better understand the complexity of dynamic social risk.[2] In December 2021, under the International Development Association's 20th replenishment (IDA20), US$30 billion in financing for FCV-affected countries was approved. Building on this progress and a subsequent comprehensive strategy to address the drivers of FCV and their impact on vulnerable populations, with the ultimate goal of contributing to peace and prosperity, the World Bank Group is developing a subsequent strategy to further embed the efficacy of policy and operations in FCV contexts.

2. World Bank. 2025. An Evaluation of the World Bank Group Strategy for Fragility, Conflict, and Violence, 2020–25. Independent Evaluation Group. World Bank, p. xxv.

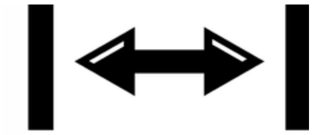
Climate change is a compounding risk factor that is not well understood. The World Bank's IDA20 special theme paper on climate change points out that most FCV countries struggle with climate impacts and have limited institutional capacity to respond to shocks, including increasingly frequent and severe natural disasters (World Bank 2021). Significant anecdotal evidence links climate change, poverty, and violence. The World Bank Group Climate Change Action Plan (2021–2025) commits 35 percent of overall funding to climate adaptation and mitigation (World Bank Group 2021). However, practitioners lack the reliable quantitative evidence that would illuminate context-specific dynamic pathways toward and away from violence.



Building on its strong track record of strengthening client countries' financial resilience to climatic shocks, the World Bank Group is exploring how emerging data sources might enable forecasting of social risks such as social unrest and extreme poverty.[3] Over the last 15 years, the World Bank Group's Social Policy Department has been active in over 100 (119*) countries, delivering 725 operations between 2010 and 2025, contributing to lending of over US$76.16bn to support social policy. The social resilience agenda is central to the management of inflationary, social, climate, and other macro-fiscal pressures. Measuring social resilience, anticipating its change, and understanding its context-specific drivers are increasingly first-order tasks for development policy targeting and effectiveness.

3. This policy note considers risks emanating (at least in part) from human behavior such as social unrest, violence, human displacement, antisocial behavior, criminal conduct, and poverty. The modeling team was informed by the social risk modeling advances experienced by Peloria P.B.C. a public benefit company. In the past, the World Bank Disaster Risk Financing and Insurance Program (part of the Finance, Competitiveness and Innovation Global Practice) focused on natural disaster risks like floods, earthquakes, or droughts.

Challenges to Modeling Social Risk



The significant knowledge gaps surrounding the multidimensional nature of social risk are only now beginning to be acknowledged and considered—let alone robustly explored. Social scientists cite local episodes of peacebuilding and national reform as "breaking" cycles of phenomena like violence (Wakenge and Vlassenroot 2020; UN and World Bank 2018; Kleinfeld 2019). They test the relationship of different phenomena to changes in levels of violence, including across contexts, while accounting for other phenomena.[4] However, econometric and other social science methods often presume to know what phenomena to account for, and they do little to capture real and perceived change across the natural, built, and social environments, which may be fluid across time and space.[5] Systems-based approaches proceed on the basis that phenomena rarely function alone when affecting other phenomena (Flood 2010). Some recent work, moreover, has identified certain persistent factors, like social group–specific grievances or stressors, that are heightened during natural disasters, significant economic adjustments, or other shocks. Such work explores how shocks and grievances interact, noting in particular the self-reinforcing interactions that trap societies in cycles of fragility and violence (Besley, Collier, and Khan 2018).

The complexity of large numbers of continuously evolving and interacting social risk drivers (along with the perceptions of them) limits attempts to quantify risk, thereby undermining the efficacy of development policy. Development practitioners' limited capacity to predict and explain the likelihood of displacement, violence, poverty, and other social risks undermines the efficacy of development planning, design, and implementation. In contrast, there is a long-standing, profitable, and robust industry established to assess, quantify, and price natural disaster and climatic risk. This quantified risk can then be accounted for, targeted with development policy and operations, and even underwritten and transferred via insurance and capital markets.[6] Quantified risk can also be managed via public spending and design of development activities that target the location-specific issues identified by models (with verified accuracy) as most associated with high levels of risk.

Machine learning enables the capacity to navigate complexity—to better identify relationships between billions of data points representing a range of real and perceived phenomena that are not simplistically or conveniently linear. Risk modeling approaches to climate forecasting rely predominantly on real measurable phenomena with consistent properties and behaviors, such as temperature and precipitation. But modeling social risk may be more complex because human behavior is driven by inconsistent interactions between changes in a plethora of both real and perceived phenomena. The joint UN–World Bank (2018) Pathways for Peace report noted that social groups' perceptions of exclusion—from services, natural resources, political power, and security—play a greater role in driving violence than the actual exclusion of those groups. Unlike dynamic interactions between dimensions of geography and climate, the interactions of human cognition and behavior with climate, the built environment, and social phenomena are under-evidenced (Casebeer et al. 2018).

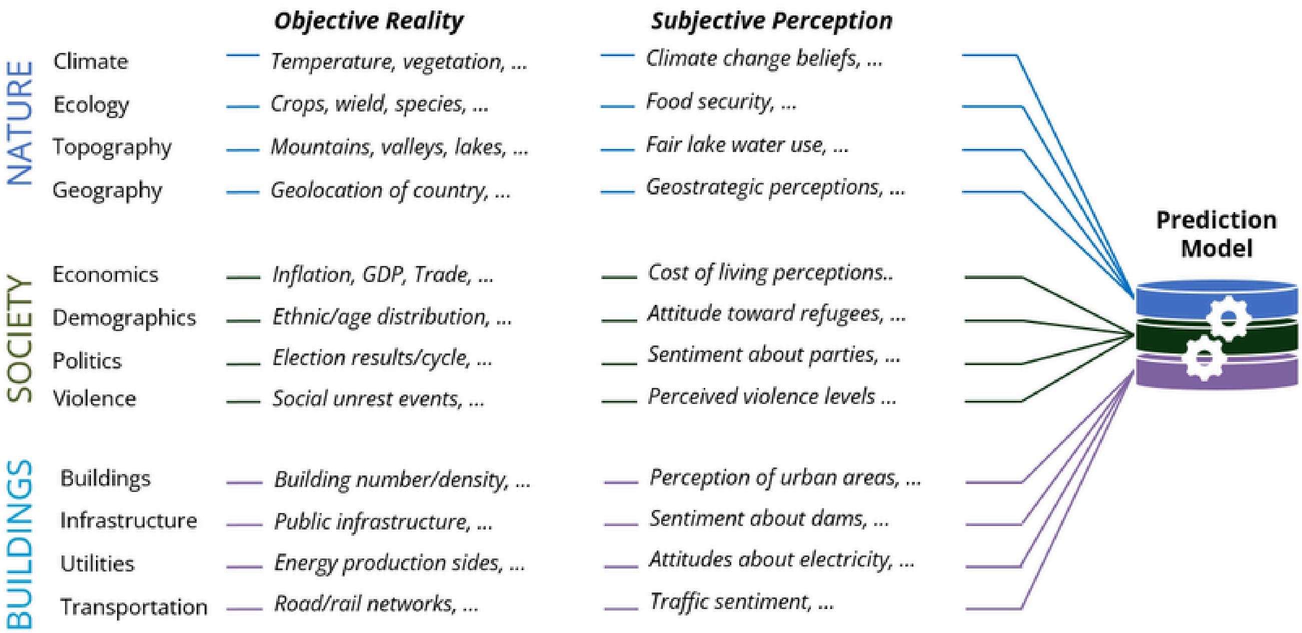
4. Randomized controlled trials (RCTs) deploy programmatic or policy interventions to randomly chosen populations with an excluded control group also chosen at random from the same eligible population. RCTs that study violence presume a particular phenomenon's role can be identified based on the belief that other relevant phenomena can be controlled for by ensuring an eligible population meets criteria understood to be associated with violence. See Barash and Webel (2013); Höglund and Öberg (2011); Lee (2010); Wolfe (2020); Bock, Velleman, and De Veaux (2006); and Borradaile (2003).
5. The "natural" world may encompass climate, ecological, and environmental change. The "social" world may encompass change in economic, political, demographic, and other social phenomena. The "built" world may include any form of built structure, machine, or constructed change to the natural world, such as transportation infrastructure and buildings. See Clayton (2003); Moffat and Kohler (2008); and Rus, Kilar, and Koren (2018).
6. In many low- and middle-income contexts, there remains a significant need for insurance and capital market development to enable such risk management and mitigation.

Unleashing the Power of Big Data and Machine Learning: Seeing through the Fog of Social Risk

The World Bank used a range of online language metadata along with economic, climate, and geospatial data to develop models predicting change in violence in the Democratic Republic of Congo, change in population in the Horn of Africa, and change in crime in a SIDS. A multidisciplinary team leveraged the explosion in availability of data—including language data from online news and social media, satellite imagery data, and economic and climate data—and methods for measuring relevant social phenomena to help predict historical change in population, crime, and violence.[7] This step enabled the models to capture change in key dimensions of reality and perceptions of it.[8] The team then identified which phenomena most assisted the models in optimizing predictive accuracy. Identifying the factors most associated with change can inform hypotheses regarding drivers of social risks and support decisions on future policy interventions. Relevant breakthroughs include methods that recognize and measure language about topics and sentiment in text, the number and size of objects in images, and the number of online newspaper-reported events. However, the team also mitigated the risk of bias by leveraging social science knowledge to optimize each stage of model development, including identification of relevant phenomena, identification of data that best represent those phenomena, curation of data, and design of experiments.

Because periods of increasing, decreasing, or stable conditions occur with different frequency, presenting accuracy figures together with the proportions of these outcomes provides a clearer understanding of the forecasting task and the model's performance across the full range of situations.

Figure 1. A conceptual framework of social risk modeling



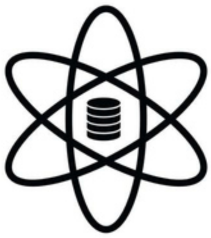
Source: World Bank Group.

7. A multidisciplinary team, including Dr. Chris Mahony, Professor Rohini Srihari, Dr. Christopher Trisos, Dr. Weifeng Zhong, and Dr. Murugarj Odiethevar, worked on this modeling with data scientists, climate scientists, economists, psychologists, political scientists, linguists, anthropologists, and development specialists, among other experts. The team also interacted with context-specific World Bank experts.
8. Initial efforts to leverage social media language metadata to forecast change in levels of violence suggest significant potential. See Mahony, Albrecht, and Sensoy (2019).

Models forecasting change in social risks offer significant potential for policy development and operational utility, particularly when complemented and informed by traditional methods and sources. Policy development and program design and implementation are commonly undertaken without context-specific data related to the likelihood of change in levels of violence, population, or poverty. Data science approaches to forecasting social phenomena and identifying the factors most associated with change—including both objective realities and subjective perceptions—provide evidence that can optimize development policy and practice. However, the impact of these approaches could be enhanced, for example, by using less regularly collected but more detailed data, such as that from household surveys. Household surveys might identify the average number of persons living in built structures, average household incomes, and therefore the neighborhoods with the highest levels of poverty or vulnerability.

Photo credit: Masaru Goto / World Bank

Modeling to Inform World Bank Group Operations Affected by Complex Social Risk



To reduce knowledge gaps surrounding social risk by using social science–informed approaches to data science, the World Bank is fostering collaboration between data scientists and multidisciplinary context-specific experts. The latter group vets the data scientists' assumptions about what they are modeling, thereby increasing the efficacy of (for example) data selection or experiment design. This effort requires continued investments in social science–informed collection of high-frequency data and model development.

The World Bank Group has developed three proof-of-concept machine learning models for social risk: one for conflict in eastern Democratic Republic of Congo (box 1), another for migration in the Horn of Africa's borderlands (box 2), and a third for crime in a SIDS (box 3). Each of the social risks constitutes a first-order development issue, and each model is designed to forecast change in the social risk and to identify the factors most associated with that change:

- In the eastern Democratic Republic of Congo, the team sought to explore the optimal potential forecasting accuracy (and the forecasting look-ahead horizon) for change in the level of armed conflict. The eastern Congolese provinces of Ituri, North Kivu, and South Kivu have experienced armed conflict of varying levels since the mid-1990s.

- In the borderland regions of northeastern Kenya, western Somalia, and southern Ethiopia, the team sought to model change in population across cities and towns, which is currently poorly monitored. Models that can forecast change in built structures, when triangulated with survey data identifying the poorest neighborhoods, can also forecast change in poverty and identify the factors most associated with this change. Social science research suggests that climate pressures are causing anomalous migration patterns, particularly among agropastoralists, whose increasing interaction with unfamiliar communities is associated with increased intergroup tension.

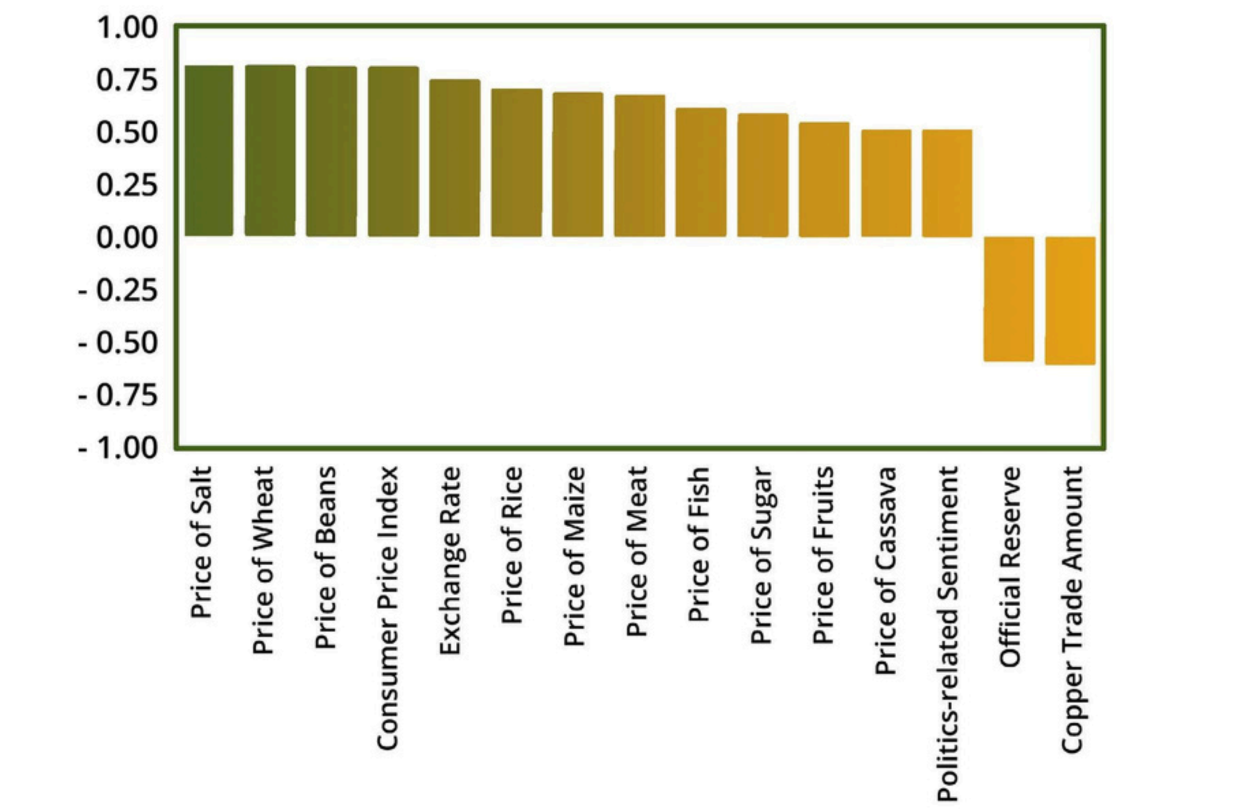
- In SIDS (and other states), data representing frequent change in crime is commonly unavailable. For this reason, the team developed a model that creates data representing the level of crime reported daily by online news sites. This model enabled the team to employ its social science–informed data science approach to predict change in crime levels and identify the most associated factors.

Box 1. Conflict-affected eastern provinces of Democratic Republic of Congo

In the Democratic Republic of Congo, the team developed a model predicting change in levels of conflict in the North Kivu, South Kivu, and Ituri Provinces. The team drew on a conceptualization of the complex interactions of real and perceived phenomena. The model achieved validation accuracies of 76% for Ituri, 63% for North Kivu, and 69% for South Kivu, with a highest validation score of 87% at the 150-day forecast horizon in Ituri. These figures reflect performance across periods where violence increased, periods where it decreased, and periods where levels remained broadly similar. In the dataset used for this work, approximately 44% of periods were classified as increases, 32% as decreases, and 22% as similar. Presenting accuracy alongside these proportions gives a more complete view of how the model performed across the different types of conditions it encountered. While validation results were stronger, test-set performance was lower, reflecting the presence of unusual patterns in the later months that made forecasting more challenging. Validation results were higher than test results, which is expected in real-world time-based forecasting and is explained in more detail in the technical study.

Before constructing the model, the team, including multidisciplinary social science expertise on the region, reviewed simple correlations to ensure that key economic, climate, conflict-history, and sentiment variables were included. These correlations formed part of an initial screening process rather than an attempt to explain violence patterns, and their role was limited to confirming that the modeling captured a wide set of relevant factors. The more substantive insights come from understanding which variables contributed most to improving forecast performance.

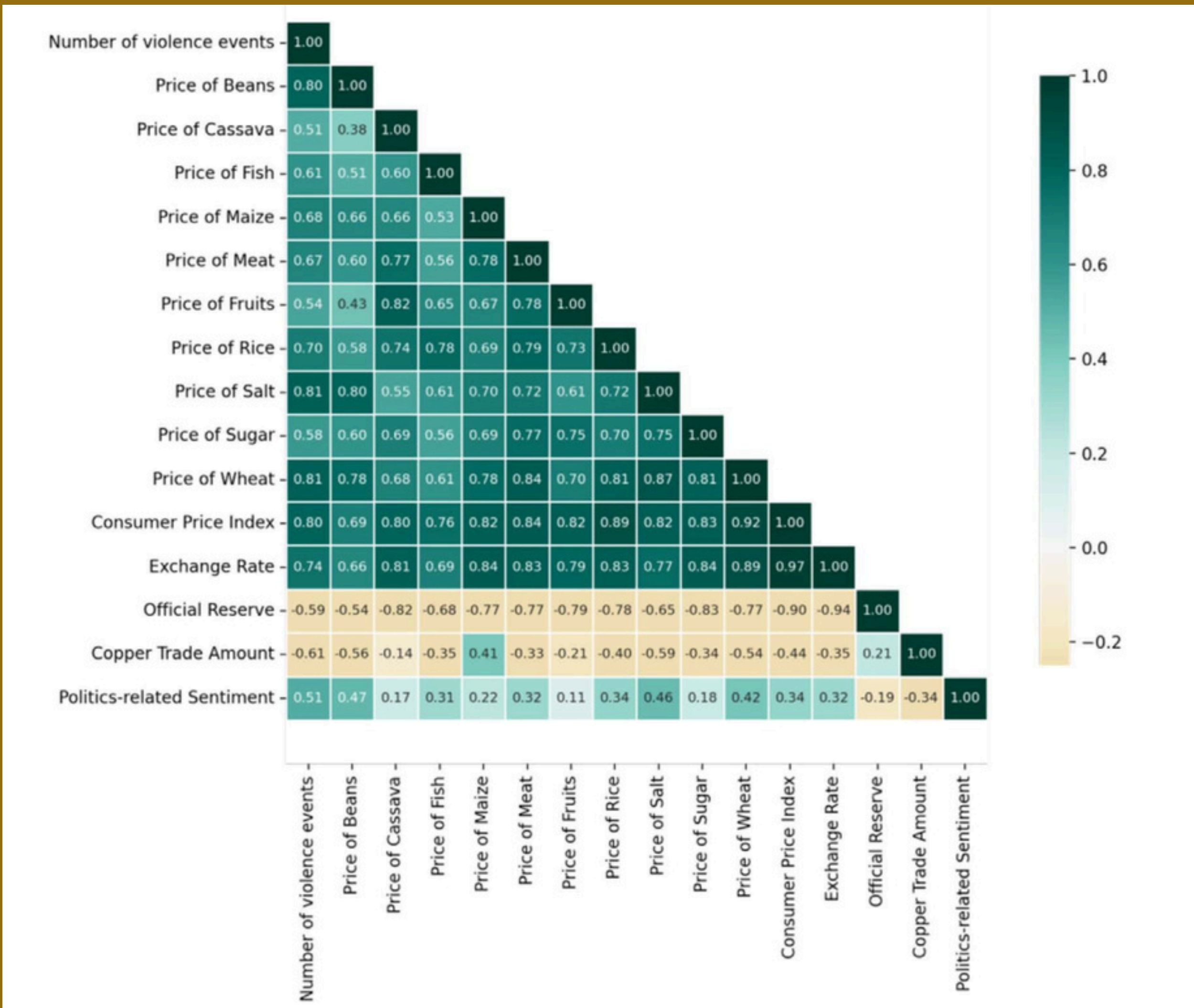
Figure 2. Correlation between variables and violence events



Source: World Bank Group.

9. The team expected to achieve best model performance during testing (historical data are split into three, with years of data used to train the model, validate the model, and test the model). However, the COVID-19 pandemic occurred during the period of the test data. Subsequent individual briefs on the Democratic Republic of Congo and Horn of Africa models will explore this challenge.

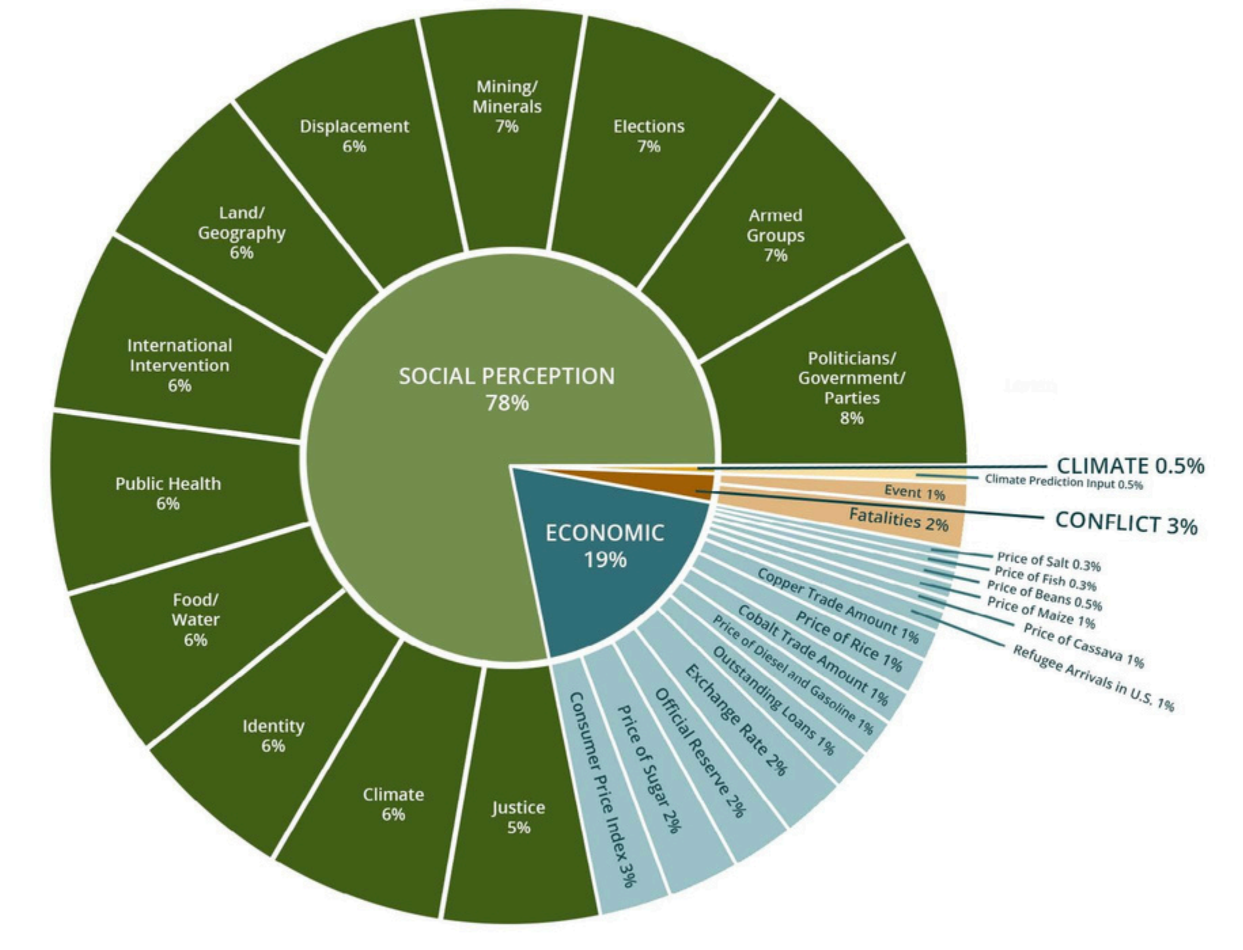
Figure 3. Correlation between all variables in Democratic Republic of Congo model



Source: World Bank Group.

The developed model showed that the change in language about sensitive topics had some of the highest proportions of influence over change in violence. The results showed that economic pressures, recent conflict patterns, and public discussion of political actors were the strongest contributors to anticipated changes in violence, while climate-related factors played a more limited and location-specific role. Some of the most significant factors included social perceptions of issues like politics, armed groups, and mining, as well as real factors such as inflation, official reserves, currency fluctuation, and conflict patterns (figure 4). These patterns might be explored further by triangulating from alternate data sources.

Figure 4. Model-informed factors' influence over change in violence



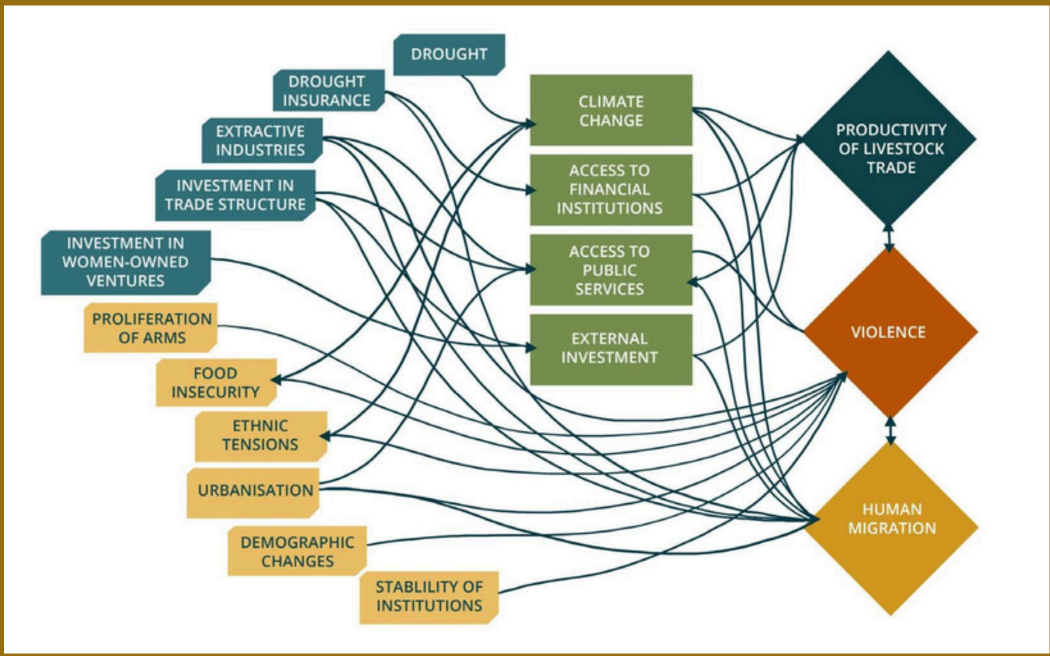
Source: World Bank Group.

The objectives and design of the World Bank's Stabilization and Recovery in Eastern DRC project respond to primary factors identified by the model. Upon full implementation (expected by mid-2025), the project will explore a potential Crisis Risk Mechanism linked to the model. The project cites a live version of the model as complementing and enhancing monitoring and evaluation, project implementation security, knowledge, and learning, as well as supporting more precise resource allocation via a conflict risk financing mechanism similar to the Displacement Crisis Response Mechanism in Uganda (Mahony and Maher 2020). Under the envisaged Conflict Crisis Response Mechanism, a level of observed or forecast violence would trigger a disbursement to scale up the project's de-risking components in the model-identified location.

Box 2. The Horn of Africa

In the Horn of Africa, the team forecast population change in the borderlands regions (Ethiopia, Kenya, and Somalia) across one-month, two-month, and three-month look-ahead periods and achieved 72 percent, 74 percent, and 70 percent accuracy respectively. The team drew on a multidisciplinary expert-informed theory of change to identify factors relevant to population movement, violence, and the livestock trade (see figure 5).

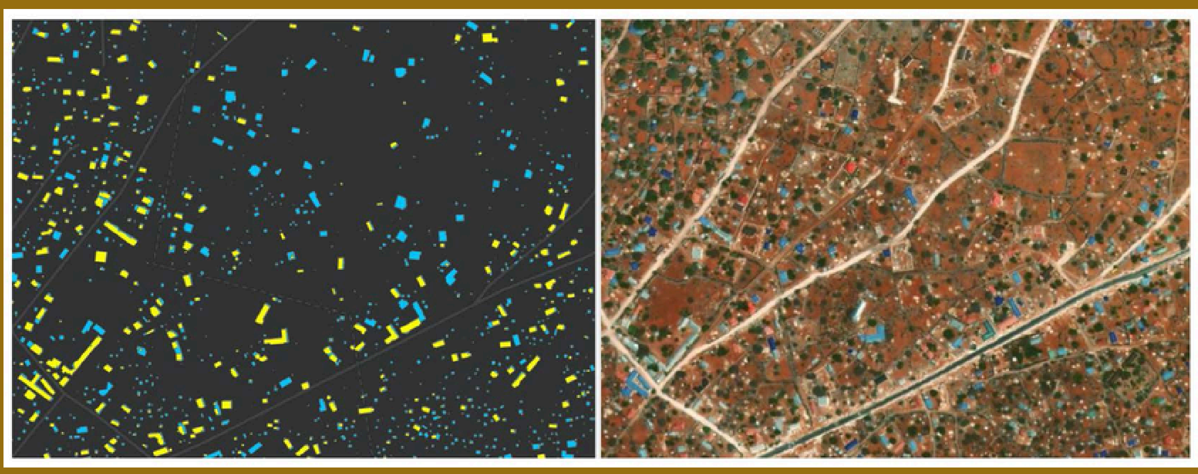
Figure 5. Expert-informed theory of migration, violence, and livestock



Source: World Bank Group.

To produce the population change data to be forecast, the team developed an object recognition algorithm achieving over 99.9 percent accuracy (relative to Google Earth) in built structure identification across the 56 towns and cities of interest. For example, figure 6 below shows a photo of a Wajir, Kenya neighborhood alongside the model-detected number of built structures in that territory in 2017 versus 2021.

Figure 6. Built structure identification in a Wajir, Kenya, neighborhood

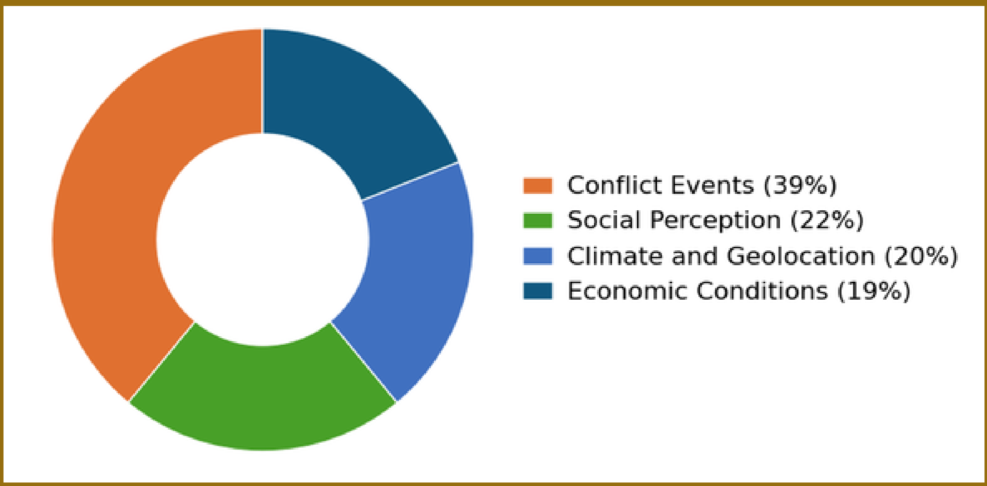


Source: World Bank Group.
Note: Yellow indicates structures present in 2017; blue indicates additional structures present in 2021.

Capacity to forecast and explain population change, particularly in poor communities, holds significant potential for development policy and operations. By combining built structure data with household surveys that identify both the average number of persons living in built structures and their level of socioeconomic vulnerability, it is also possible to identify the factors most associated with the prediction of change in population and poverty levels. Training of the model drew on data representing 32 features across six categories: economic conditions, climate conditions, COVID-19 prevalence and response, geolocational information, conflict events, and social perceptions. Social perceptions drew from online language in English, Arabic, Somali, and Swahili, among others, about expert-identified topics found in 23 online news sites, 207 Twitter accounts belonging to influential actors (people and entities), and 141 Facebook accounts.

The climate and fragility drivers of migration, as identified by the model, suggest a need for more programming focused on the climate-fragility nexus, such as the US$330 million DRIVE project. The model identified several drivers as most significant: violence (associated with 39 percent of population change), climate (20 percent), economic conditions (19 percent), and perceptions of these phenomena (22 percent) (see figure 7). Among climate phenomena, geolocational features are more significant drivers than orthodox climate features, which exhibit less geographic specificity; thus mountain proximity and geographic elevation have a higher association with population change (7.9 percent and 6.8 percent respectively) than precipitation (0.2 percent). Multiple microclimates may exist within the territory of a single temperature or precipitation data point. This illuminates not only the limitations of testing such data's relationship to other phenomena, but also the necessity of social science–informed exploration of the efficacy of a range of phenomena measures for multidimensional modeling.

Figure 7. Model-identified factors' association with population change

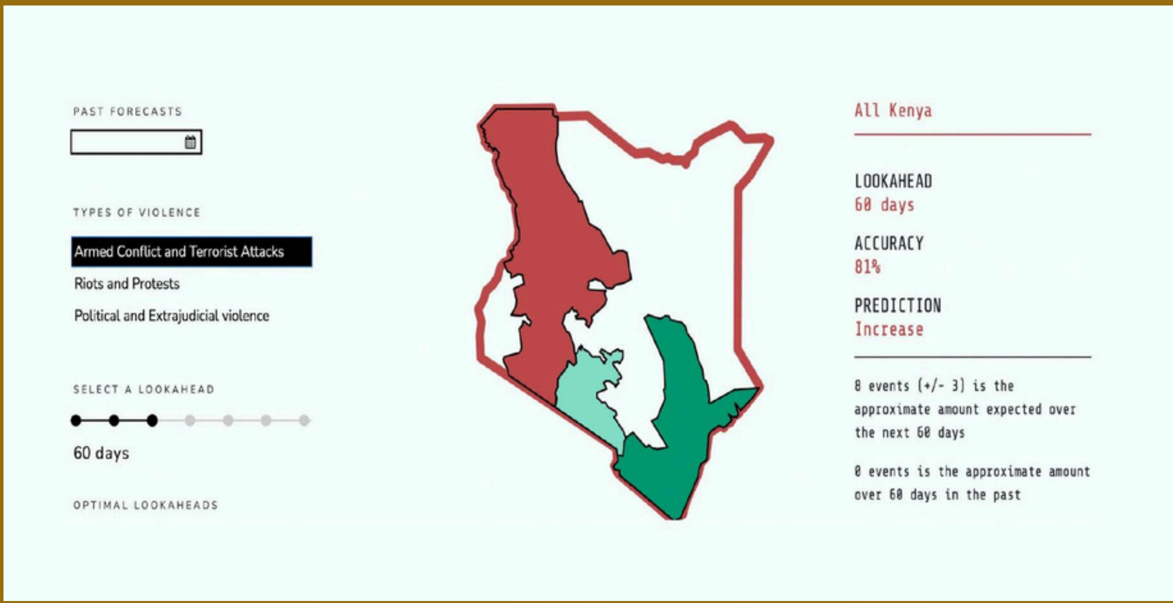


Source: World Bank Group.

Information on drivers of change in migration could significantly enhance several components of the DRIVE project, including (1) project design, (2) project monitoring and evaluation, and (3) security of project implementation. It could also help in development of a potential risk financing component triggered by observed or forecast levels of financial vulnerability, livestock value chain pressures, violence, or human displacement. A mock-up of a real time analytics dashboard showing forecasts of conflict events is shown in figure 8.

The DRIVE project is now exploring further development and adaptation of the population model to inform these different dimensions of operations. It is also exploring scope for the model to forecast and explain change in potential measures of the livestock supply chain most related to agropastoralists' vulnerability.

Figure 8. Potential live visualization of violence model forecasts



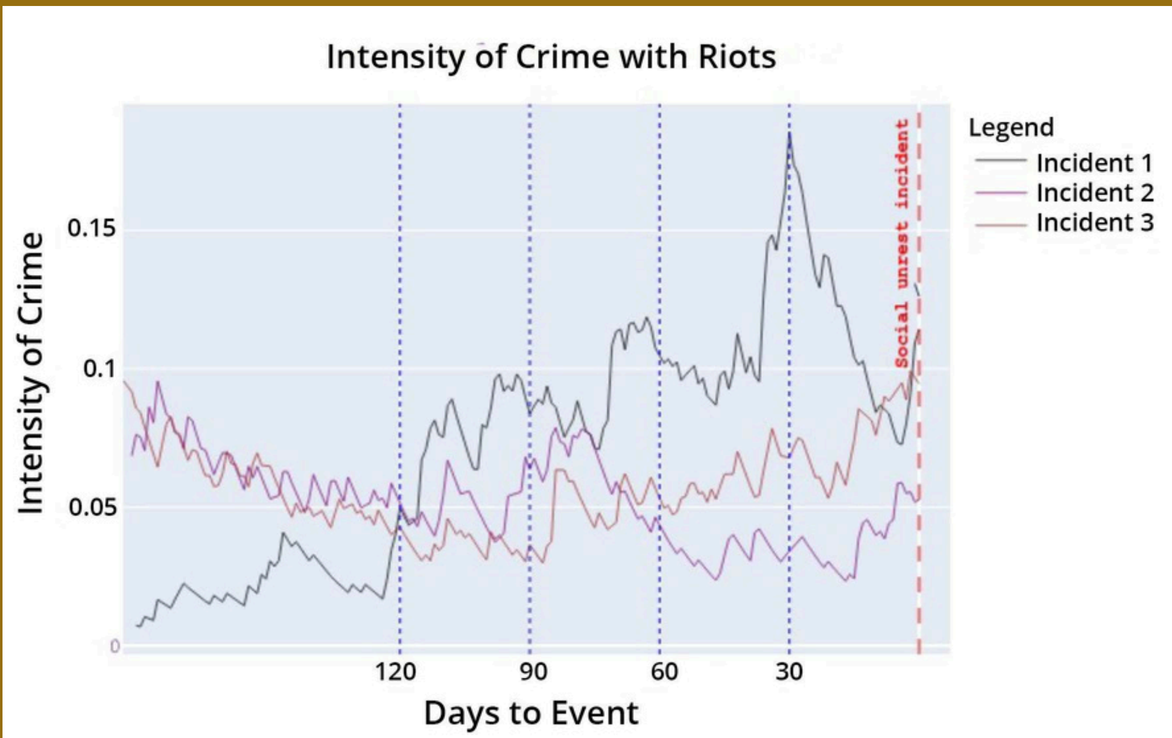
Source: World Bank Group.

Photo credit: Vladimir Tretyakov / Shutterstock

Box 3. Small Island Developing State

In the SIDS, the team developed models to forecast and identify the factors associated with the occurrence of social unrest and change in levels of crime. Because social unrest is not a frequent event in the examined country, the team explored how change in real and perceived phenomena leading to two unrest events was able to help forecast the number of days until the third. To overcome the absence of available data representing annual change in crime levels, the team also developed a model that identifies the number of daily articles about crime incidents in the country's three online newspapers. Aside from making it possible to explore the relationship of crime to social unrest, the model also delivered crime data with enough frequency that crime itself could be forecast and its drivers identified using machine learning methods. Figure 10 illustrates the level of crime increase preceding three social unrest events.

Figure 10. Change in crime preceding social unrest events

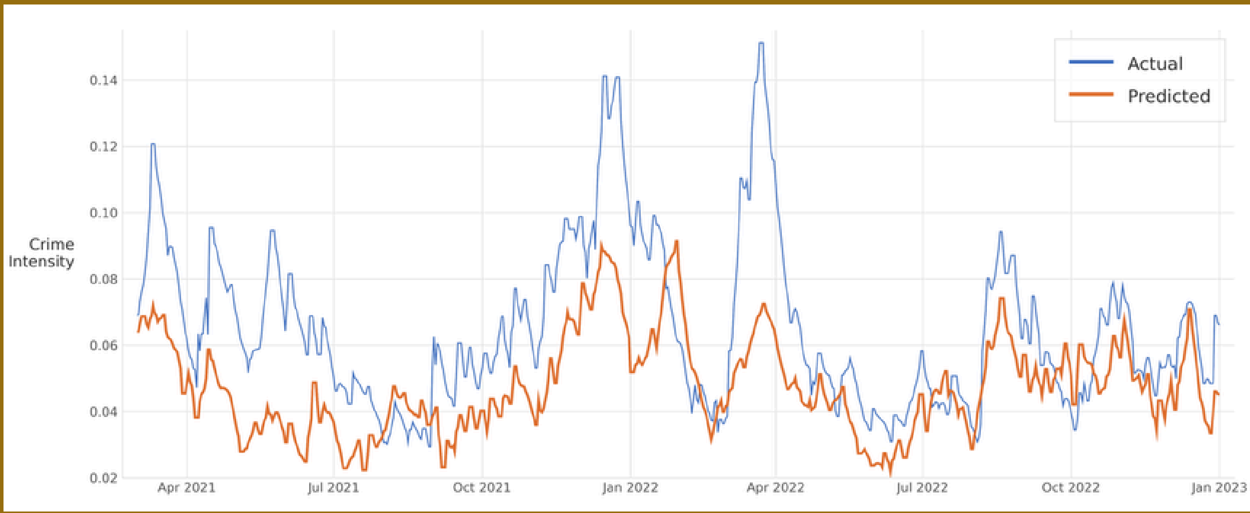


Source: World Bank Group.

The team then developed a model predicting change in levels of crime; this involved ingesting data representing 200 different phenomena across the natural, social, and built worlds, as well as different dimensions of perception about them from both social media and news media platforms in both English and the local language.

The model's predictions differed from observed daily crime-reporting levels by around 12.9%, representing the average deviation across the dataset and indicating how closely the model followed broader reporting patterns. That is, if there were 100 crime news articles on a single day, the model would predict between 88 and 112 articles on that day (see figure 11).

Figure 11. Predicted versus actual volume of reported crime events



Source: World Bank Group.

By itself, the production of crime proxy data constituted a significant step forward for World Bank Country Office colleagues' capacity to observe change in crime. Because official crime statistics are limited, the model-generated dataset supported the Country Office in assessing CPIA Question 12, which examines elements of rule-based governance, including crime and violence.

High levels of model accuracy foster confidence in acting on model-identified factors associated with change. This could be used for evidence-based policy and operations that mitigate levels of crime and associated poverty. As identified by the model, the factors most associated with change in levels of crime were change in food prices and the volume and sentiment of language about women and youth, public services, government, elections, and land use and land rights.

Conclusion

The optimal predictive and explanatory utility of machine learning and AI methods requires certain conditions, including the availability or producibility of data representing change in frequently occurring phenomena. Two of the three models developed by the World Bank demonstrate that emerging methods can produce otherwise unavailable data representing such phenomena. Object classification models applied to satellite-generated imagery-produced data representing five years of monthly change in the number and density of built structures. Large language models and natural language processing applied to online newspaper reporting produced data representing change in the volume of newspaper-reported crime events. These emergent capabilities indicate the potential for machine learning models to measure previously unmeasured dimensions of development and poverty, predict and explain change in those phenomena, or use that data to better predict fiscal metrics and other social phenomena critical to human development, such as food insecurity and citizen-expressed development priorities. Table 1 charts some of the key questions applied to the three cases to determine whether a given context and phenomenon to be forecast and explained are appropriate for a machine learning model.

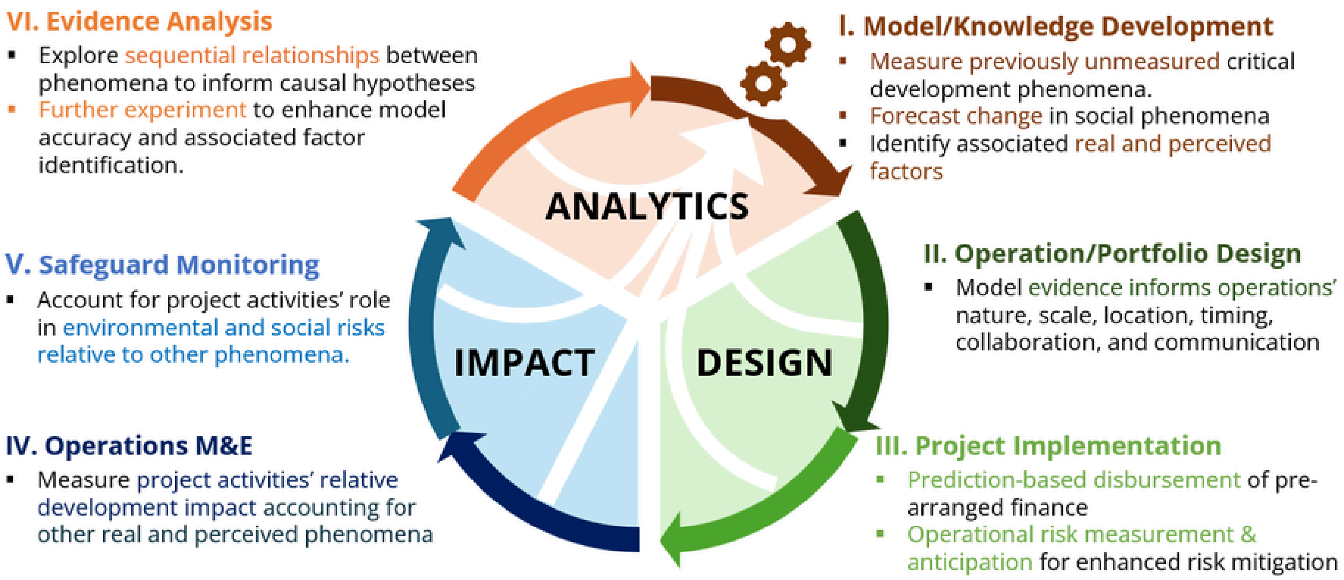
Table 1. Considerations for the viability of machine learning model–produced predictions

Consideration	Democratic Republic of Congo	Horn of Africa	Small Island Developing State
Is phenomenon frequently occuring?	Conflict events frequently occur	Human movement occurs constantly	Unrest: no; crime:yes
Is phenomenon historically occuring?	Yes, for three decades	Yes	Crime: Yes
Are data available that appropriately measure the phenomenon?	Multiple sources produce conflict event data	Daily or weekly change in different places is not measured	No, annual data are available but are not frequent enough
Can proxy data be produced?	Not necessary	Yes, by automating identification of built structures in satellite imagery	Yes, from automated interpretation of online news
Do proxy data require triangulation?	Not applicable	Yes, using representative household surveys identifying average no. of persons per household	No, but they can be triangulated with change in police-reported data
Are triangulating sources avilable?	Not applicable	Yes	No
Are independant variable data sources available?	Yes, real phenomenon and online language data	Yes	Yes

Development policy, financing, and practice could be transformed by machine learning methods that leverage a variety of data sources, thereby enabling practitioners to forecast, understand, and more proportionately and accurately allocate resources for the greatest risk mitigation. The capacity to forecast change in different social phenomena—including unrest, violence, population shifts, and poverty—and to identify the factors associated with change could assist other methods in informing and shaping what development activities are supported; where, when, and with whom activities are undertaken; and what communication language should be employed, to who, to whom, and via what platforms. This potential capacity is significant for development efforts to address extreme poverty and drive shared prosperity. Use of models to monitor and forecast change in violence or poverty could also support evidence-based risk financing approaches and enhance existing monitoring and evaluation of projects and management of project security risks. Risk financing or Program-for-Results approaches could scale up model-identified activities associated with change in violence in response to (for example) observed or forecast violence increase. The enhanced precision and adaptability supported by such a mechanism could drive greater World Bank impact, including at the time of greatest need.

Key takeaways on use of AI and machine learning to understand and forecast social risks are summarized in figure 12.

Figure 12. Model applications in development policy and operations



Source: World Bank Group.

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Abstract

AI- and machine learning–based social risk forecasting and explanation are applied across fragile and climate-affected contexts to predict change in conflict (DRC), population movement (Horn of Africa), and crime (a SIDS), using large multimodal datasets (satellite imagery, NLP on news/social media, economic and climate indicators, geospatial data). Three proof-of-concept models achieve out-of-sample accuracies of 63–76% (conflict) and 70–74% (population change) and generate crime risk proxies where official statistics are scarce. Key associated factors include language about sensitive topics and political actors, economic pressures and prices, climate stress, and social perceptions. Results illustrate how social science–informed AI complements conventional analytics and supports policy and operations for risk monitoring, early action, and targeted resource allocation

Keywords: Machine learning for social risk; climate resilience; post-conflict recovery; community-led development; skills development; informal economy; youth employment

JEL Codes: O33, I38, F22, Q54, K42