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Weather Derivatives for Climate Risk Management in Hospitality: A Predictive Approach from Spanish Hotels

*Derivados Climáticos para la Gestión del Riesgo
Climático en Hoteles: Un Enfoque Predictivo a
Partir de Hoteles Españoles*

I. INTRODUCTION

The tourism sector is particularly susceptible to climate changes. Variability in weather and meteorological phenomena influence travelers' decisions regarding their destination, the duration of their stay, and the frequency with which they choose to visit a location (Craig & Feng, 2018). Consequently, the tourism industry is increasingly interested in understanding how climate impacts tourist movement patterns. If weather conditions influence the attractiveness of destinations throughout the year, tourism products and financial and commercial strategies must be appropriately adjusted. Furthermore, given the new challenges posed by climate change, it is crucial for policymakers to analyze how average weather conditions and climate variability affect tourism flows (Becken, 2013; Fang, Yin, & Wu, 2018). The planning and development of tourist destinations are influenced by multiple external factors, including weather conditions, which can have a significant impact on visitors (McCreary et al., 2024). In these destinations, weather generates both tangible effects (such as its impact on the local economy) and intangible effects (such as the perception of the destination). This influence can represent both risks and opportunities in the strategic planning and development of



EXECUTIVE SUMMARY

Climatology significantly influences tourism, and climate change has raised concerns about future impacts. While climate risk management studies suggest derivatives like temperature futures for the hospitality sector, they often overlook market feasibility. Effective hedging requires an accessible, cost-efficient market, which depends on its profitability. This study evaluates the viability of a derivatives market for Spanish hotels to hedge temperature-related climate risks. Data from 2016–2023 across selected Spanish tourist cities was analyzed using Elastic Net Regression to identify locations where climate derivatives are most relevant. Findings show that temperature derivatives effectively hedge risks in cities where climate strongly affects hotel occupancy. The study offers findings into hospitality risk management and supports the creation of climate derivative markets tailored to tourism.

RESUMEN DEL ARTÍCULO

La climatología influye significativamente en el turismo, y el cambio climático ha incrementado la preocupación por sus posibles impactos futuros. Aunque los estudios sobre gestión del riesgo climático proponen el uso de derivados, como los futuros sobre temperatura, para el sector hotelero, a menudo pasan por alto la viabilidad del mercado. Una cobertura eficaz requiere un mercado accesible y eficiente en costes, lo que depende de su rentabilidad. Este estudio evalúa la viabilidad de un mercado de derivados para que los hoteles españoles puedan cubrir los riesgos climáticos relacionados con la temperatura. Para ello, se analizan datos del periodo 2016-2023 de una selección de ciudades turísticas españolas mediante regresión Elastic Net, con el objetivo de identificar las localizaciones en las que los derivados climáticos resultan más relevantes. Los resultados muestran que los derivados sobre temperatura pueden cubrir eficazmente el riesgo en aquellas ciudades donde el clima tiene una incidencia significativa sobre la ocupación hotelera. El estudio aporta evidencia útil para la gestión del riesgo en el sector hotelero y respalda la creación de mercados de derivados climáticos adaptados al turismo.

tourism, particularly in natural locations such as ski resorts (Rivera & Clement, 2019), coastal and maritime centers (Matthews, Scott, & Andrey, 2021), national parks (Liu, Huang, & Hsieh, 2020), and camping areas (Craig & Ma, 2022). As a result, weather impacts tourists' decisions and behaviors, such as destination selection and preferred services (Tang et al., 2021). Empirical research has also demonstrated that weather affects tourists' psychological experiences (Kramer, 2023) and has a direct effect on visitor satisfaction (Wilkins & de Urioste-Stone, 2018).

The impact of climate risk on tourism businesses varies by region, as it depends on factors such as geographical characteristics, key economic activities, and the level of protection against such risks. In this context, climate derivatives serve to mitigate risks associated with weather conditions, where the contract value is determined by specific meteorological phenomena or related climate indices (Lin & Kwon, 2020). These indices can be developed and calculated using data from weather stations and/or satellite imagery. Several studies have examined the utility of derivative products for climate risk mitigation. One group of studies has focused on modeling temperature to provide valuations for futures and options (Alaton et al., 2002; Campbell & Diebold, 2005; Benth & Benth, 2007; Alexandridis et al., 2021; Huang, Yang, and Chang, 2018; Bressan and Romagnoli, 2021). Another group has explored business risk management using climate derivatives across various sectors. For instance, in the energy sector (Wieczorek-Kosmala, 2020), agriculture (Bibi & Rahman, 2023), and tourism, including winter sports (Bank & Wiesner, 2011; Tang & Jang, 2012), golf courses (Leggio, 2007), sporting events (Dawkins & Stern, 2004), sun-and-beach tourism (Canales & Pardo, 2011), and traditional celebrations (Martínez-Salgueiro & Tarrazón-Rodón, 2021).

In the tourism sector, previous studies on business risk management with climate derivatives typically propose hedging strategies using futures and options. However, the literature assumes—without empirical evidence—that these instruments would be effective and viable, merely stating that climate derivatives could address a real need. Consequently, it overlooks a key element: the existence of a sufficiently liquid market where these products can be traded and, therefore, become more affordable and accessible than alternatives such as insurance or over-the-counter (OTC) derivatives. This

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constitutes the main research gap, as although the potential usefulness of climate derivatives for the tourism sector is acknowledged, no study has analysed whether their trading could generate sufficient liquidity to make the creation of an organized market viable, an essential condition for the widespread use of these instruments.

Currently, weather derivatives are available in certain US cities. Still, they are scarce in Europe and Asia, including in relevant tourism markets such as Spain and Italy, as well as in key destinations within these countries. For this reason, the existing literature advocates for further studies exploring the potential development of weather derivatives markets, particularly to mitigate the risks faced by the hotel sector (Afshardoost et al., 2024; Martínez-Salgueiro & Tarrazon-Rodon, 2021). Our work directly addresses this gap, evaluating the effectiveness and feasibility of a market for derivative products that would enable Spanish hotels to hedge their climate risks, specifically those related to temperature fluctuations. To achieve this, 13 Spanish cities were selected, accounting for approximately 40% of the country's hotel capacity. Spain has consistently ranked among the top three most visited countries globally, receiving over 85 million international tourists in 2023 (INE, 2024). Using data on hotels and temperatures from the sampled cities for the period 2016 to 2023, Elastic Net Regression techniques were applied. These methods identified the cities where climate derivative hedge proves particularly effective. Additionally, the findings confirmed that hedging with futures contracts is effective in smoothing revenue fluctuations and improving the overall financial stability of hotels in the selected cities. These results have significant implications for understanding risk coverage in the hospitality industry and lay the groundwork for the development of new climate derivative markets for tourism.

The remainder of the study is structured as follows. After this introduction, a review of the existing literature on climate risk hedging in the hospitality industry is provided. Next, the methodological process is outlined, with a particular focus on the sample, data, and research model. Finally, the main results, conclusions, and potential avenues for future research are presented.

KEYWORDS

Weather derivatives,
Climate risk, Hedging.

PALABRAS CLAVE

Derivados de
Temperatura, Riesgo
climático, Cobertura.

2. LITERATURE REVIEW

In the field of tourism, the effects of climate have been studied through various approaches, encompassing both demand and supply perspectives. Firstly, from the demand side, researchers have explored the influence of socioeconomic factors, tourist motivations, and expectations regarding destinations. Socioeconomic factors (e.g., age, gender, income, and education) significantly affect tourists' decisions related to climate. For instance, Tang et al. (2021) demonstrate that low-income and older demographic groups are more likely to alter their travel decisions due to weather conditions. Similarly, Ruddy and Scott (2016) indicate that female sun-and-beach tourists are more sensitive to heat compared to their male counterparts. Personality is another internal factor influencing tourists' decision-making and behavior, particularly under uncertain conditions. For example, certain segments of travelers display a greater inherent adaptability to weather, which is linked to their personalities or varying degrees of tolerance toward climatic conditions (Becken & Wilson, 2013). Additionally, tourists' travel decisions are often driven by various motivations related to their specific objectives. Denstadli, Jacobsen, and Lohmann (2011) argue that travelers' motives should be considered when studying the impact of climate on tourist behavior. Becken and Wilson (2013) found that first-time summer visitors to New Zealand are more likely to make substantial changes to their travel plans in response to climatic variations.

Moreover, the relationship between travel experience, life cycle stage, and weather preferences has been examined among summer campers in Ontario (Hewer, Scott, & Gough, 2018). This study found that travelers with advanced camping experience prefer warmer nighttime temperatures compared to less experienced campers. Recently, Mushawemhuka, Hoogendoorn, and Fitchett (2021) discussed the implications of misinformation in media coverage of tourism at Victoria Falls, Zimbabwe, and how it affects tourist perceptions and demand. Other studies have highlighted that tourists often have specific expectations and objectives regarding their travel experiences. These expectations are partially influenced by destination factors, such as anticipated weather conditions (Denstadli, Jacobsen, & Lohmann, 2011). Weather expectations thus affect tourists' cognitive dissonance, leading them to adapt and cope accordingly (Jeuring, 2017). Tourist expectations are also closely linked to risk and uncertainty, playing a crucial role in

destination selection and visitor preparation (Williams & Balá, 2013). As such, weather conditions influence tourists' perceived value both before embarking on a trip (i.e., expected value) and afterward when reflecting on their travel experience (Coghlan & Prideaux, 2009). Secondly, from the supply side, previous studies have examined the impacts of climate on destinations, businesses, and their protection against climate risks. From this perspective, weather conditions have significant repercussions on economic performance, the attractiveness, and the image of destinations (Gössling, Abegg, and Steiger, 2016). Favorable weather has been linked to increased tourist arrivals (Craig, 2023), highlighting the importance of destination planning and development. Similarly, adverse weather conditions raise maintenance and replacement costs for tourism infrastructure and services, such as roads, transport systems, attractions, and activities (Palin et al., 2021). Regarding destination image, Lohmann & Kaim (1999) reported that poor weather conditions can negatively affect a destination's image and, ultimately, reduce its long-term attractiveness without proactive planning. Moreover, climate is a critical factor in the economic performance of tourism businesses (Amelung, Nicholls, & Viner, 2007). Specifically, studies by Mun and Park (2023) and Becken, Zammit, and Hendrikx (2015) confirm the critical role of abnormal weather conditions in the financial performance of hotels, including metrics such as revenue per room and occupancy rates.

Literature on reducing climate risk exposure for tourism businesses highlights that derivatives have been introduced as a critical adaptation strategy to protect against the risk of unexpected weather changes (Martinez Salgueiro & Tarrazon-Rodon, 2021; Hernandez & Ryan, 2011; Hoogendoorn & Fitchett, 2018). Roselló & Waqas (2015) employed tourism demand models to estimate the impacts of climate change on tourism. Their research underscores the importance of integrating climate derivatives into tourism planning and management to reduce the industry's vulnerability to climatic changes. Similarly, Franzoni and Pelizzari (2016) argue that to mitigate the negative effects of environmental risks, tourism businesses should use financial instruments, such as weather derivatives, designed to provide coverage by compensating for the economic damages resulting from such risks.

Bank and Wiesner (2011), Sileo (2012) and Ballotta et al. (2019) investigated risk management using climate derivatives in ski

resorts. These studies demonstrated the utility of such instruments in mitigating risks associated with climate variability in winter tourism. Kobert, Pretenthaler, and Bird (2016) compared tourism demand in Sardinia (Italy) and Cap Bon (Tunisia) under different climate scenarios, utilizing models to predict demand and evaluate the usefulness of climate derivatives.

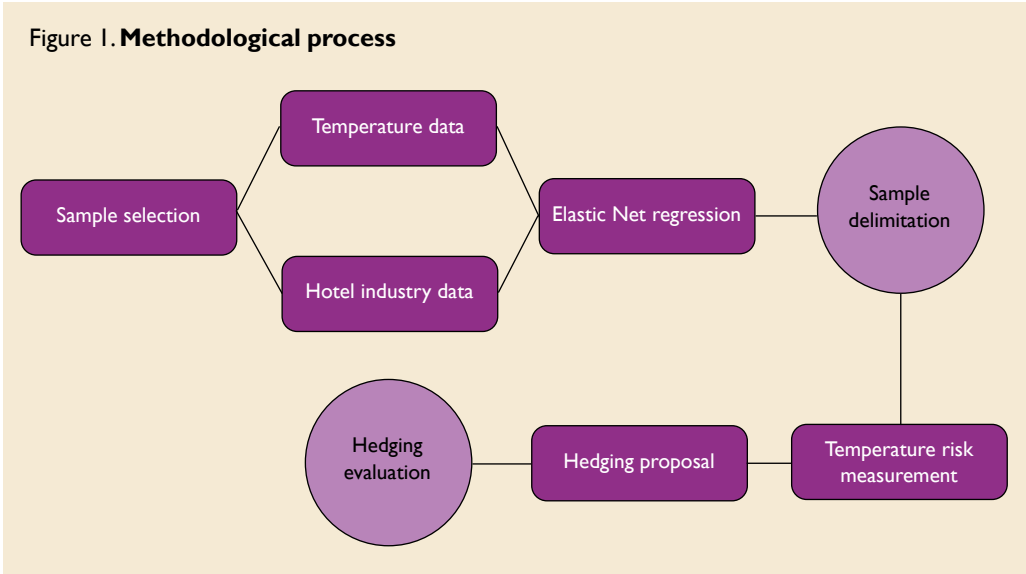
Rajendra (2020) analyzed the impacts of climate change on coastal tourism businesses, suggesting that climate derivatives can be an effective tool for mitigating economic losses caused by extreme weather events. Franzoni and Pelizzari (2019) applied a model to manage rainfall risk in the hospitality industry, focusing on 25 hotels in Lake Garda (Italy). Their findings provided evidence that rainfall derivatives could mitigate the negative impacts of rain on profitability and business performance. Martínez-Salgueiro and Tarrazón-Rodón (2021) highlighted the potential of temperature- and precipitation-based derivatives to mitigate weather risk in cultural and tourism events in Spain. They proposed temperature- and rain-based options as tools to reduce exposure to weather risks in such events. Canales and Pardo (2011) examined the impact of climate change on tourism demand in the Costa de Valencia destination, Spain. Their findings revealed that the number of tourists, both residents and non-residents, is positively related to temperature. They also noted that the number of stays by residents does not change during cold months but increases during warm months, while the number of stays by non-residents decreases during cold months but remains unchanged during warm months. Finally, they proposed derivative-based alternatives for sun-and-beach destinations to manage their exposure to weather risks.

3. METHODS

3.1. Research model description

To assess the effectiveness and feasibility of a market for derivative products that allow Spanish hotels to hedge their temperature-related risks, the following methodological process was designed: First, a sample of 13 cities was selected based on the significance of their hotel supply and representation of the three main climate types in Spain. Data on temperature trends and key hotel metrics were collected from these cities. Second, temperature indices were constructed for each city in the sample according to the specifications of the

Cumulative Average Temperature (CAT). These indices were used to analyze the impact of temperatures on hotel occupancy rates through Elastic Net regression models. This analysis identified which cities meet the criteria for hotel climate risks to be hedged by temperature derivatives. Third, the temperature risk for hotels operating in these cities was quantified, hedging options with temperature derivatives were proposed, and their effectiveness was evaluated. These results provided insights into the feasibility of a climate derivative market for the Spanish hospitality industry. **Figure 1** provides a summary of the different phases of the proposed methodological process.



3.2. Elastic Net Regression

Elastic Net is a regression model used in statistics and machine learning that combines two common techniques: Lasso (Least Absolute Shrinkage and Selection Operator) and Ridge Regression. Lasso adds a penalty based on the L1 norm of the model coefficients, which results in some coefficients being reduced exactly to zero, effectively eliminating certain variables. On the other hand, Ridge applies a penalty based on the L2 norm, which reduces the coefficients without bringing them to zero, making it useful in cases of multicollinearity (Zou & Hastie, 2005). Elastic Net combines both penalties, controlling the proportion of L1 and L2 penalties through two parameters. The first is the Alpha parameter, which determines

the balance between Lasso (L1) and Ridge (L2). For example, a value of 1 focuses solely on Lasso, while a value of 0 focuses entirely on Ridge. The second parameter, Lambda, controls the overall amount of regularization (penalty). Elastic Net regression techniques have been shown to be effective in previous studies on climate risk management, primarily due to their strong predictive capabilities and high interpretability (Jurgilevich et al., 2017).

This approach is particularly suited to our context for several reasons. First, climate-related datasets typically exhibit strong multicollinearity among predictors (such as temperature, precipitation, humidity, and wind speed), which destabilizes OLS estimates even when augmented with seasonal or temporal dummies. Elastic Net explicitly mitigates multicollinearity and produces more stable coefficient estimates than traditional regression models (Hastie, Tibshirani & Friedman, 2009). Second, our analysis involves a high-dimensional set of potential climate drivers, several of which may have weak, interacting, or non-linear effects. Unlike classical time-series or panel-data approaches, which usually require manual variable selection, Elastic Net performs automated, data-driven selection, reducing overfitting and improving generalization (Friedman, Hastie, & Tibshirani, 2010). Third, because our objective is predictive accuracy (a crucial requirement when assessing climate-risk exposure relevant for the feasibility of weather-derivatives markets), Elastic Net provides superior out-of-sample predictive performance compared with standard econometric models, especially under noisy climate data and limited historical observations (Jurgilevich et al., 2017).

In the present study, the Elastic Net model employed is defined as shown in **Eq. 1**.

$$Gha_{it} = \beta_1 + \beta_2 Temp_{it} + \beta_3 Nhot_{it} + \beta_4 HPI_{it} + \beta_5 ADR_{it} + \varepsilon \tag{1}$$

where *Gha* is the dependent variable and represents the hotel occupancy rate. The independent variables are as follows: *Temp*, which refers to the temperatures measurement using the CAT index; *Nhot*, the number of hotels in each city; *HPI*, the Hotel Price Index; and *ADR* the Average Daily Rate. Finally, *i* identifies the city, *t* represents the year of measurement, and ε denotes the estimation error.

The variables are estimated using Ordinary Least Squares (OLS), minimizing the sum of squared residuals, as shown in **Eq. 2**.

$$\varepsilon = \text{Min} \left(\frac{1}{n} \sum_{i=1}^n \left(Y_{Gha} - Y_{Gha}^{\wedge} \right)^2 \right) \quad (2)$$

Finally, by adding Elastic Net regularization, which combines Lasso and Ridge penalties, we reduce the number of variables and address the multicollinearity problem, as shown in **Eq. 3**.

$$\varepsilon = \text{Min} \left(\frac{1}{n} \sum_{i=1}^n \left(Y_{Gha} - Y_{Gha}^{\wedge} \right)^2 + \lambda \left[\frac{(1-\alpha)}{2} \sum_{j=1}^p \hat{\beta}_j^2 + \alpha \sum_{j=1}^p \left| \hat{\beta}_j \right| \right] \right) \quad (3)$$

3.3. Cumulative Average Temperature

Cumulative Average Temperature (CAT) is a comprehensive index that accumulates the daily average temperature during a month. This index is used for standardized futures and options trading on temperature indices at the Chicago Mercantile Exchange, specifically for European cities (CME, 2024).

The CAT index during a month $[x]$ is calculated as appears in **Eq. 4**.

$$CAT index_x = \sum_{d=1}^n \frac{T_i^{MAX} + T_i^{Min}}{2} \quad (4)$$

where the temperature is measured in degrees Celsius.

4. CASE STUDY

The present study examines the population of hotels located in 13 cities across various climatic regions of Spain. Spain is a country renowned for its diverse climate, geography, and culture. Traditionally, it has been an internationally significant tourist destination, with offerings that vary considerably depending on the climatic conditions of its different regions. Each region presents unique characteristics that can influence the seasonality of demand, the length of stays, and tourist preferences, making this approach essential for understanding the effects of climate on the hotel sector throughout the Spanish territory.

The three climatic zones selected for this study (Mediterranean, Atlantic, and Continental) represent the main climate types that define Spain's climatic diversity and, therefore, influence tourist behavior and hotel activity. The Mediterranean climate is characterized by mild winters and hot summers, with pronounced seasonality in tourism demand, especially in coastal destinations. This zone is popular among tourists seeking sun-and-beach experiences, particularly during the summer months. The Atlantic climate is distinguished by mild winters and cool summers, with more frequent rainfall throughout the year. This supports a more evenly distributed tourism demand throughout the year, with less pronounced seasonality. Finally, the Continental climate, characterized by cold winters and hot summers with significant temperature variations, influences a type of tourism more associated with cultural and nature-related activities, exhibiting more marked seasonality.

Building on the climatic and demand-seasonality patterns described above, we explicitly considered the potential non-stationarity and seasonal dynamics of the data before estimation. Given that each climatic zone in Spain (Mediterranean, Atlantic, Continental) exhibits distinct seasonal demand patterns and weather variability, we assessed the stationarity of all climate variables using standard unit-root tests and inspected their autocorrelation structures. To control for seasonal fluctuations that could otherwise bias the regression, we incorporated monthly (or seasonal) indicators as temporal controls, which capture zone-specific seasonality in tourism activity and climate conditions. This approach effectively removes deterministic seasonal components, ensuring that the Elastic Net model operates on data that do not exhibit problematic non-stationarity and that the estimated relationships reflect genuine climate-risk patterns.

The selection of the 13 cities included in this study is based on their significance in terms of tourism activity and their representativeness within Spain's main climatic zones. These cities were chosen for their high concentration of hotels and strategic location in different climatic regions, providing a broad and balanced perspective on how climate influences hotel activity. The climatic characteristics of each region can have differentiated effects on tourism demand and behavior. By including cities from various climatic zones, the study aims to achieve greater generalization of the results, allowing for the identification of patterns and specificities that may be of interest to hotel managers. **Table 1** details the cities included in the case study,

their corresponding climatic zones, and key metrics of the hotel sector in each city for the period 2016-2023. The information has been obtained from the National Institute of Statistics (INE, 2025), which provides monthly data on the hotel sector of each city, resulting in a sample size of 93 observations per city (totalling 1,209 observations).

Table 1. Cities in the Sample and Characteristics of Hotel Supply (2016-2023)

	NUMBER OF HOTELS	NUMBER OF ROOMS	OCCUPANCY RATE	AVERAGE DAILY RATE	TURNOVER (EUROS)	PRICES INDEX
Atlantic Zone						
A Coruña	61.55	2685.26	55.88	61.07	33896168.92	26.90
Santander	48.49	2074.29	58.81	80.84	36629343.76	23.30
Bilbao	76.81	4317.94	63.69	85.40	89265716.74	22.00
Continental Zone						
Madrid	753.02	41076.24	65.09	97.03	1019699605.36	21.90
Segovia	37.90	1140.70	59.44	67.24	17142843.17	24.30
Burgos	56.63	1911.59	54.93	57.35	22511722.65	24.30
Granada	146.39	6476.07	61.62	68.19	105191720.38	23.80
Cáceres	30.90	1216.57	51.69	69.88	16241885.14	22.50
Mediterranean Zone						
Barcelona	590.73	36721.16	68.09	121.44	1237451181.97	22.10
Málaga	106.83	5483.66	69.26	96.18	140365275.64	23.80
Sevilla	204.24	10631.45	65.55	89.89	244382861.35	23.80
Cádiz	30.81	1258.57	64.34	98.33	29713539.97	23.80
Valencia	150.35	8559.15	66.80	83.37	182534787.84	24.90

Number of hotels, Number of rooms, Occupancy rate, Average daily rate and Turnover are expressed as average in 2016-2023 period; Prices index is expressed as percentage of variation in 2016-2023 period.

Table 2 shows the evolution of temperatures in the cities included in the sample from 1980 to December 2023 (AEMET, 2024). The table highlights the different average temperatures characterizing the studied zones, with higher temperatures in the Mediterranean zone and the lowest temperatures in the Continental zone (Global average). Additionally, the table presents the lowest temperatures (10th percentile) and the highest temperatures (90th percentile) for each zone. Regarding the evolution of temperatures, a notable increase in average temperatures has been observed in recent decades, confirming that Spain is among the countries most affected by global warming. This trend is evident across all climatic zones

and nearly every month of the year, with differences of up to almost 3 degrees Celsius between the 1980s and the 2020s.

Table 2. Temperatures of the cities in the sample

	GLOBAL AVERAGE	GLOBAL MEDIAN	GLOBAL PERC. 10	GLOBAL PERC. 90	1980'S AVERAGE	1990'S AVERAGE	2000'S AVERAGE	2010'S AVERAGE	2020'S AVERAGE	1980'S ST. DEV.	1990'S ST. DEV.	2000'S ST. DEV.	2010'S ST. DEV.	2020'S ST. DEV.
Atlantic zone														
A Coruña	13.97	13.90	12.55	15.51	13.46	13.93	13.95	14.25	14.70	1.14	1.09	0.91	1.18	1.10
Santander	14.73	14.68	13.19	16.28	14.16	14.55	14.68	15.09	15.88	1.23	1.08	1.11	1.03	1.16
Bilbao	14.86	14.78	13.17	16.75	14.55	14.55	14.84	15.12	15.84	1.42	1.29	1.40	1.37	1.43
Continental zone														
Madrid	14.74	14.68	13.01	16.66	14.16	14.57	14.61	15.24	15.76	1.73	1.36	1.22	1.19	1.30
Segovia	12.46	12.46	10.27	14.73	11.77	12.22	12.51	12.81	13.53	2.24	1.65	1.36	1.53	1.53
Burgos	10.86	10.78	9.02	12.81	10.18	10.63	11.23	11.01	11.84	1.75	1.43	1.27	1.31	1.37
Granada	15.72	15.69	13.86	17.63	15.06	15.52	15.54	16.23	17.06	1.59	1.40	1.05	1.31	1.06
Cáceres	16.49	16.42	14.69	18.31	16.09	16.34	16.40	16.69	17.34	1.96	1.40	1.14	1.25	1.25
Mediterranean zone														
Barcelona	16.47	16.52	14.65	18.19	15.51	16.10	16.53	17.20	17.80	1.34	1.29	1.25	1.09	1.01
Málaga	18.77	18.77	17.37	18.86	18.09	18.33	18.89	19.31	19.92	1.13	0.93	0.79	0.74	0.90
Sevilla	19.32	19.31	17.56	21.07	18.51	19.22	19.68	19.60	20.00	1.60	1.32	0.98	1.20	1.10
Cádiz	18.84	18.84	17.38	20.20	18.62	18.56	18.75	19.07	19.74	1.36	1.12	0.86	1.05	0.94
Valencia	17.76	17.77	16.22	19.45	17.29	17.73	17.77	17.88	18.70	1.36	1.09	1.17	1.16	1.18

5. RESULTS

5.1. Climate Risk Delimitation

Following the proposed methodological process, this section aims to determine whether temperature volatility affects hotel occupancy in the sampled cities. This is essential to understand whether temperature variations pose a financial risk to Spanish hotels. To this end, as a preliminary step, a climate variation analysis was conducted by calculating the CAT indices for the 13 cities in the sample from January 2016 to December 2023. The CAT indices were selected due to their use in major climate derivative markets. After calculating the CAT indices, unusually low or high temperatures were identified. This was done using the inter-decile range, calculated based on the 10th and 90th percentiles, as proposed by AEMET (2023). The results are presented in **Annexes 1, 2 and 3**.

Once the CAT values for the cities in the sample were determined, an analysis was conducted to assess whether temperature is a significant variable in explaining hotel occupancy levels, which would constitute a financial risk suitable for hedging. To achieve this, the regression model proposed in **Eq. 1** was applied using average CAT values for the period 2016–2023. The results, presented in **Table 3**, indicate that the temperature-related variable is significant only for cities in the Mediterranean and Atlantic zones, with the exception of Burgos in the Continental zone (R^2 significant at 0.05 level, and DW test close to the value 2). Consequently, there is no significant effect of temperatures on hotel occupancy in Madrid, Granada, Segovia, Cáceres, and Sevilla. These cities exhibit much lower seasonality, as they attract visitors regardless of the weather conditions. The reasons for this may vary, but the findings clearly show that cultural and gastronomic tourism, typical of the Continental zone, is less affected by temperature compared to sun-and-beach tourism, which is more prominent in the Atlantic and Mediterranean zones.

Figure 2 provides a graphical representation of the regression results for those cities in which temperature exhibits a statistically significant relationship with hotel occupancy. Each panel displays the fitted values from the Elastic Net model alongside the observed occupancy levels, enabling a visual assessment of the model's ability to capture the underlying climate–demand relationship. The plots illustrate both the direction and magnitude of the estimated temperature effects, as well as their stability over time.

Table 3. Elastic Net Regression (Dependent variable: Gha)

	LAMBDA	TEMP	NHOT	HPI	ADR	CONSTANT	R ²	ADF TEST	P-VALUE	DW
Atlantic zone										
A Coruña	0,7953	2,0956*	-0,0665	0,0000	0,2032	21,9228	0,7443*	-5,1660	0,0000*	2,0001*
Santander	0,7531	2,7898*	0,2708	0,0000	0,0136	5,4617	0,7973*	-5,4656	0,0000*	1,9869*
Bilbao	0,1925	1,6124*	-0,5873*	-0,7767	0,3458	61,8519	0,7579*	-6,6650	0,0000*	1,7898
Continental zone										
Madrid	0,6382	0,2619	0,0632	1,5630*	-0,0025	18,8613	0,2709	-0,8042	0,8107	2,1007*
Segovia	0,7203	0,4648	0,5052*	0,0000	0,2537	20,1173	0,3380	-8,1986	0,7916	2,2242
Burgos	0,9266	1,4705*	0,4248	0,0059	0,4735	-10,2864	0,8573*	-6,2562	0,0000*	2,0286*
Granada	0,0173	0,6313	0,2945	2,1396*	0,4098	-19,0685	0,5505	-0,9067	0,7795	1,7454
Cáceres	0,0053	0,4846	0,7255*	1,9857*	0,3988	-3,0042	0,3818	-7,6057	0,5310	2,1665
Mediterranean zone										
Barcelona	0,0489	0,9858*	0,0808	2,3528*	0,1497	-11,6331	0,6601*	-6,9784	0,0000*	1,9173*
Málaga	0,5415	1,1683*	0,0084	0,7404	0,0683	47,0284	0,6664*	-7,4058	0,0000*	2,0688*
Sevilla	0,0309	0,3451	-0,0713	-3,2532*	0,3160	53,7910	0,4548	0,8264	0,8048	2,0833*
Cádiz	1,1900	2,3156*	0,0086	0,0702	0,1104	13,2146	0,7310*	-4,6927	0,0002*	1,8345
Valencia	1,5800	0,8984*	-0,2435	0,0000	0,5160*	50,0562	0,7497*	-6,1064	0,0000*	1,7912

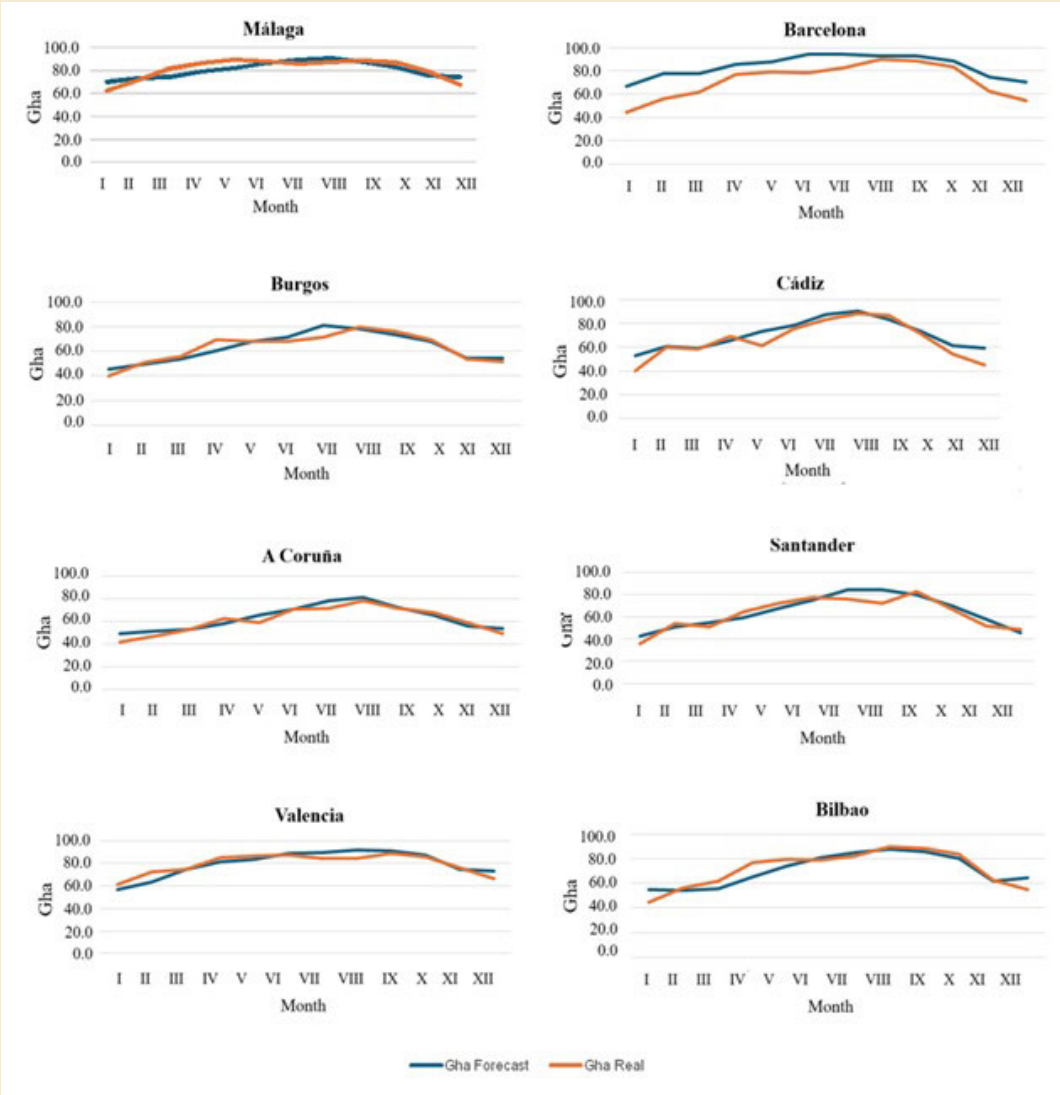
*: Sig. at 0.05 level; Alpha used for the estimation: 0.5

The previous results indicate that the cities where temperature risk is high for hotel activity are A Coruña, Bilbao, and Santander (in the Atlantic zone), Burgos (in the Continental zone), and Barcelona, Cádiz, Málaga, and Valencia (in the Mediterranean zone). Consequently, this group of 8 cities has been selected to analyze whether temperature risk can be hedged by hotels.

5.2. Quantification of climate risk

Table 4 provides an estimation of the impact of temperatures within the inter-decile range on hotel revenues. Specifically, it shows the difference in the average monthly revenue per hotel if the temperature falls below the normal range (10th percentile) or rises above the normal range (90th percentile). For the set of cities and specific months, particularly October, the loss in revenue due to temperature variations represents a significant monthly amount for each hotel. Consequently, we confirm that for hotels in this group of cities, the use of temperature derivatives to mitigate this risk is a sensible approach. In this regard, to quantify the hotel sector's exposure to

Figure 2. Regression model accuracy



climate-related risk, we compute a measure of risk exposure based on the difference in expected turnover under extreme but plausible temperature scenarios. Specifically, we compare the turnover predicted under high-temperature conditions (90th percentile) with the turnover predicted under low-temperature conditions (10th percentile). This provides an economically meaningful estimate of the sensitivity of hotel revenues to adverse temperature variations.

Table 4. Hotel risk exposure (in euros)

	A CORUÑA	BILBAO	SANTANDER	BURGOS	BARCELONA	CÁDIZ	MÁLAGA	VALENCIA
January	3568.21	7260.14	5345.69	1900.03	5458.15	4583.83	1974.92	2387.07
February	5379.59	9569.08	8082.82	3295.29	10161.75	7299.96	4555.82	5015.78
March	3647.59	5465.54	3020.92	2289.77	2906.67	4783.03	2931.77	2735.98
April	3640.91	7456.56	3585.30	3164.20	4910.30	6011.22	4317.47	2814.31
May	6340.62	11116.88	6340.44	3278.14	10519.06	5785.71	3691.05	3193.99
June	6746.08	8848.97	7453.22	2941.46	11379.70	11749.26	4546.04	4568.69
July	2940.57	7075.35	8202.13	1599.06	5296.93	15679.93	3565.43	3541.40
August	4883.46	6132.11	8768.69	2571.33	4738.67	7632.47	3709.38	4179.76
September	4279.52	7680.99	5635.10	2729.65	5676.55	5099.08	2830.92	2047.33
October	6936.06	16096.70	12494.38	4309.04	13599.58	9659.76	4377.08	5155.25
November	4700.74	7336.16	6178.82	2449.87	5947.89	6295.15	5168.16	4927.50
December	3743.18	6038.29	9209.08	2279.40	3747.88	5759.76	3956.20	4913.36
Total	56806.52	100076.76	84316.58	32807.22	84343.12	90339.16	45624.25	45480.41

Risk Exposure = Turnover for percentile 90° Temp - Turnover for percentile 10° Temp; Turnover for percentile 90° Temp = (Rooms/Hotels) × ADR × GHa forecast with percentile 90 × Month days; Turnover for percentile 10° Temp = Rooms/Hotels × ADR × GHa forecast with percentile 10 × Month days

5.3. Estimation of hedging strategies

The improvement in predictive technologies, increased awareness of climate change, and the rise in extreme weather events have led an increasing number of companies in the insurance, agriculture, construction, and tourism sectors to hedge their climate risks using temperature derivatives (CME, 2024). However, the Chicago Mercantile Exchange remains the only market in the world that offers these derivative products. Available contracts include futures and options on temperature indices for 13 U.S. cities (Atlanta, Boston, Burbank, Chicago, Cincinnati, Houston, New York, Dallas, Las Vegas, Minneapolis, Sacramento, Philadelphia, and Portland), 4 European cities (Paris, London, Essen, and Amsterdam), and 1 Asian city (Tokyo).

If a temperature derivatives market existed in Spain with indices based on the Spanish cities analyzed in this study, hotels could hedge their climate risks using temperature futures. They would simply need to take a short position in futures, representing a bearish stance that benefits from a decrease in the CAT temperature index. In this context, and according to the results of the proposed Elastic Net regression model, temperature has a direct and significant effect on

hotel occupancy. Therefore, it is evident that the primary risk for a hotel lies in exceptionally low temperatures.

To assess the effectiveness of the proposed hedging strategy, the number of CAT index futures that must be sold to offset the loss in hotel revenues due to adverse temperature variations has been determined. For this purpose, the average parameter values from the Elastic Net models, obtained using data from the 2016-2023 period, were used to perform simulations with real data from January to May 2024. In these simulations, real data were used for the variables Nhot, HPI, ADR, and the number of hotel rooms (**Table 5**). For the Future Price, an estimation over the average value of the 10th percentile of the CAT index during the 2016-2023 period was used. This approach ensures that the estimates are made under the assumption that buyers of the futures contracts sold by hotels will offer their counterpart at a reasonably low price.

Table 5. Input real data for simulation

	NHOT	HPI	ADR	NUMBER OF ROOMS
A Coruña				
January 2024	45	0.1	67.73	2371
February 2024	63	0.6	60.21	2723
March 2024	64	0.8	60.46	2801
April 2024	67	0.8	64.22	2849
May 2024	66	0.6	71.73	2833
Bilbao				
January 2024	83	-0.3	77.31	4700
February 2024	86	0.9	79.96	4782
March 2024	90	0.6	116.49	4924
April 2024	83	1.5	112.14	4876
May 2024	85	1.1	137.47	5121
Santander				
January 2024	52	0.2	65.6	2130
February 2024	55	0.6	66.17	2288
March 2024	60	0.7	83.72	2380
April 2024	59	0.5	78.52	2362
May 2024	59	0.3	99.14	2366

	NHOT	HPI	ADR	NUMBER OF ROOMS
Burgos				
January 2024	61	-0.7	56.61	1966
February 2024	67	1.3	57.35	2058
March 2024	65	0.7	61.1	2037
April 2024	68	0.5	66.16	2080
May 2024	68	0.8	76.12	2080
Barcelona				
January 2024	640	0.1	119.32	41391
February 2024	638	1.1	153.07	41902
March 2024	673	0.7	150.36	42986
April 2024	676	0.8	190.78	43073
May 2024	684	1.0	198.13	43036
Cádiz				
January 2024	37	-0.1	85.10	1683
February 2024	40	1.0	107.57	1734
March 2024	41	0.8	95.31	1755
April 2024	41	1.3	104.58	1755
May 2024	41	0.6	109.54	1755
Málaga				
January 2024	138	-0.1	114.83	6554
February 2024	140	1.0	116.24	6576
March 2024	144	0.8	131.16	6620
April 2024	144	1.3	136.01	6627
May 2024	142	0.6	144.26	6592
Valencia				
January 2024	193	0.2	87.73	9456
February 2024	194	0.6	104.85	9913
March 2024	199	0.8	122.19	10136
April 2024	198	0.7	118.54	10149
May 2024	199	0.7	129.12	10157

Table 6 presents the overall results of the simulation. It includes the delta indicator, which measures how much the hotel room occupancy rate (*Gha*) changes for each point variation in the *CAT index* (**Eq. 5**).

$$Delta = \frac{\delta(Gha)}{\delta CAT Index} \tag{5}$$

Delta is necessary for subsequently estimating the *Hedge Ratio*, calculated according to **Eq. 6**, which determines the number of futures contracts required to achieve the hedge.

$$\text{Hedge Ratio} = \frac{\text{Delta} \times \text{ADR} \times \text{Number of rooms} \times \text{days per month}}{\text{Multiplier}} \quad (6)$$

where *Multiplier* takes the value of 20 euros (similar to the one available on the Chicago Mercantile Exchange).

Table 6 also includes the estimated price of the *CAT index* future (*Estimated Future Price*) and the actual price of the future at the end of each month (*Real Future Price*). Additionally, it presents the estimated hotel occupancy rate (*Estimated Gha*) and the actual occupancy rate based on real temperatures (*Real Gha*).

$$\text{Futures settlements} = (\text{Estimated future price} - \text{Real future price}) \times \text{Hedge Ratio} \times 20 \text{ €} \quad (7)$$

The results in **Table 6** indicate the performance of the hedging strategy across all cities. For each month, the difference between the turnover based on estimated GHa and that based on real GHa represents the revenue impact of unexpected temperature deviations. The settlement of the temperature futures matches this difference almost perfectly in all cases. For every city and month, the “Difference” column and the “Settlement of futures” column exhibit the same magnitude with opposite signs, meaning that the payoff from the futures contract fully offsets the revenue shortfall (or surplus) generated by temperature shocks. This one-to-one compensation demonstrates that the hedging strategy provides adequate coverage against temperature-driven fluctuations in hotel occupancy and revenues. In practical terms, whenever real temperatures result in lower-than-expected occupancy (and thus lower income), the futures settlement yields a positive payoff of the same amount; conversely, when real temperatures increase revenues above expectations, the settlement is negative and neutralises the gain. The result is that net income remains stable, confirming that temperature futures, when combined with the estimated hedge ratios, are capable of smoothing climate-related income variability across different climatic zones and months.

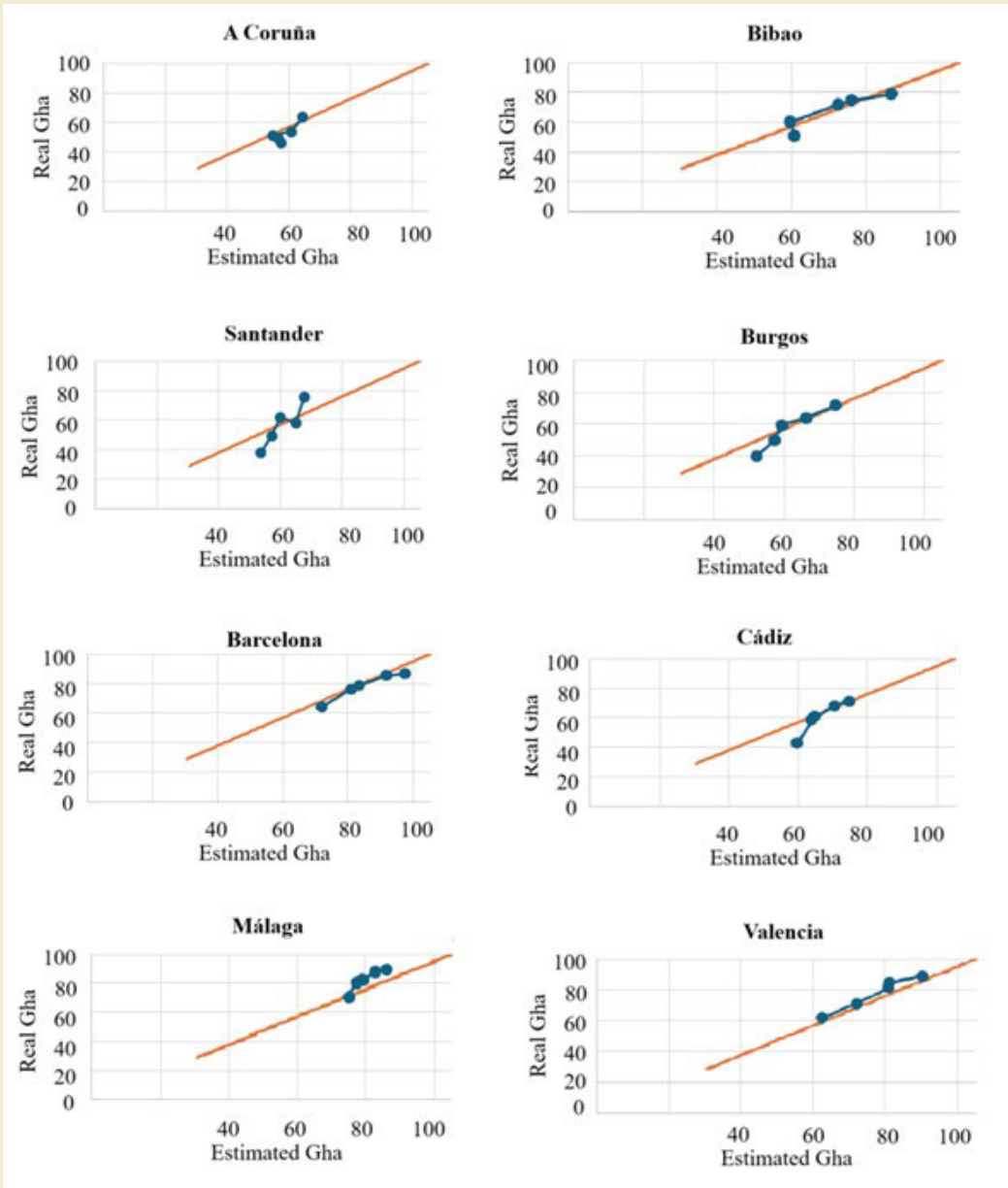
Table 6. Hedging evaluation

	DELTA	HEDGE RATIO	ESTIMATED FUTURE PRICE	REAL FUTURE PRICE	ESTIMATED GHA	REAL GHA	ESTIMATED INCOME	REAL INCOME	DIFFERENCE	SETTLEMENT OF FUTURES
A Coruña										
January 2024	0.07	168.00	335.00	337.90	55.34	55.53	2754769.74	2764529.32	9759.58	-9759.58
February 2024	0.07	172.00	325.00	333.20	54.29	54.90	2492210.75	2520384.88	28174.13	-28174.13
March 2024	0.07	177.00	390.00	344.10	56.31	53.21	2956332.33	2793434.86	-162897.47	162897.47
April 2024	0.07	192.00	435.00	405.00	60.90	58.80	3342722.25	3227694.02	-115028.22	115028.22
May 2024	0.07	213.00	515.00	446.40	66.92	62.28	4215665.90	3923525.29	-292140.61	292140.61
Total	-	-	-	-	-	-	15761700.98	15229568.38	-532132.60	532132.60
Bilbao										
January 2024	0.05	293.00	350.00	359.60	58.28	58.78	6565235.29	6621481.70	56246.41	-56246.41
February 2024	0.06	308.00	350.00	338.80	58.46	57.81	6258705.25	6189651.00	-69054.25	69054.25
March 2024	0.05	462.00	410.00	406.10	70.15	69.94	12473005.43	12436934.16	-36071.26	36071.26
April 2024	0.05	441.00	450.00	423.00	74.91	73.46	12288801.38	12050745.98	-238055.40	238055.40
May 2024	0.05	568.00	550.00	477.40	87.23	83.46	19037033.50	18212915.58	-824117.92	824117.92
Total	-	-	-	-	-	-	56622780.84	55511728.42	-1111052.42	1111052.42
Santander										
January 2024	0.09	195.00	360.00	350.30	52.84	51.96	2288683.52	2250871.50	-37812.01	37812.01
February 2024	0.10	211.00	340.00	341.60	55.14	55.30	2337280.86	2344038.76	6757.90	-6757.90
March 2024	0.09	278.00	410.00	390.60	59.75	58.00	3690717.28	3582876.63	-107840.66	107840.66
April 2024	0.09	259.00	440.00	432.00	63.43	62.68	3529126.58	3487733.78	-41392.80	41392.80
May 2024	0.09	327.00	500.00	473.06	67.79	65.37	4929326.57	4753033.25	-176293.33	176293.33
Total	-	-	-	-	-	-	16775134.80	16418553.91	-356580.90	356580.90
Burgos										
January 2024	0.05	82.00	160.00	173.60	50.02	50.67	1725893.82	1748152.81	22258.99	-22258.99
February 2024	0.05	87.00	200.00	190.40	55.84	55.33	1845270.34	1828607.85	-16662.49	16662.49
March 2024	0.05	92.00	275.00	235.60	59.30	57.44	2288132.93	2216019.14	-72113.79	72113.79
April 2024	0.05	101.00	330.00	285.00	66.11	63.90	2729101.89	2638034.86	-91067.03	91067.03
May 2024	0.05	116.00	450.00	365.80	75.99	72.00	3729886.97	3533838.23	-196048.73	196048.73
Total	-	-	-	-	-	-	12318285.95	11964652.90	-353633.05	353633.05

	DELTA	HEDGE RATIO	ESTIMATED FUTURE PRICE	REAL FUTURE PRICE	ESTIMATED GHA	REAL GHA	ESTIMATED INCOME	REAL INCOME	DIFFERENCE	SETTLEMENT OF FUTURES
Barcelona										
January 2024	0.03	2434.00	350.00	350.30	69.27	69.28	106056596.59	106071202.73	14606.14	-14606.14
February 2024	0.04	3161.00	360.00	358.40	78.06	78.00	140185446.96	140084279.74	-101167.22	101167.22
March 2024	0.03	3186.00	410.00	418.50	79.90	80.17	160094649.06	160636242.33	541593.27	-541593.27
April 2024	0.03	4050.00	470.00	450.00	88.83	88.18	218997946.82	217377768.02	-1620178.79	1620178.79
May 2024	0.03	4203.00	600.00	564.20	94.69	93.55	250283888.55	247274625.55	-3009263.01	3009263.01
Total	-	-	-	-	-	-	875618527.98	871444118.38	-4174409.61	4174409.61
Cádiz										
January 2024	0.07	166.00	440.00	471.20	55.48	57.81	2463116.13	2566594.16	103478.02	-103478.02
February 2024	0.08	216.00	440.00	453.60	61.48	62.60	3210864.08	3269607.48	58743.39	-58743.39
March 2024	0.07	194.00	515.00	508.40	62.21	61.71	3225598.11	3200033.49	-25564.62	25564.62
April 2024	0.08	213.00	560.00	558.00	67.99	67.83	3743362.60	3734862.27	-8500.33	8500.33
May 2024	0.07	223.00	665.00	626.20	74.98	72.08	4468562.44	4295834.96	-172727.48	172727.48
Total	-	-	-	-	-	-	17111503.37	17066932.35	-44571.01	44571.01
Málaga										
January 2024	0.04	440.00	450.00	437.10	72.91	72.43	17011285.88	16897860.28	-113425.60	113425.60
February 2024	0.04	447.00	460.00	428.40	76.08	74.76	16282650.90	16000446.31	-282204.59	282204.59
March 2024	0.04	507.00	480.00	489.80	75.88	76.25	20423464.24	20522877.67	99413.43	-99413.43
April 2024	0.04	527.00	530.00	543.00	79.13	79.63	21396366.00	21533261.99	136896.00	-136896.00
May 2024	0.04	556.00	640.00	644.80	82.64	82.82	24360928.12	24414257.19	53329.06	-53329.06
Total	-	-	-	-	-	-	99474695.14	99368703.44	-105991.70	105991.70
Valencia										
January 2024	0.03	373.00	385.00	412.30	59.48	60.27	15296126.43	15499579.52	203453.09	-203453.09
February 2024	0.03	467.00	390.00	392.00	69.43	69.49	20204647.42	20223321.94	18674.53	-18674.53
March 2024	0.03	556.00	450.00	455.70	77.68	77.85	29825848.81	29889268.36	63419.55	-63419.55
April 2024	0.03	540.00	500.00	507.00	77.98	78.19	28142826.28	28218480.34	75654.07	-75654.07
May 2024	0.03	589.00	625.00	635.50	86.33	86.64	35098358.09	35222065.10	123707.01	-123707.01
Total	-	-	-	-	-	-	128567807.02	129052715.27	484908.25	-484908.25

Finally, **Figure 3** illustrates the effectiveness of the hedging strategy using futures, comparing the *Estimated Gha* and *Real Gha* for each of the selected cities.

Figure 3. Effectiveness of hedging with futures



6. DISCUSSION

The results of this study provide new empirical evidence on the financial exposure of hotels to temperature variability and on the potential role of climate derivatives as an effective hedging instrument. These findings contribute to the growing body of literature that links weather

conditions with tourism performance, from both demand and supply perspectives. Previous studies have demonstrated that tourists' motivations, expectations, and socio-demographic characteristics shape their sensitivity to climatic conditions (Tang et al., 2021; Rutty & Scott, 2016; Becken & Wilson, 2013; Denstadli et al., 2011). At the same time, destination-level research has established that weather influences tourist arrivals, destination image, infrastructure maintenance costs, and hotel performance indicators such as occupancy rates and revenue per room (Gössling et al., 2016; Mun & Park, 2023; Becken et al., 2015).

Our analysis extends these findings by quantifying, for the first time in the Spanish hotel context, the magnitude of temperature-related revenue fluctuations and demonstrating the feasibility of hedging such risk using temperature futures. While earlier research has proposed climate derivatives as a tool to mitigate weather risk in tourism (Martínez-Salgueiro & Tarrazón-Rodon, 2021; Hernández & Ryan, 2011; Franzoni & Pelizzari, 2016; Roselló & Waqas, 2015), empirical applications remain scarce, often limited to winter tourism or case studies in specific destinations (e.g., Bank & Wiesner, 2011; Sileo, 2012; Ballotta et al., 2019). By contrast, this study examines 13 cities, which account for 40% of Spain's hotel capacity. It demonstrates that hedging based on estimated occupancy responses to temperature is both practical and economically meaningful across different climatic regions.

Notably, the hedging simulations demonstrate that temperature futures fully offset the revenue deviations resulting from unexpected temperature realizations. This finding strengthens previous conceptual arguments on the usefulness of climate derivatives in tourism (Franzoni & Pelizzari, 2019; Kobert et al., 2016; Rajendra, 2020) and provides empirical validation in the hotel sector, where coverage has rarely been tested using real data and occupancy forecasts.

The effectiveness of the hedging strategy also contributes to the discussion on the broader economic feasibility of climate-derivative markets. Although temperature is a non-tradable asset and cannot be hedged through classical arbitrage mechanisms, the results suggest that natural counterparties exist whose climatic exposures are opposite—for example, hotels benefiting from warmer conditions and energy firms suffering reduced heating demand during mild winters. This supports prior work highlighting the need to identify suitable

counterparties for derivative transactions (Martínez-Salgueiro & Tarrazón-Rodón, 2021) and demonstrates how hedged positions could align with real economic incentives.

Furthermore, the methodological contribution of this study is relevant for climate-risk modelling in tourism. Elastic Net regression proved to be an effective tool for identifying high-dimensional climate drivers of occupancy, while addressing multicollinearity and enhancing predictive accuracy. This aligns with earlier research advocating for the use of advanced statistical and machine-learning techniques in climate-risk analysis (Jurgilevich et al., 2017) and underscores their usefulness when applied to tourism, where climatic influences are complex and nonlinear.

7. CONCLUSION

This study has analyzed the effectiveness and feasibility of a market for climate derivative products that could enable the Spanish hotel industry to hedge its temperature-related risks. For this purpose, 13 Spanish cities representing 40% of the country's hotel capacity were selected. Using data on hotels and temperatures from the sampled cities for the period 2016 to 2023, Elastic Net Regression techniques were applied to identify the cities where climate derivatives coverage is particularly effective. The results also confirmed that hedging with futures contracts is effective in smoothing revenue fluctuations and improving the overall financial stability of hotels in the selected cities. A key issue with temperature derivatives is that they are non-arbitrageable assets. Unlike financial derivatives, temperature is not storable, and therefore, there can be no financial counterparties offering the product through replication. For a temperature future or any other type of temperature derivative to be tradable, there must be one counterparty negatively affected by a rise in temperature and another positively impacted by it. In this context, energy companies are negatively impacted by mild winters because their customers use less heating, resulting in reduced revenue. For this reason, they might purchase temperature futures to offset the loss of income due to higher-than-normal temperatures, a concept known as volumetric risk. On the other hand, the counterparties to these energy companies would need to be businesses for which lower-than-normal temperatures result in losses, requiring compensation through the sale of futures. Hotels could be ideal candidates to serve as counterparties for energy

companies, as they benefit from higher temperatures (except for those focused on winter sports).

For hotel managers, the empirical results provide tangible evidence of the financial relevance of climate risk, given that temperature variability can create substantial revenue volatility. Yet these deviations are fully offset by the futures settlement amounts, indicating that hotels can transform unpredictable weather fluctuations into stable financial outcomes. This opens the door to a more sophisticated risk-management culture in the hotel sector, where climate risk becomes a quantifiable and hedgeable component of revenue strategy. The findings also have implications for policymakers and financial regulators. Since temperature is a non-storable asset and thus cannot be hedged via traditional arbitrage, the development of climate-derivative markets depends on identifying natural counterparties with opposite exposures. The results confirm that Spanish hotels lose revenue during unexpectedly cold periods, whereas energy companies typically experience reduced demand during warm winters. This complementarity of exposures is precisely the kind of condition needed for market creation. Public–private initiatives, standardized temperature indices, and support for initial liquidity could further enable these markets to serve as climate-adaptation instruments for tourism-dependent regions.

Considering the conclusions reached, future studies could delve deeper into the geographic basis risk associated with the climate derivatives proposed in this research. It would be valuable to investigate synthetic indices designed to mitigate the geographic basis risk for broader areas, as this could enhance the liquidity of climate derivatives and promote the development of a market for these products in Spain. It is also important to note that this study quantified hotel risks based solely on room occupancy rates, which represent only a portion of a hotel's total revenue. A hotel's finance department has access to more comprehensive and precise revenue data, including income from additional services such as restaurants and events. Incorporating these data into the model would significantly improve the accuracy of predictions and the effectiveness of the proposed hedging strategies.

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ANNEXES

Annex I. CAT indexes of the Atlantic zone

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	$\mu+2 \sigma$	$\mu-2 \sigma$
A Coruña															
January	347.2	266.6	316.1	245.7	307.0	265.6	285.2	294.5	291.0	259.6	325.4	65.8	32.5	355.9	226.0
February	298.7	294.0	220.5	287.5	346.8	326.9	277.2	238.0	286.2	232.8	332.9	100.1	41.9	369.9	202.5
March	316.2	368.9	293.4	343.4	348.3	333.9	344.1	387.5	342.0	309.4	374.5	65.1	29.1	400.2	283.7
April	351.0	393.0	366.1	356.8	403.4	386.1	354.0	417.0	378.4	353.1	407.5	54.4	24.9	428.3	328.6
May	443.3	520.8	449.5	453.9	524.0	418.0	496.0	517.7	477.9	435.7	521.8	86.1	41.5	560.9	394.9
June	507.0	540.0	519.8	467.7	476.9	490.8	528.0	588.0	514.8	474.1	554.4	80.3	38.7	592.2	437.4
July	613.8	598.3	615.6	596.9	606.7	572.0	638.6	601.4	605.4	589.4	622.5	33.1	19.0	643.5	567.4
August	610.7	598.3	615.9	604.0	601.5	602.3	644.8	657.2	616.8	600.5	648.5	48.0	22.1	661.0	572.7
September	534.0	504.0	579.5	558.3	552.0	564.8	561.0	600.0	556.7	525.0	585.7	60.7	28.8	614.3	499.2
October	433.5	505.3	462.2	478.7	449.9	485.6	539.4	554.9	488.7	445.0	544.1	99.1	42.4	573.5	403.9
November	333.0	330.8	356.2	350.6	388.5	316.0	399.0	408.0	360.3	326.4	401.7	75.3	34.4	429.0	291.6
December	344.1	290.5	361.7	322.2	306.2	377.1	362.7	366.5	341.4	301.5	369.7	68.2	31.6	404.5	278.2
Santander															
January	296.7	269.7	344.4	273.4	326.4	284.4	282.1	310.0	298.4	272.3	331.8	59.5	26.6	351.6	245.2
February	314.1	319.2	223.3	296.6	366.4	365.1	302.4	266.0	306.6	253.2	365.5	112.3	47.7	402.0	211.3
March	379.0	378.2	358.9	371.8	379.0	379.8	406.1	424.7	384.7	367.9	411.7	43.8	20.8	426.2	343.1
April	401.2	384.0	436.8	395.9	401.2	390.6	399.0	426.0	404.4	388.6	429.2	40.6	17.9	440.2	368.5
May	503.6	533.2	470.1	458.8	552.4	471.7	536.3	520.8	505.9	466.7	541.1	74.4	35.3	576.5	435.2
June	560.8	588.0	563.3	536.9	530.9	552.7	594.0	627.0	569.2	535.1	603.9	68.8	32.1	633.3	505.1
July	650.7	629.3	675.6	657.9	649.5	612.0	682.0	660.3	652.2	624.1	677.5	53.4	22.9	698.0	606.3
August	657.3	641.7	670.5	656.7	663.7	623.0	688.2	682.0	660.4	636.1	683.9	47.8	21.1	702.6	618.1
September	598.4	549.0	608.7	589.1	597.7	606.8	603.0	657.0	601.2	577.1	623.2	46.1	29.5	660.2	542.2
October	518.6	530.1	487.8	529.8	491.0	508.6	641.7	592.1	537.5	490.0	607.0	116.9	53.2	643.8	431.2
November	380.4	372.8	398.4	379.0	437.4	349.8	429.0	441.0	398.5	365.9	438.5	72.6	33.8	466.0	330.9
December	359.6	307.6	370.6	360.5	339.0	371.2	393.7	380.6	360.4	329.6	384.5	54.9	26.7	413.7	307.0

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	$\mu+2 \sigma$	$\mu-2 \sigma$
Bilbao															
January	350.3	217.0	314.1	238.0	320.7	271.8	273.3	272.8	282.3	231.7	329.6	97.9	44.1	370.5	194.0
February	284.2	327.7	187.7	314.9	369.3	365.3	282.4	257.6	298.6	236.6	366.5	129.9	59.8	418.2	179.1
March	310.0	396.8	350.3	368.8	347.1	365.7	395.3	437.1	371.4	336.0	408.9	72.9	38.5	448.4	294.4
April	369.0	390.0	444.7	392.5	470.1	375.0	381.8	423.0	405.8	373.2	452.3	79.1	36.4	478.5	333.1
May	502.2	573.5	462.2	442.1	561.7	461.5	550.1	511.5	508.1	455.7	565.2	109.6	50.1	608.4	407.8
June	552.0	621.0	570.8	562.4	531.9	557.7	607.2	636.0	579.9	546.0	625.5	79.5	36.9	653.7	506.0
July	635.5	657.2	685.6	677.9	651.2	608.4	701.1	657.2	659.3	627.4	690.3	62.9	29.3	717.9	600.6
August	672.7	663.4	678.1	671.3	687.0	620.9	723.2	694.4	676.4	650.7	703.0	52.4	29.1	734.5	618.2
September	618.0	546.0	628.3	587.2	612.1	625.5	606.0	672.0	611.9	574.8	641.4	66.6	36.0	684.0	539.8
October	492.9	548.7	490.8	542.0	471.4	502.9	641.7	616.9	538.4	485.0	624.3	139.4	62.2	662.7	414.1
November	348.0	354.9	399.6	357.1	434.1	321.5	420.0	423.0	382.3	340.1	426.3	86.3	42.0	466.2	298.4
December	341.0	292.2	355.1	357.4	320.8	378.8	384.4	372.5	350.3	312.2	380.5	68.3	31.3	412.9	287.6

μ : Average 2016-2023; P: Percentile; Range: P 90 – P 10; σ : Standard Deviation.

Annex 2. CAT indexes of the Continental zone

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	$\mu+2 \sigma$	$\mu-2 \sigma$
Madrid															
January	254.2	151.9	203.1	174.7	205.3	98.2	167.4	182.9	179.7	135.8	220.0	84.2	45.3	270.3	89.1
February	234.9	232.4	157.6	211.3	284.7	260.5	243.6	184.8	226.2	176.6	267.8	91.1	40.8	307.8	144.6
March	279.0	337.9	284.4	347.7	345.1	308.0	303.8	365.8	321.5	282.8	353.1	70.4	32.0	385.4	257.5
April	357.0	435.0	384.1	373.1	417.3	379.2	366.0	492.0	400.5	363.3	452.1	88.8	45.4	491.2	309.8
May	483.6	595.2	513.2	566.9	603.1	545.7	613.8	554.9	559.6	504.3	606.3	102.0	45.2	649.9	469.2
June	661.9	771.0	651.8	691.4	652.3	671.0	729.0	699.0	690.9	652.2	741.6	89.5	41.7	774.4	607.5
July	840.1	796.7	772.5	852.4	873.5	775.5	895.9	855.6	832.8	774.6	880.2	105.6	46.0	924.8	740.8
August	815.3	796.7	828.6	798.2	788.0	811.8	846.3	852.5	817.2	794.1	848.2	54.1	23.6	864.3	770.0
September	657.0	612.0	703.4	631.2	618.8	613.1	639.0	618.0	636.6	612.8	670.9	58.2	31.0	698.6	574.5
October	508.4	545.6	469.3	498.7	413.3	478.7	564.2	548.7	503.4	452.5	553.4	100.9	50.0	603.3	403.5
November	267.0	283.2	307.2	306.1	309.7	245.8	345.0	342.0	300.8	260.6	342.9	82.3	34.4	369.5	232.0
December	232.5	191.7	209.1	261.9	201.3	246.8	285.2	238.2	233.3	198.4	268.9	70.5	31.8	296.9	169.8
Segovia															
January	204.6	108.5	132.2	115.7	174.2	102.0	161.2	120.9	139.9	106.6	183.3	76.8	36.3	212.6	67.2
February	145.0	204.4	72.8	214.4	274.5	239.7	210.0	140.0	187.6	119.8	250.1	130.3	64.4	316.4	58.8
March	176.7	300.7	178.5	296.5	265.3	259.3	241.8	310.0	253.6	178.0	303.5	125.5	52.2	358.1	149.1
April	267.0	387.0	321.3	284.4	339.8	310.8	276.0	402.0	323.5	273.3	391.5	118.2	50.2	423.8	223.2

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	$\mu+2\sigma$	$\mu-2\sigma$
May	399.9	523.9	414.5	444.2	509.7	432.7	530.1	430.9	460.7	410.1	525.8	115.6	52.1	564.9	356.6
June	576.0	681.0	542.9	587.2	536.4	561.2	630.0	588.0	587.8	541.0	645.3	104.4	47.8	683.4	492.3
July	728.5	703.7	676.2	738.6	746.4	663.2	809.1	728.5	724.3	672.3	765.2	92.9	45.3	815.0	633.6
August	731.6	700.6	727.0	703.5	676.6	715.3	762.6	747.1	720.5	693.4	751.8	58.4	27.5	775.5	665.6
September	588.0	534.0	632.5	541.6	544.9	531.9	540.0	567.0	560.0	533.4	601.4	68.0	34.9	629.8	490.2
October	471.2	511.5	402.8	445.4	362.1	439.5	533.2	505.3	458.9	390.6	518.0	127.4	58.2	575.2	342.6
November	228.0	238.3	253.4	213.0	309.1	154.2	285.0	294.0	246.9	195.4	298.5	103.2	50.4	347.6	146.2
December	204.6	134.0	239.0	232.7	156.2	239.5	257.3	207.9	208.9	149.5	244.8	95.3	43.4	295.6	122.2
Burgos															
January	164.3	83.7	120.4	91.2	130.2	64.3	99.2	89.9	105.4	77.9	140.4	62.6	31.5	168.4	42.4
February	130.5	176.9	58.3	149.5	224.1	197.4	140.0	98.0	146.8	86.1	205.4	119.3	53.4	253.7	40.0
March	155.0	238.7	173.5	228.2	225.0	216.1	204.6	272.8	214.2	168.0	248.9	81.0	37.0	288.3	140.2
April	222.0	285.0	297.9	260.0	334.6	248.8	243.0	339.0	278.8	236.7	335.9	99.2	42.9	364.7	192.9
May	365.8	461.9	365.9	351.7	454.8	382.0	455.7	393.7	403.9	361.6	457.6	96.0	46.1	496.0	311.8
June	507.0	588.0	495.3	530.3	469.0	496.7	570.0	549.0	525.7	487.4	575.4	88.0	41.0	607.6	443.8
July	635.5	632.4	623.2	636.2	635.6	588.3	675.8	647.9	634.4	612.7	656.3	43.5	24.4	683.1	585.6
August	626.2	620.0	633.9	623.7	616.8	621.6	678.9	672.7	636.7	619.0	674.6	55.5	24.7	686.1	587.4
September	528.0	459.0	557.9	481.3	483.2	510.7	501.0	546.0	508.4	474.6	549.6	75.0	34.1	576.5	440.3
October	399.9	427.8	354.1	405.7	322.6	354.7	477.4	458.8	400.1	344.7	464.4	119.7	54.0	508.1	292.2
November	180.0	193.1	220.7	201.5	255.3	154.4	240.0	273.0	214.8	172.3	260.6	88.3	40.0	294.8	134.7
December	161.2	110.5	175.0	188.4	140.2	186.8	223.2	189.8	171.9	131.3	199.8	68.5	34.5	241.0	102.8
Granada															
January	306.9	204.6	235.3	184.8	222.5	221.2	223.2	223.2	227.7	198.7	256.8	58.1	35.5	298.7	156.7
February	269.7	294.0	212.4	240.9	328.8	300.8	296.8	246.4	273.7	232.4	309.2	76.9	38.4	350.5	197.0
March	306.9	375.1	337.6	352.2	377.5	359.6	341.0	403.0	356.6	328.4	385.2	56.8	29.4	415.3	297.9
April	429.0	495.0	445.2	380.6	430.3	430.7	381.0	531.0	440.4	380.9	505.8	124.9	51.6	543.6	337.1
May	551.8	651.0	532.3	603.3	626.4	580.6	635.5	579.7	595.1	546.0	640.2	94.2	41.5	678.1	512.0
June	729.0	801.0	685.9	683.5	659.2	689.6	738.0	708.0	711.8	676.2	756.9	80.7	44.2	800.2	623.4
July	883.5	858.7	774.8	835.1	892.0	835.6	889.7	892.8	857.8	817.0	892.2	75.2	41.4	940.5	775.1
August	843.2	858.7	835.2	818.2	826.5	843.3	852.5	874.2	844.0	824.0	863.4	39.3	17.9	879.8	808.1
September	702.0	678.0	693.7	664.2	669.7	682.0	675.0	678.0	680.3	668.1	696.2	28.1	12.3	705.0	655.7
October	576.6	610.7	486.8	530.4	473.7	559.8	641.7	582.8	557.8	482.9	620.0	137.1	58.2	674.2	441.5
November	321.0	359.7	309.5	295.3	393.2	280.0	378.0	369.0	338.2	290.7	382.6	91.9	42.0	422.3	254.2
December	294.5	224.7	259.0	285.7	248.3	282.9	344.1	292.6	279.0	241.2	309.4	68.2	35.9	350.7	207.2
Cáceres															
January	300.7	235.6	262.8	239.7	261.8	221.8	258.8	238.7	252.5	231.5	274.2	42.7	24.3	301.1	203.9
February	269.7	307.4	229.0	274.5	347.8	316.9	304.3	238.0	286.0	235.3	326.2	90.9	40.6	367.1	204.8
March	310.0	381.3	317.0	397.9	384.6	375.2	355.7	415.4	367.1	314.9	403.2	88.3	37.3	441.8	292.5

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	μ+2 σ	μ-2 σ
April	393.0	501.0	408.3	405.9	435.8	457.9	403.8	540.0	443.2	400.6	512.7	112.1	53.0	549.2	337.2
May	502.2	626.2	522.8	622.0	616.7	565.8	653.5	585.9	586.9	516.6	634.4	117.8	53.2	693.3	480.4
June	696.0	795.0	660.2	658.9	643.8	677.6	719.5	732.0	697.9	654.4	750.9	96.5	49.8	797.4	598.3
July	874.2	833.9	756.5	813.6	901.6	792.3	926.9	840.1	842.4	781.6	909.2	127.6	56.6	955.7	729.1
August	868.0	837.0	874.3	820.0	809.3	834.4	864.9	871.1	847.4	816.8	872.1	55.3	25.3	898.1	796.7
September	711.0	684.0	764.2	692.9	683.4	652.9	672.0	663.0	690.4	660.0	727.0	67.0	34.8	760.0	620.9
October	573.5	644.8	536.2	563.9	501.7	565.7	632.4	613.8	579.0	525.9	636.1	110.3	48.8	676.5	481.5
November	339.0	375.2	359.5	361.7	406.3	310.0	393.0	390.0	366.8	330.3	397.0	66.7	31.5	429.8	303.9
December	279.0	267.9	279.1	327.7	278.4	344.4	372.0	327.4	309.5	275.3	352.7	77.4	38.4	386.3	232.7

μ: Average 2016-2023; P: Percentile; Range: P 90 – P 10; σ: Standard Deviation.

Annex 3. CAT indexes of the Mediterranean zone

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	μ+2 σ	μ-2 σ
Barcelona															
January	378.2	354.8	377.1	309.4	341.5	300.0	312.7	294.5	333.5	298.4	377.4	79.1	34.0	401.5	265.6
February	345.1	362.5	230.3	311.5	391.2	354.8	340.7	268.8	325.6	257.3	371.1	113.9	53.0	431.5	219.7
March	378.2	395.5	386.0	403.1	400.9	380.3	387.5	430.9	395.3	379.7	411.4	31.8	17.0	429.3	361.3
April	444.0	441.0	467.3	425.5	450.4	403.8	435.3	462.0	441.2	419.0	463.6	44.6	20.3	481.8	400.6
May	542.5	589.5	550.7	481.5	611.7	533.4	608.5	567.3	560.6	517.8	609.5	91.6	43.4	647.5	473.8
June	663.0	738.0	643.2	625.7	621.3	667.2	715.9	705.0	672.4	624.4	722.5	98.2	43.1	758.7	586.2
July	781.2	796.7	790.2	784.4	787.8	764.2	837.0	818.4	795.0	776.1	824.0	47.9	22.8	840.6	749.4
August	787.4	812.2	807.8	792.2	799.7	763.3	846.3	815.3	803.0	780.2	824.6	44.4	24.1	851.3	754.7
September	702.0	648.0	702.1	678.3	663.4	700.6	720.0	705.0	689.9	658.8	709.5	50.7	24.3	738.5	641.3
October	585.9	623.1	535.0	566.8	537.3	579.7	657.2	647.9	591.6	536.6	650.7	114.1	46.9	685.4	497.8
November	429.0	419.4	430.0	406.2	461.6	396.4	486.0	450.0	434.8	403.3	468.9	65.7	29.7	494.1	375.5
December	359.6	342.9	390.1	405.0	351.2	374.8	390.6	376.2	373.8	348.7	394.9	46.2	21.4	416.5	331.1
Málaga															
January	446.4	384.4	399.7	399.0	389.4	384.9	409.2	406.1	402.4	384.8	420.4	35.6	20.1	442.5	362.3
February	423.4	403.2	346.1	353.3	450.4	411.9	417.2	358.4	395.5	351.1	431.5	80.4	38.2	471.8	319.2
March	474.3	474.3	457.0	493.0	500.9	459.8	461.9	523.9	480.6	459.0	507.8	48.8	23.5	527.6	433.7
April	534.0	528.0	491.2	499.6	507.2	526.1	510.0	579.0	521.9	497.1	547.5	50.4	27.4	576.7	467.1
May	613.8	635.5	601.3	654.6	643.0	630.5	672.7	635.5	635.9	610.1	660.0	50.0	22.3	680.4	591.3
June	720.0	759.0	715.5	712.2	699.8	715.0	783.0	744.0	731.1	708.5	766.2	57.7	28.3	787.6	674.5
July	824.6	796.7	836.2	840.5	829.0	844.2	830.8	914.5	839.6	816.2	865.3	49.1	33.6	906.8	772.4

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	μ+2 σ	μ-2 σ
August	849.4	818.4	842.1	840.0	872.5	852.6	855.6	895.9	853.3	833.5	879.5	46.0	23.1	899.5	807.2
September	732.0	735.0	763.9	736.7	726.4	746.8	774.0	747.0	745.2	730.3	766.9	36.6	16.4	778.1	712.4
October	657.2	644.8	615.3	651.2	589.5	652.0	675.8	660.3	643.3	607.6	665.0	57.4	27.7	698.6	587.9
November	468.0	476.5	457.9	496.5	502.7	461.3	540.0	528.0	491.4	460.3	531.6	71.3	30.8	553.0	429.7
December	430.9	402.4	426.2	465.8	422.0	456.8	468.1	471.2	442.9	416.1	469.0	52.9	25.8	494.5	391.4
Sevilla															
January	406.1	316.2	346.5	328.9	352.7	319.9	357.2	322.4	343.7	318.8	371.9	53.1	29.7	403.1	284.4
February	379.9	394.4	309.9	357.6	462.5	390.8	386.7	341.6	377.9	332.1	414.8	82.7	44.8	467.5	288.4
March	415.4	481.4	420.4	493.4	496.9	459.1	437.3	496.0	462.5	418.9	496.3	77.4	34.3	531.2	393.8
April	504.0	582.0	489.9	484.6	530.4	547.3	475.1	630.0	530.4	481.8	596.4	114.7	53.9	638.3	422.6
May	620.0	688.2	599.5	710.9	719.9	662.8	717.3	682.0	675.1	613.9	718.1	104.2	45.0	765.1	585.0
June	780.0	840.0	709.1	717.5	541.0	738.9	780.9	789.0	737.1	658.7	804.3	145.6	90.0	917.0	557.1
July	923.8	880.4	794.2	804.7	951.7	854.8	948.8	911.4	883.7	801.6	949.7	148.1	61.3	1006.4	761.1
August	923.8	908.3	918.5	849.4	894.2	887.6	871.5	926.9	897.5	864.9	924.7	59.9	27.3	952.1	843.0
September	783.0	771.0	810.9	768.0	777.5	704.2	747.0	720.0	760.2	715.3	791.4	76.1	34.8	829.9	690.5
October	669.6	737.8	625.0	644.6	612.8	627.9	706.8	682.0	663.3	621.3	716.1	94.8	43.8	751.0	575.6
November	441.0	461.6	440.8	443.4	511.4	400.3	495.0	471.0	458.1	428.7	499.9	71.3	34.9	527.9	388.3
December	403.0	355.2	398.2	434.6	367.6	395.1	437.1	391.2	397.8	363.9	435.4	71.5	28.6	454.8	340.7
Cádiz															
January	458.8	381.3	393.7	396.9	410.7	374.9	430.9	415.4	407.8	379.4	439.3	59.9	27.5	462.9	352.8
February	408.9	411.6	346.8	386.6	466.7	435.7	428.4	394.8	409.9	374.7	445.0	70.3	35.8	481.6	338.3
March	437.1	496.0	452.0	510.9	497.0	501.3	468.1	520.8	485.4	447.5	513.9	66.3	29.6	544.7	426.1
April	504.0	552.0	493.8	507.9	525.9	548.4	507.0	594.0	529.1	500.9	564.6	63.7	33.7	596.5	461.8
May	604.5	657.2	587.6	645.6	658.2	635.8	675.8	647.9	639.1	599.4	663.5	64.1	29.3	697.7	580.4
June	693.0	750.0	637.0	641.8	649.1	673.2	702.0	747.0	686.6	640.4	747.9	107.5	44.7	776.1	597.2
July	802.9	775.0	716.2	711.3	819.4	761.7	843.2	793.6	777.9	714.7	826.5	111.8	46.9	871.6	684.2
August	767.5	812.2	811.0	768.6	791.2	773.9	787.4	827.7	792.4	768.3	816.9	48.6	22.5	837.4	747.4
September	732.0	726.0	765.8	707.9	734.9	720.0	693.0	711.0	723.8	703.4	744.2	40.7	21.8	767.5	680.1
October	666.5	619.1	639.6	612.1	612.7	677.0	703.7	703.7	654.3	612.5	703.7	91.2	38.8	731.8	576.8
November	486.0	512.1	487.1	485.6	550.0	462.6	549.0	531.0	507.9	478.7	549.3	70.6	32.7	573.3	442.6
December	468.1	408.6	458.6	471.9	454.6	473.2	517.7	480.0	466.6	440.8	491.3	50.5	30.3	527.2	405.9
Valencia															
January	384.4	282.1	358.9	317.4	321.8	311.9	305.0	331.7	326.7	298.1	366.6	68.4	32.0	390.7	262.6
February	368.3	359.6	264.5	309.5	419.2	383.7	351.1	268.8	340.6	267.5	394.4	126.8	55.0	450.6	230.6
March	409.2	430.9	426.6	429.3	425.0	388.3	400.8	492.9	425.4	397.1	449.5	52.5	31.3	487.9	362.8
April	480.0	447.0	473.1	456.3	482.9	434.1	453.1	525.0	468.9	443.1	495.5	52.4	28.2	525.4	412.5

	2016	2017	2018	2019	2020	2021	2022	2023	μ	P 10	P 90	RANGE	σ	$\mu+2 \sigma$	$\mu-2 \sigma$
May	567.3	616.9	587.8	574.2	645.4	607.9	627.4	601.4	603.5	572.1	632.8	60.7	26.6	656.7	550.4
June	681.0	750.0	692.7	675.7	677.3	699.4	773.0	735.0	710.5	676.8	756.9	80.1	37.2	784.9	636.1
July	796.7	821.5	824.4	837.3	816.3	802.4	861.0	874.2	829.2	800.7	865.0	64.3	27.1	883.3	775.1
August	790.5	806.0	843.0	828.9	836.1	821.1	882.7	871.1	834.9	801.4	874.6	73.2	30.9	896.8	773.1
September	705.0	675.0	721.6	709.4	702.1	718.6	747.0	714.0	711.6	694.0	729.2	35.3	20.3	752.2	671.0
October	620.0	613.8	569.2	621.9	570.3	605.4	660.3	666.5	615.9	570.0	662.2	92.2	35.8	687.5	544.4
November	414.0	395.3	422.0	454.4	452.4	414.5	504.0	519.0	447.0	408.4	508.5	100.1	44.7	536.3	357.6
December	353.4	314.0	384.5	404.9	355.9	409.7	440.2	452.4	389.4	341.6	443.9	102.3	46.8	483.0	295.8

μ : Average 2016-2023; P: Percentile; Range: P 90 – P 10; σ : Standard Deviation.