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Mapping the exposure of tourism to weather extremes: the need for a spatially-explicit gridded dataset for disaster risk reduction

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Abstract

Tourism is a highly important economic sector worldwide, yet it is often less than optimally represented in terms of detailed spatial information. An accurate spatial representation of tourism can provide valuable insights into the spatial distribution of tourism vulnerabilities and exposure, allowing policymakers to make informed decisions and develop effective strategies for disaster risk reduction and climate change adaptation policies. Here, we stress the need for and propose a first prototype of an open-access spatially-explicit gridded database based on social media data for over 150 different tourism-related classes that depicts tourism density (supply and demand) and perceived satisfaction in Europe. We showcase the potential benefits of such database by mapping the exposure of specific tourism sectors to a range of weather extremes, including floods, windstorms, and heat stress. Based on these results, we argue that a homogeneous spatially-explicit database of tourism is essential to support efficient investments in preparedness and disaster resilience.

← **Previous** article in issue

Next article in issue →

1. Introduction

Tourism plays a pivotal role globally, driving significant contributions to economic growth, job creation, and social and environmental progress (UNWTO 2021). Despite its importance, a shortfall in tourism statistical frameworks persists, particularly in what pertains to the spatial consistency representation of touristic activities across regions, thus hindering a comprehensive grasp of the multitude of factors influencing tourism resilience (Baggio and Del Chiappa 2016, Volo 2020, Gazoni and Silva 2022). Such shortfall becomes evident when dealing with complex and dynamic phenomena, such as climate-related extreme events. In this context, it is imperative to accurately represent the different components of the tourism system in space so to promote successful climate change adaptation and disaster risk management, particularly when addressing long-term challenges inherent to the spatial complexity of the tourism sector (Loehr and Becken 2021).

Indeed, climate-related disasters are a major source of concern to the tourism industry in Europe, as recently seen by the wildfires in Greece during the summer of 2023 and the combined drought and heatwaves during the European 2022 summer. Climate-related extreme events can potentially lead to physical damage to attraction sites, changes in visitor use patterns and satisfaction, and cascading impacts on the economy (Rindrasih *et al* 2019, Carroll *et al* 2020, Benhamou 2022). The impacts of disasters and extreme weather events can already be noted on the sustainable development of rural tourism (Zsarnoczky 2017) and on the winter tourism industry in the European Alps (Pröbstl *et al* 2008). Over the longer-term, according to Amelung and Moreno (2012), climate-related extremes could have significant impacts on the regional distribution of the physical resources supporting tourism in Europe. Evidence from regions of the world other than Europe also highlight the relevance of extreme weather events in tourism, as shown by Sungip *et al* (2018) on the impacts of floods in the tourism sector in Kelantan, Malaysia, and shorter winter seasons and reduced snowfall, leading to economic losses and decreased tourist visits in the United States (Cai *et al* 2019). The impact of climate-related extremes on the tourism sector is also multifaceted: while extreme events like windstorms and flooding can cause significant short-term disruptions to tourism activities (Rosselló *et al* 2020), over the long-term regions with fragile ecosystems such as the glaciers and Alpine environment can become increasingly vulnerable to climate change due to rising temperatures, potentially impacting tourism. To address these complex temporal and spatial issues, tourism-related information systems must transcend traditional statistics often constrained by limited spatial and temporal dimensions and move, instead, towards creating comprehensive databases that encompass various data sources and are capable of reflecting tourism-related characteristics and phenomena holistically (Ritchie *et al* 2018, Bertocchi *et al* 2023).

In this context, recent advancements in tourism-related data availability and big data analytics can support a better geographical localization of touristic destinations by allowing for incorporating spatially-relevant information (Gössling 2020). Notably, social media platforms such as TripAdvisor play a crucial role in characterizing attractiveness, identifying density of attractions, and assessing tourism experiences, including individual service roles (Kim and Wang 2018, Minkwitz 2018, Van der Zee and Bertocchi 2018). Recently, scientific research has highlighted the benefits in combining social media data with statistical and spatial tourism data in the tourism industry. For instance, Kang *et al* (2018) employed spatial statistical techniques to analyze the spatial patterns of domestic tourism in South Korea, thus allowing for a better understanding of past and present tourism activity in that country and for effectively responding to future tourism trends. In turn, Silva *et al* (2018) produced a novel and consistent dataset describing tourist density at high spatial resolution with monthly breakdown for the whole of the European Union, allowing to uncover key spatiotemporal patterns of tourism in Europe at specific spatial locations and highlighting the usefulness of complementing official statistical data with emerging big data sources. Similarly, Yallop and Seraphin (2020) discuss the opportunities and risks associated with big data and analytics in tourism and hospitality, highlighting the benefits of big data in providing valuable business insights for marketing activities and gaining a competitive advantage. Finally, Silva *et al* (2021) made use of spatial data analysis to classify EU regions based on hotel location patterns and geographical criteria, showing distinct profiles concerning tourism intensity and seasonality across the studied area.

A spatially-explicit and consistent tourism-related database is useful beyond tourism management. For instance, disaster risk management and climate change adaptation are areas that can particularly benefit from a detailed and spatially-explicit tourism database. When a disaster hits, preparedness is of utmost importance (Bello *et al* 2021) in a tourism-focus context as tourists often find themselves in an unfamiliar environment where language and services can be very different from their expectations, thus increasing their vulnerability to disasters (Hansson *et al* 2020b); thus, having access to detailed spatial information pertaining to touristic attractions can enhance integrated disaster risk management approaches (SFDRR 2015) as in the planning and development of emergency response plans (Fathianpour *et al* 2023). Similarly, the tourism sector can build resilience to climate change by leveraging on detailed spatially-explicit tourism information thus allowing for the integration of climate risks and tourism-related information to develop adaptive strategies that promote sustainable tourism development and reduce exposure to natural hazards (European Commission 2010). Essentially, by better understanding the risks, decision-makers can develop appropriate strategies and plans to mitigate and respond to these risks effectively, an information that can be particularly important for triggering financial instruments such as the European Union Solidarity Fund and the Loss and Damage Fund. In this paper, we address these issues by presenting a comprehensive and replicable methodological framework for the geo-localization of touristic destinations density and related user interaction and satisfaction for three tourism sub-sectors (hospitality, culinary, and attractions) in Europe by using social media data from TripAdvisor. Exploiting the potential of a collected dataset of over 17 million records for over 150 different tourism-related classes, we present, to the best of our knowledge, a first homogeneous spatially-explicit database of tourism density (both supply and demand) and perceived satisfaction in Europe. We show how this can serve as a foundation for a more detailed exploration of the presence and relationships among multifaceted factors underlying the complexity of the tourism system, and emphasize the need for comprehensive spatial databases to assess tourism vulnerabilities and exposure to weather extremes. Specifically, we showcase a potential application by mapping the exposure of specific tourism sectors in Europe to a range of weather extremes, including floods, windstorms, and heat stress. The resulting database is made open-access aiming to foster spatially-explicit research in tourism.

2. Data and methods

2.1. Tourism mapping

Tourism data is sourced from TripAdvisor, focusing on the tourism-related categories of hospitality, culinary, and attractions as of March 2021. The dataset spans Europe and nearby countries including parts of Russia, Turkey, and Georgia. With over 17 million rows, it covers 110289 locations and 162 tourism-related classes (4 hospitality types, 149 culinary types (which can be also classed into 15 culinary categories), and 9 attraction types, see table 1 for reference). The data is collected counting for the total number of facilities, such as a hotel or a restaurant, for a specific location (i.e. Macros), the number of reviews given by users for each facility in a given location (i.e. Reviews), and the average rating score (between 1 and 5) given by the users (i.e. Stars).

Table 1. The tourism-related classes for hospitality, culinary, and attractions as sourced from the TripAdvisor database.

Tourism-related classes [162]				
Hospitality [4]	**Culinary [a] [149]**			
Apartment	Afghani	Central European	Jamaican	Romana
B&B	African	Chilean	Japanese	Romanian
Hostel	Albanian	Chinese	Japanese Fusion	Russian
Hotel	Algerian	Colombian	Japanese sweets parlour	Salvadoran
	American	Costa Rican	Kapiseki	Sardinian
Attraction [9]	Apulian	Croatian	Kappo	Scandinavian
Bar and clubs	Arabic	Cuban	Korean	Scottish
Cultural sites	Argentinean	Czech	Kyoto cuisine	Seafood
Entertainment & events	Armenian	Danish	Kyushu cuisine	Sicilian

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Tourism-related classes [162]				
Hospitality [4]	**Culinary [a] [149]**			
Landmarks & sites of interest	Asian	Deli	Latin	Singaporean
Natural sites	Assyrian	Dutch	Latvian	Slovenian
Relax and wellness	Australian	Eastern European	Lazio	Soups
Shopping	Austrian	Ecuadorean	Lebanese	South American
Tour and activities	Azerbaijani	Egyptian	Ligurian	Southern-Italian
Transports & services	Bahamian	Emilian	Lombard	Southwestern
	Balti	Ethiopian	Malaysian	Spanish
Culinary categories [15]	Bangladeshi	European	Mediterranean	Sri Lankan
Bakeries	Bar	Fast Food	Mexican	Street Food
Bars & Pubs	Barbecue	Filipino	Middle Eastern	Sushi
Coffee & Tea	Beer restaurants	French	Mongolian	Swedish
Contemporary	Beijing cuisine	Fruit parlours	Moroccan	Swiss
Delivery Only	Belgian	Fujian	Native American	Taiwanese
Dessert	Brazilian	Fusion	Neapolitan	Thai
Dine with a Local Chef	Brew Pub	Georgian	Nepali	Tibetan
Diner	British	German	New Zealand	Tunisian
Dining bars	Burmese	Greek	Nigerian	Turkish
Gastropub	Cafe	Grill	Northern-Italian	Tuscan
Medicinal foods	Cajun & Creole	Guatemalan	Norwegian	Ukrainian
Quick Bites	Calabrian	Hawaiian	Pakistani	Uzbek
Restaurants	Cambodian	Healthy	Persian	Venezuelan

Tourism-related classes [162]				
Hospitality [4]	**Culinary [a] [149]**			
Specialty Food Market	Campania	Hokkaido cuisine	Peruvian	Vietnamese
Steakhouse	Canadian	Hungarian	Pizza	Welsh
	Caribbean	Indian	Polish	Wine Bar
	Catalan	Indonesian	Polynesian	Xinjiang
	Caucasian	International	Portuguese	Yunnan
	Central-Italian	Irish	Pub	
	Central American	Israeli	Puerto Rican	
	Central Asian	Italian	Romagna	

[a] Culinary class can also be grouped into categories.

The data sourced from TripAdvisor is available at the local level, indicating the country, municipality, neighborhood (or an area of interest), postal code, and address, depending on the level of detail in which the information is available from TripAdvisor. This level of detail allows for the geographical localization of the collected information at a specific coordinate point in space, in a process known as geocoding. We use OpenStreetMap geocoding services (OpenStreetMap 2022) assisted by the R package 'tidygeocoder' (Cambon *et al* 2021) to convert the location-descriptive information from the TripAdvisor database, such as a physical address, into geographical coordinates for a specific point on the Earth's surface. A schematic representation of the geocoding process is shown in figure 1.

Figure 1. Methodological framework depicting the data flow for converting the collected TripAdvisor data into spatially-explicit geo-locations. The resulting information generated by implementing the methodological framework is a series of

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spatially-explicit tourism-related maps depicting the density for the total number of facilities (i.e. Macros), the number of reviews given by users (i.e. Reviews), and the average rating score (i.e. Ratings).

Information for individual tourism-related classes is grouped resulting in a database that contains a unique identifier code of the record, a place field (e.g. city or neighborhood), a region field (e.g. region or province), a country name field, a description field of the tourism-related class, the number of tourism-related classes for that location (i.e. Macros), the number of reviews given by the users for each tourism-related class in that location (i.e. Reviews), and the average rating score (between 1 and 5) given by the users (i.e. Stars). Rows of geocoded information are dropped in the cases where an address is not found or results in an ambiguous localization, such as locating a place outside of the case study area (both cases represent less than 0.05% of the total number of rows). This consolidated database reflects supply (Macros), demand (Reviews), and satisfaction (Stars) at different European locations as a snapshot of March 2021. The database's coordinate points are transformed into a 5 km × 5 km spatial regular grid in order to make possible the spatial data analysis of the exposure of tourism to weather extremes. Each individual 5 km × 5 km cell of the resulting spatially-explicit gridded dataset of tourism-related indicators shows the sum of values for the Macros and Review classes, while Stars are calculated as the average of the points within each grid cell. The final dataset is accessible as an open-access source material at [permanent link to be generated after a potential revision of this manuscript; data for revision purposes can be provided on request].

2.2. Exposure to weather extremes mapping

Extreme weather events can significantly impact the tourism sector through various channels, including reduced tourist numbers due to cancellations, revenue and employment losses, and broader regional economic effects (e.g. Dunz *et al* 2023). The nature and impacts of these events differ, occurring across diverse locations and timeframes. This study focuses on three distinct extreme weather events—riverine floods, windstorms, and heat stress—using probabilistic descriptions. The goal is to map and assess their significance within each of the 162 tourism-related classes, as follows:

- River flooding is a major concern in urban centers (Essenfelder *et al* 2022) and can lead to direct physical damage (e.g. damage or destruction of infrastructure) and indirect revenue loss (e.g. reduced mobility of people and interruption of businesses). Both direct and indirect flood impacts can lead to the disruption of tourism activities, impacting the overall tourism experience and attractiveness of a touristic destination. Moreover, factors such as media coverage following a disaster can have a significant impact on the tourism industry, and a prolonged negative media attention can extend the recovery period for the destination, delaying the return of tourists and hindering the revival of tourism activities (Littlefield and Quenette 2007). The magnitude of a flood event is one of the factors relevant to determine the extent in which flood impacts are expected. To account for different magnitude of flood events, we consider probabilistic river flood hazard maps at ~100 m resolution for Europe and the Mediterranean Basin region (Dottori *et al* 2022). The considered flood maps are produced by means of the combined hydrological model LISFLOOD and the hydrodynamic model LISFLOOD-FP. The intensity of a flood event is the result of a combination of factors, including, among other factors, the duration of the event, the flow velocity and flood water depth; among these, water depth is the most important predictor of flood impacts (Amadio *et al* 2019). As such, flood intensity is mapped using water depth across the European continent for six different frequencies ranging from 1-in-10 years to 1-in-500 years. To account for tourism activities that can be exposed to river flood events, we adopt the inundation depth threshold of flooded areas of over 0.15 m as in Rentschler *et al* (2022).

- Windstorms are usually the result of strong winds in areas of low atmospheric pressure. Windstorms can result in property damage and safety concerns, disrupt travel plans, and lead to economic losses in tourism-dependent regions (Woosnam and Kim 2013). The impact of windstorms on tourism can range from physical damage to facilities and attractions to disruptions in transportation and accommodation services, affecting the overall tourism experience. We use a probabilistic pan-European dataset of windstorm at ~10 km resolution (Groenemeijer *et al* 2016) for four different frequencies (from 1-in-5 years to 1-in-50 years). Windstorm intensity is commonly measured by the intensity of the maximum 10 m wind speed (m s^{-1}), and their classification vary depending on the specific event and the organization issuing classifications. For instance, the Deutscher Wetterdienst issues windstorm warning levels based on six different wind speed thresholds: 14, 18, 25, 29, 33 and 39 m s^{-1} (Primo 2016), while wind comfort can be classified using the LDDC Lawson comfort criteria (Lawson 2001), for which windspeed values above 10 m s^{-1} might indicate uncomfortable conditions. For our application, we consider windstorm exposure as the areas affected by maximum wind speeds of at least 10 m s^{-1}, following the threshold used in Eslamirad *et al* (2021).
- Heat stress can be defined as the physiological stress experienced by individuals as a result of excessive exposure to heat. Heat stress can lead to uncomfortable conditions, and in extreme cases to increased risk of mortality and morbidity (Anderson and Bell 2011,

Hansson *et al* 2020a). Extreme heat events can disrupt tourism activities and attractions, leading to changes in visitor behavior and preferences. For example, tourists may avoid outdoor activities during heatwaves, impacting revenue for outdoor tourism businesses, or affect the attractiveness of destinations, particularly those known for their outdoor attractions or natural landscapes. Potentially leading to a decrease in tourism activity, revenue, and satisfaction. At the urban scale, urban heat events have been linked to thermal-related inequality, highlighting the need for a better understanding of heat injustice to support plans and actions for alleviating heat-related risks and threats in urban environments (He 2023). Several indicators exist to measure heat stress, including the Wet Bulb Globe Temperature (WBGT) which is a measure used to estimate the heat stress experienced by humans taking into account temperature, humidity, wind speed, and radiation, and the Universal Thermal Climate Index. We use a probabilistic global heat stress indicator at ~10 km resolution (WBG 2017) measured as WBGT (in °C) for three different frequencies (from 1-in-5 years to 1-in-100 years) to map heat stress intensity over Europe. We consider heat stress exposure as the areas affected by WGBT values of at least 28 °C (Jacklitsch *et al* 2016), indicating a very high risk of heat stress.

We combine each probabilistic spatial dataset from each natural hazard with the gridded supply (Macros), demand (Reviews), and satisfaction (Stars) tourism indicators produced in figure 1 by spatially overlaying each combination of hazard-exposure data. Geospatial operations, such as spatial overlay and zonal statistics, require the input information to have consistent spatial resolutions. When integrating spatial data with varying resolutions, interpolating one dataset to match the resolution of another can introduce uncertainties that impact the accuracy of spatial overlay analyses. This uncertainty arises from factors such as the density of input data, biases in the original data, and variations within grid cells. Since the spatial resolution of the probabilistic natural hazard maps and the developed tourism-related spatially-explicit database do not necessarily match, we apply a conservative approach to avoid the introduction of biases to the natural hazard maps by implementing a bilinear interpolation of the tourism-related data to match the spatial resolution of the different natural hazard maps, taking particular attention to keeping the total number of attractions and reviews consistent with the original data (i.e. avoid the introduction of biases due to the interpolation of absolute values). We then evaluate the spatial overlaying results in terms of potential impacts on tourism-related classes per hazard probability by considering the exposure levels and their respective effects on tourism supply, demand, and overall satisfaction. We compute the Expected Annual Exposure (EAE) of any tourism-related class by taking the integral of the probability-exposure curve for any given spatial location (Marzi *et al* 2021), as in equation (1):

$$\mathrm{EAE} = \frac{1}{2}\sum_{t=1}^{n}\left(\frac{1}{T_t} - \frac{1}{T_{t+1}}\right)\left(E_t + E_{t+1}\right) \tag{1}$$

where *n* is the length of the available return periods, *T* is the return period for index *t*, and *E* is the exposure for a return period of index *t*. The numerical integration of the probability-exposure curve allows for a straightforward comparison of the results between the different probabilistic weather extremes and the related exposure of tourism-related classes across space.

3. Results and discussion

The mapping process outlined in '2.1. Tourism Mapping' and the subsequent exposure analysis detailed in '2.2. Exposure to Weather Extremes Mapping' yield a significant number of files—486 maps dedicated to tourism-related classes and an additional 5832 maps for each combination of tourism-related class and weather extreme probability, plus 1458 maps for the EAE analysis of each weather extreme type and tourism-related class. Below, we show a representation of the total quantity of Macros (i.e. supply) and Reviews (i.e. demand) for the main classes of the three tourism sub-sectors (hospitality, culinary, and attractions) in Europe.

From figure 2 it is possible to verify some interesting patterns emerging from the richness of information collected from TripAdvisor. With respect to hospitality, supply is dominated by hotels and apartments, while demand is largely dominated by hotels. This difference between supply and demand in hospitality is due to the fact in the way these variables are accounted for in the database; while a hotel can accommodate hundreds of tourists, apartments and B&Bs can usually accommodate only a handful of tourists, a difference that is reflected in the higher number of reviews given to hotels with respect to the other categories. In terms of culinary supply, touristic destination countries such Italy, France and Spain dominate the share of restaurants, dominating also, in turn, the total number of reviews received by users. Interestingly, the United Kingdom is the leading country in terms of both supply and demand of Bars & Pubs in Europe, an information that is also reflected in the attractions tourism sub-sector, where the United Kingdom is the top country for Bars and Clubs. With respect to top destinations for cultural and landmark sites, countries such as Italy, France, Spain, and the United Kingdom stand out, with Italy accounting alone for about 32.5% and 21.3% of the Macros and Reviews of all Cultural Sites in Europe.

Figure 2. The relative distribution of the main three tourism sub-sectors (hospitality, culinary, and attractions) in Europe. The inner pie chart displays the overall distribution of the tourism-related classes, while the outer pie chart depicts the relative contribution of each country to the inner chart tourism-related class. For culinary preferences, the culinary categories classes are used for easier visualization of the results.

From figure 2, it becomes clear that the extensive volume of data produced in the tourism database and the subsequent exposure spatial data analysis makes it impractical to display each tourism-related class in spatial terms as separate maps or figures. To address this challenge and highlight meaningful insights drawn from the dataset, we concentrate on showcasing selected culinary types' tourism mapping outcomes across Europe. Specifically, we present results for the total number of restaurants (i.e. Macro, representing tourism supply) for the Italian, French, and Spanish cuisines in figure 3. A similar analysis but instead considering tourism demand (i.e. Reviews) is shown in the Annex section (figures A1–A3).

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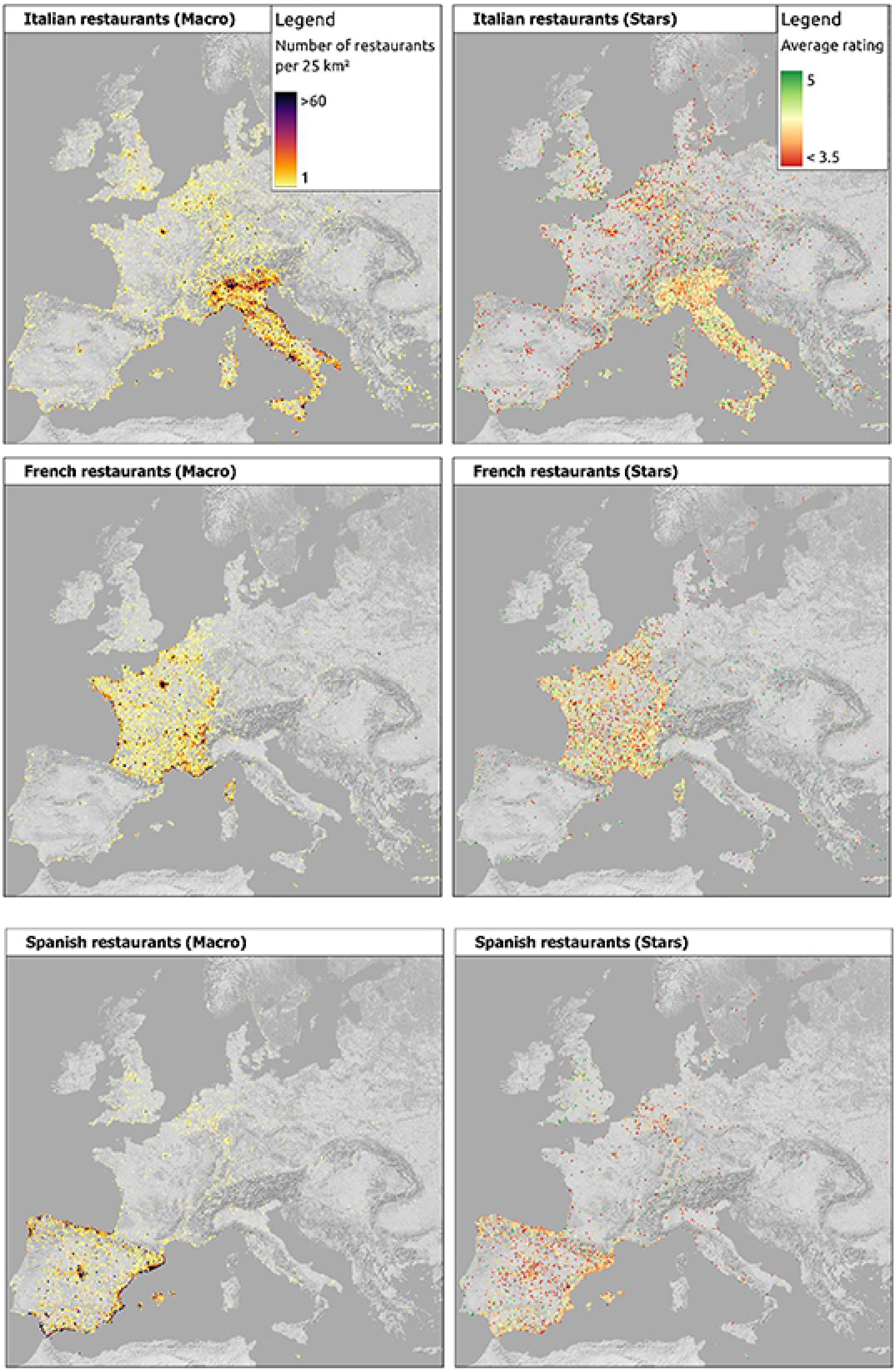

Figure 3. The spatially-explicit supply density (Macro) and perceived satisfaction of tourists (Stars) for restaurant types classified as Italian (top row), French (middle row), and Spanish (bottom row) in Europe.

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The spatial distribution of Italian, French, and Spanish restaurant types in figure 3 aligns almost perfectly with the respective countries' cuisine boundaries. Notably, Spanish restaurants cluster along Spain's coastline and major cities, such as Madrid and Barcelona. French restaurants are concentrated around Paris and the French Riviera. However, national cuisines extend beyond their home countries; French cuisine is prominent in Belgium and the Netherlands, while Spanish restaurants are found in the Netherlands, parts of Italy (e.g. around Naples), and the United Kingdom. Italian cuisine, in comparison, is widely distributed across Europe, particularly in western Germany and major capitals like London, Paris, and Madrid. The figure also reveals variations in tourists' perceived satisfaction regarding different restaurant types across the continent. For instance, Italian restaurants receive higher average appreciation in Tuscany compared to Lombardy.

Having a spatially-detailed tourism database enables the evaluation of how the exposure of tourism classes to extreme weather events varies across Europe. Indeed, spatial explicit information is fundamental for disaster risk management due to its crucial role in various aspects of disaster preparedness, response, and recovery. Additionally, and in a context of tourism, accurate and detailed information on the spatial patterns of tourist population density is important for disaster risk management as it enables the assessment of population exposure to natural hazards and supports risk assessment. Figure 4 demonstrates an example of the exposure analysis for heat stress and using the 'landmarks and sites of interest' tourism-related class.

Figure 4. The Expected Annual Exposure (EAE) of tourism in landmarks and sites of interest in Europe to heat stress. On the top-left, the spatially-explicit heat stress hazard characterized by means of the WBGT at RP 1-in-5 years; on the top-right, the spatially-explicit density (Macro) of landmarks and sites of interest in Europe; on the bottom-left, the areas considered as under potential risk of heat stress, and; on the bottom-right the exposure areas of landmarks and sites of interest in Europe to heat stress.

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The results presented in figure 4 highlight that while the distribution of landmarks and sites of interest remains relatively uniform across diverse European regions and countries, their exposure to different weather extremes varies significantly. For instance, exposure to floods is notably elevated in continental zones and spans much of the European landmass, particularly along densely populated major river valleys like the Po and Rhine valleys. Heat stress exposure, on the other hand, is notably pronounced in Mediterranean areas such as Italy's Po valley, coastal regions of the Iberian Peninsula, and the south-west of France. Conversely, windstorm exposure is particularly notable in north-western European regions and Great Britain—regions historically associated with high wind speeds—and along the majority of the continent's coastlines. These results can be better visualized when aggregated at an administrative unit level, such as for the NUTS3 level for Europe and shown in figure 5.

Figure 5. The expected annual exposure (EAE) of 'landmarks and sites of interest' at NUTS3 level to the different probabilistic weather extreme events considered in this study. On the top left, the spatially-explicit supply density (Macro) of landmarks and sites of interest, while the exposure of this tourism class to river floods, heat stress, and windstorms is shown on the top right, bottom left, and bottom right, respectively.

As shown in figure 5, having the capability to aggregate data at both individual attraction and larger administrative levels can be crucial not only for disaster risk management but also for adaptation in the tourism sector. Timely interventions are often needed at the destination level, or even at the level of specific attractions, to address issues such as the conservation of cultural heritage or the protection of particular natural sites, while smaller-scale and more precise data, focusing on individual tourist attractions and municipal areas, enable the development of autonomous and targeted policies that are best organized at the local level. Adaptation to climate change is a critical issue for the tourism sector, as it faces significant challenges due to the impacts of climate change. The understanding of regions where different types of touristic attractions and facilities are exposed to weather extremes can support the development of successful adaptation strategies in tourism (e.g. Wong *et al* 2013). Moreover, the tourism sector's vulnerability to climate change necessitates the implementation of adaptation strategies to minimize climate change-related damages (Vourdoubas 2022).

Conversely, addressing challenges in tourism often requires interventions on a broader scale, necessitating coordination across different local administrative levels. In this context, aggregated data at the NUTS3 level becomes indispensable, especially for large-scale initiatives involving infrastructure, managing environmental impacts, and allocating substantial financial resources. The combination of both granular and aggregated data ensures a comprehensive approach to tourism planning, allowing for nuanced local strategies as well as coordinated responses to broader issues. Moreover, the consideration of spatially explicit hazard and exposure enables the identification of countries and regions more likely to have specific tourism sectors at risk. For example, by evaluating the totality of touristic attractions in a single country, it becomes possible to rank countries that are expected to be at higher exposure to various climate-related hazards such as river floods, heat stress, and windstorms, an information that is displayed in figure 6.

Figure 6. Relative EAE of attractions in each country to the climate-related hazards considered in this study. Relative values are shown with respect to the total value in the case study area.

The ranking information shown in figure 6 is crucial for effective resource allocation and solidarity initiatives, directing funds and support to regions that are either impacted or at risk of natural disasters, such as the European Union Solidarity Fund (EUSF). The ability to generate such rankings facilitates targeted interventions and aids in the strategic allocation of resources to enhance resilience in vulnerable tourism sectors. Figure 6 visually depicts the relative values of attractions exposed to specific climate-related hazards, grouped at the country level, providing a valuable tool for informed decision-making in disaster-prone regions. Indeed, the consideration of spatially explicit hazard and exposure allows for the identification of countries and regions that are more likely to have specific tourism sectors to be more at risk. For instance, when accounting for the totality of touristic attractions in a single country, it is possible to rank the countries which are expected to be at higher exposure to river floods, heat stress, and windstorm. As shown in the figure above, the touristic sector of France, Italy and the United Kingdom are particularly exposed to river flood hazard, while Italy is also particularly exposed to heat stress and the United Kingdom is particularly exposed to windstorms.

4. Conclusions

Currently available official statistical data on tourism are often limited in terms of both spatial and temporal resolutions. By harnessing emerging big data sources from social media, we have enhanced the spatial representation of tourism in Europe for over 150 different tourism-related classes. In this research, we have developed a comprehensive and consistent dataset that provides detailed insights into the supply, demand, and perceived satisfaction of several tourism-related classes across regions and countries in Europe. This dataset has allowed us to unveil critical spatial patterns and characteristics of tourism at both regional and local scales, as exemplified in a disaster risk management context.

To construct this dataset, we collected over 17 million rows of data from TripAdvisor for the tourism-related classes of hospitality, culinary, and attractions over Europe and nearby countries, including parts of Russia, Turkey, and Georgia. With this dataset, we were able to geographically pinpoint the collected information at a specific coordinate point in space using OpenStreetMap geocoding services. While TripAdvisor provides a relatively complete, spatially detailed, and up-to-date information on accommodation establishments to date, completeness cannot be fully guaranteed.

Our analysis of the exposure of tourism to weather extremes has yielded important insights into the current regional patterns of tourism density and exposure to river floods, heat stress, and windstorms in Europe. Using the developed spatially-explicit database, it becomes evident that the exposure of tourism varies significantly between disaster type but also across countries, regions, and localities. Major tourism exposure hotspots include major cities and coastal areas.

The spatially explicit dataset created in this study is an invaluable support for large-scale and regional tourism research and extends its relevance to other fields that are part of tourism as a complex system, such as risk assessment and vulnerability studies. This dataset helps answer questions like '*Where are the highest densities of Italian restaurants outside of Italy*?' and '*How exposed are European natural sites to extreme weather events*?' Consequently, it has the potential to inform decision-making, in particular to integrate place-specific tourism data into climate change adaptation strategies by relating them to objects and phenomena that are difficult to observe with other ordinary data sources (e.g. national cuisine IRT climate change). The homogeneity and specificity of the data also allow the exploration of these questions, creating a fertile ground for the direct use of big data analysis techniques and artificial intelligence methodologies. In this context, we the authors have begun exploring the utilization of this database to with artificial intelligence methods to help understanding the intricate relationships between tourism supply, demand and satisfaction with regards to a range of factors including climate suitability, infrastructure, and demographics. Moreover, the consideration of different climate periods and climate change scenarios is also recommended in order to deliver a more holistic perspective in terms of tourism adaptation to climate-related extremes.

While our research provides a comprehensive description in space of a wide range of tourism classes, future research should aim to enhance the temporal dimension of regional tourism demand, supply, and satisfaction by leveraging data from emerging big data sources, such as TripAdvisor and Booking.com. These sources can provide relevant data to support seasonal tourism analysis, enabling the generation of consistent seasonal curves across different geographical delineations.

Data availability statement

The data that support the findings of this study are openly available at the following URL: https://zenodo.org/records/11035000.

The spatially-explicit tourism-related dataset developed in this study can be accessed as individual raster GeoTIFF (.tif) files from the link above. The adopted projection for the raster files is the World Geodetic System 1984 (EPSG:4326). The files follow the naming convention '*TourismSubSector_MacroClass_Metric*', where *TourismSubSector* is one of Attractions, Culinary, or Hospitality, *MacroClass* is one of the 162 tourism-related classes covered in this study (e.g. Natural sites or Italian Restaurants), and *Metric* is either Macro (proxy for supply), Reviews (proxy for demand) or Stars (proxy for satisfaction). Further details of the variables represented in the individual files can be found in the metadata file. For creating quick plots and exploratory data analysis of individual files, open-access Geographical Information System (GIS) tools such as QGIS (https://qgis.org/en/site/) are recommended.

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Annex: Results of the spatial exposure analysis for total reviews

This section presents the spatially-explicit results of the exposure analysis of tourism demand, represented as total number of reviews, to the natural hazards covered in this study (figures A1–A3).

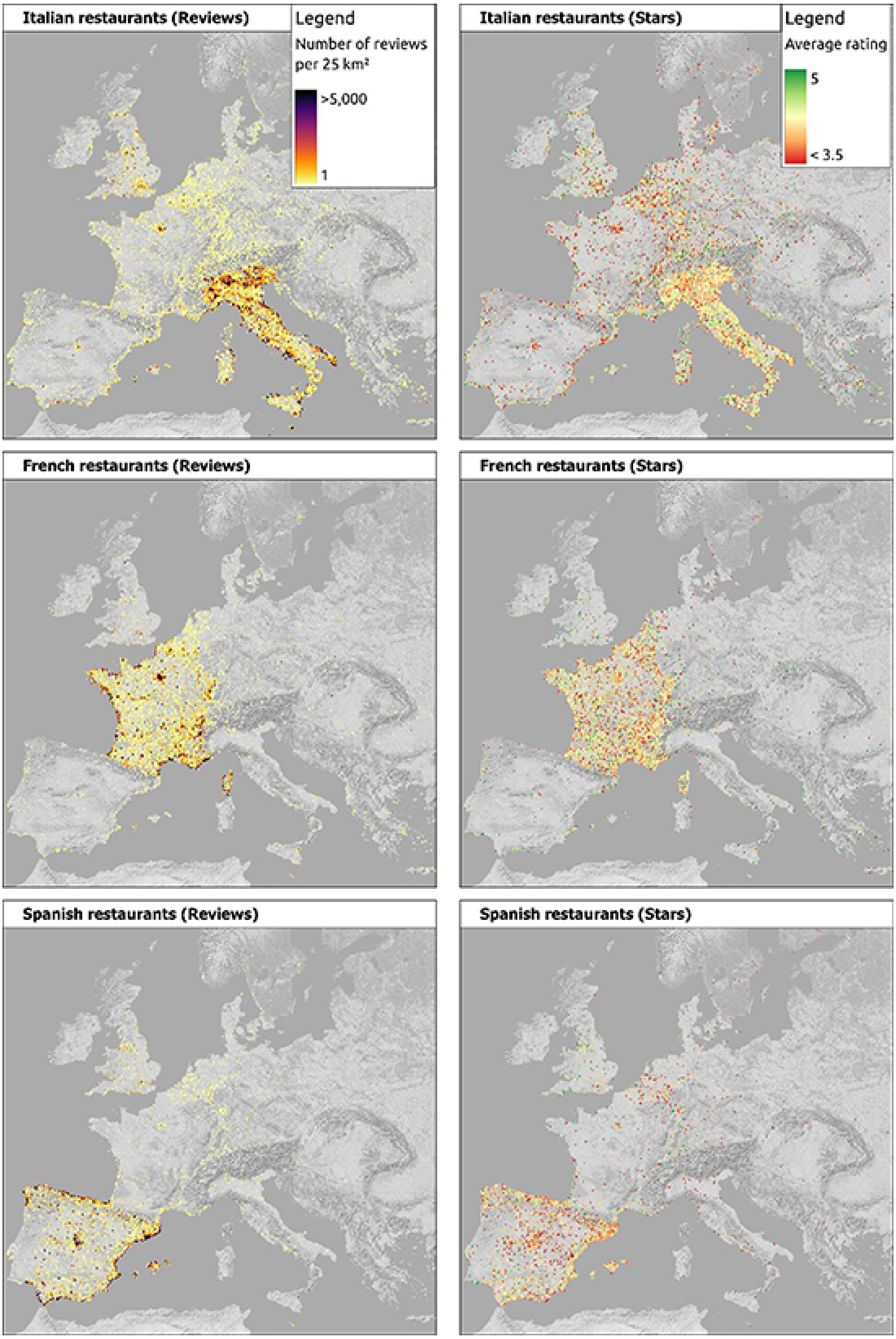

Figure A1. The spatially-explicit demand density (Review) and perceived satisfaction of tourists (Stars) for restaurant types classified as Italian (top row), French (middle row), and Spanish (bottom row) in Europe.

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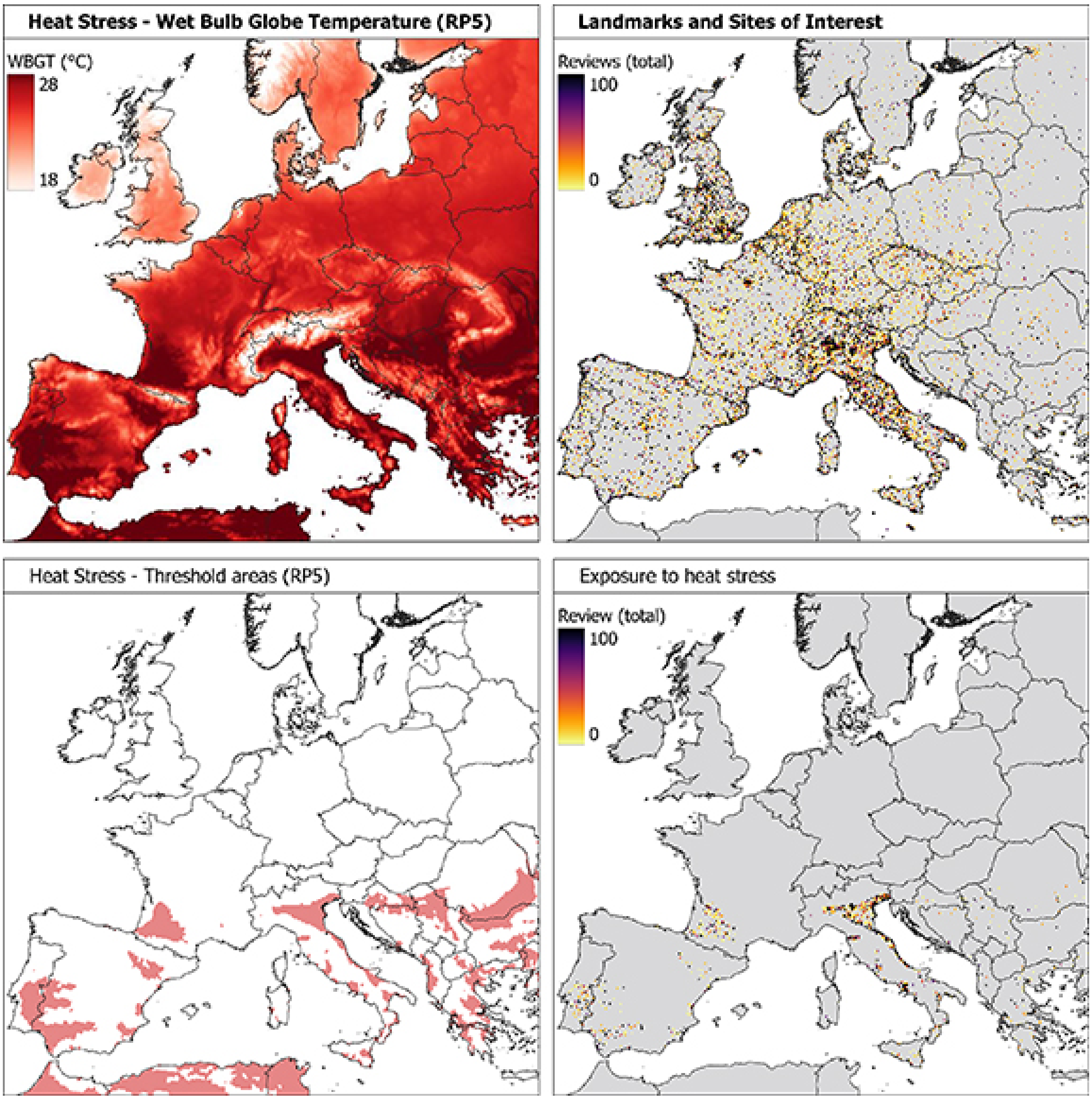

Figure A2. The expected annual exposure (EAE) of tourism demand in landmarks and sites of interest in Europe to heat stress. On the top-left, the spatially-explicit heat stress hazard characterized by means of the WBGT at RP 1-in-5 years; on the top-right, the spatially-explicit demand density (Review) of landmarks and sites of interest in Europe; on the bottom-left, the areas considered as under potential risk of heat stress, and; on the bottom-right the exposure tourism demand density areas of landmarks and sites of interest in Europe to heat stress.

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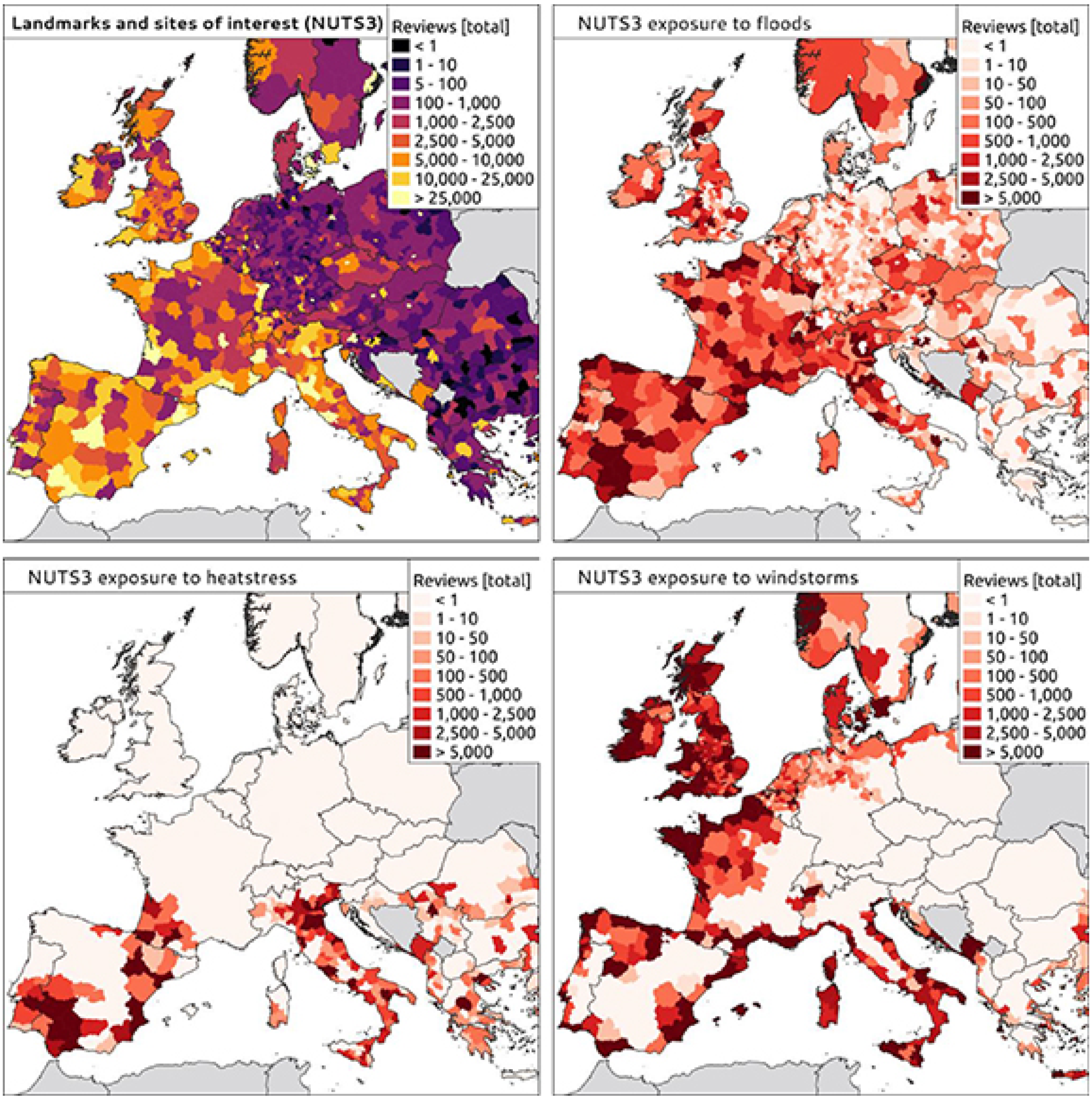

Figure A3. The expected annual exposure (EAE) of 'landmarks and sites of interest' at NUTS3 level to the different probabilistic weather extreme events considered in this study. On the top left, the spatially-explicit demand density (Review) of landmarks and sites of interest, while the exposure of this tourism class to river floods, heat stress, and windstorms is shown on the top right, bottom left, and bottom right, respectively.

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