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REVIEW ARTICLE

# Multiple dimensions of extreme weather events and their impacts on biodiversity

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**Abstract**
Climate change is a multidimensional phenomenon. As such, no single metric can capture all trajectories of change and associated impacts. While numerous metrics exist to measure climate change, they tend to focus on central tendencies and neglect the multidimensionality of extreme weather events (EWEs). EWEs differ in their frequency, duration, and intensity, and can be described for temperature, precipitation, and wind speed, while considering different thresholds defining "extremeness." We review existing EWE metrics and outline a framework for classifying and interpreting them in light of their foreseeable impacts on biodiversity. Using an example drawn from the Caribbean and Central America, we show that metrics reflect unequal spatial patterns of exposure across the region. Based on available evidence, we discuss how such patterns relate to threats to biological populations, empirically demonstrating how ecologically informed metrics can help relate EWEs to biological processes such as mangrove recovery. Unveiling the complexity of EWE trajectories affecting biodiversity is only possible through mobilisation of a plethora of climate change metrics. The proposed framework represents a step forward over assessments using single dimensions or averages of highly variable time series.

**Keywords** Climate change · Vulnerability assessment · Extreme climate · Population demography · Biodiversity threats

## 1 Introduction

One defining feature of contemporary climate change is the increasing frequency, intensity and duration of extreme weather events (EWEs) (Lange et al. 2020; Laufkötter et al. 2020). EWEs—including unusual and severe events (Seneviratne et al. 2012)—present a major challenge to human society and to the long-term persistence of biodiversity, as we know it today (Lange et al. 2020; Smith 2011; Thompson et al. 2023). Extreme weather events can affect different levels of biological organisation, ultimately altering ecological and evolutionary processes. Among their known impacts, EWEs can exert strong selection pressures on organisms (e.g., Grant et al. 2017; Stroud et al. 2020), change individuals' behaviour (e.g., Cohen et al. 2021), trigger phenological shifts (e.g., Butt et al. 2015; Jentsch et al.

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2009), cause local population collapses (e.g., Frederiksen et al. 2008; Smale and Wernberg 2013), and destabilise community and ecosystem organisation when tipping points are overcome (e.g., Armstrong McKay et al. 2022; Heinze et al. 2021; Kreyling et al. 2014). Yet to date vulnerability assessments for climate change have primarily focused on how changes in central tendencies of climate change are influencing biodiversity (Chapman et al. 2014; Jones et al. 2016), with only limited attention being paid to the effects of EWEs on biota (Harris et al. 2018; Sabater et al. 2022; Wethey et al. 2011).

While detection and attribution of climate change effects on biodiversity is challenging (Gonzalez et al. 2023; Taheri et al. 2021b), with concurrent environmental drivers affecting species and communities differently across sections of their geographical distributions (Taheri et al. 2021a), the issue is further complicated when dealing with highly dimensional phenomena such as EWEs. An extreme weather event can be defined according to its unusual frequency, intensity and/or duration, and measured from different sets of variables (e.g., temperature, precipitation, wind speed), while using different thresholds to determine its "extremeness" (McPhillips et al. 2018; Stephenson 2008). The resulting combination of EWE measurements can be massive and can often lead to results that are difficult to interpret.

A plethora of metrics exist to quantify one or more dimensions of extreme climate change (see, for instance, Zhang et al. 2011; Sillmann et al. 2013; Donat et al. 2013; Perkins and Alexander 2013; Garcia et al. 2014; Buckley and Huey 2016; Xu et al. 2019; McClanahan 2022), but much indeterminacy exists regarding their information content (Latimer and Zuckerberg 2019; McClanahan 2022): what climate change properties do different metrics convey? How are different metrics linked to biodiversity's vulnerability? Answering these questions is important for anticipating threats to biodiversity. Here, we first review existing metrics describing EWEs and then develop a conceptual framework for classifying and interpreting the different metrics of EWEs considering their foreseeable impacts on biodiversity. We then establish the connection between EWE metrics and biodiversity threats by drawing on an example from the Caribbean and Central America, two regions of the world with the highest exposure to extreme climate change (Castellanos et al. 2022). We explore the patterns of covariation among 89 metrics calculated for the region and over a 70-year period. We then link the areal exposure to extreme weather events and the potential effects on biodiversity. Finally, we conduct a case study to test the usefulness of ecologically relevant EWE metrics in assessing mangrove's vulnerability to heat waves, droughts, and heavy rainfall events in the Caribbean and Central America.

## 2 Metrics describing extreme weather events

Climate is a complicated phenomenon, and no single measurement can describe all its multiple dimensions. While the climate of a region represents "the finite distribution of climate variables over time relative to a regime of varying external conditions" (Werndl 2016), there are several approaches to measuring changes in climate over space and time. These approaches, referred to as "climate change metrics," can be used to summarise the central tendencies or the variability of extreme values in meteorological time series (Buenafe et al. 2023; Garcia et al. 2014). Our review of the literature enables identification of several metrics commonly used by researchers to characterise EWEs (Table 1). Although under different names, all existing metrics represent a measurement of one or two dimensions of extreme weather events using different climate parameters and thresholds. As a first step

**Table 1** Metrics used to describe the intensity, frequency, and duration of extreme weather events. The list is not meant to be exhaustive, but rather shows the metrics most used in literature. Metric names and acronyms are given by the authors, possible synonyms are registered in the table

| Dimension | Metric | Description | Refs. | Notes |
|---|---|---|---|---|
| Intensity | Mean Standardised anomalies **(MSA)** | The mean standardised anomalies computed using minimum or maximum values for a given period (i.e., season, year, decade). | (Garcia et al. 2014) | The standardised anomalies are defined as the 24h accumulated precipitation or daily average wind or temperature to which we subtract the climatology and then divide by the standard deviation of the 24h accumulated precipitation or average wind or temperature over the baseline period. |
| | Number of extreme standardised anomalies **(neSA)** | The number of standardised anomalies above 2-to-4 SD computed using minimum or maximum values a given time (i.e., season, year, decade). | - | |
| | Anomalies above the seasonal mean **(HS)** | These anomalies are estimated by adding a certain value (representing a biological threshold) to the monthly or seasonal mean of maximum or minimum values.<br>In marine studies, they are defined as the 'HotSpot' (HS) metric of coral bleaching and estimated as HS = MMM + 1°C equation. | (Goreau and Hayes 1994; McClanahan 2022) | This type of anomalies was the first to be used as proxies of thermal stress in Corals. The cumulative sum of these anomalies over 84 days or 12 weeks formed the Degree-heating week (DHW) and the - months DHMs metrics, which have since been used frequently in ocean temperature data compilations. |
| | Daily variability **(dV)** | The difference between daily maxima and minima. | (McClanahan and Azali 2021) | The metric can also measure differences between yearly, weekly, or daily values. The use depends on the research questions and/or biological processes. |
| | Intraseasonal difference in the most extreme values **(D)** | The difference between lower ("lP" - 5 or 10) and upper ("uP" - 90 or 95) percentiles of maximum (or minimum) values for seasons (or period) and the baseline period. | (Ashcroft et al. 2012) | The metric can also measure differences between yearly, weekly, or daily values. The use depends on the research questions and/or biological processes. |
| | Inter-seasonal extreme weather range **(EWR)** | EWR is estimated as the difference between the highest daily observation of any season and the lowest reading of the same season:<br>$\mathbf{EWR_{i,j} = max(X_{i,j}) - min(X_{i,j})}$, where EWR in any grid cell with coordinates i and j is the difference between seasonal maximum and minimum value.<br>The range-based EWR is estimated as an effect size $(t_1 - t_0)$ by means of the Hedges' g estimator using the average EWR in $t_0$ and $t_1$ periods:<br>$\Delta EWR\ (g) = \frac{\left(\widetilde{EWR}_{t1} - \widetilde{EWR}_{t0}\right)}{\sqrt{\frac{(n_{t1}-1)-SD_{t1}^2+(n_{t0}-1)-SD_{t0}^2}{n_{t1}+n_{t0}-2}}}$<br>Where, $\widetilde{EWR}_t$ is the estimated average of the coefficients for every year in $t_1$ or $t_0$, and *SD* their respective standard deviations. | (Frich et al. 2002) | A value of 1 indicates the two groups differ by 1 standard deviation, a g of 2 indicates they differ by 2 standard deviations, and so on. Positive values indicate a higher weather range in $t_1$ compared to $t_0$, and negative values indicate a lower weather range. |

**Table 1** (continued)

| Dimension | Metric | Description | Refs. | Notes |
|---|---|---|---|---|
| Intensity and Duration | Heating degree weeks (or months) **(DHW or DHM)** | The cumulative sum of 'HotSpot' (HS) anomalies over 84 days or 12 weeks formed the Degree-heating week (DHW) and Degree-heating months (DHM), respectively.<br>HS anomalies are commonly computed as the sum of the mean maximum monthly temperature denominator (MMM) plus 1°C: HS = MMM + 1°C. | (Goreau and Hayes 1994; Hobday et al. 2018; McClanahan and Azali 2021; Winter et al. 1998) | Multiples of the 90th percentile difference (2× twice, 3× three times, etc.) from the mean climatology value define each of the categories I–IV, with corresponding descriptors from moderate to extreme. Each category with a different meaning for Coral bleaching. |
| | Cumulative intensity of persistent climate extremes **(MCIpe)** | Cumulative mean of the excess magnitude of any climatic parameter linearly weighted by the duration of the event. A "persistent event" (pe) is defined as five or more consecutive days above or below the threshold. | (McClanahan 2022; Perkins-Kirkpatrick and Lewis 2020) | **Computation example:** for a 5-day event with exceeding temperature (magnitude above the threshold) by 1 °C, 2°C, 2 °C, 5°C and 2 °C, *intensity* = (1x1) + (2x2) + (2x3) + (5x4) + (2x5) |
| Duration | Extreme weather residence time **(RT)** | The number of consecutive hours, days, or weeks that a determined threshold is exceeded. | (Morán-Ordóñez et al. 2018; Sillmann et al. 2013; Sully et al. 2019) | When using temperature this metric is referred to as duration of cold (minimum values) or warm (maximum values) spells. |
| | Duration of persistent climate extremes **(MRTpe or LRTpe)** | The average (MRT) or maximum (LRT) number of consecutive days per season, year or time window where the daily maximum is above or below the baseline. | (Sillmann et al. 2013; Zhang et al. 2011) | The metric can also measure differences between yearly, weekly, or daily values. The use depends on the research questions and/or biological processes. |
| | Change in timing of persistent climate extremes **(CTpe)** | Historical change in the date at which a wave starts. It is estimated as a coefficient of variation of the Julian days at which waves start. | (Orlowsky and Seneviratne 2012) Burrows et al. (2011) | - |
| Duration and Frequency | Frequency of persistent climate extremes **(FEpe)** | The number of seasons per period where the daily maximum is above or below the baseline for more than 5 days in a row (i.e., persistent event). The baseline is defined using daily maximum values for the baseline period. | (Buckley and Huey 2016; Xu et al. 2019) | When the number of days is divided by the total number of days in the period, this metric is equivalent to the "probability of extreme events" |
| | Recurrence of persistent climate extremes **(REpe)** | Number of consecutive seasons in a period in which the daily maximum is above or below the baseline for more than 5 days in a row (i.e., persistent event). The baseline is defined using daily maximum values for the baseline period. | (Buckley and Huey 2016; Perkins and Alexander 2013) | - |

**Table 1** (continued)

| Dimension | Metric | Description | Refs. | Notes |
|---|---|---|---|---|
| Frequency | Frequency of climate extremes **(FEE)** | The number of events per period where the daily maximum is above or below the baseline defined using daily maximum values for the baseline period. | (Garcia et al. 2014; Sillmann et al. 2013; Xu et al. 2019) | When the number of days is divided by the total number of days in the period, this metric is equivalent to the "probability of extreme events." |
| | Recurrence of climate extremes **(REE)** | The number of consecutive seasons (or years) over a period with events exceeding the defined threshold. | (Hobday et al. 2016) | - |
| Compounded | Simultaneous persistent climate extremes **(maxCOpe)** **(MCOpe)** | The average and maximum number of 'persistent events' (above or below the threshold for more than 5 days in a row) estimated by using distinct climatic parameters (temperature, precipitation or wind-based) occurring in an area within a season or a year. | (Zscheischler et al. 2020) | Can be considered as a spatially compounded event according to the typology of Zscheischler et al. (2020). |
| | Consecutive, persistent climate extremes **(Cpe)** | The maximum number of 'persistent events' (above or below the threshold for more than 5 days in a row) estimated by using distinct climatic parameters (temperature, precipitation or wind-based) occurring consecutively in a season or year. | (Cardil et al. 2014) | Can be considered as a temporarily compounded event according to the typology of Zscheischler et al. (2020). |
| | Longest duration of cumulative, persistent climate extremes **(LCED)** | The maximum number of consecutive days in a season (or year) in which one or more 'persistent events', estimated by using distinct climatic parameters (temperature, precipitation or wind-based), occur in an area within a season or a year. | (Butt et al. 2015) | Can be considered as a spatio-temporarily-compounded event according to the typology of Zscheischler et al. (2020). |
| | Intensity of cumulative, persistent climate extremes **(MCCI)** | The grand mean of the cumulative means of the excess magnitude of weather parameters (temperature, precipitation, or wind speed) linearly weighted by the duration of the event. | (Schlegel and Smit 2018) | Can be considered as a temporarily compounded event according to the typology of (Zscheischler et al. 2020).<br>**Computation example for one parameter:** for a 5 day event with exceeding temperature (magnitude above the threshold) by 1 °C, 2°C, 2 °C, 5°C and 2 °C, *intensity* = (1x1) + (2x2) + (2x3) + (5x4) + (2x5) |

*Persistent events are formally defined as events in which the threshold is exceeded for at least a five-day period, with no more than two below-threshold days towards understanding the metrics' properties, we propose categorising EWE metrics hierarchically according to their dimensions, variables, and types of thresholds considered.

The first hierarchical level describes the dimensions of change captured by the metrics. These can measure the "Intensity" of the EWE, i.e., the excess over the threshold; the "Frequency," i.e., the number of times that the threshold is exceeded in a period, often referred as probability or empirical probability of an extreme event; or the "Duration," i.e., the time span between the start and end of the extreme weather event. It is important to acknowledge that metrics typically characterise one or two dimensions of climate change but rarely, if ever, characterise three or more dimensions (by more than three, we mean dimensions resulting from interactions among the three main dimensions described earlier) (see Fig. 1).

The second and third levels of the categorisation of EWE are the variables and thresholds utilised to determine "extremeness," respectively. Any calculation of EWE metrics requires a time series of meteorological variables so that excesses beyond an established threshold can be quantified. For example, among the most widespread metrics, we found those describing heat waves and warm spells, which are metrics that capture the intensity and duration of EWEs by using a combination of maximum temperatures and upper percentiles of the distribution as thresholds (McClanahan 2022; Zhang et al. 2011). However, metrics can be computed using other variables, such as precipitation or wind speed, as well as different types of thresholds (see Table 1). Different approaches to establishing thresholds exist, some of which focus on the statistical descriptions of the climatic variables of interest (henceforth termed statistically-derived threshold), while others focus on the thresholds known to trigger biological responses to climate changes (henceforth termed mechanistically-informed threshold) (see, for instance, van de Pol et al. 2017).

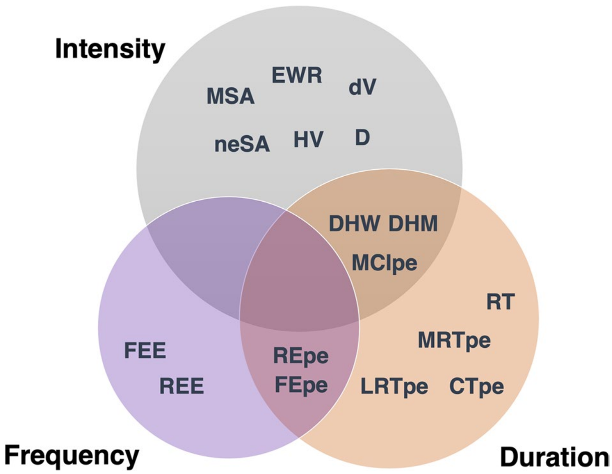


**Fig. 1** A conceptual classification of metrics according to their ability to capture one or more dimensions of EWEs (see Table 1 for a description of the metrics). neSA - Number of extreme standardised anomalies; MSA - Mean standardised anomalies; HS Anomalies above the seasonal mean; dV – Daily variability; D - Intraseasonal difference in the most extreme values; EWR - Inter-seasonal extreme weather range; DHW or DHM – Heating degree weeks (or months); MCIpe - Cumulative intensity of persistent climate extremes; RT - Extreme weather residence time; MRTpe or LRT - Duration of persistent climate extremes; CTpe - Change in timing of persistent climate extremes; FEE - Frequency of climate extremes; REE - Recurrence of climate extremes; FEpe - Frequency of persistent climate extremes; REpe - Recurrence of persistent climate extremes

Thresholds based on statistical analysis of climatic drivers over time are established under the principle that extreme events are those events occurring in the tails of a frequency distribution of meteorological data values (Davison and Huser 2015; Stephenson 2008). Distributions are usually built using the maximum or minimum values of a climate variable per unit of time (e.g., per day, month, year) in a time series encompassing at least 30 years (as recommended by the World Meteorological Organisation). The lower (1$^{st}$, 5$^{th}$ or 10$^{th}$) or upper (90$^{th}$, 95$^{th}$ or 99$^{th}$) percentiles of the distribution are computed to determine the size of the tail. In turn, mechanistically informed thresholds are established based on prior knowledge of the value, or range of values, at which an event can qualitatively alter the state or development of the biological system of interest (Lenton et al. 2008). For example, wind speeds above 100km/h represent a mechanistically informed threshold that would likely lead to mangrove die-off (Amaral et al. 2023; Servino et al. 2018). Critical temperatures over 45–47°C are deadly for most eukaryotes and plants (Araújo et al. 2013), although complex interactions with water availability in terrestrial systems can alter perceived heat stress (Herrando-Pérez et al. 2020). Likewise, the occurrence of a high number of days with 1 or 2°C above the Monthly Maximum Mean (MMM) or climatological mean of the warmest month (McClanahan 2022) likely leads to mass mortality events in Corals due to high physiological stress (e.g., coral bleaching, quenching reaction, diseases) (Baker et al. 2008; Randall and van Woesik 2017).

## 3 Linking dimensions of change to threats to biodiversity

The best use of EWE metrics is achieved when their information content is analysed in light of the expected biological responses they are likely to trigger. Yet linking multidimensional patterns of climate change with biological responses is not straightforward since organisms' sensitivity to climate dynamics (whether species, populations, communities, ecosystems, or biomes) involves responses that can be sometimes reported as individualistic (Baselga and Araújo 2009; Mcgeoch et al. 2006), while on other occasions they may be qualified as collective (Gilman et al. 2010; Mendoza and Araújo 2019). Individualistic responses are interpreted as the responses of the constituent parts of a system and are rooted in the view that organisms seek to maximise their own fitness, hence responding individually to external environmental pressures (Dawson et al. 2011). In contrast, collective biological responses are system-wide responses affecting the constituent parts of the system, and are easier to forecast once the rules of the system are understood (Gilman et al. 2010; Mestre et al. 2022). A comprehensive account of both, organismal or system-wide, responses before, during, and after EWEs is thus needed to gain understanding on the implications of extreme climate change on biodiversity. However, to date, empirical and quantitative evidence of such interactions is rather limited, requiring a number of simplifying assumptions linking measurements of climate change and biodiversity change (Buenafe et al. 2023; Garcia et al. 2016).

To begin structuring thinking about the links between extreme weather events and biological impacts, we classify impacts into critical dynamic population features, such as birth rates, growth rates, and mortality rates (Table 2). In contrast with gradual changes in climate, an increase in one or more dimensions of EWEs can cause abrupt demographic collapses and rapid disassembling of community dynamics, while preventing species adaptation as might be expected with gradual tracking of climate conditions (Hof et al. 2011; Hughes et al. 2018). We prioritise the demographic aspects of populations as their response

**Table 2** Dimensions of extreme weather events and associated threats to biological populations

| Dimension | Threats to populations | Evidence | Metric example | Refs. |
|---|---|---|---|---|
| Intensity | Demographic changes linked to abrupt mass mortality events. Threat greatest for species with narrow tolerance ranges, lower dispersal ability and/or specialised habitat requirements.<br>*However, even species with broad tolerance ranges can be at risk if the intensity overpasses thresholds beyond physiological functions quickly breaks down. | - Mangrove tree die-off due to an intense hurricane (wind speed above 100km/h); or local extinctions of corals due to extreme thermal anomalies.<br>- Mass mortality events of vertebrate populations due to intense heat waves or cold spells.<br>* Population declines in birds and plants with broad tolerances to warm/cold spells and droughts, respectively. | **neSA**: Number of 'extreme' (>3SD) standard anomalies | (Cunningham et al. 2013; DeCarlo et al. 2017; Latimer and Zuckerberg 2019; Mazzotti et al. 2016; McKechnie and Wolf 2010; Sergio et al. 2018; Yu et al. 2022) |
| Frequency | Demographic change linked to decreased birth rates and lower recruitment, or local extinctions. Threat greatest for species with reduced capacity to recover quickly following disturbances (species with small population size or restricted distribution). | - Decrease in the population size of the Lesser Antillean Iguana, (*Iguana delicatissima*) after two consecutive hurricanes, or progressive decline in coral recruitment due to more frequent exposure to oceanic heat events.<br>- Increased heat wave frequency across all seasons, and interactions with other disturbances, have lethal and sub-lethal effects at leaf and plant scales. | **fee**: Frequency of extreme events. | (Breshears et al. 2021; Pearson et al. 2014; Sheppard et al. 2020; van den Burg et al. 2022) |
| Duration | Demographic changes linked to increased death rates and lower survival and recruitment rates. Threat greatest for sessile species with longer generation times and specialised conditions for physiological functioning. | - Coral bleaching due to prolonged exposure of temperatures above 35°C; or regional extinction, and subsequent loss of resilience, of Sea grasses after water was 4°C above the normal summer temperatures for almost 2 months. | **RTpe**:<br>Duration of persistent climate extremes | (Kendrick et al. 2019; Perkins-Kirkpatrick and Lewis 2020; Sully et al. 2019) |

**Table 2** (continued)

| Dimension | Threats to populations | Evidence | Metric example | Refs. |
|---|---|---|---|---|
| Frequency and duration | Phenological change linked to alterations in the timing of life-history events (e.g., breeding or mating). Threat greatest for species dependent on environmental triggers to initiate life stages (e.g., seed germination, egg laying or floral opening).<br>Changes in the phenology of one species may also affect interspecific interactions | -More frequent and prolonged heat waves and rainfalls alter the reproductive cycles of mammals and cause.<br>-Changes in tree phenology alter the availability of resources for bird and mammal species and affect their reproduction and survival via indirect pathways (i.e., resource limitation). | **REpe**: Recurrence of persistent (five or more days over the threshold) extreme events. | (Butt et al. 2015; Marcelino et al. 2020) |

encompasses both the direct impacts of EWEs on physiology, behaviour, and life history traits of organisms (Cerini et al. 2023; Sergio et al. 2018), as well as the indirect impacts caused by changes in biological interactions (Haberstroh and Werner 2022). Hence, all else being equal, increasing exposure to EWEs is likely to decrease the fitness of local populations, particularly when (i) organisms cannot tolerate changes in any dimension of extreme weather events exceeding known historical baselines (Allen et al. 2021; Hansen et al. 2022) or physiological limits (Jiguet et al. 2006; Valladares et al. 2014); (ii) individuals' adaptive capacity is surpassed by compounded EWEs that shorten recovery times (Artigas et al. 2013; Fivash et al. 2021); (iii) biological populations have lower growth rates and narrower distributional ranges (Boyce et al. 2022); and (iv) other highly competitive or pathogenic species increase their abundances owing to EWEs (Haberstroh and Werner 2022; Morley and Lewis 2014).

It is also important to recognise that biological responses to extreme weather events depend on the specific dimension of change involved. Different threats can be inferred from the individual or joint assessment of the dimensions of change (see Table 2). Events characterised by extreme intensity, for instance, are likely to increase mortality rates across all the developmental stages of a population, triggering mass mortality events and decreasing post-disturbance survival rates (Buckley and Huey 2016; Frederiksen et al. 2008; Smale and Wernberg 2013). Events involving an increase of frequency are likely to impact population dynamics in the long-term by reducing recruitment and impacting growth rates, such that has been consistently observed across populations of plants, corals, insects and reptiles (Enright et al. 2015; Hughes et al. 2018; Maxwell et al. 2019; Neilson et al. 2020; Yu et al. 2022). Finally, events of increasing duration are likely to impact population dynamics by gradually altering the ratio between birth and mortality rates. For example, prolonged, but not necessarily more intense, EWEs have been shown to affect the recruitment process in corals and their symbionts by increasing mortality rates and decreasing birth rates as long as the event endures (Baker et al. 2008; Glynn 1996).

Interactions among multiple dimensions and variables can magnify the impact over the different features of population dynamics. Evidence from marine systems shows that prolonged ocean heat waves decrease the size of populations and make them more vulnerable to events of greater intensity in temperature or other climatic variables (Hughes et al. 2019; Kendrick et al. 2019). Likewise, evidence from terrestrial systems shows that the frequency and duration of droughts and heat waves interact to trigger population-level die-offs or magnify the impacts on the reproductive phenology of trees (Breshears et al. 2021). In the Tropics, such an impact on trees, together with water- and temperature-related stress, have been shown to change the population demography of mammals that rely on fruits and seeds (Butt et al. 2015; Campos et al. 2020; Marcelino et al. 2020).

## 4 Characterising multiple dimensions of EWEs across Central America and the Caribbean region

Central America and the Caribbean have been dubbed a "miner's canary" of climate change due to the marked increase in extreme weather events. Nowhere in the world coincide so many climate hazards over a global hotspot of biodiversity, within a background of marked human socioeconomic vulnerability (Castellanos et al. 2022; Gould et al. 2020; Reyer et al. 2017). The region is known for its hurricanes and cyclones but droughts and heat waves are not unusual (Cook et al. 2022; Taylor et al. 2012). Documented impacts of such extreme events include direct economic losses (Devis-Morales et al. 2017; Lewsey et al. 2004), and erosion of human health (Di Napoli et al. 2022) and biodiversity (Amaral et al. 2023; Muñiz-Castillo et al. 2019). Yet a comprehensive assessment of EWEs, across their multiple dimensions and climatic variables, has not yet been undertaken.

To begin addressing this gap, we implement 89 EWE metrics, using ERA5-Land climatological time series (daily records at 0.1-degree spatial resolution, Hersbach et al. 2020), across the Caribbean and Central America over the last 70 years (1950–2020). ERA5 is a reanalysis product that effectively combines model data with global observations using the laws of physics to create a comprehensive gridded dataset spanning the entire globe. Despite the high uncertainty in some estimates for the Tropics, due to limited data availability (Hersbach et al. 2020), recent studies have demonstrated the ability of ERA5 to accurately capture spatiotemporal changes in climatic variables for Central and South America (Balmaceda-Huarte et al. 2021; Gouveia et al. 2022), including changes in extreme values (Avila-Diaz et al. 2023; Bian et al. 2021). The ERA5 dataset is thus a valuable resource for investigating regional patterns of exposure, and spatiotemporal concordance between different types of EWEs. Nevertheless, it should be noted that achieving more accurate assessments may require a systematic quantification of the uncertainty associated with every metric, particularly in those capturing the intensity since reanalysis data might underestimate the actual daily value (Tan et al. 2023).

The number of selected metrics ($n$=89) results from combining multiple dimensions (intensity, frequency, and duration) and variables (wind speed, precipitation, and temperature), as well as interactions amongst such combinations (see Figure SM1.1 and Table SM1.1). Interactions were described by counting the number and duration of events of different nature (i.e., distinct climatic parameters) occurring within the same season or year. Metrics were computed separately for $0.1 \times 0.1°$ grid cells using daily values of wind speed, precipitation and temperature for the dry season (DJFMA, i.e., December to April) and the wet season (JJASO, i.e., June to October), using as climatic thresholds the 5th (or 95th) percentiles for the daily minimum or maximum values obtained in every grid cell during the baseline period (1951–1981). EWE patterns for the last 40 years—excluding the 30-years baseline—were characterised by computing the average, frequency, or maximum value per grid cell (see Table 3). In an exploratory analysis, we found that a considerable proportion of these metrics showed low (54.4% with Spearman rho < 0.03) and/or non-significant correlation (24.5% with $p < 0.05$) with other metrics (Figure SM1.2). An extended version of the methods can be found as Supplementary Material (SM1). Data and code, as well as a dynamic overview of the spatiotemporal of EWE in the region is available in a GitHub repository (https://github.com/jdgonzalezt/multipleDimensionsExtremeClimateChange).

To understand the internal variability of EWE, as measured with the 89 metrics, we employed a Principal Components Analysis (PCA) on the standardised outputs of all metrics (with mean 0 and standard deviation 1). We then use PCA results to group metrics and grid cells sharing a similar EWE profile, explore the geographical patterns displayed by EWE profiles, and hypothesise links between the distribution of EWEs and biodiversity based on the conjectures developed in the conceptual framework (Section 4).

The PCA revealed exceptionally high variability among EWE metrics calculated for the Caribbean and Central America in the past 40 years. Specifically, the first Principal Component (PC) captured just 19% of the total variation among metrics, with 21 additional principal components being needed to account for ca. 80% of the variance (Figure SM1.3 and Table SM1.2). Should metrics display a greater level of redundancy, as one would expect in low-dimensional phenomena, the PCA would reduce metrics variability into a

**Table 3** Metrics implemented to quantify the exposure to EWEs of the Caribbean and Central America regions. Persistent events are defined as five or more consecutive days with values over the established threshold. P95 and P5 represent the percentiles 95$^{th}$ and 5$^{th}$ of the baseline distribution, respectively

| Metric | n | Climate variable (and threshold) | Baseline |
|---|---|---|---|
| Intensity<br>- Number of standardised anomalies above 3SD in the last 40 years (neSA)<br>- Mean standard anomalies in the last 40 years (MSA*) | 12 | Wind speed (anomalies > 3SD)<br>Surface temperature (anomalies > 3SD)<br>Accumulated precipitation (anomalies > 3SD) | Daily maxima from December to April (DJFMA) and from June to October (JJASO) from 1951-1981<br>Daily minima in DJFMA and JJASO from 1951-1981 |
| Intensity<br>- Mean difference in the most extreme values of the last 40 years (P95 - P5) (D) | 10 | Wind speed (P95)<br>Surface temperature (P95, P5)<br>Accumulated precipitation (P5,P95) | |
| Intensity and Duration<br>- Mean cumulative intensity of the persistent events that occur in the last 40 years (MCI) | 10 | | |
| Duration<br>- Longest residence time of persistent events over the last 40 years (LRT)<br>- Mean residence time of persistent events over the last 40 years (MRT) | 30 | | |
| Frequency<br>- Frequency of extreme events in the last 40 years (fee)<br>- Frequency of persistent events in the last 40 years (FEpe)<br>- Average number of consecutive seasons exposed to persistent events in the last 40 years (REpe) | 20 | | |
| Compounded events<br>- Number of consecutive years with persistent events co-occurring in space in the last 40 years (Cpe_y)<br>- Maximum number of persistent events co-occurring in space within a year or a season over the last 40 years (maxCOpe)<br>- Average number of persistent events co-occurring in space within a year or a season over the last 40 years (MCOpe)<br>- Maximum number of consecutive days exposed to two or more EWEs within a year or a season over the last 40 years (LCED) | 7 | The simultaneous occurrence of two or more EWEs in a grid cell in the same year or season (DJFMA or JJASO) | |

*A metric without threshold.

few components. In several ecological studies examining patterns of covariation among climate variables, two to three components are typically identified (Araújo et al. 2001; Petitpierre et al. 2017) with the first component accounting for a disproportionately high proportion of the total variation.

To identify areas where biodiversity is likely at risk due to increasing trends of EWE occurrence, and for simplicity, we focus on describing the spatial patterns captured by the first four principal components (Fig. 2, amounting ca. 43% of the total variance). The geographical patterns of the metrics with the highest correlation to these four principal components are included in the supplementary material (Figures SM1.3-6). Note that PCA groups together variables that have a similar relationship with each other. It then calculates a linear function that summarises the trends shared by the variables within each group, or component. This procedure ensures that the components have low correlation among themselves (also known as "quasi-orthogonal," Jolliffe and Cadima 2016) and, as a result, describe distinct types of EWEs.

Geographically, the first component specifies areas of Central America and the Southern Caribbean that were highly exposed to more frequent and intense warm days during the historical baseline period studied (cells in red in PC-1 of Fig. 2), and areas highly exposed to heavy precipitation and cold days towards the north of the region (cells in grey in PC-1 Fig. 2). Heat waves and cold spells can compromise population persistence by increasing mortality, reducing birth rates, and altering sex ratios (Mazzotti et al. 2016; Wiederholt and Post 2010; Wright et al. 2015). Under limited dispersal conditions, the threat might be greatest for those small-sized populations at the edge of their physiological limits or distributional ranges (DeCarlo et al. 2017; Gutschick and BassiriRad 2003). As described by the second principal component, the threat for populations with such characteristics can be further exacerbated around the margins of Central and North America, where compounded events were detected (i.e., extreme wind, temperature, or precipitation occurring at the same location within the same year or season, cells in red in PC-2 of Fig. 2). Recent evidence indicates that the synergistic interaction between heat waves and meteorological droughts, for example, will result in more lethal events, which jeopardise the long-term survival of several species across the globe (Breshears et al. 2021; Sheppard et al. 2020).

The third and fourth principal component show that areas in the Caribbean islands and Central American corridor have been highly exposed to extreme winds and temperatures (red cells in PC-3 and PC-4 of Fig. 2). Hurricanes, cyclones and heat waves have immediate and lagged effects on population growth by simultaneously decreasing survival and fecundity (Morcillo et al. 2020; van den Burg et al. 2022). Given the available evidence, the increased exposure to more intense and frequent extreme winds, and prolonged high-temperature events, can potentially threaten species with lower fecundity, smaller population sizes, and narrow distributional ranges (Maxwell et al. 2019). In the case that dispersal of individuals from the mainland is restricted, the population size of such species would be reduced and likely lead to local extinctions across the islands and across fragments with low connectivity in the corridor. A similar process can occur in montane systems, in which extreme (and novel) climatic conditions may increase local extinction risks for high-altitude populations by exceeding the tolerances of individuals and increasing climatic barriers to their dispersal (Kerr 2020).

The fourth principal component also reveals that a wide extension of Central America and the Southern Caribbean has been exposed to sharp deficits of precipitation (grey cells in PC-3 of Fig. 2). While droughts and megadroughts are common to the American continent (Cook et al. 2022), and tropical species exhibit different adaptations to water deficit (Oliveira et al. 2021), there are different groups of species that can be at risk due

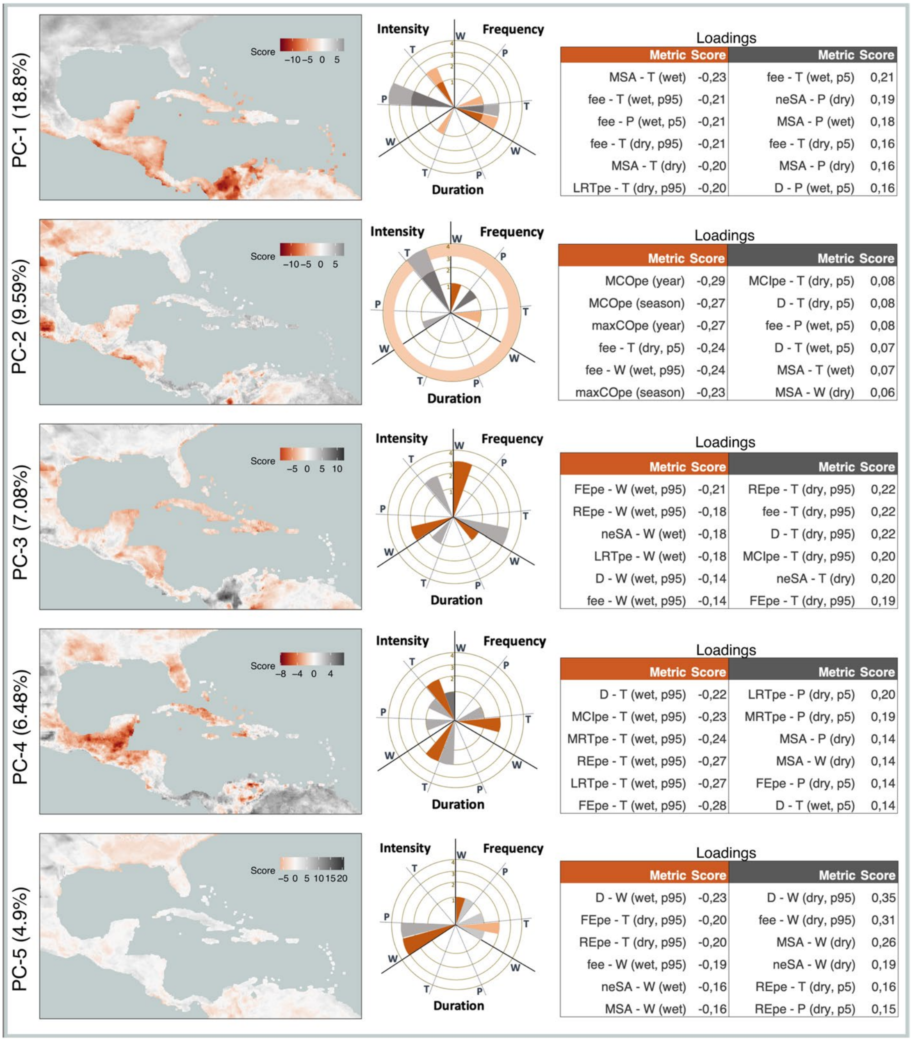


**Fig. 2** Spatial variability across the multiple EWE metrics as summarised by Principal Component Analysis (PCA). To facilitate visualisation, PCA scores and loadings are represented individually on the left and central sides of the figure. Loadings describe the correlation of the metrics with every PC, where metrics with the highest loadings exhibit similar variability across space. Scores describe the position of grid cells along the principal components. Colours represent their association with the group of metrics correlated with each PC. To simplify interpretation, only the six metrics exhibiting the highest negative (red) and positive (grey) loadings are shown (names and correlation values are included in the tables on the right). Radar plots help identify the number, dimension, and climatic parameter (T - temperature, P - precipitation, and W - wind) of the 12 metrics with the highest loadings in each PC. Compounded metrics are represented with a circle. Full names of metrics can be found in Table 1

to direct and indirect drought-induced effects. Population size of fast-growing plant species, for example, is directly affected by droughts because they do not invest resources in forming hydraulically-safe tissues that protect their structures from coping with water constraints (González-M et al. 2021; Guillemot et al. 2022). Likewise, population growth rate of frugivores, such as small primates, can be directly affected by water deficits and higher temperatures, or indirectly by food deficits resulting from tree die-off (Campos et al. 2020).

## 5 Linking multiple dimensions of EWEs to mangrove recovery in the Caribbean and Central America

The high dimensionality of the EWE metrics, revealed by 21 principal components needed to summarise 80% of the data, demonstrates that extreme weather events cannot be fully characterised unless a multidimensional analysis is performed. However, such high dimensionality further complicates the establishment of links between metrics and biodiversity. Instead of using “brute force” to navigate the “jungle” of metrics, i.e., computing several metrics before undertaking a ‘post hoc’ evaluation of their patterns of covariation to identify non-redundant patterns, an alternative is to select a set of metrics based on a priori knowledge of their ecological relevance.

To illustrate the principle, we select a subset of metrics to evaluate how greater exposure to heatwaves, droughts, and unusual rainfalls in the dry season (December to May) might have interfered with the post-hurricane recovery of mangrove populations in the North Atlantic Basin (NAB). Available evidence suggests that increased exposure to the intensity, frequency, and duration of such EWEs could be preventing mangrove recovery via direct and indirect effects on tree growth, resprouting, and seedling production (Amaral et al. 2023; Harris et al. 2010; Jimenez et al. 1985; Lagomasino et al. 2021). Decreasing individuals’ fitness is a direct effect of extremely intense temperatures and prolonged droughts, particularly for species such as *Avicennia germinans* or *Laguncularia racemosa*, or in poorly drained areas with lower fertility, such as in the Yucatán peninsula (Harris et al. 2010; Imbert 2018; Lagomasino et al. 2021; Vogt et al. 2012). In addition, both heat waves and droughts can induce indirect changes to biotic and abiotic conditions for biodiversity, via both natural and human induced processes. Natural processes include changes in the occurrence of early-successional plant species, which facilitate the establishment of mangrove propagules after disturbances, especially in the case of *Rhizophora mangle* (Donnelly and Walters 2014).

We asked whether the exposure to such EWEs in the dry season was lower in grid cells that exhibited some degree of recovery in mangrove forest coverage than in cells where no signs of recovery were evidenced. To assess exposure differences, we first identified grid cells with hurricane-damaged and recovered mangrove forests between 1998 and 2018. The geographic positions and status (damaged or recovered) of grid cells were retrieved from Amaral et al.’s (2023) study on the drivers of mangrove vulnerability and resilience to tropical cyclones in the NAB. For damage estimation, Amaral and colleagues traced changes in the Normalized Difference Vegetation Index (NDVI) over time. Specifically, they classified grid cells as ‘damaged’ if the mean ex-ante NDVI value (2 years before disturbance) differed from the mean ex-post NDVI value (after the disturbance) by more than -0.2, a threshold that had been field-validated for tree death (Lagomasino et al. 2021). For recovery estimation, on the other hand, they used the ex-post NDVI slope trend 1 year after the disturbance. Specifically, they classified cells with negative or zero NDVI trends as “not recovered,” while those with positive trends were classified as “recovered.” For further details on the NDVI-based analysis, including image pre-processing for water reflectance, refer to Taillie et al. (2020), Lagomasino et al. (2021) and Amaral et al. (2023).

We then estimated the degree of exposure to droughts, heat waves and heavy rainfall in both recovered and non-recovered grid cells. As proxies of such EWEs, we computed a set of metrics capturing the intensity (MCIpe), duration (RTpe) and frequency (FEpe) using two climate variables (temperature and precipitation) and two climatic thresholds (percentiles 95th and 5th of the baseline distribution: 1951 to 1981) (see Table SM1.3). We also quantified the occurrence of multiple events at the same location and year (Cpe). To determine the statistical difference between the two groups of grid cells (recovered vs. non-recovered), we used Wilcoxon signed-rank tests, and the Cliff's delta (Cliff 1993) effect size to assess the magnitude and direction of the differences. Cliff's delta estimates the probability that a value selected from one of the groups being compared is greater than a value selected from the other group. It varies from −1 to +1, with values farther from zero indicating the absence of overlap between the two groups. In our analysis, negative values indicate that non-recovered cells had greater exposure to extreme climate than recovered cells, whereas positive values indicated the opposite.

In the last two decades, mangrove forests exhibited low short-term resilience in areas that were damaged by hurricanes, with half of the affected areas (48%) showing no recovery signs 12 months after hurricane made landfall (Amaral et al. 2023). EWEs such as droughts, heat waves and intense rainfalls have been suggested as major factors delaying forest recovery, but a formal quantification of exposure has not been performed to date. By using a meaningful combination of climate change metrics, we show that exposure to EWEs during the dry season was significantly higher in grid cells with less mangrove recovery (Fig. 3a). We also identified the geographical areas where increased exposure has coincided with a lack of recovery (Fig. 3b–f). Such results suggest that post-cyclone recovery in mangrove forests can be reduced by the occurrence of individual or compounded events of extreme temperature and lack of precipitation in the dry season.

However, it is important to note that the assessment provided represents only an approximation of the effect of increased climate exposure. For more robust estimates, it is essential to consider other environmental and biological factors alongside extreme climate. Key environmental factors, including land use, slope, distance from the coast, and soil depth, play a crucial role in determining the magnitude of hurricane damage and the post-landfall recovery process (Amaral et al. 2023). Moreover, greater exposure does not necessarily indicate greater risk, as species with similar levels of exposure might experience greater or lesser impacts due to species' intrinsic sensitivity and adaptive capacity (e.g., Bailey et al. 2019; Valladares et al. 2014). Future studies should explore how adaptive responses (i.e., tolerance, migration, or evolutionary adaptation) can modulate mangrove vulnerability to the multiple dimensions of EWEs. The results presented herein can guide the establishment of a network of distributed experiments to assess such responses of mangroves across sites exposed to different stressors, including EWEs. They also provide a glimpse on the variables and dimensions that need to be accounted for when assessing the impacts of extreme climate change in the Caribbean and Central America regions.

## 6 Concluding remarks and outlook

Climate change is affecting living systems worldwide and we lack the models to appropriately characterise and forecast such changes. Weaknesses are particularly striking when it comes to modelling the effects of extreme events on biological systems. In the absence of comprehensive models that mechanistically link extreme climate dynamics to biodiversity dynamics, a first approach is to conduct a comprehensive analysis of extreme weather event patterns, while conceptually linking them with biodiversity threats.

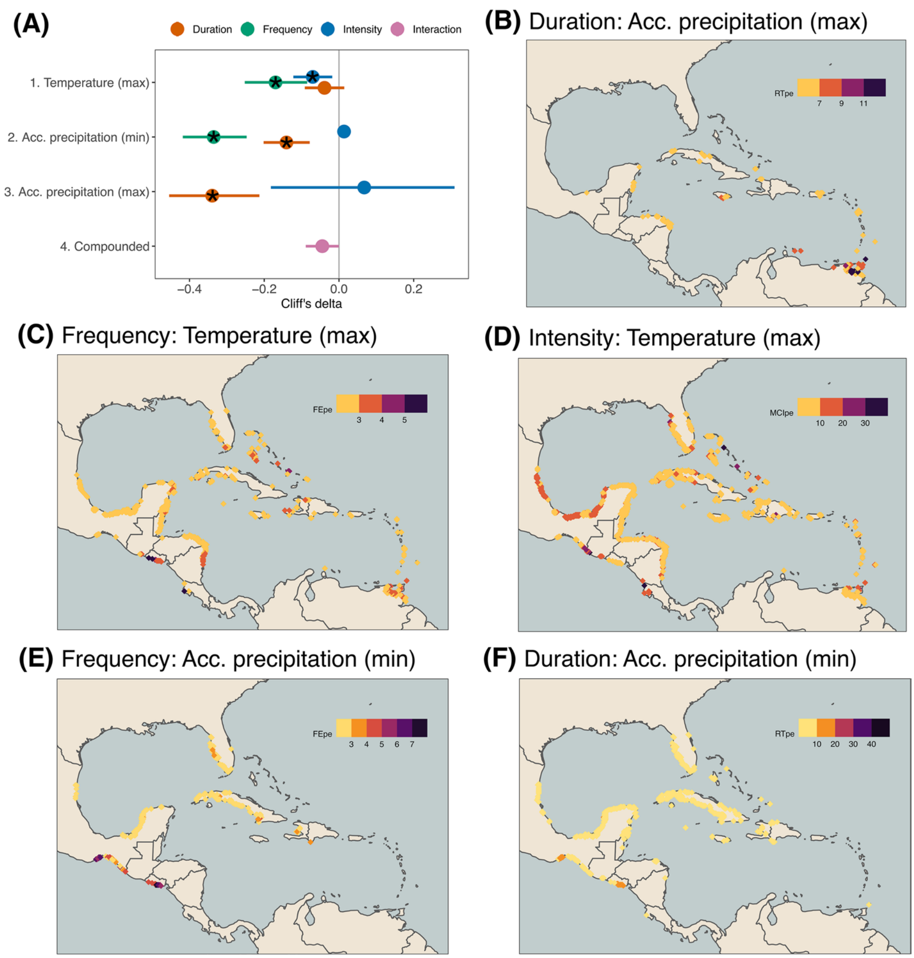


**Fig. 3** Comparison of exposure to the multiple dimensions of extreme climate change between grid cells with recovered and non-recovered mangrove forests from 1998 to 2018. (**A**) The effect size estimations using Cliff's delta are shown here for metrics describing the intensity, duration, frequency, and compounded occurrence of EWEs. Lines to the left and right of the circles indicate the 95% confidence intervals of the calculated Cliff's delta. Asterisks indicate significant differences between groups using the Wilcoxon signed-rank test (alpha $< 0.05$). (**B**-**F**) Levels of exposure to different dimensions and variables in grid cells where mangrove forests showed no recovery signs after cyclones made landfall. 'Intensity' is described as the cumulative intensity of five (or more) consecutive days with values exceeding the established threshold (MCIpe); "Duration" as the number of consecutive days with values exceeding the established threshold (RTpe); and "Frequency" as the maximum number of persistent events (five or more days exceeding the threshold) that occurred (FEpe). Thresholds were established as the percentiles 95th and 5th of maximum and minimum values from 1951 to 1981

Numerous climate change metrics exist to conduct such pattern analysis. Our review focused on metrics capturing different dimensions of extreme climate change (see Table 1). Using an example drawn from the Caribbean and Central American regions, we show that existing climate change metrics reveal extremely high dimensionality, meaning that no reduced set of metrics can describe the multiple patterns of change that follow from extreme weather events. Metrics capturing different dimensions (intensity, duration, and frequency), considering different variables (wind speed, temperature, and precipitation) and using distinct thresholds for defining "extremeness," often lead to dissimilar assessments of exposure to EWE across different regions.

Although empirical evidence is patchy and vastly incomplete, we provide a coherent framework linking critical population dynamic features (e.g., birth, growth, and mortality rates) to the multiple dimensions of extreme climate change, thus overcoming some of the limitations of sparse observational data for predicting future threats to biodiversity. In addition, when more ecological information is available, the framework can help guide assessments of the underlying threats to species persistence under different scenarios of future climate change. As shown in our case study, interpreting exposure patterns in the context of EWE dimension, variable and threshold provide insight into factors impacting the recovery of mangrove populations after hurricanes made landfall. While connections have been established at the population level, achieving a comprehensive understanding requires systematic establishment of links at the community and ecosystem level.

Our review provides evidence supporting the usefulness of climate change metrics for studying environmental risks associated with EWEs. It also reinforces the view that the metrics provide an exploratory tool to examine past, current, and future consequences of EWE. The proposed framework can also guide the selection of metrics in empirical studies addressing the impacts of the multiple dimensions of extreme weather events on biological systems. As we move forward, it is essential for future studies to address potential biases and uncertainties specific to each metric, particularly concerning climatic data. In regions with limited long-term observations, the representation of extreme climatic values in datasets from reanalyses and model projections (both CMIP5 and CMIP6) may be inaccurate in space and time (Avila-Diaz et al. 2023; Gouveia et al. 2022; Ortega et al. 2021), leading to potential over- or underestimation of the intensity, frequency, and duration of EWEs. By undertaking sensitivity analyses, researchers can gain insights into the reliability and accuracy of these metrics in assessing the potential threats to biodiversity (see, for instance, Buenafe et al. 2023). Such analyses can provide valuable information for making more informed decisions and developing robust strategies for conservation and mitigation efforts, ensuring the protection and preservation of biodiversity in the face of climate change challenges. By addressing uncertainties in climate change forecasts, we can enhance the applicability and reliability of climate change metrics, strengthening our ability to effectively manage and respond to environmental risks associated with extreme weather events.

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**Author contribution** JDGT and MBA conceived the study. JDGT curated the data collection, built the models, and performed the analyses. JDGT, RMR-C and MBA discussed the results. JDGT and MBA wrote the manuscript with contributions from all co-authors.

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**Data availability** Era5 Climate data is readily available at https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview. Scripts, as well as a dynamic overview of the spatiotemporal of EWE in the region are available in https://github.com/jdgonzalezt/multipleDimensionsExtremeClimateChange.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.



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