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Technical Note: Including hydrologic impact definition in climate projection uncertainty partitioning: a case study of the Central American mid-summer drought

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Abstract. The Central American mid-summer drought (MSD) is a defining precipitation pattern within the regional hydrologic system linked to water and food security. Past changes and future projections in the MSD show a strong sensitivity to how the MSD is defined. The question then arises as to whether multiple definitions should be considered to capture the uncertainty in projected impacts as climate warming continues and a need to understand the impacts on regional hydrology persists. This study uses an ensemble of climate models downscaled over Nicaragua using two methods, global warming levels up to 3 °C, and different definitions of the MSD to characterize the contributions to total uncertainty of each component. Results indicate that the MSD definition contributes the least to total uncertainty, explaining 5-8% of the total. At the same time, evidence suggests a shift of the MSD to later in the year. As warming progresses, total uncertainty is increasingly dominated by variability among climate models. While not a dominant source of uncertainty, downscaling method adds approximately 10-15% to total uncertainty. Future studies of this phenomenon should include an ensemble of climate models and can take advantage of archives of downscaled data to adequately capture uncertainty in hydrologic impacts. This approach could serve as a template to quantify the relative importance of uncertainty for projections of other precipitation-driven phenomena in different geographic contexts.

1 Introduction

Central America is consistently identified as a global hotspot for anthropogenic climate change, being prone to exacerbated impacts of already considerable natural climate variability and change (e.g., Giorgi, 2006; Hidalgo et al., 2017; Stewart et al., 2021). Any effort to develop strategies for mitigating impacts of future climate disruption or adapting to probable hydrologic impacts is based on climate model projections (IPCC, 2023; Lemos and Rood, 2010; Zhao et al., 2021). A quantitative assessment of how variability in precipitation is partitioned into other hydrologic processes, especially the evaluation of changes in extremes such as droughts and floods, can help anticipate variability in impacts (Yin and Roderick, 2020).

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Characterizing future precipitation-driven hydrologic changes, the focus of this study, introduces a cascade of uncertainties into impact projections (Aitken et al., 2023). The uncertainty associated with each step along this cascade, which can include future greenhouse gas concentrations, climate response, downscaling, and hydrologic response can be estimated using multi-model ensembles (discussed in more detail below), which can become a daunting task for stakeholders preparing strategies to cope with the projected changes in the timing and availability of water. Improved understanding of the comparative magnitudes of different sources of variability in impact projections can highlight opportunities to reduce them and, more importantly, help identify which steps in the modeling chain may be simplified without adversely affecting metrics relevant to decision-making related to adaptation and mitigation strategies in water resources (Steinschneider et al., 2023).

As characterized by early efforts to compare variability among precipitation and temperature predictions (Hawkins and Sutton, 2009, 2011), uncertainties arise from imperfect representation of the earth system in numerical models (scientific uncertainty), the inability to know future atmospheric concentrations of greenhouse gases (forcing or scenario uncertainty), and the impossibility of precisely predicting a chaotic system (internal variability). Hawkins and Sutton found that, using climate model projections from the third Coupled Model Intercomparison Project (CMIP3), internal variability becomes less important than scientific or scenario uncertainty later in the 21st century. They also observed a marked difference between precipitation projections, with greater internal and model variability persisting late into the 21st century, and temperature projections, which showed scenario uncertainty dominating projections in most regions late in the 21st century. This reflects the dominant physics of temperature being a primary response to the increased radiative forcing of accumulating greenhouse gases, and precipitation being driven by secondary physical processes that are more challenging to model, such as the moisture holding capacity of the atmosphere, the variety of phenomena that can cause precipitation, and feedbacks with the land surface, ocean, and cryosphere (Neelin et al., 2022; O'Gorman and Schneider, 2009; Stainforth et al., 2005). Other recent studies have found similar results with more recent climate model simulations at continental scales (Lehner et al., 2020; Woldemeskel et al., 2016).

In the most recent sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC), a new emphasis was placed on assessing impacts at specified levels of global warming (relative to pre-industrial conditions of 1850–1900) to facilitate comparisons with earlier reports and coordination with targets in international agreements (IPCC, 2023). Assessing impacts at specific global warming global warming levels also allows the use of models irrespective of their sensitivity (Hausfather et al., 2022). This approach essentially combines scientific and scenario uncertainties into a single 'projection' uncertainty, reducing the variability in simulated projections, but leaving the time at which any specified level of warming occurs less well defined. An advantage for stakeholders is that policies can be developed to respond to locally important hydrologic impacts at different levels of warming without having to cope with forming an ensemble by culling models (based on correspondence of model sensitivity to likely range) or with selecting atmospheric greenhouse gas concentration

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scenarios (Merrifield et al., 2023). In fact, demonstrable skill may be lost when excluding models from an ensemble based solely on correspondence of model sensitivity to observational estimates (Goldenson et al., 2023; Swaminathan et al., 2024).

Because hydrologic impacts analysis often requires projections at a finer spatial scale than what climate models produce, some type of downscaling is performed, which adds an additional layer of uncertainty that has been included in more recent studies (Lafferty and Sriver, 2023; Michalek et al., 2024; Wootten et al., 2017). The selection of downscaling method has been found in some locations to add a significant amount of uncertainty to projections, sometimes persisting at levels comparable to other sources through the 21st century, though results can vary widely in different regions (Lafferty and Sriver, 2023; Wootten et al., 2017).

When expanding an analysis to include specific impacts, the total uncertainty in projections will include that uncertainty that is due to imperfect simulation or definition of impacts (Chegwidden et al., 2019; Clark et al., 2016). The importance of this level of uncertainty can vary widely, based on the specific impact assessed (Bosshard et al., 2013). For example, for future projections of potential evaporation (PE) for France, Lemaitre-Basset et al. (2022) found the PE formulation had a minor contribution to total projection uncertainty, except when only a single scenario was used. How droughts were characterized for compound hot and dry events was a dominant uncertainty source for low precipitation events but was a much smaller portion of uncertainty for other formulations (Jha et al., 2023). Hydrology model parameterization did not significantly influence total uncertainty in a study of projections of subsurface drainage at an experimental site in France (Jeantet et al., 2023).

Across Central America, the midsummer drought (MSD) is a phenomenon where boreal summer seasonal rainfall is characteristically divided into two distinct rainy periods by a relative lull in precipitation, and it is a critical component of the regional hydrologic system (Anderson et al., 2019). Changes in the MSD can lead to lower soil moisture, reduced groundwater recharge, and increased evaporation rates, which can have important impacts on the agricultural calendar, and local food and water security (Stewart et al., 2021). Thus, understanding the causes and impacts of the disruption of midsummer droughts is crucial for managing water resources, predicting agricultural outcomes, and mitigating the effects of such dry periods. A recent study MSD explored the variability in historical trends based on how the MSD is defined (Maurer et al., 2022). In addition, many studies have examined projected future changes in the MSD (Corrales-Suastegui et al., 2020; Maurer et al., 2017; Rauscher et al., 2008), though whether the uncertainty added by the MSD definition is important relative to other projection uncertainties remains to be determined and is the focus of this study.

The Central American Dry Corridor (CADC) is a highly climate sensitive region that occupies much of the Pacific side of Central America. The CADC is generally dry and has highly seasonal and variable climatic conditions, one expression of which is the MSD. The MSD persists across much of the region, strongly influencing smallholder farmers who depend on

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rainfed agriculture (Stewart et al., 2021). In Nicaragua, distinctly precarious socio-economic and climatic vulnerabilities intersect with a scarcity of observational (station) data, rendering advances in the understanding of the regional hydrologic system particularly pertinent.

In this study, we present a demonstration of uncertainty partitioning for the MSD in Nicaragua to determine whether the choice of MSD definition is important to include as an additional source of uncertainty when estimating projected future impacts. We also recast the typical uncertainty analysis using specific warming levels rather than defined time windows so the results will be less sensitive to changes in the models selected or future emissions scenarios in projecting impacts, in this case to MSD characteristics.

2 Methods

The uncertainties in the projections of the MSD are determined based on climate projections of daily precipitation and the simulated MSD characteristics (the impacts of concern for this study). These are described as follows.

2.1 Climate model projections

Downscaled daily precipitation data are obtained from two sources: the climate impacts lab (CIL) data set (Gergel et al., 2023), and the NASA-NEX archive (Thrasher et al., 2022). While both data sets use statistical downscaling, their methods are distinct. CIL uses a quantile delta mapping method for bias adjustment (Cannon et al., 2015) with a downscaling method that preserves climate model trends at quantiles. The NASA-NEX data set uses a similar bias correction, but a very different spatial disaggregation method based on perturbing the historical observations with bias corrected anomalies, without preserving climate model precipitation trends of the climate models. Additionally, the two methods use different observational baselines for bias correction, which has been shown to influence results (Rastogi et al., 2022; Wootten et al., 2021). Both the NASA-NEX and CIL downscaled data have a resolution of 0.25 degrees (approximately 27.5 km in Nicaragua).

This study uses a set of 8 climate model runs that are shared between both data sets for both historic and future projections, using shared socioeconomic pathway (SSP) 5-85 (Meinshausen et al., 2020). These are listed in Table 1, which also includes the original spatial resolution before downscaling. SSP5-85 is the scenario with the highest anthropogenic emissions and resulting radiative forcing, which means all the models used in this study produce in excess of 3 °C of warming during the 21st century, allowing all to be used in analyses at global warming levels of 1.5, 2.0, and 3.0 °C.

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Table 1: Climate model runs used by downscaling methods in this study. Nominal resolution is the approximate horizontal resolution of the archived data for the model land component.

Model	Variant	Institution	Nominal Resolution (km)
BCC-CSM2-MR	r1i1p1f1	Beijing Climate Center	100
CMCC-ESM2	r1i1p1f1	Euro-Mediterranean Center	100
EC-Earth3-Veg-LR	r1i1p1f1	EC-EARTH consortium, The Netherlands/Ireland	250
GFDL-ESM4	r1i1p1f1	NOAA Geophysical Fluid Dynamics Laboratory	100
INM-CM5-0	r1i1p1f1	Institute for Numerical Mathematics (INM), Russia	100
MIROC6	r1i1p1f1	National Institute for Environmental Studies, Japan	250
MPI-ESM1-2-HR	r1i1p1f1	Max Planck Institute for Meteorology (MPI), Germany	100
NorESM2-MM	r1i1p1f1	Norwegian Climate Center, Norway	100

By only including those downscaled runs that use identical climate model simulations for both CIL and NASA-NEX as input, the variability due to model selection is separated from that due to internal variability represented by different model initial conditions or parameterizations. All model projections are considered equally plausible, and are thus equally weighted as in Michalek et al. (2023).

2.2 Warming levels

The years at which each model projection reaches 1.0, 1.5, 2.0, and 3.0 °C of global mean warming (relative to pre-industrial conditions) were determined by Hauser et al. (2022) for CMIP6 climate models using the mid-year of a 20-year moving window. In this experiment, a 30-year window was used around the defined mid-year for each model run and the mean of each impact in that 30-year period was determined at different levels of warming. The years at which the model projections simulate the different levels of warming are shown in Figure 1. The 1.0 °C warming level is not used in this study as it has already been exceeded.

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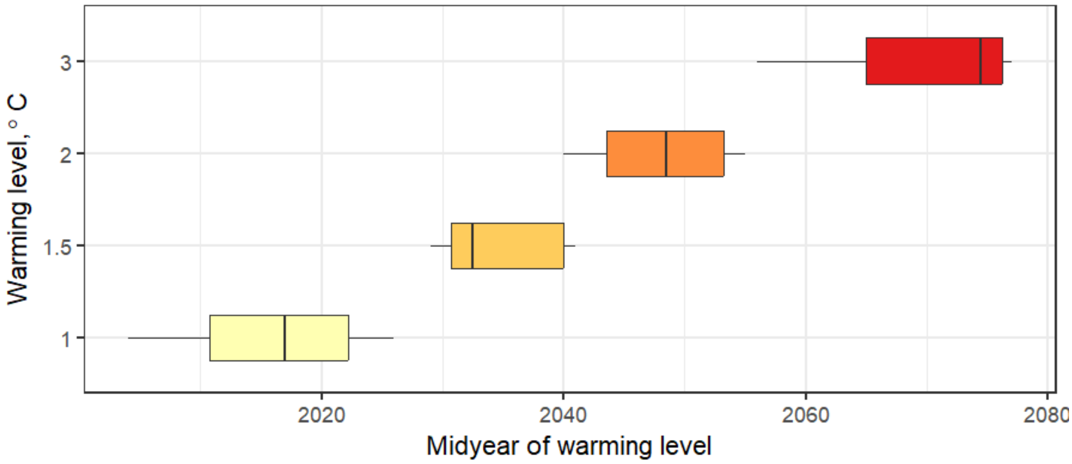

Figure 1: The years at which each warming level is reached for the climate model ensemble in Table 1.

2.3 MSD characteristics

The MSD as a hydrologic phenomenon is defined using local stakeholder descriptions and the methods described in Maurer et al. (2022). The methods are implemented in the R package msdrought (Uyeda et al., 2024). The MSD characteristics are entirely derived from the timing and magnitude of smoothed daily precipitation, and the occurrence of two maxima and a relative minimum within two defined windows, as depicted in Figure 2. For a year to be considered an MSD year, the MSD must have a minimum duration of 15 days and a minimum intensity of at least 3 mm d-1. Years that do not display an MSD by these criteria are designated as NULL. The default definition for the Central American region requires that the MSD maxima must occur between May 1st and October 31st, the minimum within the June 1st - August 31st window (Figure 2).

The two MSD characteristics evaluated in this study are the duration (the number of days between the peaks) and the intensity (the average of the two peaks minus the minimum precipitation), producing one value for each impact per year. For this experiment, the dates are shifted 14 days earlier and then 14 days later from those in Figure 2 to estimate the effect of this definition on MSD variability.

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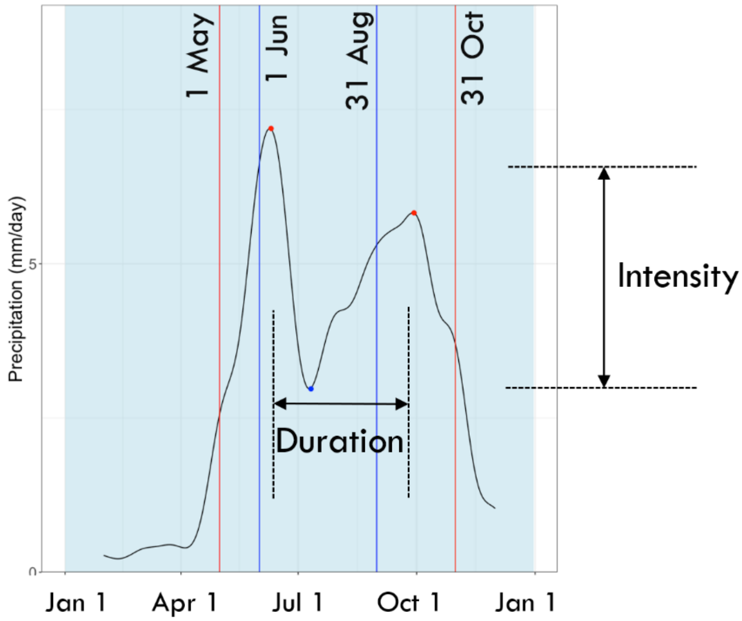

Figure 2: A schematic of a typical MSD year, highlighting the definition (dates) and the impacts (intensity and duration) of interest in this study. Duration is the number of days between the peaks; intensity is the average of the two peaks minus the minimum between them. To estimate the effect of the definition on MSD variability, dates are shifted 14 days earlier and later from the definition dates shown here.

2.4 Variance partitioning

The partitioning of variance among the different sources generally follows Michalek et al. (2023). Variance partitioning was done for each MSD characteristic/impact (duration and intensity), for each grid cell in the domain bounded by longitudes -83° and -88° and latitudes 10° and 15°.

First, for each climate model, downscaling method, and definition (the experiments varying the MSD dates) an 11-year smoothing window was applied to the values for each year and the anomalies relative to a 1970-1999 base period were calculated. Internal variability was then estimated by fitting a LOESS curve to the anomalies of each impact and calculating the variance of the LOESS residuals for each defined warming level and impact of interest (1.5, 2.0 and 3.0 °C) using a 30-year window centered on the midyear of warming for each climate model. Some prior studies have used other methods to estimate internal variability, such as fitting a polynomial rather than a LOESS curve (Hawkins and Sutton, 2009). The choice of method for estimating internal variability has been shown to add substantial uncertainty when a single climate model is used (with many runs); using multiple climate models lessens this impact (Lehner et al., 2020).

Model variability is estimated by calculating the variance of the LOESS predicted values for each defined warming level and impact of interest.

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$$\text{Model Variance} = \frac{1}{N_1}\sum_{d,e} \text{var}[\hat{x}(t,d,e,m)] \quad (1)$$

Here $\hat{x}$ is the set of LOESS predicted values for the set of years, t, associated with the warming level specified for each climate model, m. N_1 is the number of unique subsets of $\hat{x}$ with valid (non-NULL) MSD impact data for each combination of downscaling method, d, and MSD definition experiment, e. Similarly, uncertainty due to the downscaling method is calculated by

$$\text{Downscaling Variance} = \frac{1}{N_2}\sum_{m,e} \text{var}[\hat{x}(t,d,e,m)] \quad (2)$$

where N_2 is the number of unique subsets of $\hat{x}$ with valid (non-NULL) MSD impact data for each combination of climate model, m, and MSD definition experiment, e. Finally, the uncertainty due to MSD definition is calculated by

$$\text{MSD Definition Variance} = \frac{1}{N_3}\sum_{m,d} \text{var}[\hat{x}(t,d,e,m)] \quad (3)$$

N_3 is the number of unique subsets of $\hat{x}$ with valid (non-NULL) MSD impact data for each combination of downscaling method, d, and climate model, m.

3 Results and Discussion

To frame the impacts of a warming climate on the MSD in Nicaragua, Figure 3 shows the median changes in intensity and duration projected by the complete ensemble used for this study. Figure 3 also shows the boundary of the Central American Dry Corridor (CADC) as objectively determined by Stewart et al. (2021). The CADC is a relatively arid region with highly seasonal precipitation in Central America that exhibits a high sensitivity to climatic changes and is especially susceptible to drought impacts. It is therefore a focus for some of the analysis in this study.

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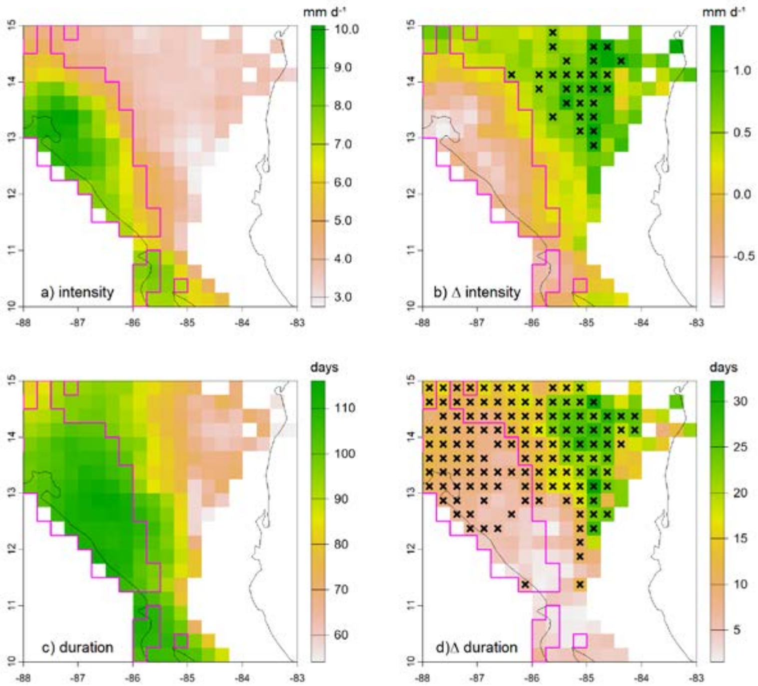

Figure 3: Historical values of MSD intensity (a) and duration (c) for 1970-1999, and the projected changes (b and d) with 3 °C of global warming, using the dates in Figure 2 in the MSD definition. Grid cells marked with an "X" indicate the change is significant at a 5% level based on a Wilcox (Mann-Whitney) test. The magenta line is the boundary of the Central America Dry Corridor (CADC), the black line denotes the coastline. Grid cells with less than 50% of years having an MSD, in both historical and future periods, are white. In addition, if less than half of the models in the ensemble show an MSD, the grid cell is white.

Figure 3 shows the highest intensity and longest duration MSDs for 1970-1999 are experienced in the CADC on the Pacific side of Nicaragua. Changes in MSD intensity anticipated with 3 °C of global warming are focused on the East, in the area that has historically experienced the lowest intensity (least pronounced) events of the shortest duration. Duration changes are more widespread, indicating a longer lull in the rainy season as climate disruption progresses.

Figures 4 and 5 show the effect of shifting the default dates in the MSD definition (Figure 2) on projected changes to MSD intensity and duration. Figure 4 shows that shifting the dates 14 days earlier dramatically reduces the area that would be classified as having an MSD, compared to Figure 3. Conversely, Figure 5 shows that shifting the time windows 14 days later expands the area with an MSD. These results are consistent with prior work that found the MSD tending to shift later and to have a longer duration with climate change impacts (Maurer et al., 2022).

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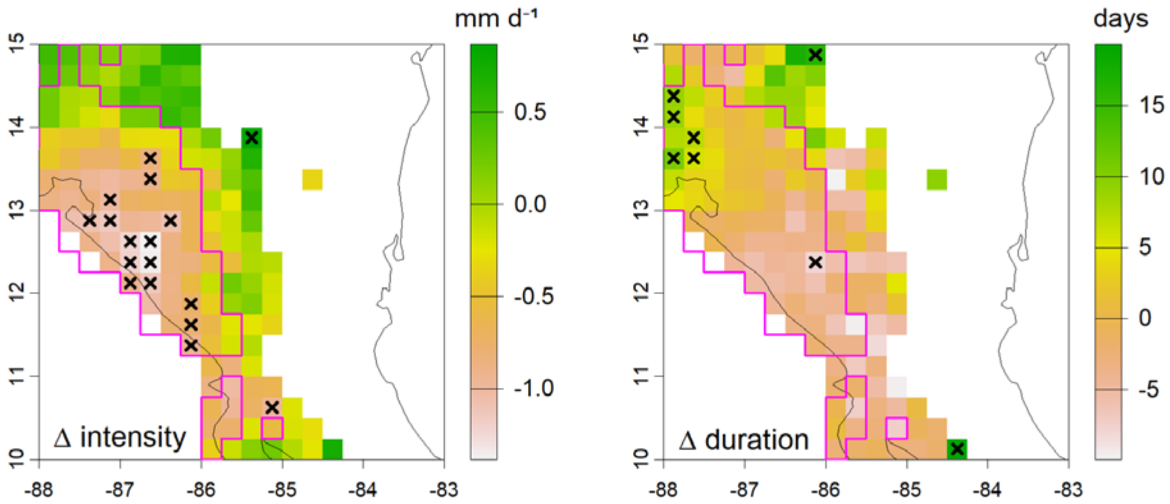

Figure 4: As in Figure 3 but showing only mean changes in MSD intensity and duration when changing the MSD definition to use dates 14 days earlier than shown in Figure 2.

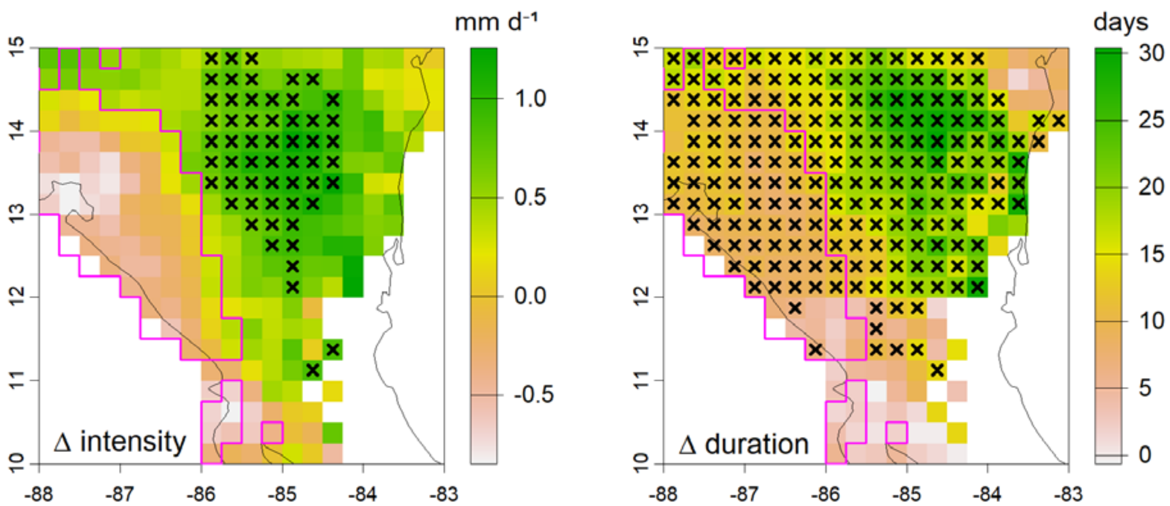

Figure 5: Similar to Figure 4, but with the MSD definition using dates shifted 14 days later than in Figure 2.

Focusing on the CADC in the Nicaragua domain considered in this study, Figure 6 shows the variability of the changes in MSD duration and intensity, averaged over the CADC, among the 16 different projections (8 climate models and two downscaling methods) when shifting the MSD definition dates 14 days earlier and 14 days later.

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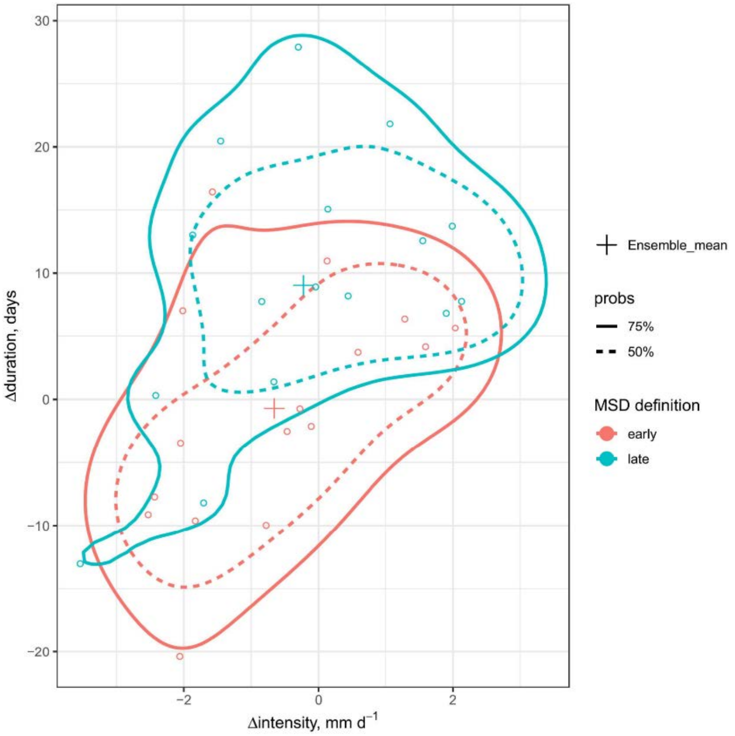

Figure 6: Mean individual projections (points) for the CADC (Nicaragua) and probability contours (based on a Gaussian kernel density estimator) at 3 °C global warming with the MSD definition shifted 14 days earlier or 14 days later than in Figure 2.

Figure 6 shows that for the CADC (the portion in Nicaragua) the definition of the dates has a strong impact on the projected changes, especially in MSD duration, with the shift in projected duration change being comparable to the variability among individual projections. This raises the question of whether the choice of MSD definition adds enough uncertainty to the MSD impacts, relative to the other sources of uncertainty, where stakeholders should include multiple definitions in impacts analysis. This is explored below.

Figure 7 shows the contributions to total variance of MSD intensity due to the different sources considered in this study at different global warming levels. As has been found in other analyses of precipitation uncertainties (Lehner et al., 2020; Wu et al., 2022), this precipitation-derived MSD impact also shows internal variability dominating for the historical period. Internal variability contributes a substantial amount of uncertainty as warming progresses, though even at the lowest 1.5 °C level the model projection uncertainty constitutes the majority of the uncertainty to the projection of MSD impact. While not shown, the MSD duration shows similar patterns.

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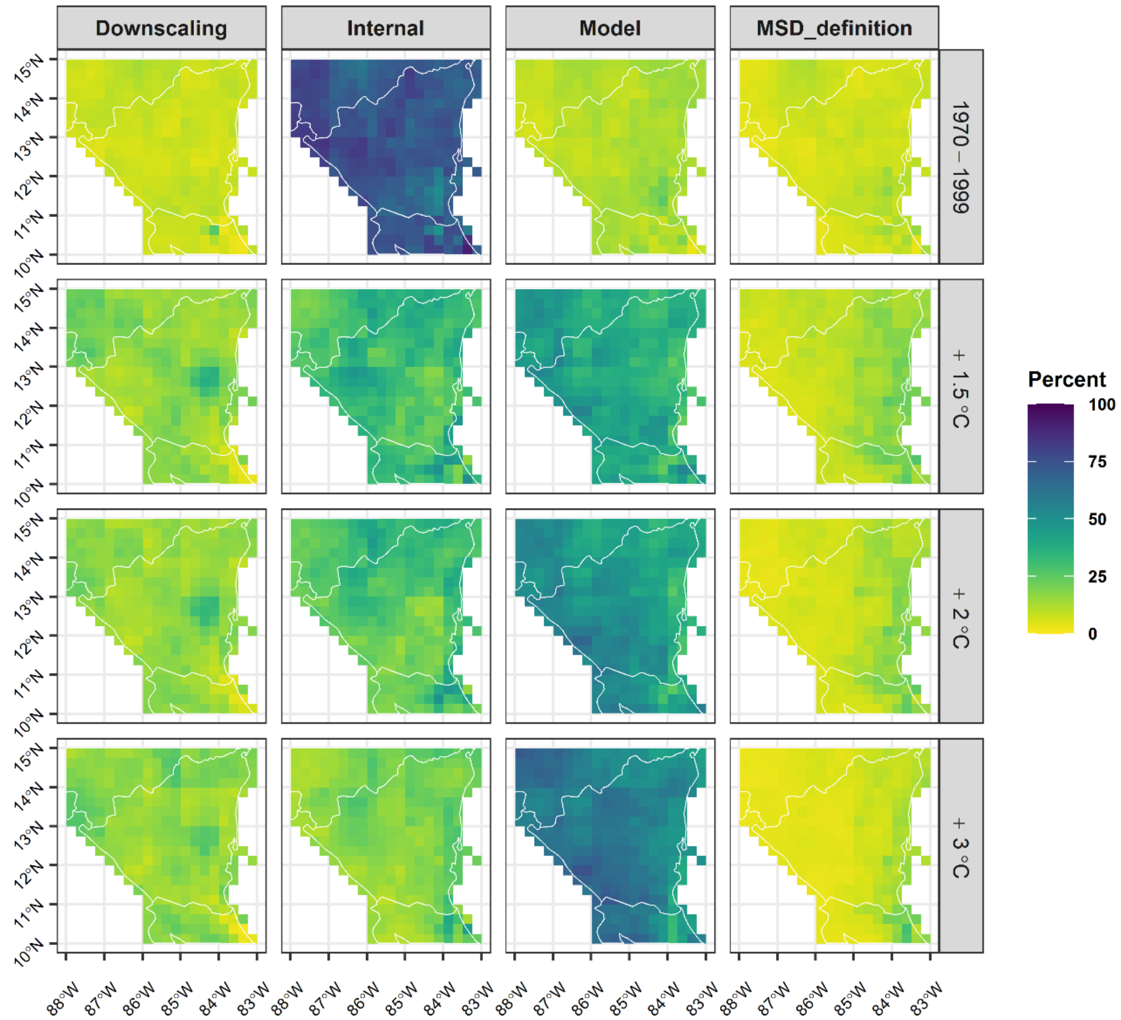

Figure 7: For MSD intensity, the percent of total variance contributing to each source included in this analysis, for the base period of 1970-1999 (top row) and for different levels of global warming.

Despite very different spatial characteristics of changes in MSD frequency (indicated by the white grid cells in Figures 3-5) and MSD intensity, Figure 7 shows relatively consistent fractional uncertainty for all sources across the domain. This reflects the larger contributions to MSD intensity uncertainty of climate model and internal variability, both inherited from the larger spatial scales of the climate models (as shown in Table 1). The bias correction and spatial downscaling included with the downscaling methods aligns the climate model output to finer gridded observations but adds a relatively small portion to the overall uncertainty in MSD impacts.

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While MSD impacts in this study are based on (smoothed) daily precipitation, there might be more spatial heterogeneity in impacts derived from extreme precipitation events, since mean daily precipitation is generally more skillfully simulated by climate models than extremes, (Volosciuk et al., 2017), and would therefore be adjusted more dramatically during the downscaling process. Exploring the uncertainty contribution of downscaling to impacts driven by more extreme events may benefit from more varied, regionally-focused downscaling efforts (e.g., Tamayo et al., 2022).

The progression of uncertainty through different levels of warming for both MSD intensity and duration is shown in Figure 8. At levels of warming above 2.0 °C model projection uncertainty is the largest component to uncertainty in both MSD impacts. Even at 3.0 °C of warming, internal variability contributes 15 – 30% of the total uncertainty in MSD intensity and duration over the CADC. Downscaling variability contributes a relatively constant 10 – 15% of the total uncertainty at all warming levels, and a larger percentage for MSD intensity than duration. The uncertainty due to the MSD definition is the smallest portion at all warming levels, but generally larger for duration than for intensity.

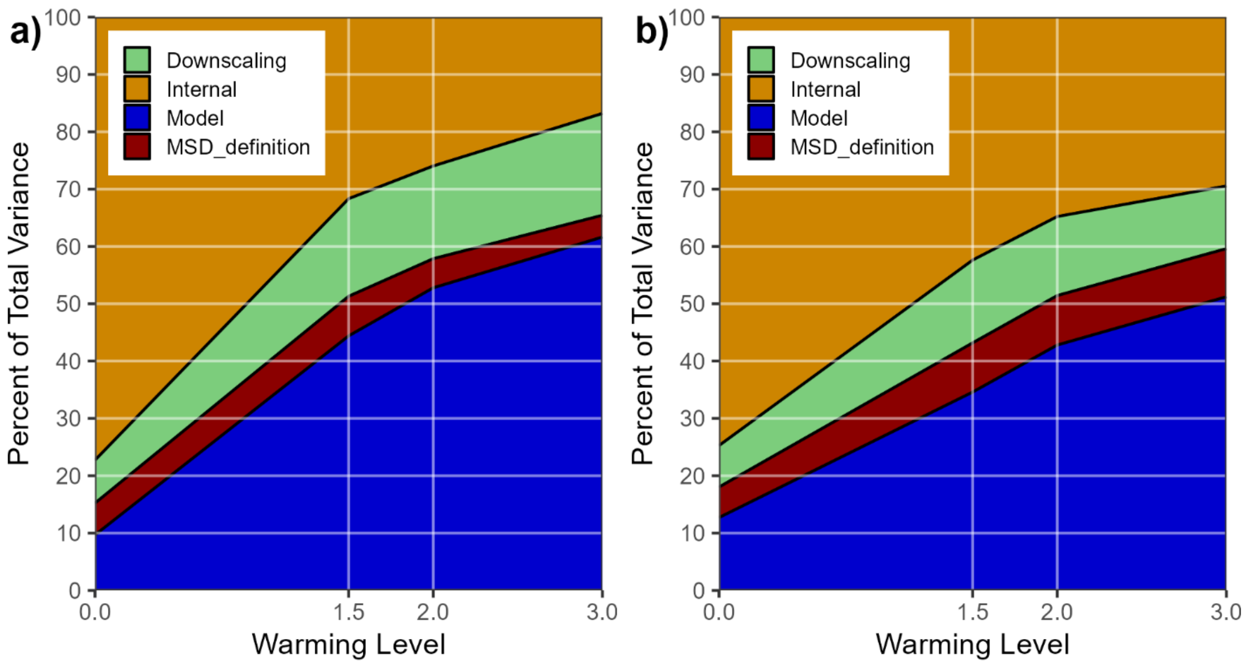

Figure 8: Mean fraction of variance for a) MSD intensity and b) MSD duration, averaged over the CADC in Nicaragua (see Figures 4 and 5). The Warming level labeled 0 is for 1970-1999.

4 Conclusions

The advances in understanding the hydrologic system in this study focus on refining the methods for projecting future precipitation changes and their impacts on the Central American Midsummer Drought (MSD). In considering projections of future precipitation on the Central American MSD, this study indicates the dominant sources of uncertainty are internal variability (especially for near term, or lower levels of global warming) and variability among climate models (increasingly so as warming level increases). While precipitation downscaling has the potential to introduce large uncertainties in some hydrologic impacts, for the MSD impacts included in this study downscaling generally contributes less to total uncertainty compared to other sources. Despite having a strong impact on the magnitude and spatial extent of the MSD, the exact definition of the MSD has a minor effect on the uncertainty of MSD projections at all warming levels.

The main implication of these findings for future work on climate disruption and the future of the Central American MSD is that selecting an ensemble of climate models is essential for characterizing the uncertainty in precipitation and its impact on the MSD. By analyzing impacts at specific levels of warming, rather than future spans of years, the selection of models may be done without excluding models based on sensitivity, which simplifies the process as other climate model skill metrics may be used. Using a single precipitation downscaling method for all climate models would still capture the majority of MSD impact uncertainty, though with multiple archives of downscaled data freely available, multiple methods can be readily included. The definition of the MSD can be chosen to capture impacts of interest, but the specific definition of the time windows for the MSD does not add substantially to the uncertainty in impacts.

While two precipitation downscaling methods were used to characterize the uncertainty in downscaling on the MSD impacts, including additional methods could improve this, especially if dynamic downscaling were represented. Expanding the domain would allow a greater exploration of the spatial variability in the different components of uncertainty on the regional MSD. Future research will further explore these improvements to this study. The approach presented in this study could serve as a template to quantify the relative importance on uncertainty for the projection of other precipitation-driven impacts in different geographic contexts and regional hydrologic systems, such as monsoon patterns or the timing and duration of the rainy season in other highly seasonal climates.

Code availability

An R package is available at https://cran.r-project.org/package=msdrought for determining the characteristics of the mid-summer drought using daily precipitation data. Processing code is archived at https://github.com/EdM44/msd_variance.

Data availability

The NASA-NEX downscaled climate model output data are available at https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6. The CIL downscaled climate model output data may be obtained from https://planetarycomputer.microsoft.com/dataset/group/cil-gdpcir.

Author contribution

EM and IS conceived of the project. EM conducted the analysis. EM and IS directed the development of the msdrought software. EM and IS prepared the original draft of the manuscript.

Competing interests

The authors declare that they have no conflict of interest

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