

Perspective

To understand climate change adaptation, we must characterize climate variability: Here's how

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SUMMARY

Climate change adaptation involves the management of climate-related risks, and the Intergovernmental Panel on Climate Change says we must prioritize adaptation immediately. However, researchers and policymakers have little systematic understanding of which adaptations are effective at *reducing* risks, including under different climate conditions. Drawing on data from human communities past and present, we review how features of climate variability—temporal autocorrelation, frequency, and severity—may predict which candidate climate change adaptations communities innovate or adopt. Using a case study of climate and remittances in Africa, we outline how researchers can characterize features of climate data relevant to adaptation—autocorrelation, frequency, and severity—and then qualitatively compare these data to candidate adaptations. We include suggestions for how to involve communities in these explorations, from setting climate thresholds to identifying impactful hazards. By better understanding the relationship between climate variability and common solutions used by communities, researchers and policymakers can better support communities as they adapt to contemporary climate change.

INTRODUCTION

As climate continues to change, communities on the frontlines are increasingly being impacted by compounding climate events that are upending people's lives, resources, well-being, and livelihoods.¹ With an eye to these impacts, leaders are calling for increased focus on and funding for climate change adaptation domestically and internationally,² where adaptation broadly refers to managing risks associated with climate change (e.g., risks to homes, livelihoods, health, infrastructure). Not everyone agrees on what climate change adaptation will require going forward: whether communities can generate the solutions that work best for them,³ whether the world needs all-new, transformative solutions,⁴ or a combination of the two. However, for any of these approaches to work, there is an urgent need to understand what makes climate change adaptation effective^{1,4,5}—including which adaptations tend to work well given different characteristics of climate, as not all are identical in their impacts on lives, resources, and livelihoods (e.g., Zscheischler et al.¹).

To understand what makes climate adaptation effective, researchers, organizations, and policymakers need to look at the

interplay between the characteristics of climate variability and the climate change adaptations people have used successfully in the past and present. This requires a decidedly local approach, involving attention to local experiences of climate variability and extremes.⁶ Much of climate science has largely focused on studying climate extremes at coarse regional scales, motivated by the need to characterize how the climate is changing, improve predictability on various timescales, evaluate societal and ecosystem impacts, and galvanize and inform mitigation efforts.^{1,6,7}

In this Perspective, we provide an overview of adaptation to climate change, and we draw on social data—from archeology, ethnography, and more—to illustrate how features of climate variability shape adaptation: first, the temporal autocorrelation and frequency of climate events, whether of univariate hazards (e.g., floods) or multivariate hazards (e.g., hot and dry conditions); and second, the duration, intensity, magnitude, and severity (DIMS) of events. Temporal autocorrelation, frequency, and DIMS capture how climate events cluster together in time, how often they recur, how long they last, and their peak and cumulative severity. These features of climate variability are not usually considered together and



some, such as temporal autocorrelation, are understudied, making it difficult for researchers to systematically examine observed data for links between climate characteristics and the climate change adaptations communities use to reduce risk effectively.

To encourage the study of these links by climate-focused researchers across disciplines and to generate datasets that are usable for studying climate change adaptation,⁶ we offer a framework for characterizing climate data by their temporal autocorrelation, frequency, and DIMS. Such a framework is particularly important in middle and low income countries that are at the frontlines of climate change, where lives, livelihoods, and resources are more vulnerable to climate hazards,⁸ and where there is an urgent need to better understand and inform adaptation efforts.⁴ Further, given voices from the Global South are often missing from climate research, in no small part due to hurdles like limited funding,^{9,10} we illustrate how to deploy this framework using publicly available data and we make recommendations for how researchers can use it in collaboration with communities—efforts that can both improve empirical work on climate change adaptation and allow us to support communities as they adapt.

CLIMATE CHANGE ADAPTATION IS CULTURAL ADAPTATION

The Intergovernmental Panel on Climate Change (IPCC) defines adaptation in human systems as “the process of adjustment to actual or expected climate and its effects.”¹¹ This process of adjustment is cultural^{12–14}—regardless of whether candidate adaptations emerge locally, among community stakeholders, or externally, among policymakers or organizations.¹⁵ Researchers often refer to “behavioral adaptations” (e.g., reducing water consumption, planting crops earlier) as cultural,⁴ and they are. However, culture is transmitted between individuals, between communities, and across generations, and it has impacts on people’s behavior, social structure, human-constructed objects, and the environment.¹⁶ Accordingly, even if the focus is on infrastructure,¹⁷ resource management strategies,^{15,16,18} and other interventions popular in the development sector, what researchers, organizations, and policymakers think is adaptive or is not is a product of culture too.^{14,19}

Innovations that may manage risk, or “candidate adaptations,” originate in communities or are introduced into communities from the outside—for example, by communities sharing ideas with one another, or by policymakers or governmental or non-governmental organizations. If a candidate adaptation is effective at reducing risk locally, it can be called an adaptation in that local context. Relative to innovations less effective at reducing risk, adaptations are more likely to be transmitted—whether, e.g., from individual to individual, from community to community, or via the interventions of organizations—across space and time.²⁰ If conditions change, individuals and communities may modify an adaptation and retain the modified version if it continues to reduce risk.^{12,14} In short, the process of adaptation involves innovation, transmission, modification, and persistence, in a manner broadly analogous to genetic evolution.²¹ Climate change adaptation is cultural adaptation.^{5,12,19} (For definitions of terms we use in this paper, see [Box 1](#), Glossary. For

overviews of cultural adaptation to climate change, see Pisor et al.¹⁴ and Waring et al.²⁰)

When candidate adaptations emerge at the local level, this process is sometimes called community-based adaptation,³⁷ autonomous adaptation,³⁸ or autochthonous adaptation,^{12,39} each with a slightly different meaning. Importantly, candidate climate change adaptations that emerge locally can be more effective at both reducing the negative impacts of climate events and at persisting through time^{3,40–42}—that is, can be adaptive. Unfortunately, the impact of candidate climate change adaptations on risk reduction and their persistence through time, the very things that make adaptations adaptive, are often not studied.⁴ In other words, we know little about the effectiveness of different candidate climate change adaptations, let alone given different climate impacts across space and time.

HOW CLIMATE VARIABILITY IMPACTS CULTURAL ADAPTATION

We also know little about which characteristics of climate events are related to which kinds of adaptations—that is, why one particular innovation emerged or was adopted given the local experiences of climate. This is not to say that researchers do not consider the context in which adaptations occur. For example, focus on complex risk⁷ or social and ecological regimes⁴³ emphasizes the importance of context, including integrated social and environmental systems.⁴⁴ These approaches are key to risk assessments: when, for example, governments or organizations contract researchers to help them better prepare for climate change.⁷ However, because regime-focused research and risk assessments are explicitly aimed at understanding risk and human responses in context, it makes it difficult to study the relationship between characteristics of climate and climate change adaptation systematically across contexts—at scale and across time—providing insight into which characteristics of climate are systematically related to which adaptations.

One of the quintessential features of contemporary climate change is change in day-to-day, season-to-season, or year-to-year climate variability²³ (see [Box 1](#) for definitions). Risk is inherently about variance in outcomes—deviations from some expected conditions or long-term mean⁴⁵—and researchers recognize that these changes in variability impact human lives and livelihoods.^{8,46} Climate variability is not just one thing: it has different patterns and features, on timescales from seasonal to multi-decadal, that can impact which candidate adaptations reduce risk and where (e.g., Ember et al.,³⁴ Piero et al.,⁴⁷ and Pisor and Jones⁴⁸). For example, are climate events clustered in time or of long duration, eliminating people’s savings? Are they frequent, such that communities expect another one is coming and form risk-sharing networks accordingly? Are they widespread, such that neighboring communities experience the same hazard simultaneously, limiting the value of risk pooling? Communities “in 96 countries on all continents report increased duration and severity of climate hazards, like droughts and storms, and changes in their predictability.”⁸ Characterizing the features of, for example, climate variability and comparing these patterns with climate adaptations in use can provide insight into which candidate adaptations are likely to emerge,

Box 1. Glossary

Adaptation/to adapt. *Noun:* A trait (behavioral, cultural, physical, or physiological) that effectively manages risk posed by a given environment, thereby promoting the persistence and/or replication of an entity (e.g., an individual, a group) in a particular environment. *Verb:* The process by which an entity becomes better able to manage the risk posed by its environment. Drawing on concepts from biology, adaptation often occurs through innovation, modification of innovations to better match risks, persistence of those that work well, and transmission—which can both spread adaptations across space and promote their continuity across time.

Candidate adaptation. A trait that may effectively manage risk, but its effects on persistence and/or transmission in a particular environment have not yet been determined.

Climate change. A change in the statistics (e.g., mean, day-to-day variability, skewness) of climate variables (e.g., temperature) that persists over multiple decades or longer due to natural processes or external forcings in the Earth system. Human-caused climate change refers to changes that are attributed to human activities such as emissions of greenhouse gasses and anthropogenic aerosols or land-use/land-cover changes including deforestation and agricultural expansion and intensification.

Climate variability. Fluctuations of a climate variable from the mean state on timescales including weeks to decades and longer. Climate variability typically refers to variations due to natural climate processes or natural forcings. Modes of natural climate variability such as the El Niño Southern Oscillation can lead to coherent climate fluctuations across large regions. However, climate variability has changed under anthropogenic climate change in many regions through changes in the frequency and magnitude of low and high extremes.

Climate change adaptation. A change (*noun*) or the process of change (*verb*) in response to existing experiences of climate change or in anticipation of future climate change.

Climate event. An instantiation of a climate hazard. Usually the beginning and end of an event are identified by exceedances of absolute or relative thresholds in climate variables (e.g., precipitation, temperature) demarcated by researchers and/or community members.

Exchange. Exchange is commodity-for-commodity trade, including exchanging the commodity of currency for a good.²²

Force. Refers to robbery, theft, and armed conflict, including raiding and warfare. Force is typically used against those who have desired resources—for example, because of long-standing social inequality, resources are discontinuous across space and individuals are defending them, or some individuals were less affected by recent climate events than others.

Hazard. Generally, risk of negative outcomes; in practice, often used in the phrase “climate hazards,” referring to physical climate events that can cause negative outcomes for people.²³ Here, we refer to “types of hazards” accordingly, e.g., flood, drought, hurricane, etc.

Livelihood diversification. Livelihood diversification means drawing on various resource streams,²⁴ increasing mean return for a given level of variability. Diversification can apply to diet breadth,^{25,26} crops planted or animals raised, locations where crops are planted or animals are kept,^{27,28} or income streams, often realized by performing different tasks.^{24,29}

Migration. Short-term migration is a common response to climate variability, including seasonality—for example, in the form of migrant labor (e.g., Clech et al.³⁰), circular migration,³¹ and visitation (e.g., Wiessner³²)—long-term migration is less common given the potential costs of lost capital and moving (or abandoning) possessions and one’s community. In the face of climate change, long-term migration is often used when all other adaptations have failed^{33,31} (though cf. Ember et al.³⁴), in which case it is sometimes called “forced migration.”

Risk. Variation in outcomes; sometimes outcomes may be positive, but in the context of climate change, they are often negative.

Risk pooling. Smooths risk across people, as individuals with a surplus provide resources to those with a deficit; this may occur via, for example, transferring money between households, sharing food, and sharing labor.

Savings. Called storage,³³ technological storage,³⁵ and rationing³⁶ when applied to food, savings broadly refers to caching resources—including money—to buffer potential future events.

spread, and persist in the face of which features of climate variability.

Existing social data provide a useful starting point, allowing researchers to both (1) identify which characteristics of climate variability likely matter for climate change adaptation, and (2) make informed predictions about how these characteristics influence which climate change adaptations individuals use. Humans have myriad climate change adaptations, but many of those that emerge in communities fall into six larger categories: risk pooling, exchange and markets, mobility and migration, savings, livelihood diversification, and force, like armed conflict and theft^{27,33,36,39,48–50} (see Box 1 for a brief overview of each). Of course, not all adaptations can be attrib-

uted to climate; social network structure affects the transmission of adaptations,¹² for example, while path dependence can constrain the innovation of new adaptations.⁵¹ Further, not all of the adaptation types are equally desirable. What is adaptive for an individual may have negative impacts on their community or society²⁰: for example, theft and other kinds of force, which may become more common with continuing climate change (e.g., with floods and droughts),^{52–54} harm others, can undercut other adaptation strategies, and can worsen already existing global conflicts, even if theft helps an individual manage climate risk in the moment. Understanding the conditions that make force more likely can help us prepare to intervene before it is used.

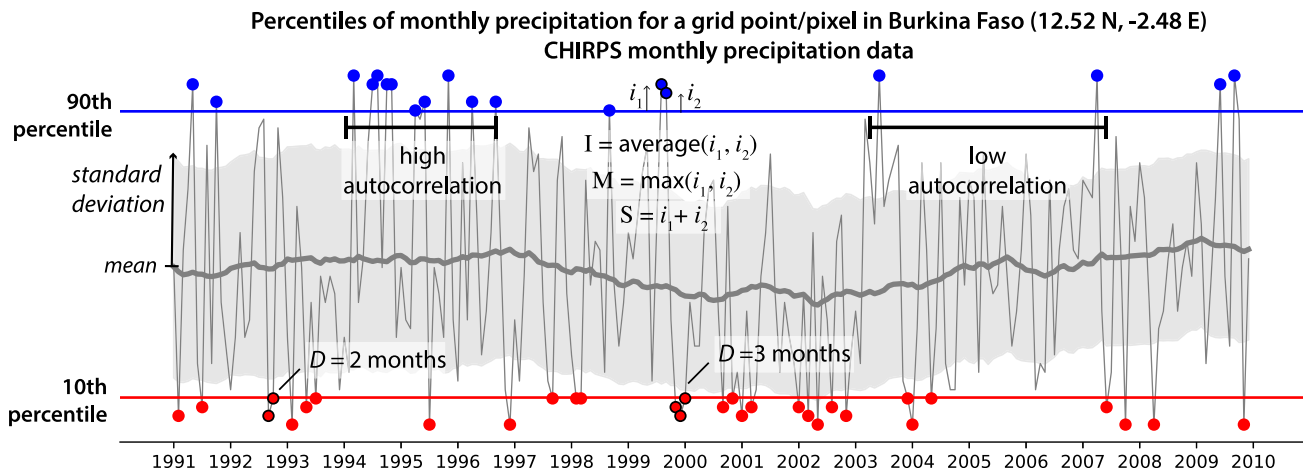


Figure 1. Illustration of autocorrelation, duration, intensity, magnitude, and severity for precipitation in Burkina Faso
Monthly precipitation data come from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, standardized using month-specific distributions for a grid point from 1991 to 2009 (thin gray line). The 10th and 90th month-specific percentiles are used for dry and wet thresholds, respectively. We provide examples of different durations (D) and autocorrelation for extremely dry (red points) or wet (blue points) months. The calculation of intensity (I), magnitude (M), and severity (S) is also shown for a 2-month wet event with a departure of i_1 and i_2 from the threshold. The 5-year moving mean (thick gray line) and \pm standard deviation (gray shading) are also shown.

As an illustration of the relationship between climate and candidate climate change adaptations, consider migration and risk pooling—such as sharing or gifts, exchange, loans, remittances, and microinsurance, all of which can involve households in one or multiple communities. On the one hand, climate events that have high temporal autocorrelation and high DIMS “can overwhelm the capacity of natural and human systems to cope.”¹ In that case, households may exhaust their existing risk-management solutions and turn to migration⁵⁵; this will be especially true if the events are high in DIMS but low in frequency, such that households do not anticipate them and do not have the adaptations in place to cope.^{56,57} On the other hand, when events have higher frequency, individuals can anticipate the events will recur and, assuming variance in outcomes across households, invest in social relationships or local arrangements that permit risk pooling (e.g., Ncube et al.⁵⁸). In some cases, households in societies with high mobility, like fishers or pastoralists, may use migration when events are high frequency (that is, occur regularly) as part of a suite of adaptations.⁴⁷

Importantly, these climate events could involve different hazard types, such as (1) high heat and humidity that compound heat stress (e.g., Rogers et al.⁵⁹); (2) high heat and low precipitation that compound drought conditions (e.g., Diffenbaugh et al.⁶⁰ and Sarhadi et al.⁶¹); (3) co-occurring heavy rains, winds, and storm surge that compound flooding risks in coastal communities (e.g., Bevacqua et al.⁶²); or (4) periods of severe droughts followed by heavy rains that compound agricultural impacts (e.g., Raymond et al.⁶³). Accordingly, when considering time series of events that may impact communities and, in turn, community-based adaptation, researchers must both establish which climate events impact communities on the ground⁸ and consider how they might compound—for example, by including multivariate hazard types in a single time series. Efforts to characterize such compound events are needed, especially in the Global South where data and

studies are more limited but compound events are already acutely impacting vulnerable communities.⁶⁴

As becomes clear, the temporal autocorrelation of climate events, their frequency, and severity-related measures we call DIMS impact how adaptation unfolds (Figure 1). Climate scientists rarely characterize climate time series by all these dimensions, instead mainly focusing on frequency and one or two components of DIMS (e.g., intensity-duration-frequency curves used commonly in hydrology); further, while recent contributions to the compound events literature have started to investigate temporally correlated risks, these studies are largely limited to certain hazards and are disproportionately focused on regions in the Global North. Characterizing all of these dimensions—temporal correlation, frequency, and DIMS—will help systematically understand how the impacts of contemporary climate change on lives, resources, well-being, and livelihoods translate into adaptations.⁴⁸ This basic science is the first step; after establishing which candidate adaptations tend to be associated with which features of climate variability, applied research opportunities and policy recommendations may then emerge. For example, given projections of climate hazards with warming, we can potentially predict (with appropriate uncertainty) which adaptations may emerge in which places; risk assessments could then incorporate the projected efficacy of adaptations likely to emerge given other features of a particular place, like population density and existing cultural practices.

Temporal autocorrelation

Climate events such as heatwaves, droughts, and heavy precipitation can be temporally autocorrelated, occurring back-to-back or in clusters^{65–67} (Figure 1). Such clustering can have compounding impacts on human lives and livelihoods, and can limit people’s coping capacity by depleting resources; for example, storm landfalls are projected to become more sequential along the Gulf Coast of the United States, meaning households have less time to recover between storms.⁶⁸ Another example is

that back-to-back heatwaves are projected to occur more often with warming, with the largest increase in their risk in tropical countries.⁶⁷ Indeed, temporal autocorrelation in temperature is increasing with anthropogenic climate change and is expected to continue increasing across this century.⁶⁹

Climate events can be temporally autocorrelated across scales of days, months, seasons, or even years, and each type of autocorrelation can affect the types of human adaptation in use. Autocorrelation across days is very common and is often managed with savings^{33,70} (think “rainy day funds”) or through within-community risk pooling—sharing within a household or between neighboring households.⁷¹ Temporal autocorrelation across seasons and across years (think of two bad harvests in a row or multiple years of drought) requires different solutions, as savings can be depleted. Diversifying crops, livestock, or income sources can buffer against multiple consecutive bad harvests: for example, for pastoralists in sub-Saharan Africa, cattle are preferred as livestock but goats are more resilient to drought.^{72,73} That said, the longer the run of climate events, the more likely it is that individuals will exhaust local options, including savings and within-community risk pooling⁴⁸; this is often when individuals rely on options like migration or on between-community risk-pooling.⁵⁵

Importantly, temporal autocorrelation in climate variables, like temperature or precipitation, can impact adaptation even if the measures do not cross an event threshold; for example, consecutive hot days can desiccate crops or cause negative health impacts or heat-related mortality, even if temperature data do not cross thresholds set for identifying heatwaves. The difficulty in detecting these impacts can be overcome by the use of multiple thresholds to identify different levels of extremes (e.g., National Oceanic and Atmospheric Administration Drought Monitor), or by using more complex definitions that capture the cumulative impact of sequential extremes and short “breaks” between extremes (e.g., across extreme temperature events that occur over a season⁶⁷). Further, in consultation with communities or using local data on how climate variables translate into impacts, researchers may consider using lower relative thresholds (e.g., 90th percentile instead of 95th percentile), identifying absolute thresholds, or using different criteria to establish extreme events; see below.

Frequency

The frequency or recurrence interval is the number of times the data exceed threshold(s) within a predefined time interval (Figure 1). These thresholds are often (1) a known magnitude for a climate variable, usually specific to a region and/or season (e.g., $\geq 45\text{C}$ on the Indian plains⁷⁴); (2) the percentile of the observed distribution (e.g., exceedance 99th percentile of daily rainfall to capture extreme wet events, or falling below the 20th percentile of monthly rainfall to capture drought events); or (3) using a specified return interval to establish a threshold (e.g., 20-year rainfall event). Frequency often appears in the climate literature (1) as part of intensity-duration-frequency curves (IDF curves, e.g., in flooding⁷⁵), which assess the continuous relationship among the three measures; (2) as part of assessing the number of “exceptional events” (e.g., in extreme temperature, air quality, or landslide time series^{76,77}); or (3) as a contributor to temporal compounding: for example, a higher frequency of

events can affect the ability of communities to cope even to less extreme events.¹

Important to the frequency of a time series is accounting for the non-stationarity of its mean and variance; changes to each can have different impacts on the frequency of extremes—that is, crossing of thresholds. For example, increasing variance may favor adaptations to frequent hot and cold extremes. That said, if the mean increases without an increase in variance, or if the mean increases *faster* than the variance, hot extremes may become more frequent and cold extremes less frequent, with subsequent impacts on climate change adaptation.⁷⁸ Though we focus here on climate variability, emerging literature shows that future climates will be shaped by changes in both the mean and variance of the climate,⁷⁹ and therefore, adaptation measures will need to account for both.

Social data suggest that people are more likely to have cultural adaptations for responding to events that are not low frequency because they know such events will happen again.^{80,81} For example, when individuals anticipate rough times ahead, the marginal value of saving for the future is higher^{82–84} and individuals tend to invest in diversification, which lowers overall returns but hedges against risk.²⁴ When events are low frequency or “rare,” however, marginal returns to saving and diversification are lower. As we discuss above, when candidate adaptations do not offer benefits, individuals are less likely to retain or transmit them.⁸⁵ This may partially explain why risk pooling becomes less common and things like theft more common when societies face rare megadroughts: cultural adaptations for managing the risks they pose are not in circulation.^{86–88}

DIMS: Duration, intensity, magnitude, and severity

When climate scientists discuss different kinds of climate events, they may focus on the duration of an event, its intensity, its magnitude, its severity, or some combination of the four (e.g., intensity and duration for tropical storms⁸⁹; intensity and magnitude for floods⁹⁰). Various definitions for these characteristics exist—we provide the common ones here—but what all definitions share is their focus on the severity of impact. Duration refers to the length of an event—usually implicitly scaled relative to other events of the same hazard, given extreme events can manifest on sub-hourly (e.g., tornadoes) to multi-annual (e.g., droughts) time scales. For example, a long-duration hurricane is of long duration relative to other hurricanes. Severity is the total excess (e.g., flood) or deficit (e.g., droughts) of a climate variable across an event—the area under or over the curve.^{91,92} Intensity is typically severity divided by a unit of time, often by minute (e.g., for tornado intensity⁹³) or by day (e.g., for precipitation extremes⁶⁵). Magnitude refers to the cumulative value or most extreme value on a scale of measurement during an event or time interval. For tornadoes, for example, this can be the highest value on the Enhanced Fujita Scale during an event,⁹³ while for floods, this can be the maximum discharge of water on a daily or annual interval.⁹⁴

We treat duration, intensity, magnitude, and severity together—calling them DIMS—because, regardless of the hazard type or means of quantification, researchers are estimating the severity of impact of a single event (Figure 1); for this reason, these characteristics are often discussed in the context of compounding.¹ That said, in contrast to some treatments in the

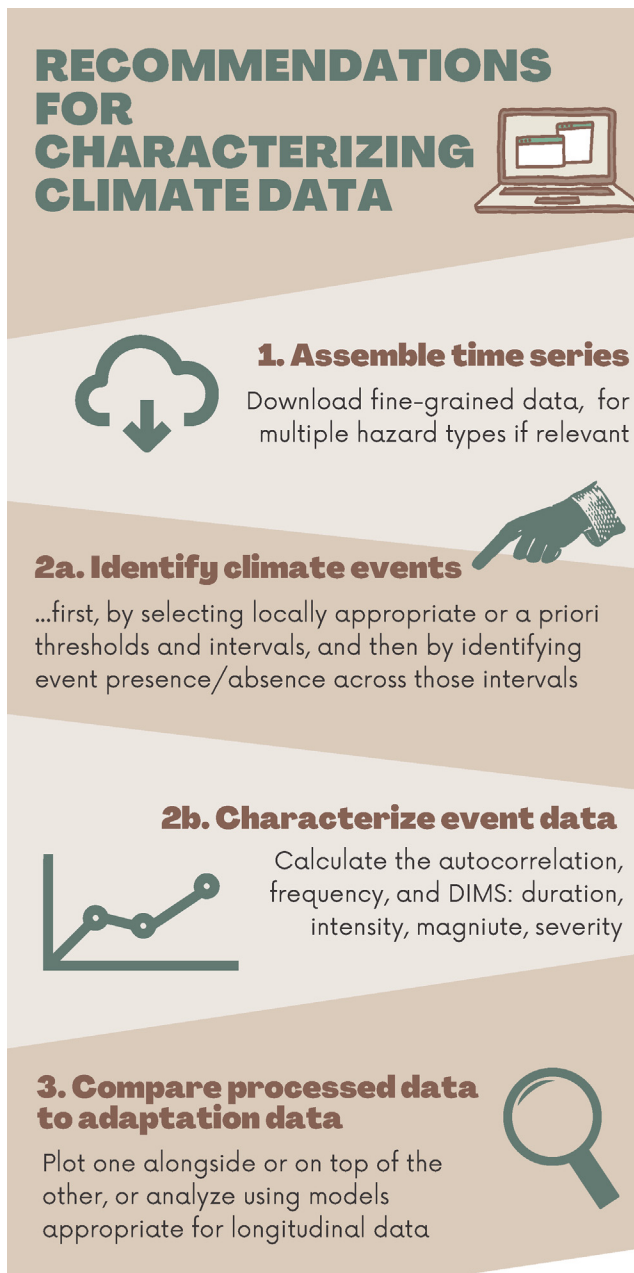


Figure 2. Our recommended steps for characterizing climate data on dimensions relevant for climate change adaptation
Note that steps 1 and 2a should be reversed if researchers are collaborating with communities.

literature on compounding, we recommend separating DIMS from autocorrelation and from frequency to systematically study how the characteristics of individual events—or even these average characteristics across a time series of events—affect adaptation to climate change.

When an event has low DIMS, it is more easily managed by cultural adaptations like savings, diversification, and risk pooling; however, when an event has high DIMS, it can exhaust the resources these cultural adaptations provide.^{53,56,85,95} When these options are exhausted, individuals may be more likely to

turn to candidate adaptations that can reflect desperation. However, if a series of events happens both to be high DIMS and to recur with some frequency, individuals may turn to some of their weaker social ties—those with whom they are connected but interact less frequently or less intensively—to pool risk.

CHARACTERIZING ADAPTATION-RELEVANT CLIMATE DIMENSIONS

Existing social data indicate that characteristics of climate—temporal autocorrelation, frequency, and severity-related measures (DIMS)—impact which cultural adaptations to climate change are innovated, sustained, and transmitted in human populations. Targeted study of the relationships between climate and cultural adaptation is important for at least two reasons: first, so researchers can assess the strength and generalizability of the relationships described above across communities and geographies, and second, looking to the future, potentially leveraging this insight to help organizations and policymakers anticipate how communities will respond, or which candidate adaptations introduced by organizations might work for communities, as they face the impacts of climate change over the coming years.

Here, we overview how to characterize climate data by temporal autocorrelation, frequency, and DIMS (Figure 2)—an approach that could help researchers meet the above empirical and applied goals. In a perfect world, such approaches would involve communities in this work—identifying the climate hazards that matter for them, ground-truthing the data collected, and delivering data they can use (if they choose) to guide their selection of different candidate adaptations, as is often the case in risk-assessment approaches.^{7,96} However, because our framework focuses on larger geographic areas, ground-truthing can be especially challenging because the experience of one community may not generalize to others.⁹⁶ Further, we recognize that not all researchers will be able to work directly with communities, partly due to limited funding to support field travel and community engagement. Accordingly, we begin by reviewing how to obtain relevant public climate data and characterize its temporal autocorrelation, frequency, and DIMS, working through an example of precipitation and remittances in Burkina Faso. We then detail some of the benefits of community collaboration (including improving the empirics of climate change adaptation research) and, drawing on existing examples and their limitations, provide suggestions for engaging in community collaborations. We recognize that some researchers will not need a primer on working with climate data, and some will not need a primer on collaborating with communities; however, we provide details on both, as we recognize that the majority of researchers will be unfamiliar with some aspects of the framework we describe below.

Working with publicly available data

Researchers may start with some *a priori* expectations about the relationship between climate characteristics and adaptation, as we do here. Remittances are between-community risk pooling, as money and other resources move across space—often between places with different experiences with climate.⁹⁷ Like other kinds of risk pooling, decisions to remit do not occur in a

vacuum affected only by climate; for example, the availability of government social safety nets or services may have a more immediate effect on people's everyday lives.^{98,99} However, looking systematically at how climate variability is related to cultural adaptation across space and time, we expect that all else equal, people are more likely to maintain connections that span distance when climate events (1) frequently affect their lives, resources, well-being, and livelihoods, such that individuals expect they will recur, and (2) have either high temporal autocorrelation or high DIMS, as both can exhaust resources available through locally based adaptations (e.g., storage and within-community risk pooling); individuals can then call on these connections during climate events.⁴⁸ There are detailed data available on both remittances and precipitation for six countries in Africa; as a case example, given variability in precipitation across its provinces, we present exploratory analyses on Burkina Faso here.

First, assemble relevant time series

There are numerous free sources of high-quality climate data publicly available, many of which can be found through the National Center for Atmospheric Research Climate Data Guide.¹⁰⁰ We recommend using the finest-grain, reliable data available, multiple data sources where possible to improve the match of climate data to on-the-ground experiences in communities, and using datasets that include satellite data, given sparse station coverage in rural areas and in the Global South. In our illustrative example, we work with Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data,¹⁰¹ which combine station and satellite data with model interpolation to achieve high coverage, with a granularity of 0.05°, of most of the globe. All data processing and visualization were done using Python version 3.11.1.¹⁰² Data and annotated code are available in Python at <https://github.com/detouma/adaptation>.

To capture people's experience of climate variability on the ground, researchers should consider creating a multivariate time series of multiple climate variables—for example, both near-surface temperature, precipitation, and humidity. This may involve downloading more than one dataset, characterizing the variability in each, and then merging the resulting time series. In our example, we use a univariate time series of precipitation for assessing dry extremes.

Second, characterize the data

If researchers have not consulted with communities, they can adopt commonly used thresholds for identifying extreme observations. We recommend (1) a known magnitude for a climate variable usually specific to a region, season, and/or resource, e.g., daily rainfall amounts exceeding 100 mm that have the potential to cause flooding; (2) a percentile of the observed distribution, e.g., exceedance 95th/99th percentile of daily rainfall to capture extreme wet events; or (3) using a specified return interval to establish a threshold (e.g., 20-year rainfall event). We then create a binary variable that identifies if a data point is an extreme observation or not. In our example, we use the 10th percentile of monthly rainfall, and we identify drought events as those that fall below that threshold. (Though using a variable that also accounts for deficits due to evapotranspiration is preferred for drought characterization, we opted to use precipitation only for illustrative purposes.)

Note that in the absence of relevant data, these characterizations reflect assumptions. First, without community input, our choice of thresholds may not reflect salient event thresholds on the ground. Second, here we assume that a 5-year interval is relevant for calculating the frequency and the averages for DIMS—in other words, we assume that events occurring over a 5-year interval have effects on adaptations in use (in our case, that events in Burkina Faso from 2005 to 2009 are associated with remittances in 2009). In general, researchers have few data about the time intervals over which climate events can impact human behavior. Hurricane Katrina offers one counterexample. Following the powerful hurricane, flooded households used candidate adaptations from some of the six categories identified here: members of flooded households were likely to move away from the city, either temporarily or permanently, and drew on their storage (i.e., retirement savings) and available risk pooling (i.e., flood insurance).^{103,104} Two to 5 years later, depending on the measure, flooded households were more likely to be without wage income and to have impacted credit scores, and wealthier houses were still making early withdrawals on their retirement savings.^{103,104} Drawing on this case study, we chose a 5-year interval, but the question of appropriate interval length is an empirical one researchers can address through examining adaptation and climate data.

DIMS, frequency, and autocorrelation can be quantified using basic or more complex definitions. In our case example, we use well-known, basic definitions to quantify each (illustrated in Figure 1). For all grid points in Burkina Faso from 2005 to 2009, we first identify all drought events when the time series falls below the threshold for at least 1 month and calculate the frequency of those events. We then calculate the characteristics for each event: D is the length of the event, and I, M, and S are the average, maximum, and total departure from the threshold during the event, respectively. To calculate temporal autocorrelation of a time series of binary events, we use a dispersion metric that divides the variance by the mean.¹⁰⁵ We then average the characteristics of all the events for each grid point over the time period of interest. Our results for this example are shown in Figure 3; Python code is available at <https://doi.org/10.5281/zenodo.10002023>.

Third, compare processed time series with adaptation data

Some researchers may wish to stop once they have completed the above characterizations and make the resulting time series available to colleagues or the public. However, some may wish to compare the characterized climate variability data with social data, to investigate the relationship between climate and cultural adaptation. With an eye to four of the six cultural adaptations to climate change we identified—migration, livelihood diversification, savings, and risk pooling—we highlight several sources of free, publicly available data in Table 1.

In our case example, we downloaded Migration and Remittance Survey data from the World Bank¹⁰⁶ for Burkina Faso in 2009. Participants from 2,106 households answered questions about members of their social networks, both from the same household and different households; participants indicated whether members of these networks lived elsewhere and, if so, if they were sending food or money (remittances).

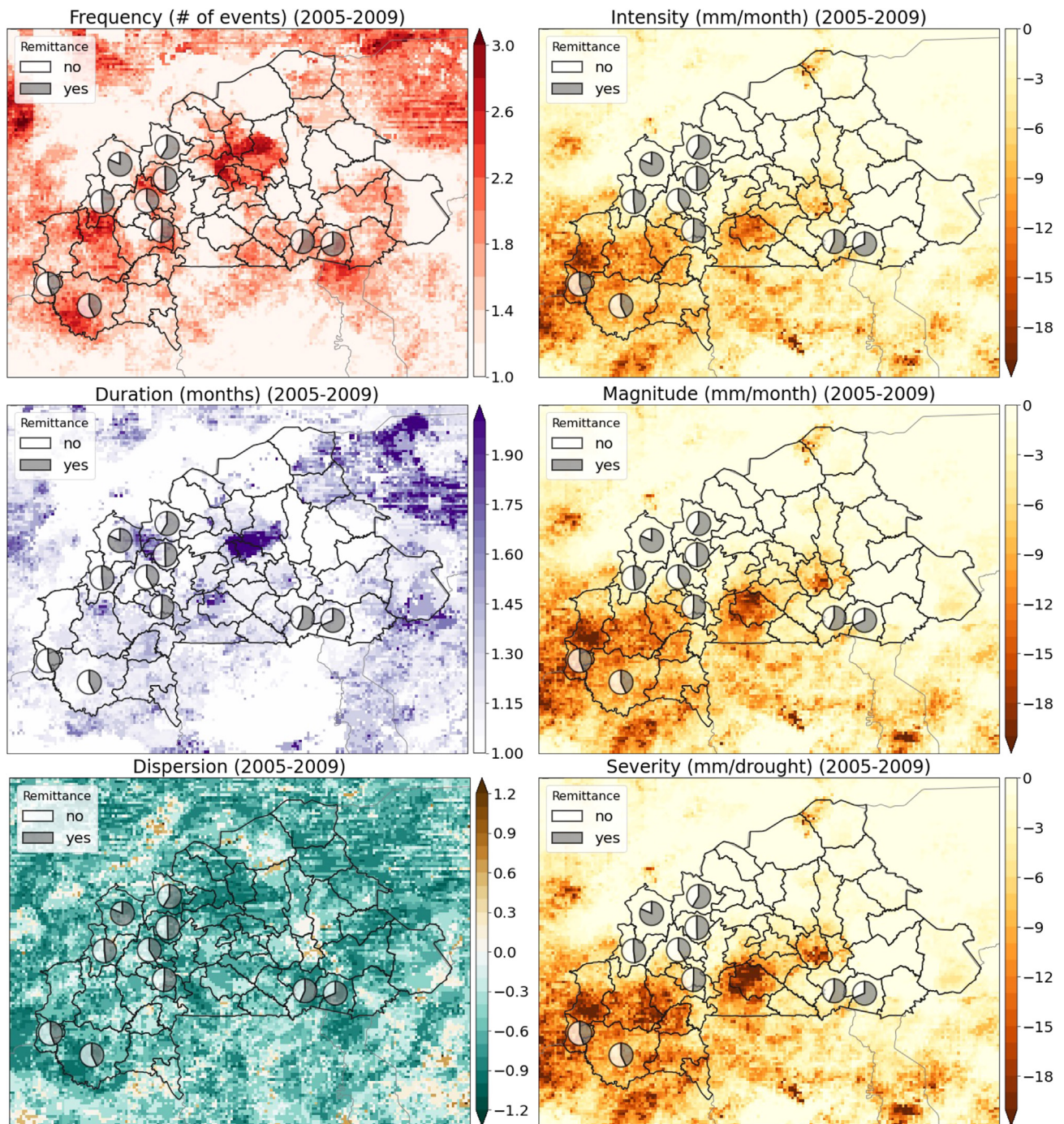


Figure 3. Example of drought frequency, dispersion (temporal autocorrelation), and DIMS for Burkina Faso with remittance data (percentage of households receiving remittances) overlaid
Frequency, temporal autocorrelation, and DIMS are calculated for the interval 2005–2009.

In Figure 3, we plot the locations of these participants, indicating the percentage of households in each province that reported receiving remittances from connections living elsewhere (gray) or not (white) on top of the frequency, DIMS, and dispersion metric data. Focusing just on locations with >50% remittances, we see lots of variance in frequency, DIMS, and dispersion. For example, the locations in the southeast have relatively

high drought frequency (up to 1.5 events/year) but relatively low DIMS and dispersion, while the locations in the northwest have relatively low frequency, but relatively high duration (up to 2 months/event). Statistical or machine learning methods can quantitatively assess the strength and significance of relationships between remittance and climate characteristics—for example, by using appropriate multilevel models that account

Table 1. Candidate sources of freely available social data on one or more of four categories of adaptation: Migration, livelihood diversification, savings, and risk pooling

Source	Link	Data	Resolution	Geographical coverage	Time period
World Bank microdata	https://microdata.worldbank.org/index.php/home	censuses and surveys	individual-level	varies	varies
ICPSR (Inter-university Consortium for Political and Social Research)	https://www.icpsr.umich.edu/web/pages/ICPSR/index.html	censuses and surveys	individual-level	varies	varies
D-Place (Database of Places, Language, Culture and Environment)	https://d-place.org/parameters	coded ethnographic data	culture-level	quasi-global	varies

for participant location. Researchers could also collaborate directly with communities to understand which hazards impact them the most, whether between-community risk pooling affects their livelihoods and well-being or whether other adaptations have stronger impacts, and more.

Best practices: Collaborating with communities

When possible, we recommend that researchers directly collaborate with communities on the frontlines of climate change—at minimum, to use their research to support climate change adaptation.^{2,96} Collaborating with communities helps us establish which climate characteristics, alone or in combination, create risks to lives, resources, well-being, and livelihoods on the ground,^{8,107} and identify which candidate adaptations reduce risk given these conditions. Consultations need not involve months in the field, but rather can use rapid-assessment techniques: a few days in the field can be sufficient to produce a timeline for locally salient hazards and types of adaptations that communities have adopted or are considering—especially when following best practices for these short trips, which will often include working with community leadership and/or local organizations and institutions.¹⁰⁸ In [Note S1](#), we provide detailed recommendations of how to consult with communities to establish relevant hazards, construct time series of events, and establish which candidate adaptations communities are using. If collaborating with communities, researchers should wait to download pertinent data until they have first completed consultations (that is, reverse steps 1 and 2a in [Figure 2](#)).

Using time series of past climate variability constructed in collaboration with communities, organizations and policymakers may engage in scenario planning—they can work with communities to plan for a variety of future scenarios using data on past climate variability, future projections of climate hazards, and different hypothetical socio-economic and development scenarios.¹⁰⁹ However, this is just one of several possible uses of these datasets; for example, another may be to allocate support for risk pooling based on a locale’s experience of climate variability over the last 5 years. We provide detailed suggestions and resources for leveraging these time series in [Note S1](#).

WHY THIS FRAMEWORK—AND WHAT NEXT?

In their February 2022 report, the IPCC Working Group II called for more effective climate change adaptation, but warned of “unintended consequences ... [which] can be avoided by involving

everyone in planning, attention to equity and justice, and drawing on Indigenous and local knowledge.”² There are two hurdles to meeting this challenge, however: first, researchers, organizations, and policymakers have very few data on which candidate climate change adaptations are effective in reducing risk and persisting across time,⁴ and second, the solutions local communities already have for managing climate risks are often sidelined in favor of those from the development sector.⁵ Researchers should expect that the candidate adaptations communities innovate, or even the suggested candidate adaptations they adopt, reflect both the climate risks they face and Indigenous and local knowledge of risk management passed on through generations; in other words, different climate characteristics likely favor different solutions.¹² Understanding which candidate adaptations emerge in response to which climatic conditions, and which candidate adaptations are actually *effective* under those conditions, requires not just targeted study of adaptation in communities,⁵ as is common in risk-assessment frameworks⁹⁶ or in the integrated socio-environmental systems literature.⁷ It requires characterizing climate along the dimensions that have shaped human adaptation before, and then systematically investigating the relationship between climate characteristics and candidate adaptations in use, across space and across time.

Here, we drew on social data to highlight dimensions of climate variability that have been associated with different human adaptations: temporal autocorrelation, frequency, and DIMS (duration, intensity, magnitude, and severity). Climate data from observations or models are often not characterized along these dimensions—for example, recent focus has shifted to how risks can compound or cascade to make impacts worse.^{1,7} However, examining temporal autocorrelation, frequency, and DIMS separately allows study of the relationship between features of climate and the candidate adaptations that emerge or are adopted, and persist—or fail to. We outlined a framework for how researchers can use publicly available datasets to characterize climate along these dimensions—in a perfect world, in collaboration with communities, who knows best which hazards and which adaptations have the most impact on the ground. Using climate and remittance data from Burkina Faso, we provided an illustration of how to use these tools. With this framework, researchers from across fields can better study the relationship between characteristics of climate and adaptation, including which candidate adaptations tend to emerge under which conditions. Studying these associations

opens up additional possibilities, such as investigating whether adaptations will be effective under projected climate scenarios, including “extreme extremes”¹¹⁰—data and knowledge more directly usable for understanding and informing adaptation research.

In addition to the temporal characteristics of climate discussed here, spatially correlated risks can impact where people migrate to or where their risk-pooling partners are located; however, because the question of “where” is secondary to the question of what adaptations are in use locally, we chose not to focus on spatial autocorrelation in this article. Once researchers have better data on the relationship between candidate adaptations and climate characteristics, researchers will be better equipped to tackle such second-order questions.

In sum, by paying attention to adaptations that have successfully managed risk for communities before, and by investigating which of these adaptations are most successful given different characteristics of climate variability, researchers, organizations, and policymakers will better understand the relationship between features of climate, climate change adaptation, and its effectiveness. With this improved understanding, organizations and policymakers will be better positioned to heed the IPCC’s warning and direct adaptation funding into programs and efforts that can better support communities as they respond to ongoing change.

Resource availability

Lead contact

For further information on code, please direct correspondence to lead contact Danielle Touma (danielle.touma@utexas.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

All original code has been deposited at Zenodo under the DOI <https://doi.org/10.5281/zenodo.10002023> and is publicly available as of the date of the publication.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.oneear.2023.11.005>.

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AUTHOR CONTRIBUTIONS

A.P.: conceptualization, writing - original draft, project administration. D.T.: methodology, programming, data curation, writing - original draft, visualization. D.S.: conceptualization, validation, writing - original draft. J.H.J.: conceptualization, writing - original draft.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

One or more of the authors of this paper self-identifies as a gender minority in their field of research. One or more of the authors of this paper self-identifies as a member of the LGBTQIA+ community.

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