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Machine learning-based climate risk sharing for an insured loan in the tourism industry

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Abstract

Higher risks for commercial banks correspond to lower probability of access to financing transactions. Climate change risk strongly impacts bank loan supply. In particular, in the tourism industry, it is noteworthy that lenders charge higher interest rates for mortgages that face a greater risk of rising sea levels. As loans are one of the most important businesses for commercial banks, innovative strategies can lead to the design of a composite bank loan supply for building resilience, especially against physical climate risk. In this work, we propose a new tool, which is an insured loan relying on a climate change risk-sharing mechanism, where we develop a bioclimatic composite indicator based on machine learning naïve technique.

Keywords Climate change · Insured loan · Machine learning · Random forest

1 Introduction

Financial planning in the beach tourism industry consists of controlling special financial security, which includes climate change risk as a relevant component of its risk profile. The impact of climate change that cannot be avoided such as sea level rise, flooding, heat

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waves, desertification, crop failures, etc. leads to strong direct effects on tourism, which has become one of the world's fastest-growing industries. In particular, seaside industry activities generate significant revenues in coastal and marine areas, even if the areas that attract tourists are also coming under increasing pressure from the damage and pollution caused by tourist facilities and the supporting infrastructure and from the increase in the frequency and severity of adverse climate events. There is a strand of recent literature in the field of climate change impact that stresses the climate-tourism relationships (Gambarelli and Goria 2004; Sygna et al. 2004; Hamilton and Tol 2007, Hein et al. 2009, Jennings 2004; Phillips and Jones 2004; Surugiu and Surugiu 2009; Surugiu et al. 2011, Filho 2022). The World Economic Forum highlights the alteration of traditional tourist trends due to rising temperatures that are likely to result in tourists travelling in spring and autumn rather than summer (World Economic Forum, 2023). Some authors emphasise the duality of climate change risk in the tourism sector, which is highly vulnerable to climate change and contributes to the emission of greenhouse gases (GHG), which cause global warming (for instance see Nazir 2023).

In particular, climate change impacts on the coast, such as storm surges and rising sea levels, are inevitable, and, in some regions, they are already damaging coastal tourism economies making coastal tourism a vital part of the world economy. The big issue is that climate change has become very prominent, causing new risks also to the banking sector. This is why regulators in several countries have increasingly emphasised macroprudential supervision and control of systemic financial risks, as well as the severe challenge of climate change.

As loans are one of the most important businesses for commercial banks, innovative strategies can lead to the design of a composite bank loan supply for building resilience, especially against physical climate risk. Despite its relevance, the literature on the relationship between climate risk and bank loans is scarce (Li and Wu 2023). Some evidence indicates that corporate loans will also be affected by climate risk. It is noteworthy that lenders charge higher interest rates for mortgages that face a greater risk of rising sea levels, according to Nguyen et al. (2022). Also in Kling et al. (2021), the empirical findings show that climate vulnerability will increase debt costs for firms and limit their access to finance. In Li and Wu 2023, physical climate risk could affect leverage via larger expected distress costs and higher operating costs or by non-linear relationships.

In this research, the aim is to provide an innovative tool for funding seaside firms. Broadly speaking, higher risks for commercial banks correspond to a lower probability of access to financing transactions. For firms operating in the seaside industry, climate change is most prominent. The extreme and not-extreme adverse climate events involve losses in revenues and, accordingly, higher default probabilities. In this framework, we propose a pricing model for climate change risk, particularly physical risk, for providing a bancassurance product, a type of climate risk-insured loan, by guaranteeing a decrease in the internal rate of return that expresses the cost required by the issuer bank. The cost reduction relies on a climate change risk-sharing mechanism in which we develop a bioclimatic composite indicator. The fundamental concept behind the proposed bioclimatic index is to model the spatial and temporal dependency structure of the phenomenon, given that adverse climatic events arise from a combination of interconnected factors. The use of machine learning is deemed beneficial for this purpose. The contributions of this study are as follows: first, in Sect. 2, we propose the model framework relating to the climate change risk developed in an Machine-Learning based environment (from herein ML-based). Section 3 offers the main outcome built on the complex pre-processing of the climatic data. Finally, Sect. 4 concludes.

2 Model framework

2.1 Climate risk for tourism composite indicator

Climate risk composite indicators can be created by encompassing a range of climate-related risks of various types. For instance, it involves the development of indicators related to specific physical risks for certain crops, e.g., Salgueiro (2009) used a series of indicators commonly used in viticulture; indicators assess the relationship between financial risk and climate risk (see Bingler et al. 2020 for a review and comparison of major proposed indicators); or indicators that evaluate both physical and transition risks (see, for example, Dolge and Blumberga 2021, or Angelova et al. 2023).

In our application, we propose a climate risk indicator that evaluates how physical climate events can impact business disruptions in the tourism sector. Specifically, considering the case of beach resorts, we introduce a weather-related indicator for coastal areas that combines the effects of temperature, precipitation, and wind during the operational months of the beach resorts, namely from May to September. Our indicator is based on Climate for Tourism (*CIT*) focused on beach tourism proposed by de Freitas et al. (2008), which determines an ordinal variable based on the ASHRAE scale of thermal sensation (Morgan et al. 2000). To achieve this, significant data preprocessing and the construction of a bioclimatic indicator to estimate climate risk for tourism are required. Using an ML procedure described in the next subsection, this indicator leverages the relationships between bioclimatic variables in coastal areas.

In particular, the *CIT* indicator is defined as

$$CIT = f[T, A]P \tag{1}$$

where T is the thermal, A is the aesthetic, and P is the physical variable determining the heat perception. de Freitas et al. (2008) detected the heat perception feature variables as temperature, precipitation, wind speed and cloud percentage. *CIT* computed as a daily ordinal indicator ranged from 0 to 7, where the greater the indicator, the more comfortable the heat conditions are. The indicator is aggregated at monthly granularity in terms of the number of days with favourable condition, namely $faCIT$, $CIT \geq 5$, number of day with acceptable conditions, $acCIT$, $CIT = 4$ and number of days with adverse conditions, $unCIT$, $CIT < 4$. For our analysis, the monthly indicator is taken into account, for this reason, the magnitude of the risk is measured as the number of days at risk, in temrs of both $acCIT$ and $unCIT$. To improve the forecast of future behaviour of $acCIT$ and $unCIT$, we consider a Random Forest (herein RF) model instead of a merely time series approach. In the next subsection, the adopted analysis strategy is shown in detail.

2.2 Development of climate risk composite indicators using temporal dynamic random forest

The fundamental concept behind the proposed bioclimatic index is to model the spatial and temporal dependency structure of the phenomenon, given that adverse climatic events arise from a combination of correlated factors. The use of ML is deemed beneficial for this purpose. However, it is important to note that certain models, such as tree-based algorithms, might not fully capture the temporal relationships within the data. To address this, the construction of the bioclimatic indicator relies on time series data and employs a rolling window approach. This involves specifying the features of a regression tree and using both the lagged target variable and present/lagged feature variables, as defined in Eq. (2). As a result, each regression tree functions as a distributed lag model preserve the temporal order between observations. This tree restructuring ensures the maintenance of temporal order, even when working with training or validation sets. The estimator of the target variable for a single tree $\widehat{y}_{R_j}$ is defined as follows

$$\hat{y}_{R_j} = (L)x_{R_j} + (L)y_{R_j} \tag{2}$$

where (L) is the lag operator, $\widehat{y}_{R_j}$ is the *acCIT* or *unCIT* indicator defined in SubSect. 2.1, and x_{R_j} the temperature, precipitation, wind and cloud conditions determining *acCIT* or *unCIT*. At the individual tree level, the forest can be aggregated through bagging, creating a Temporal Dynamic Forest, or boosting, producing a Temporal Dynamic Boost. This approach showed improved forecast performance compared with other models largely used to model data dependence structures, such as LSTM, under specific conditions such as the use of incomplete yearly data or a dynamic risk threshold (Carannante et al. 2023). The core idea of the Temporal Dynamic ensemble method is to mimic time series behaviour while not strictly adhering to chronological sequence, which bypasses the necessity to preserve the non-random nature of the partition as basic RF does. For simplicity, in this work we only use bagging as ensemble method, estimating a Temporal Dynamic Forest. To better understand how our proposal works, we present the basic RF model. The RF algorithm, proposed by Breiman (2001), is a robust nonparametric ML technique employed for regression and classification tasks. It comprises multiple individual trees that expand through recursive binary splits on the training dataset. Each decision tree typically showcases predictors with low bias and high variance. In the RF methodology, predictions are averaged over a considerable number of trees to diminish the overall variance of the resultant predictor, even when the bias is minimal. To achieve variance reduction, randomness is incorporated into the tree-growing process by opting for diverse bootstrap samples from the original training dataset and randomly selecting a subset of explanatory variables for each split.

Consider the training set $\left[\left(x_1, y_1\right), \ldots, \left(x_n, y_n\right)\right]$ which represents a sample of independent random variables distributed as pairs (X, Y) from an unknown distribution. The algorithm predicts the target variable Y by estimating the regression function $m(x) = E[Y|X = x]$. The mean-squared error for a numerical predictor $h(x)$ is defined as follows:

$$E_{X,Y} = (Y - h(X))^2 \tag{3}$$

The RF predictor is the results of averaging across $k = 1, \ldots, n$ trees (Breiman 2001). As outlined in Breiman (1996), the ensemble method employed to combine predictions from multiple machine learning algorithms, leading to more precise projections than individual models, is bagging (bootstrap aggregation). Bagging involves creating numerous bootstrap samples and averaging the predictors. The bootstrap mechanism introduces perturbation in the learning set by randomising the predictor, thereby enhancing accuracy. The estimator for the target variable $\widehat{y}_{R_j}$ is a combination of regression tree estimators

$$\hat{f}^{\text{tree}}(X) = \sum_{j \int J} \hat{y}_{R_j} 1_{\{X \int R_J\}} \tag{4}$$

$1_{\{.\}}$ denotes an indicator function and $(R_j)_{j \in J}$ denotes the collection of regions within the predictor space. These regionslabelled as $R_1, R_2, \ldots, R_J$, are unique and do not overlap, estimated through the minimisation of the residual sum of squares.

Let B represent the number of bootstrap samples. The RF can be defined as follows:

$$\hat{f}^{RF}(X) = \frac{1}{B}\sum_{b=1}^{B}\hat{f}^{tree}(X|b) \tag{5}$$

The future behaviour of the *nCIT* indicator will be determined on the basis of the previous behaviour of the same indicator, and the contemporary and previous behaviour of the feature variables from May to September.

2.3 Climate-insured loan proposal description

The basic idea of the climate-insured loan is that if the climate risk is properly insured, it should reduce the internal cost rate associated with the financing required by the lending bank. For this reason, we assume a scenario where the bank performs an accurate financial analysis of beach resorts, based on the historical past performance and financial health. The bank sets this financing at a particular interest rate, which we will denote as i, representing the internal cost rate for the beach resort, and it can be split into the sum of two components: the risk-free interest rate i_{rf}, and the spread s, that quantifies risk, expressed in terms of internal costs rate. In tourism business, a significant quote of the risk measured by s derives from climate risk. For this reason, beach resorts could benefit from insurance coverage against potential revenue losses caused by adverse weather conditions. On the other hand, bank needs to determine correctly the insurance strategy for climate-related risks, which allows reducing the bank spread s for the insured beach resorts. For this reason, it is necessary pricing a model for climate risk that, when adequately insured, will lead to a reduction in the internal cost rate of a loan. The advantages of a climate-insured loan are twofold: for beach resorts, insurance hedging provides a financial safety net, compensating for the loss of income due to unfavorable weather conditions, and for the banks, the counterparty risk is reduced, since beach resorts have a lower risk failing to meet its loan obligations. As a consequence, a climate-insured loan is a type of risk-sharing between the insurance company and the bank. More formally, the beach resorts has two option: the former is requesting for financing from the bank and paying an interest rate $i = i_{rf} + s_1$; the latter is requesting for financing from the bank and obtaining climate risk hedging from the insurance company, paying the bank an interest rate $i = i_{rf} + s_2$, (with $s_2 < s_1$) and paying the insurance company a premium P. The second option has the typical structure of a bancassurance product, combining a single product financial and insurance solutions jointly. The climate-insured loan proposed represents a hybrid bancassurance product, where the financial part is the loan and the insurance part is the climate risk hedging. The insurance hedging has the following characteristics: The fair premium (FP) is equal to the expected value of the income loss, which is $\mathbb{E}[S]$; The pure premium (PP) is equal to the sum of the fair premium and the safety loading

$$PP = \mathbb{E}[S] + \delta \tag{6}$$

where δ is the safety loading using the percentile calculation principle; The Expenses-loaded premium (LP) is the sum of the pure premium and the loading for commissions and expenses

$$LP = \frac{PP}{(1 - \beta - \alpha)} \tag{7}$$

being β is the loading percentage for management expenses, in our case, 5%, α is the loading percentage for commissions to be decreased to the distributor of the insurance product, in our case, also 5%.

3 Numerical application

3.1 Data sources and pre-processing

Building the *acCIT* and *unCIT* bioclimatic risk indices and thier forecasting based on satellite data requires different sources of data. In particular, we use two datasets of the NASA MERRA-2 satellite warehouse, the Single-Level Diagnostics dataset (M2SDNX-SLV version 5.12.4), containing daily temperature and precipitation data for two-dimensional pixels (latitude and longitude) and the Assimilated Meteorological Fields dataset (M2T3NVASM version 5.12.4), containing 3-hourly data of cloud fraction and wind speed for three-dimensional pixels (latitude, longitude and altitude) (see Bosilovich 2016 for more details about data). Specifically, Each NASA MERRA-2 dataset collects data with a full horizontal resolution spatial grid, for 576 longitude and 361 latitude values, for a total of 213′696 pixels of the Earth's surface of about 50 km × 50 km each one and, in the case of 3D-level data 72 levels of altitude, measured in hPa. It is possible to store the variables of interest for each latitude, longitude, altitude, and day of fraction. The native dataset is in raster format, so it is necessary to convert data into useful arrays containing the variables, time and space IDs with the following steps. Once obtained a 2D-array, with IDs and bioclimatic variables, we created the lagged target variable and the lagged feature variables. To do this, it is necessary to reduce the data granularity to daily for all the features, and then calculate the *CIT* indicator according to the reference scheme defined by de Freitas et al. (2008) showed in Fig. 1

The next step is to build the monthly risk days indicator, namely *unCIT* and *acCIT*, also aggregating the other bioclimatic indicators at the monthly granularity. Then, we create lagged variables $(L)unCIT$, and $(L)acCIT$ choosing the order of lag operator (L). Since

ASHRAE scale TSN [T]		Cloud (≤40%) [A]	Cloud (≥50%) [A]	Rain (>3mm or >1hr duration) [P]	Wind (≥6m/s at ground) [P]
Very hot	(+4)	4	3	2	3
Hot	(+3)	6	5	2	4
Warm	(+2)	7	5	2	4
Slightly warm	(+1)	6	4	1	4
Indifferent	(0)	5	3	1	2
Slightly cool	(-1)	4	3	1	2
Cool	(-2)				
Cold	(-3)				
Very cold	(-4)				

Fig. 1 Composition of CIT indicator. Source: de Freitas et al. (2018)

bioclimatic phenomena are strongly subject to seasonality, we choose order 12, which corresponds to one year. In this way, all months are well represented in the model, respecting the temporal structure of the data. For the same reason, we construct the lagged feature variables $(L)x$ of temperature, precipitation, wind and cloud fraction by applying a lag operator of order 12, for a total of 60 covariates to estimate the future behaviour of $unCIT$, and $acCIT$. In particular, we estimate a Temporal Dynamic Forest for each month of interest, composed by 500 trees to forecast $unCIT$, and $acCIT$ respectively, for a total of ten forests nested in two Temporal Dynamic Forests. We selected pixels that included all the coastal areas of insular and peninsular Italy for a total of 18 values of latitude and 15 of longitude combined in 110 pixels, 2-m of altitude, and a time range from 2009 to 2022. the ratio between training set and validation set is 70:30 and 2023 is used as the test set.

Data about beach resorts are not directly available, while the prototypes can be built starting from aggregate data. To create a prototype of an Italian beach resort for the year 2023, we consider the unit revenues from two main activities, namely, rental and food and beverage activities, representing almost three-quarters of their revenues, and the unit cost is computed proportionally to the total revenue and the tourist presences of the month and subsequently the loss relating to adverse climate events (see Istat data for presences and Nomisma report for beach resorts revenues and activities). The $acCIT$ and $unCIT$ values are obtained as the average of the pixels for the test set, which collects the observations of the year 2023.

3.2 Numerical results

Figure 2 shows the forecasting error of the Temporal Dynamic forest compared to a traditional time series approach in terms of RMSE for both $acCIT$ and $unCIT$

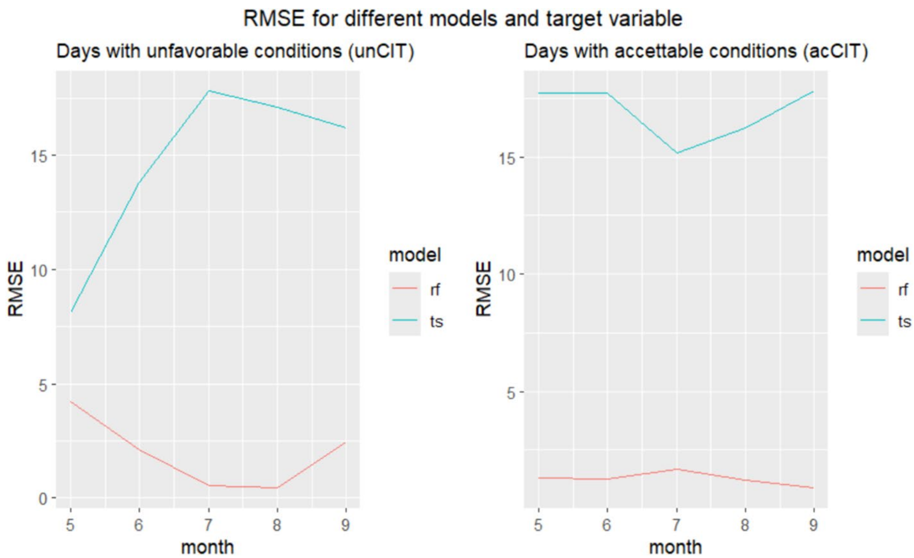

Fig. 2 RMSE for temporal dynamic forest and traditional time series

As Fig. 2 shows, the Temporal Dynamic Forest performs better for both climate risk indicators, with an average error lesser than 5 days compared to an average error between 10 and 15 days of a time series approach. The improvement depends on two factors: the former is the use of covariates, which provide a greater information basis on which to make predictions, and the latter is that the Temporal Dynamic Forest as structured is not time-dependent, therefore its ability to forecast does not decrease as the lag increases. In this sense, Fig. 2 shows that the best performance is not necessarily in the months closest to the last observed value (December), with a lower error in July and August for *unCIT* and in August and September for *acCIT*.

Table 1 shows the prototype of an Italian beach resort of medium-large size. The *acCIT* and *unCIT* values are obtained as the average of the pixels for the test set.

Table 1 shows that the total revenues of a prototype beach resort are 400,550 euros without climate risk and 357,540 euros with a climate risk. In other words, the model estimates a decrease of 40,945 euros, about 10.74% of the total. On the basis of this scheme of estimation, we perform 500 simulations of the number of days at risk *acCIT* and *unCIT* per each pixel, 55,000 in total for the Italian coastal areas, to estimate the probability distribution of revenue loss, denoted as S.

Table 2 shows the summary statistics of S

From results shown in Table 2, we can determine the Fair premium (FP), the Pure premium (PP), the Expenses-loaded premium (LP) and the Solvency Capital Requirement (SCR) for an insurance contract to hedging climate-related risk for the tourism sector. Table 3 shows the results.

To determine the cost of a loan for a beach resort, we consider the following assumptions: loan amount (A) 1,000,000 euros; interest rate $i = i_{rf} + s_1 = 1\% + 7\% = 8\%$; French amortization schedule of $n = 10$ years; and annual instalment. In other words, without a climate risk hedghing product, the interest rate cost (IRC) of the beach resort is exactly equal to the interest rate return (IRR) of the bank, that is $s_1 = 8\%$. To determine the spread s_2 and the IRC for a beach resort in case of climate-insured loan, we consider an insurance product with the following characteristics: time horizon $T = 1$, that implies the deal of n annual insurance contracts, with starting premium $LP = 48{,}854$ euros, and annually adjusted for inflation at 2%; Expected loss ratio (P/L) for the insurer, i.e., the ratio between $E(S)$ and LP, is 69.9%; management and commissions loadings due to bank are both 5% of the LP; $SCR = 6\%$; capitalisation rate of 3%, adjusted net of the cost of capital. The scheme of insured loans described above implies that profits are evenly distributed between the insurer and the bank, net of the commissions for the loan. On the contrary, losses are entirely incurred by the insurer, and the bank will receive no commissions for the insurance contract.

To make the climate-insured loan affordable for the bank, it is necessary to determine IRC and s_2 to maintain the IRR at 8% as in the baseline loan. That is, the interest rate linked to the loan amounts to $IRC = 7.15\%$, $s_2 = 6.15\%$, with a decrease of the interest rate of 0.86%.

Table 4 shows the amortization schedule embedding the cash flows related to insurance premiums.

Table 4 shows several differences of climate-insured loan with respect to traditional loans. In particular, at time 0, the beach resort does not receive 1,000,000 euros, but an amount reduced by the insurance premium; during times 1,…, 9, the beach resort pays another nine increasing premiums adjusted for inflation rate; at time 10, the outgoing cash flow embeds only the last instalment of the French amortisation schedule because the last premium was paid at time 9.

Table 1 Prototype of an Italian beach resort of medium-large size

Period	Unit rental revenue (euro)	Unit food and beverage revenue (euro)	Days of the month	Days unCIT	Days acCIT	Revenue reduction due unCIT (%)	Revenue reduction due acCIT (%)	Montly revenue without climate risk	Montly revenue with climate risk	Revenue reduction (euro)	Revenue reduction (%)
May	10	10	31	1	1	100%	80%	12,400	11,280		
June	15	15	30	3	2	95%	70%	36,000	29,700		
July	20	15	31	1	1	90%	70%	97,650	89,460		
August	30	20	31	2	1	80%	60%	170,500	152,900		
September	20	15	30	1	2	90%	80%	84,000	74,200		
Total								400,550	357,540	43,010	10.74%

Table 2 Main Statistics on revenue loss

Statistics	Value (euros)
$\mathbb{E}(S)$	34,154
$VAR(S)$	187,303,237
$P_{75}(S)$	43,969
$P_{99.5}(S)$	78,646

Table 3 Insurance economic components of innovative insured loans, (values in Euro)

Actuarial measure	Value (euros)
FP	34,154
PP	43,969
LP	48,854
SCR	34,677

Table 4 Amortization schedule of climate-insured loans by embedding insurance premiums

Time	Installment (euros)	Interest portion (euros)	Capital portion (euros)	Remaining debt (euros)	Insurance premium (euros)	Cash flows beach resort (euros)
0				1,000,000	48,854	951,146
1	143,300	71,400	71,900	928,100	49,831	−193,132
2	143,300	66,266	77,034	851,066	50,828	−194,128
3	143,300	60,766	82,534	768,532	51,84	−195,145
4	143,300	54,873	88,427	680,104	52,881	−196,182
5	143,300	48,559	94,741	585,364	53,939	−197,239
6	143,300	41,795	101,505	483,858	55,018	−198,318
7	143,300	34,547	108,753	375,105	56,118	−199,418
8	143,300	26,783	116,518	258,588	57,240	−200,541
9	143,300	18,463	124,837	133,751	58,385	−201,686
10	143,300	9,550	133,751	0	0	−143,300

Table 5 describes the development of insurance cash flows and net profit adjusted for the cost of capital for the company.

Table 5 shows, among other things, the additional cash inflow that the bank receives due to commissions annually. Considering a safety loading in the calculation of *PP*, the insurer realises profits to which must be subtracted the Cost of Capital (*CoC*). For this reason, the insurer annual revenue is given by the P/L net to CoC. At time 10, the insurer calculates the amount of profits and commissions paid to the bank, assuming a capitalisation rate of 3%. Based on these assumptions, it determines the potential extra commission to be paid to the bank, showed in Table 6

Table 7 summarise the total profit or loss account of the bank and the insurer for the climate-insured loan.

On the basis of these calculations, we can compute the bank's cash flow net to additional commissions, shown in Table 8

Table 5 Cash flows and net profit adjusted for the cost of capital for the bank and insurance company

Time	Bank commission (euros)	Insurance premium (euros)	Claim (euros)	Expenses (euros)	Cash flows Bank (euros)	SCR (euros)	Cost of capital (CoC) (euros)	P/L insurer (euros)	P/L net CoC (euros)
0	2,443	48,854			-997,557	34,677			
1	2,492	49,831	34,154	2,443	145,792	35,371	2,081	11,207	9,126
2	2,541	50,828	34,837	2,492	145,842	36,078	2,122	11,484	9,362
3	2,592	51,844	35,534	2,541	145,893	36,800	2,165	11,73	9,571
4	2,644	52,881	36,245	2,592	145,944	37,536	2,208	11,971	9,763
5	2,697	53,939	36,970	2,644	145,997	38,286	2,252	12,210	9,958
6	2,751	55,018	37,709	2,697	146,051	39,052	2,297	12,454	10,157
7	2,806	56,118	38,463	2,751	146,106	39,833	2,343	12,703	10,360
8	2,862	57,240	39,233	2,806	146,162	40,630	2,390	12,957	10,567
9	2,919	58,385	40,017	2,862	146,220	41,442	2,438	13,216	10,779
10			40,818	2,919	143,300	0	2,487	13,481	10,994

Table 6 Bank account commissions

Time	P/L net COC at maturity (euros)	Bank commission at maturity (euros)
0		3,283
1	11,908	3,251
2	11,860	3,219
3	11,771	3,188
4	11,657	3,157
5	11,544	3,127
6	11,432	3,096
7	11,321	3,066
8	11,211	3,036
9	11,102	3,007
10	10,994	

Table 7 Bank and insurance profit or loss account

Total profit or loss	Value (euros)
Financial value of bank commissions	31,430
Financial value of insurance profit	114,799
Additional commissions	41,684
Financial value of insurance profit net additional commission	73,115
Financial value of bank commisions net additional commission	73,115

Table 8 Bank cash flows net additional commissions

Time	Bank cash flow net additional commission (euros)
0	−997,557
1	145,792
2	145,842
3	145,893
4	145,944
5	145,997
6	146,051
7	146,106
8	146,162
9	146,220
10	184,985
IIR	8.00%

From Table 8, it can be noted that the criterion of maintaining the *IIR* at 8% has been met.

4 Concluding remarks

The adverse effects of climate change risk on bank loan availability could significantly impact the resilience of commercial banks. As they commonly offer business loans, which are particularly vulnerable to climate risk, especially physical risks, their stability may be compromised. Research, such as that by Nguyen et al. (2022), suggests that lenders tend to impose higher interest rates on mortgages located in areas facing increased risks of rising sea levels. In our study, we propose an innovative financial contract, potentially facilitated by bancassurance, to address this challenge. The financial instrument we investigate is founded on a climate change risk-sharing mechanism, leveraging a ML climate risk for tourism composite indicator. This approach offers advantages for all involved parties: by paying a premium, the beach resort can transfer climate risk to the insurance company while simultaneously receiving a discount on the loan interest rate. This enables the business to better manage its exposure to climate-related risks, enhancing its financial stability; implementing this contract allows the bank to mitigate counterpart risks associated with potential climate-related damages to the business. Furthermore, the bank can generate additional revenue by acting as a distributor for the insurance product; by leveraging ML to price climate risk, the insurance company can realize expected profits through the sale of insurance products tailored to climate-related risks for tourism. This innovative approach allows the insurance company to accurately assess and address climate risks, thereby contributing to its financial success.

In summary, our proposed financial contract presents a mutually beneficial solution, promoting risk-sharing among businesses, banks, and insurance companies. By effectively managing climate-related risks, this approach enhances the resilience and stability of all involved parties in the face of climate change challenges.

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Declarations

Conflict of interest The authors declare no competing interests.

References

Bingler, J. A., Colesanti Senni, C., Monnin, P.: Climate financial risks: assessing convergence, exploring diversity. In Discussion Note 2020/6. Counsil on Economic Policies (2020)

Bosilovich, M. G., R. Lucchesi, and M. Suarez.:MERRA-2: File Specification. GMAO Office Note No. 9 (Version 1.1). Accessed 11th Feb 2024 (2016) http://gmao.gsfc.nasa.gov/pubs/office_notes

Breiman, L.: Bagging predictors. Mach. Learn. **24**(2), 123–140 (1996)
Breiman, L.: Random forest. Mach. Learn. **45**(1), 5–32 (2001). https://doi.org/10.1023/a:1010933404324
Carannante, M., D'Amato, V., Fersini, P., Forte, S.: Climate risk management by using index-based analytics artificial algorithms on satellite data. SSRN J. (2023). https://doi.org/10.2139/ssrn.4741708
Dolge, K., Blumberga, D.: Composite risk index for designing smart climate and energy policies. Environ. Sustain. Indicat. **12**, 100159 (2021). https://doi.org/10.1016/j.indic.2021.100159
Filho, W.L.: Will climate change disrupt the tourism sector? Inter. J. Climate Change Strat. Manage. **14**, 1756–8692 (2022)
de Freitas, C.R., Scott, D., McBoyle, G.: A second generation climate index for tourism (CIT): specification and verification. Int. J. Biometeorol. **52**, 399–440 (2008). https://doi.org/10.1007/s00484-007-0134-3
Gambarelli G., Goria A.: Economic evaluation of climate change impacts and adaptation in Italy, Work notes, CCMP—climate change modelling and policy, Fondazione Eni Enrico Mattei (2004)
Hamilton, J.M., Tol, R.S.J.: The impact of climate change on tourism in Germany, the UK, and Ireland: a simulation study. Reg. Environ. Change **7**, 161–172 (2007)
Hein, L., Metzger, M.J., Moreno, A.: Potential impacts of climate change on tourism; a case study for Spain. Current Opinion Environ. Sustain. **1**, 170–178 (2009)
Istat.: L'andamento Turistico In Italia: Prime Evidenze Del 2023. https://www.istat.it/it/archivio/297926 Accessed 13 June 2024 (2023)
Jennings, S.: Coastal tourism and shoreline management. Ann. Tour. Res. **31**, 899–922 (2004)
Kling, G., Volz, U., Murinde, V., Ayas, S.: The impact of climate vulnerability on frms' cost of capital and access to finance. World Dev. **137**, 105131 (2021)
Krehbiel, C.: DAACDataDownload.R [Source code] Accessed 11 Feb 2024 (2019) https://git.earthdata.nasa.gov/projects/LPDUR/repos/daac_data_download_r/browse/DAACDataDownload.R
Li, S., Wu, X.: How does climate risk affect bank loan supply? Empirical evidence from China. Econ. Change Restruct. **56**, 2169–2204 (2023). https://doi.org/10.1007/s10644-023-09505-9
Morgan, R., et al.: An improved user-based beach climate index. J. Coast. Conserv. **6**(1), 41–50 (2000). https://doi.org/10.1007/BF02730466
Nazir, F.: Tourism and natural hazards: juxtaposition of tourism determinants and hazard's risk. In: Seabra, C., Korstanje, M.E. (eds.) Safety and tourism (tourism security-safety and post conflict destinations), pp. 217–226. Emerald Publishing Limited, Leeds (2023)
Nguyen, D.D., Ongena, S., Qi, S., Sila, V.: Climate change risk and the cost of mortgage credit. Rev Finance **26**(6), 1509–1549 (2022)
Nonisma.: Concessioni demaniali e imprese balneari in Italia. (2022) https://www.mondobalneare.com/wp-content/uploads/2023/02/Gestione-Valorizzazione-demanio-costiero_Nomisma-presentazione-dati-completi.pdf Accessed 13 June 2024
Phillips, M.R., Jones, A.L.: Erosion and tourism infrastructure in the coastal zone: problems, consequences and management. Tour. Manage. **27**, 517–524 (2004)
Surugiu, E., Breda, L., Surugiu, M.R., Dindi, A.I.: Climate change impact on seaside tourism Portugal and Romania: two different case studies with strong particularities. Revista Economica **1**(54), 111–133 (2011)
Surugiu, E., Surugiu, M.: Climate change and global economic status. Present and perspectives. Young Econ. J. **1**(13S), 121–133 (2009)
Sygna L., Eriksen S., O'Brien K., Noess L.O.: Climate change in Norway: analysis of economic and social impacts and adaptations. CICERO Report, Oslo, Norway (2004)
The World Economic Forum.: Rising global temperatures are already affecting the tourism industry - here's how 14 (2023) https://www.weforum.org/agenda/2023/08/temperatures-tourism-climate-impact Accessed 25 Feb 2024