Science of the Total Environment 543 (2016) 1039–1053

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Modelling climate change impacts on tourism demand: A comparative study from Sardinia (Italy) and Cap Bon (Tunisia)

Judith Köberl [a,*], Franz Prettenthaler [a], David Neil Bird [b]

[a] Institute for Economic and Innovation Research, JOANNEUM RESEARCH Forschungsgesellschaft mbH, Leonhardstraße 59, 8010 Graz, Austria
[b] Institute for Water, Energy and Sustainability, JOANNEUM RESEARCH Forschungsgesellschaft mbH, Elisabethstraße 18/II, 8010 Graz, Austria

HIGHLIGHTS

- We model climate change impacts on tourism demand in Sardinia and Cap Bon.
- Climatic conditions for beach tourism are expected to improve in shoulder seasons.
- Increased heat stress may cause tourism demand to decline in summer peak season.
- Annual net impacts on tourism demand are expected to be (slightly) positive.
- Increasing water scarcity may raise water costs and decrease tourism profits.

ARTICLE INFO

Article history:
Received 9 January 2015
Received in revised form 3 March 2015
Accepted 3 March 2015
Available online 16 April 2015

Keywords:
Climate change impacts
Tourism
Regression analysis
Weather-Value-at-Risk
Sardinia
Cap Bon

ABSTRACT

Tourism represents an important source of income and employment in many Mediterranean regions, including the island of Sardinia (Italy) and the Cap Bon peninsula (Tunisia). Climate change may however impact tourism in both regions, for example, by altering the regions' climatic suitability for common tourism types or affecting water availability. This paper assesses the potential impacts of climate change on tourism in the case study regions of Sardinia and Cap Bon. Direct impacts are studied in a quantitative way by applying a range of climate scenario data on the empirically estimated relationship between climatic conditions and tourism demand, using two different approaches. Results indicate a potential for climate-induced tourism revenue gains especially in the shoulder seasons during spring and autumn, but also a threat of climate-induced revenue losses in the summer months due to increased heat stress. Annual direct net impacts are nevertheless suggested to be (slightly) positive in both case study regions. Significant climate-induced reductions in total available water may however somewhat counteract the positive direct impacts of climate change by putting additional water costs on the tourism industry.

1. Introduction

In the surroundings of the river basins '*Rio Mannu di San Sperate*' (Sardinia, Italy) and '*Chiba*' (Cap Bon, Tunisia) – two of the altogether seven study sites investigated within the EU-FP7 project 'Climate Induced Changes on the Hydrology of Mediterranean Basins (CLIMB)' (Ludwig et al., 2010) – tourism represents an important source of income and employment. According to the Italian National Institute of Statistics (ISTAT, 2012), Sardinia's 'Accommodation & Restaurants' sector generated 2.4 billion € in direct value added in 2010, accounting for 7% of the island's gross regional product (GRP). Moreover, 6% of all Sardinian employees work in the 'Accommodation & Restaurants' sector. In Cap Bon, a peninsula in the northeast of Tunisia and the country's leading sea destination, the sector 'Hotels, Restaurants & Travel Agencies' as well contributed about 7% to GRP (Gafsi and Ben-Hadj, 2010). Besides, roughly 90,000 people were directly or indirectly employed by Cap Bon's tourism sector, compared to 51,000 and 70,000 employees in the agricultural and industrial sector (Gafsi and Ben-Hadj, 2010).

Tourism in Sardinia and Cap Bon, however, not only represents an important source of income and employment, but it is also an intensive water consumer (Corsale, 2011; Gafsi and Ben-Hadj, 2010). The seasonal coincidence of tourist and dry seasons (see Section 2.1), especially, puts additional pressure on available water resources and contributes to water conflicts. Since water of proper quantity and quality represents an important factor for tourism development, climate-induced changes in its availability could impact the regions' tourism industries considerably. Besides these indirect impacts via water availability, climate change also poses the potential to affect tourism in a direct way, as many tourism types – including the predominant **s**ea, **s**and and **s**un (3S) tourism in Sardinia and Cap Bon – show a strong link to the climate

* Corresponding author.
E-mail addresses: judith.koeberl@joanneum.at (J. Köberl), franz.prettenthaler@joanneum.at (F. Prettenthaler), neil.bird@joanneum.at (D.N. Bird).

http://dx.doi.org/10.1016/j.scitotenv.2015.03.099

(UNWTO-UNEP-WMO, 2008). 3S tourism, for instance, needs a climate characterized by plenty of sunshine, sufficiently high temperatures as well as little rain (Moreno, 2010; Rutty, 2009; Rutty and Scott, 2010). In other words, a region's climate co-determines its basic suitability for particular outdoor-based tourism types, such as 3S tourism, and hence also ranks among those factors driving a region's tourism seasonality (Lohmann and Kaim, 1999; Scott and Lemieux, 2010). The climate's short-term manifestation, i.e. the weather actually experienced by tourists at the destination, by contrast may affect the tourists' activities and holiday satisfaction and – given sufficient flexibility – lead to holiday extension, early termination or even cancellation. Hence, changes in both, the climate's mean and its variability may directly affect tourism in Sardinia and Cap Bon.

Various studies have addressed the potential direct impacts of climate change on tourism in (selected regions of) the Mediterranean, including Amelung and Viner (2006), Hein (2007), Moreno and Amelung (2009), Rutty (2009), Rutty and Scott (2010), Perch-Nielsen et al. (2010), Cai et al. (2011) and Amelung and Moreno (2012). Some of them concentrate on the supply side only by comparing the region's observed and projected climatic attractiveness for tourism purposes, using single or composite climatic indices such as Mieczkowski's (1985) Tourism Climate Index (TCI), Morgan et al.'s (2000) Beach Climate Index (BCI) or temperature thresholds indicating ideal/unacceptable conditions for particular tourism types (e.g. Amelung and Viner, 2006; Moreno and Amelung, 2009; Perch-Nielsen et al., 2010; Rutty and Scott, 2010). Others additionally account for the relationship between climatic conditions and tourism demand when assessing the potential impacts of climate change on tourism in (selected regions of) the Mediterranean (e.g. Amelung and Moreno, 2012; Hein, 2007). Depending on the region, the tourism type and the season considered, these studies suggest climate change impacts to range from improvements to deteriorations in climatic conditions and hence from tourism demand gains to losses. Using the BCI, Moreno and Amelung (2009), for instance, find the climatic conditions for beach tourism in summer to remain very well in most regions of Sardinia until the 2060s. However, some areas within Sardinia currently enjoying very good conditions are expected to see the suitability of their climate resources for beach tourism to somewhat deteriorate in summer. Regarding the climatic suitability for sightseeing, analyses of Perch-Nielsen et al. (2010) suggest conditions in Sardinia to improve or remain the same during winter, spring and autumn, but to deteriorate during summer by the end of the century. For the north of Tunisia, including the peninsula of Cap Bon, improving conditions are found for the winter season, whereas both summer and autumn are expected to face deteriorating sightseeing conditions, primarily due to an increase in too hot temperatures. Based on the relationship between TCI values and tourism demand, Amelung and Moreno (2012) find evidence for a net loss of tourism demand potential in the European Mediterranean countries by the 2080s, with increases in spring and autumn however likely to compensate for much of the decrease in summer.

The objective of the present paper is to assess the potential impacts of climate change on tourism in the case study regions of Sardinia and Cap Bon. Direct impacts are studied in a quantitative way by applying a range of climate scenario data to the empirically estimated relationship between weather/climate conditions and tourism demand, using two different approaches. In addition, potential implications from climate induced changes in water availability are shortly addressed in the Results and discussion section. The structure of this paper is as follows. Section 2 describes the methods and data used, including a short characterization of the case study regions. The potential impacts of climate change on tourism are presented along with a discussion of the results in Section 3, whereas Section 4 concludes.

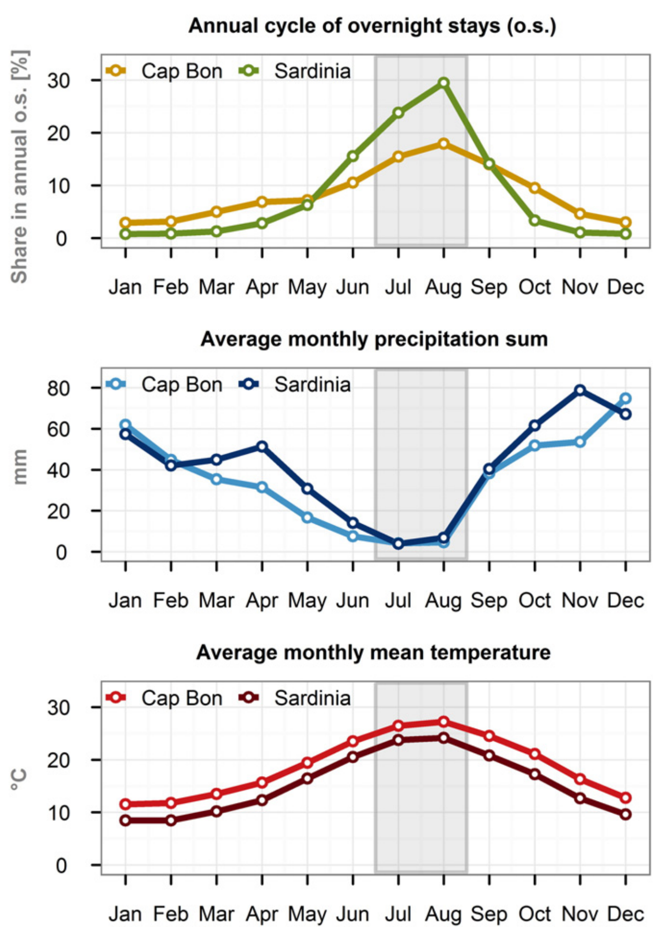

Fig. 1. Annual cycle of monthly overnight stays (first plot), precipitation sums (second plot) and mean temperatures (third plot) in Sardinia and Cap Bon.
Data sources: ISTAT (2010), ONTT (2014), ECA&D (2011).

2. Materials and methods

2.1. Case study regions

Sardinia, an island of 24,090 sq. km located 250 km west of the Italian coastline, and Cap Bon, a peninsula of 2788 sq. km in northeastern Tunisia, represent the case study regions in the focus of the present paper. The climate of both regions is characterized by hot and dry summers as well as mild and wet winters. In January, daily mean temperature in Sardinia is on average 8 °C (Cap Bon: 12 °C), whereas in August it rises to 24 °C (Cap Bon: 27 °C) (see third plot in Fig. 1). Average annual precipitation totals 500 mm (Cap Bon: 425 mm), with considerable variations from year to year. In Sardinia, these fluctuations may range from 287 mm (1970) to 948 mm (1984), in Cap Bon from 144 mm (1981) to 772 mm (2003). But variability is also high during the course of the year and dry periods occur frequently. During July and August there is often no precipitation at all (see second plot in Fig. 1). Consequently, both case study regions repeatedly suffer from water shortages due to the prevalent climatic conditions.

In both case study areas, 3S tourism represents the dominant tourism type. Overnight stays in Sardinia show a highly pronounced seasonality, with the by far highest shares of annual overnight stays reported in July and August. Overnight stays in Cap Bon are, by contrast, distributed somewhat more evenly throughout the year. Nevertheless, they still show a noticeable peak during the summer months. Hence, as illustrated in Fig. 1 by the grey-shaded rectangles, the period of the tourism industry's highest water needs, i.e. the most tourism intensive period, coincides with the driest time of the year. The increasing importance of tourism – overnight stays showed an increasing tendency over the past decades[1] – in conjunction with the (partly) pronounced seasonality concentrating on the driest months represents a growing stress factor with the potential of significantly worsening water scarcity issues and contributing to water conflicts. Already today, water restrictions in Sardinia are becoming more and more frequent (Corsale, 2011) and Cap Bon could not survive without water imports from the north of Tunisia (Gafsi and Ben-Hadj, 2010).

2.2. Methods

In order to assess the potential direct impacts of climate change on tourism demand we follow two different approaches, each of them comprising three steps. Both approaches start with estimating tourism demand models using historical monthly data and regression techniques. However, whereas '*Approach A*' fits separate regression models for each month of the year (see e.g. Agnew and Palutikof, 2006; Serquet and Rebetez, 2011), '*Approach B*' models all months of the year within one and the same regression model (see e.g. Amelung and Moreno, 2012; Becken, 2013; Bigano et al., 2005; Canales and Pardo, 2011; Castellani et al., 2010). This leads to differences in the focus of the analyses. Whereas '*Approach A*' rather focuses on the influence of the short-term climate's year-to-year variability on tourism demand, '*Approach B*' takes the influence of intra-annual climatic variations on the seasonality of tourism demand into account. Fig. 2 gives a schematic overview of both methodologies applied. A detailed description follows below.

2.2.1. '*Approach A*'

Within the first step of '*Approach A*' we somewhat follow Agnew and Palutikof (2006) by estimating 12 tourism demand models – one for each month of the year – using (linear) regression techniques[2] and historical data. The natural logarithm of monthly overnight stays in the considered region serves as regressand. Various climate indices (see Table 1) are tested for their statistical significance in explaining (parts of) the variability in overnight stays, with the most influential one being used in the final model. Additionally, we control for further important influencing variables, such as gross domestic product (GDP) per capita in sending countries, lagged overnight stays, or severe incidents (e.g. terroristic attacks).

By modelling each month of the year individually, regression analysis within '*Approach A*' focuses on the sensitivity of overnight stays towards the year-to-year variability in the short-term climate, i.e. the weather. It shows, for instance, whether a rainy June results in lower (or higher) overnight stays than an average June or whether an extremely hot July causes overnight stays to drop (or increase) compared to an average July. Consequently, the approach seems well suited for analysing the risk of tourism demand losses arising from weather variability now and in the future. Thus, in a second step meteorological data from four different Regional Climate Models (RCMs) are inserted into the month-specific tourism demand models calibrated within step 1. This way, we simulate tourism demand under the climate of a reference (1971–2000) and a future (2041–2070) period, holding all other control variables constant and assuming a stationary relationship between weather and tourism demand. Variability in the resulting simulations of tourism demand under reference and future climatic conditions is hence solely attributable to the variability in the meteorological data. Applying the concept of 'Weather Value at Risk' (Prettenthaler et al., 2015; Toeglhofer et al., 2012) to the tourism demand simulations in a third step gives the risk of weather-induced year-to-year tourism demand losses under both, reference and future climatic conditions. The 'Weather Value at Risk (α)', or just 'Weather-VaR (α)', indicates the maximum loss expected from adverse weather conditions for a given level of confidence α over a given period of time. Weather-VaR (0.9), for example, represents the weather-induced loss, which won't be exceeded with a probability of 90% within the considered period of time — or put the other way around, which will be exceeded with a probability of 10%. The measure may as well be interpreted in terms of return periods, i.e. Weather-VaR (α) expresses the lower bound of the weather-induced loss associated with an average recurrence interval of once in $1 / (1 - \alpha)$ periods. In the context of tourism demand, we define the risk measure Weather-VaR (α), or more precisely the centred Weather-VaR (α), simply as the difference between tourism demand expected under average weather conditions and tourism demand expected under adverse weather conditions as occurring with a probability of $(1 - \alpha) * 100\%$. Applying the 'Weather-VaR' concept to compare the risk of weather-induced year-to-year demand losses under reference and future climatic conditions allows us to assess the impacts of potential changes in the climate's variability. By defining the 'Weather-VaR' of tourism demand under future climatic conditions in such a way that the weather-induced loss related to adverse future conditions is calculated relative to the demand expected under average reference (instead of average future) climatic conditions, comparisons between reference and future 'Weather-VaR' figures not only indicate the impacts of changes in the climate's variability, but also include the impacts of changes in the climate's mean (see also Prettenthaler et al., 2015). We use current average expenditures per overnight stay to convert the results from 'overnight stays' to 'revenues'.

One drawback of '*Approach A*' and the individual modelling of each month is the very significant reduction in observations available for model calibration, especially compared to the approach considering all months of the year within one and the same regression model. This of course affects the robustness of the resulting sensitivity estimates and hence increases model uncertainties. Thus, when interpreting the results we have to bear in mind that uncertainty might be high, especially if the number of historical observations available for model calibration is rather limited. Moreover, the approach does not take the climate's influence on tourism seasonality into account, which may result in an underestimation of overall climate change impacts. Nevertheless, the results from '*Approach A*' give some valuable insights on the risk the tourism industry is facing due to short-term climate variability. This may be overlaid when considering the climate's influence on tourism seasonality as within '*Approach B*'.

2.2.2. '*Approach B*'

The first step of '*Approach B*' as well comprises the estimation of a tourism demand model, using (linear) regression techniques[2] and historical data. However, in contrast to '*Approach A*', all months of the year are now modelled within one and the same regression model, hence the influence of the climate's intra-annual variability on tourism demand and consequently its effect on tourism seasonality is now taken into account. Again, the natural logarithm of monthly overnight stays in the considered region serves as regressand, whereas climatic conditions are used to explain (parts of) the observed variations in overnight stays. Climatic conditions are represented by a 'Simple Beach Index' (SBI) (see Section 2.3). Additionally, we control for further important influencing variables, such as the gross domestic product (GDP) per capita in sending countries, lagged overnight stays, exchange rates, consumer price indices, severe incidents (e.g. terrorist attacks) or holidays.

As within '*Approach A*', in a second step meteorological data from four different RCMs are inserted into the calibrated models to simulate tourism demand under the climate of a reference (1971–2000) and a future (2041–2070) period, holding all other control variables constant and assuming a time-constant relationship between climate and tourism. Comparing average tourism demand according to the simulations under reference and future climatic conditions in a third step indicates

[1] Regarding Cap Bon, there was a considerable drop in overnight stays following the Jasmine Revolution in spring 2011. Countrywide, overnight stays fell by about 40% and haven't fully recovered yet (ONTT, 2014).

[2] We apply ordinary least squares (OLS) to estimate the parameters of the linear regression models.

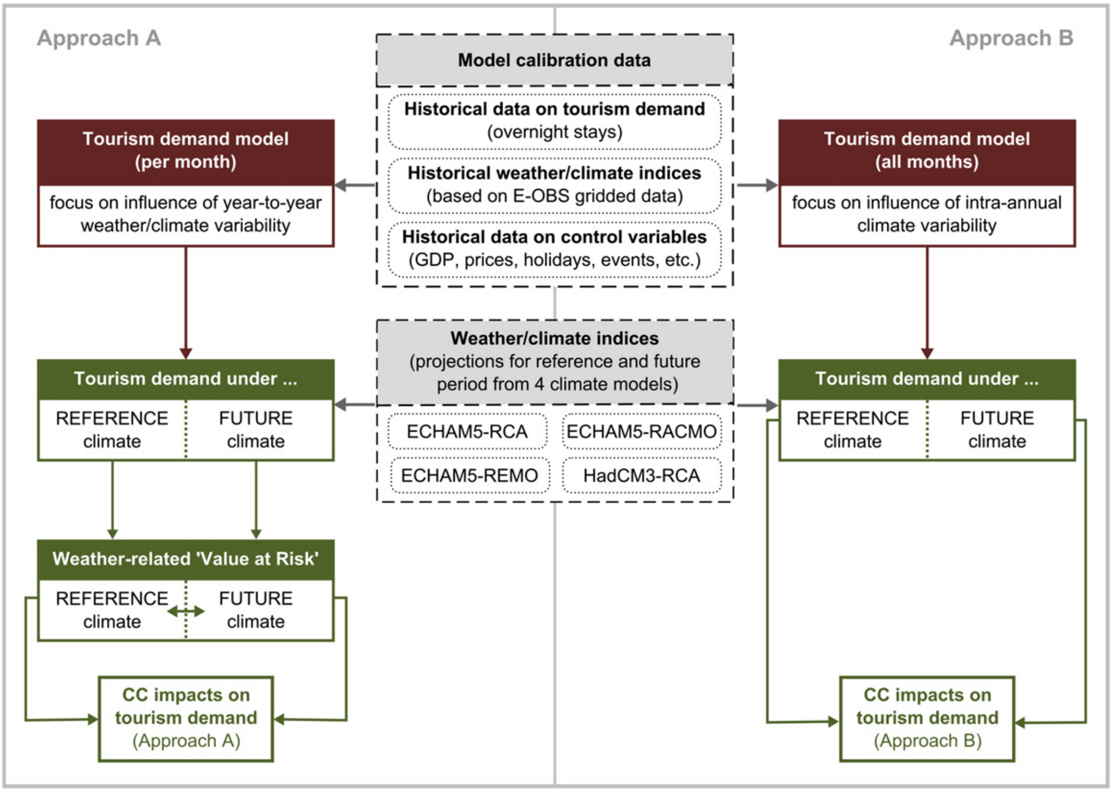

Fig. 2. Methods used for the assessment of direct climate change impacts.

the potential direct impacts of climate change on tourism demand. Again current average expenditures per overnight stay are applied to translate the outcomes from 'overnight stays' to 'revenues'.

2.3. Data

2.3.1. Meteorological data for model calibration

We use E-OBS gridded dataset (Haylock et al., 2008) version 5.0 on a 0.22° rotated pole grid in order to construct the weather and climate indices used to calibrate our tourism demand models. The E-OBS dataset contains daily data on the following parameters: precipitation sum, minimum temperature, maximum temperature, and mean temperature. Based on these daily parameters, a range of monthly weather and climate indices – listed in Table 1 – is constructed. The first nine indices in Table 1 follow the definitions outlined by ECA&D (2012). Additionally, we created some indices based on a survey of Rutty (2009) and Rutty and Scott (2010) among the young adult travel segment in five source markets (Austria, Germany, the Netherlands, Sweden and Switzerland) regarding its perception of unacceptable weather/climatic conditions for beach holidays in the Mediterranean. The (overwhelming) majority of respondents, i.e. more than 50% (80%) of respondents, perceive temperatures below 22 °C (20 °C) as unacceptably cool and temperatures above 37 °C (40 °C) as unacceptably hot (Rutty and Scott, 2010). Moreover, the majority of respondents prefer no rain at all, whereas more than 2 h of rain during the day are perceived as unacceptable for beach holidays (Rutty, 2009). Based on these findings, eight additional climate indices, including the monthly share of days with (i) 'too cold', (ii) 'too hot', and (iii) 'too cold' or 'too hot' temperatures

Table 1
Overview on the climate indices tested within tourism demand modelling.
Source: based on ECA&D (2012), Rutty (2009) and Rutty and Scott (2010).

Abbr.	Name	Explanation	Approach
TXG	Maximum temperature	Monthly mean value of daily maximum temperature [°C]	A
TGG	Mean temperature	Monthly mean value of daily mean temperature [°C]	A
TNG	Minimum temperature	Monthly mean value of daily minimum temperature [°C]	A
RR	Precipitation sum	Monthly total precipitation at wet days [mm]	A
RR1	Wet days	Monthly share of days with at least 1 mm of precipitation	A
RR10	Heavy precipitation days	Monthly share of days with at least 10 mm of precipitation	A
CDD	Consecutive dry days	Maximum length of consecutive days with less than 1 mm of precipitation	A
CWD	Consecutive wet days	Maximum length of consecutive days with at least 1 mm of precipitation	A
TXC_1	'Too cold' days (1)	Monthly share of days with maximum daily temperatures below 22 °C	A
TXC_2	'Too cold' days (2)	Monthly share of days with maximum daily temperatures below 20 °C	A
TXH_1	'Too hot' days (1)	Monthly share of days with maximum daily temperatures above 37 °C	A
TXH_2	'Too hot' days (2)	Monthly share of days with maximum daily temperatures above 40 °C	A
TXU_1	'Too cold or hot' days (1)	Monthly share of days with maximum daily temperatures below 22 °C or above 37 °C	A
TXU_2	'Too cold or hot' days (2)	Monthly share of days with maximum daily temperatures below 20 °C or above 40 °C	A
SBI_1	Simple Beach Index (1)	Monthly share of days with maximum daily temperatures below 22 °C or above 37 °C or at least 1 mm of precipitation (i.e. 'unacceptable' beach conditions)	B
SBI_2	Simple Beach Index (2)	Monthly share of days with maximum daily temperatures below 20 °C or above 40 °C or at least 1 mm of precipitation (i.e. 'unacceptable' beach conditions)	B

for beach holidays, were constructed. Moreover, we created an index indicating the monthly share of days with unacceptable temperature and/or unpleasant precipitation conditions for beach holidays — in the following referred to as 'Simple Beach Index' (SBI). Both parameters of the SBI are assumed to exhibit overriding effects. That is, in terms of the SBI the climatic conditions of a particular day are defined as unacceptable for beach holidays if either unacceptable temperature or unpleasant precipitation conditions (or both) are observed. For some of the mentioned indices, two different versions were created, where the first one is based on the temperature notion of a 'simple' majority of respondents (i.e. more than 50%) and the second one on the temperature notions of an 'overwhelming' majority of respondents (i.e. more than 80%).

Aggregation from grid to the required regional level takes account of the (approximate) distribution of tourists. In a first step we translate or aggregate the indices from grid level to the smallest administrative level, for which touristic information (e.g. number of beds) is available, by simply taking the area-weighted average. In case of Sardinia (Cap Bon), the smallest administrative level providing tourism data is the municipal (delegation) level, for which the number of touristic beds is available. In a second step, a fixed set of touristic weights – indicating the share of a municipality's (delegation's) touristic beds in total touristic beds – is used to further aggregate the indices from this 'smallest' administrative level to the regional level required. Hence, more weight is put on the climatic conditions of areas with a stronger touristic focus to result in aggregated figures more representative of the climatic conditions actually perceived by tourists within the considered region.

2.3.2. Tourism & economic data for model calibration

Both approaches, described in Section 2.2, start with the estimation of regression models using the logarithm of monthly overnight stays (lnOS) as regressand. Regarding Sardinia, data on monthly overnight stays stem from the Italian National Institute of Statistics (ISTAT) and are separately available for tourists from Italy ('residents') and tourists from abroad ('foreigners'). The data comprise the period 1980 to 2009, with data missing for the years 1990, 1992, 1995, 1996, and 1997 (see Fig. 3). Tourism data on Cap Bon is, by contrast, much more limited. Monthly data on (total) overnight stays, stemming from the Tunisian National Tourism Authority (ONTT), are only available for a few single years, i.e. 2001, 2005, 2007, and 2009. Especially for the applicability of '*Approach A*', these are however far too few observations. A considerably longer and more complete time series of monthly overnight stays, ranging from 1997 to 2009 and stemming from the Tunisian National Institute of Statistics (INS), is only available for Tunisia as a whole. Due to the mentioned data limitations, we use these national data to reconstruct the time series of overnight stays in Cap Bon by assuming the same evolution as observed at national level.[3] The resulting time series is illustrated in Fig. 3.

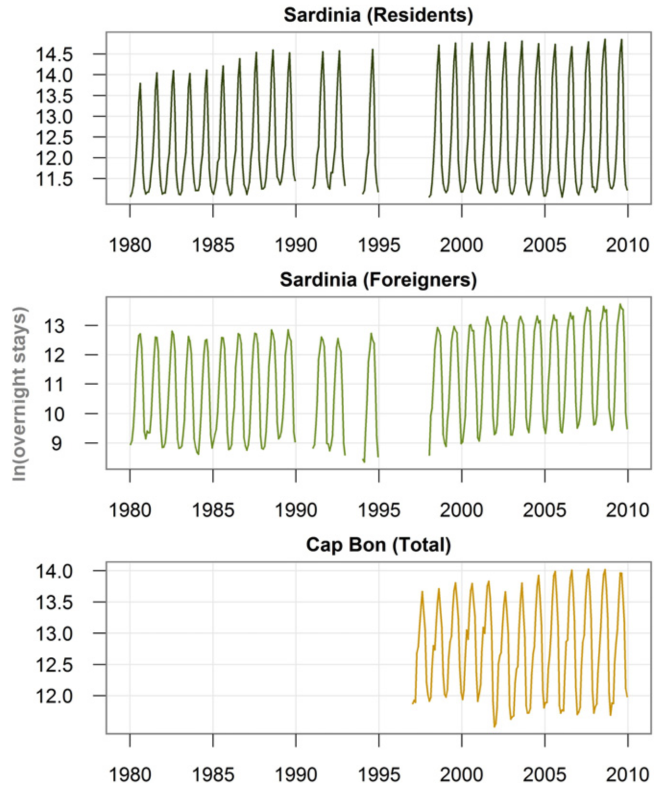

Fig. 3. Logarithm of overnight stays — data available for tourism model calibration. Data source: ISTAT, ONTT, INS.

Many other factors besides the weather/climatic conditions may influence tourism demand in a particular destination. These may include the economic situations in sending countries and the destination itself, relative price levels, exchange rates, and the political stability of the destination. When estimating the influence of weather/climatic conditions on tourism demand, we thus additionally control for the factors given below (as far as relevant). Variables, which are only available on an annual basis, are transformed into monthly data by keeping them constant over the course of 12 months.

- The logarithm of gross domestic product per capita (lnGDP) in major sending countries, weighted by the share of overnight stays attributable to each sending country and measured in constant prices as well as constant purchasing power parities, as indicator for income: Data on GDP stem from the OECD (2012) and are available on an annual basis.
- Consumer price index ratios (CPIratio) between destination and major sending countries, weighted by the share of overnight stays attributable to each sending country, as proxy for relative (tourism) prices: Data on the CPI again stem from the OECD (2012) and are available on a monthly basis.
- Logarithm of origin-destination exchange rates: With regard to Sardinia, the bulk of tourists stem from the Eurozone. However, noticeable fractions also come from Great Britain and the USA, which is why we consider the logarithm of Pounds-to-Euro ($\mathrm{lnXRT}_{\mathrm{GBP\_EUR}}$) and Dollar-to-Euro ($\mathrm{lnXRT}_{\mathrm{USD\_EUR}}$) exchange rates. Following Castellani et al. (2010) we use lagged values of exchange rates, testing for lags between 1 and 3 months. Data again stem from the OECD (2012) and are available on a monthly basis. For Cap Bon, available time series on exchange rates (e.g. Euro-to-Dinar, Pounds-to-Dinar) are too short to be included in our tourism demand models.
- Lagged dependent variable: It is quite common to incorporate lags of the dependent variable in tourism demand models to control for tourist expectations and habit persistence, i.e. stable behaviour patterns (Song and Witt, 2000). Within '*Approach A*' we test for the inclusion of the logarithm of overnight stays lagged by one period (i.e. one year). In the course of '*Approach B*', we create the variable DEPyear, which indicates the annual sum of the logarithm of monthly overnight stays. DEPyear enters the demand model in form of a one-year (i.e. a 12-period) lag.[4]
- Severe incidents: We test for the inclusion of dummy variables to account for potential influences of severe incidents, such as the terroristic attacks of 9/11 in 2001.
- Holidays: Climate is not the only factor that may influence tourism seasonality. Also institutional settings, such as the timing of major holiday

[3] To be precise, national data on monthly overnight stays in Tunisia only include non-residents. However, since overnight stays of foreigners account for about 90% of total overnight stays, we use the evolution of this data as proxy for the evolution of total overnight stays.

[4] We use 12-period-lags of the annual sum of the dependent variable instead of 12-period-lags of the dependent variable itself, since the latter causes some multicollinearity problems with the 'Simple Beach Index'.

Table 2
Climate change signals between reference (1971–2010) and future (2041–2070) periods for selected climate indices — mean of the four climate models considered.

Climate index	Sardinia	Cap Bon
Mean temperature (TGG)	[°C]	[°C]
Annual	+2.2	+2.2
Spring (MAM)	+2.1	+2.3
Summer (JJA)	+2.7	+2.6
Autumn (SON)	+2.0	+2.3
Winter (DJF)	+1.8	+1.8
Share of 'too hot' days (TXH_1/TXH_2)	[%-points]	[%-points]
Annual	+1.5/+0.2	+4.8/1.6
Spring (MAM)	+0.0/+0.0	+0.5/+0.1
Summer (JJA)	+6.0/+0.7	+16.8/+5.8
Autumn (SON)	+0.1/+0.0	+1.7/+0.5
Winter (DJF)	±0.0/±0.0	±0.0/±0.0
Share of 'wet' days (RR1)	[%-points]	[%-points]
Annual	−2.6	−4.1
Spring (MAM)	−5.0	−6.0
Summer (JJA)	−0.8	−1.0
Autumn (SON)	−3.6	−3.7
Winter (DJF)	−0.8	−5.6
Share of 'unacceptable beach condition' days (SBI_1/SBI_2)	[%-points]	[%-points]
Annual	−6.7/−7.6	−5.3/−9.3
Spring (MAM)	−12.3/−15.4	−19.3/−17.4
Summer (JJA)	−1.7/−1.6	+11.9/+2.5
Autumn (SON)	−12.4/−12.2	−10.0/−11.3
Winter (DJF)	−0.2/−1.1	−3.7/−10.9

Table 3
Overview on the weather dependencies finally considered within impact assessment based on '*Approach A*'.

Month	Sardinia (Italians)			Sardinia (foreigners)			Cap Bon (total)		
	WI	Relation	Adj. R^2	WI	Relation	Adj. R^2	WI	Relation	Adj. R^2
Jan	–	–	0.27	RR	**(−)**	0.64	–	–	0.67
Feb	RR1	**(−)**	0.42	–	–	0.70	TXC_2	(−)	0.68
Mar	RR10	**(−)**	0.46	–	–	0.90	TNG	**(+)**	0.67
Apr	TXC_2	**(−)**	0.50	–	–	0.97	–	–	0.66
May	TXC_1 (−1)	**(−)**	0.91	TXC_2 (−1)	**(−)**	0.96	–	–	0.66
Jun	TNG	**(+)**	0.99	TXG	**(+)**	0.97	TXH_2	(−)	0.82
Jul	TXH_1 (−1)	**(−)**	0.96	TXU_1	**(−)**	0.95	TXH_2	**(−)**	0.94
Aug	RR	**(−)**	0.95	–	–	0.89	CDD	(+)	0.78
Sep	TXC_2 (−1)	**(−)**	0.89	–	–	0.97	RR	**(−)**	0.78
Oct	TXC_1	**(−)**	0.60	TXC_2	**(−)**	0.96	TXC_1	(−)	0.61
Nov	–	–	0.23	–	–	0.72	–	–	0.55
Dec	RR1	**(−)**	0.49	–	–	0.81	CWD	**(−)**	0.60

– … the BIC decided on no inclusion of a weather index in the final model.
(+)/(−) … statistically significant positive/negative influence on overnight stays (o.s.) at the 10% level.
(+)/(−) … statistically not significant positive/negative influence on o.s., but chosen to be considered by the BIC.
(−1) … lagged by one period.

periods, rank among the identified causes of seasonality in tourism (Hadwen et al., 2011). Within '*Approach B*' we test for the inclusion of dummies for those months of the year showing the highest number of non-school days in major sending countries. In addition, we consider a dummy indicating the month in which Easter occurs. The inclusion of the Easter-Dummy is also tested within '*Approach A*' when it comes to the models for March and April.

- Year: We test for the inclusion of a variable indicating the year of the observation (yyyy) to capture potential unexplained (linear) trends.

Since analysing the statistical significance of the estimated coefficients requires all components of a linear model to be stationary, we performed unit root tests for all endogenous and exogenous variables. For seasonal variables (i.e. lnOS, climate indices) we carried out both, the Canova–Hansen test for seasonal unit root (Canova and Hansen, 1995) and the KPSS test (Kwiatkowski et al., 1992). For non-seasonal variables (i.e. lnGDP, CPIratio, $lnXRT_{GBP\_EUR}$, $lnXRT_{USD\_EUR}$) we only performed the KPSS test. We found evidence of a unit root for the variables lnGDP, CPIratio, $lnXRT_{GBP\_EUR}$, and $lnXRT_{USD\_EUR}$, but not for their first differences. Hence, all these variables enter the subsequent tourism demand models in the form of first differences. No evidence of a unit root was found for the remaining variables after properly accounting for deterministic effects where necessary.

In order to determine, which of the above listed potential explanatory variables are to enter the final tourism demand models, we perform stepwise model selection based on the Bayesian Information Criterion (BIC) (Schwarz, 1978). The BIC represents an index used to choose between competing models by balancing the model's goodness of fit against its complexity (i.e. the number of model parameters). Explanatory variables exhibiting a Variance Inflation Factor (VIF) of more than 10 are excluded from the model selection procedure in advance to reduce multicollinearity problems.[5] Regarding '*Approach A*' we moreover restrict the number of explanatory variables used in the final models to a maximum of four due to the limited number of observations available.

2.3.3. Climate model data for simulations

For simulating overnight stays under reference and future climatic conditions, bias-corrected temperature and precipitation data from four different Regional Climate Models (RCMs) of the EU-FP6 ENSEMBLES project (ECH-REM, ECH-RMO, HCH-RCA and ECH-RCA)[6] are used. Details on the climate model selection procedure can be found in Deidda et al. (2013). Table 2 shows the climate change signals between reference and future periods as indicated by the RCMs considered for selected climate indices. The figures reported represent the mean over the four RCMs. In both case study areas, (mean) temperatures are expected to rise, with the increase being most pronounced during summer season. The overall temperature increase also brings about a rise in the fraction of days with conditions perceived as 'too hot' for beach holidays. 'Wet' days are, by contrast, expected to decrease, particularly during springtime. Rising temperatures and decreasing 'wet' days cause an overall decline in days with 'unacceptable' beach conditions, which is most pronounced in spring and autumn. (Parts of) the summer season are however indicated to suffer from increases in 'unacceptable' beach conditions. In the case of Sardinia, increases in the number of days with 'unacceptable' beach conditions during July and August are outweighed by decreases in June though.

2.3.4. Hydrological model data for qualitative discussions

Discussions on potential implications from climate induced changes in water availability are based on hydrological results from the CLIMB project (see e.g. Ludwig et al., 2013). We assume that the climate change impacts on water resources, as simulated within the CLIMB project for the river basins '*Rio Mannu di San Sperate*' (Sardinia, Italy) and '*Chiba*' (Cap Bon, Tunisia), are indicative of the trends to be expected for the whole of Sardinia and Cap Bon, respectively. Regarding '*Rio Mannu*',

[5] According to Kutner et al. (2004), multicollinearity is only severe at variance inflation factors exceeding 10.

[6] ECH = ECHAM5 / MPI OM (Max Planck Institute for Meteorology, Germany); HCH = HadCM3 Model (Hadley Centre for Climate Prediction, Met Office, UK); REM = REMO Germany; RMO = RACMO2 Netherlands; RCA = RCA Sweden.

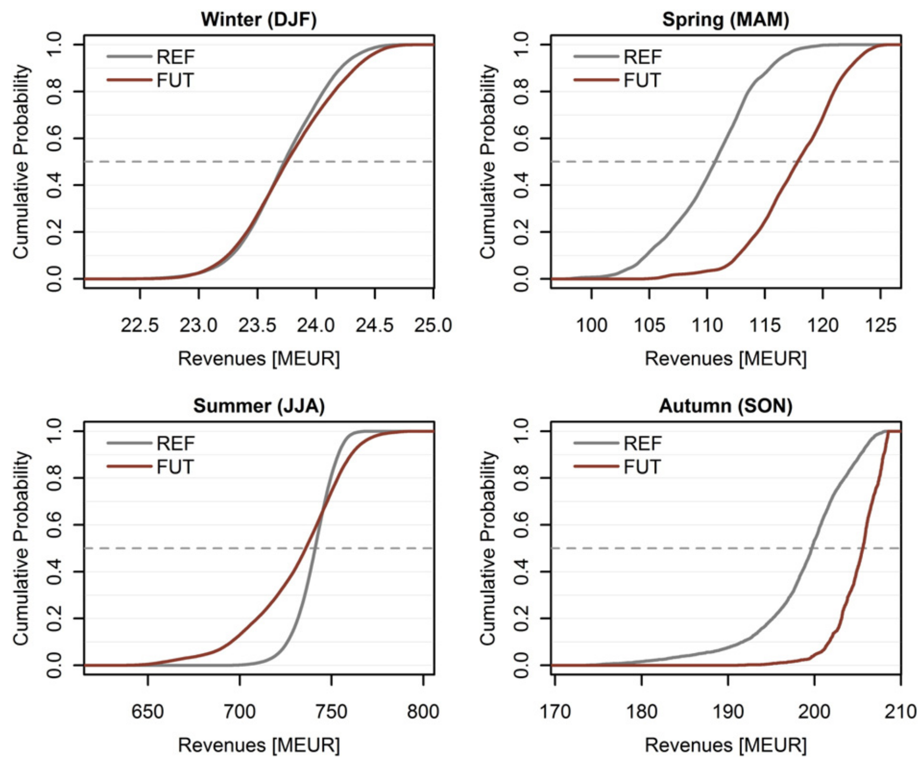

Fig. 4. Weather-dependent distribution of tourism revenues in Sardinia (residents & foreigners) under reference and future climatic conditions, considering four different climate scenarios.

total available water (TAW) is expected to decrease by 15% to 23% between reference and future periods (Ludwig et al., 2013). Impacts vary from season to season: whereas small gains in TAW are indicated during wintertime, the most pronounced decreases are expected for spring, followed by autumn. Concerning '*Chiba*', projections reveal reductions of about 30% in TAW, with much of the negative change expected for autumn and spring (Ludwig et al., 2013).

2.3.5. Data for monetarization

Figures on current expenditures per overnight stay stem from Regione del Veneto (2009) and Gafsi and Ben-Hadj (2010). Accordingly, tourists in Sardinia spend on average 88 €, and tourists in Tunisia 75 € per overnight stay. The latter figure is used as a proxy for average expenditures in Cap Bon.

3. Results and discussion

3.1. 'Approach A'

Table 3 summarizes the interim results following the first step of '*Approach A*', i.e. the estimation of month-specific tourism demand models. Various climate indices were successively tested for their statistical significance in explaining (parts of) the variability in tourism demand, indicated by the logarithm of overnight stays.[7] For each month, Table 3 presents the weather index (WI) entering the final month-specific tourism demand model along with the sign of the estimated coefficient. Hence, the column 'Relation' indicates, whether the respective weather index shows a positive or negative impact on overnight stays in the respective month. If the BIC decides on not including any of the tested weather indices in the final model – which is indicated by a dash in the columns 'WI' and 'Relation' – we assume the weather dependency of tourism demand in the respective month to be negligible, i.e. zero.[8] In addition to the weather dependency, the adjusted R^2 of each final model is given in Table 3. Note that in case of very high values, a large fraction of the explanatory power tends to be attributable to lagged overnight stays and/or the linear trend.

Following the results outlined in Table 3, residential (i.e. Italian) tourists in Sardinia are in general more sensitive towards weather conditions than foreign tourists, i.e. a higher fraction of months shows statistically significant influences of weather conditions on overnight stays. The fewest statistically significant weather dependencies are found for overnight stays in Cap Bon, where in some cases the BIC decides on the inclusion of a statistically not significant weather index. Overall, results for Cap Bon are characterized by high uncertainty due to limitations in data availability and quality (see Section 2.3).

Based on the relationships between weather conditions and overnight stays illustrated in Table 3, seasonal weather-dependent cumulative distribution functions (CDFs) of tourism revenues were derived for both, the climatic conditions of the reference (REF) and the future (FUT) period, following the methodology described in Prettenthaler et al. (2015). For this purpose, tourism revenues were approximated using current average expenditures per overnight stay. The weather-dependent empirical CDFs of tourism revenues illustrated in Figs. 4 and 5 already incorporate information from all four RCMs considered. Differences in the slope of the curve between reference and future periods indicate a change in the variability of tourism revenues due to changes in the variability of climatic conditions. The flatter a curve, the higher the variability and hence the higher the risk of revenue

[7] We also tested the simultaneous inclusion of two weather indices, i.e. various combinations of a temperature together with a precipitation index. However, in hardly any case the BIC criterion decided on the inclusion of both indices and if so, separate testing of the respective indices did not result in their inclusion.

[8] Note that if tourism demand in a particular month does not show any sensitivity towards variations in the weather conditions, impacts from changing weather/climatic conditions are as well assumed to be zero according to the approach applied. Hence, when simulating tourism demand under reference and future climatic conditions by holding all other control variables constant (see Section 2.2.1), tourism demand simulations with zero variability result for these months.

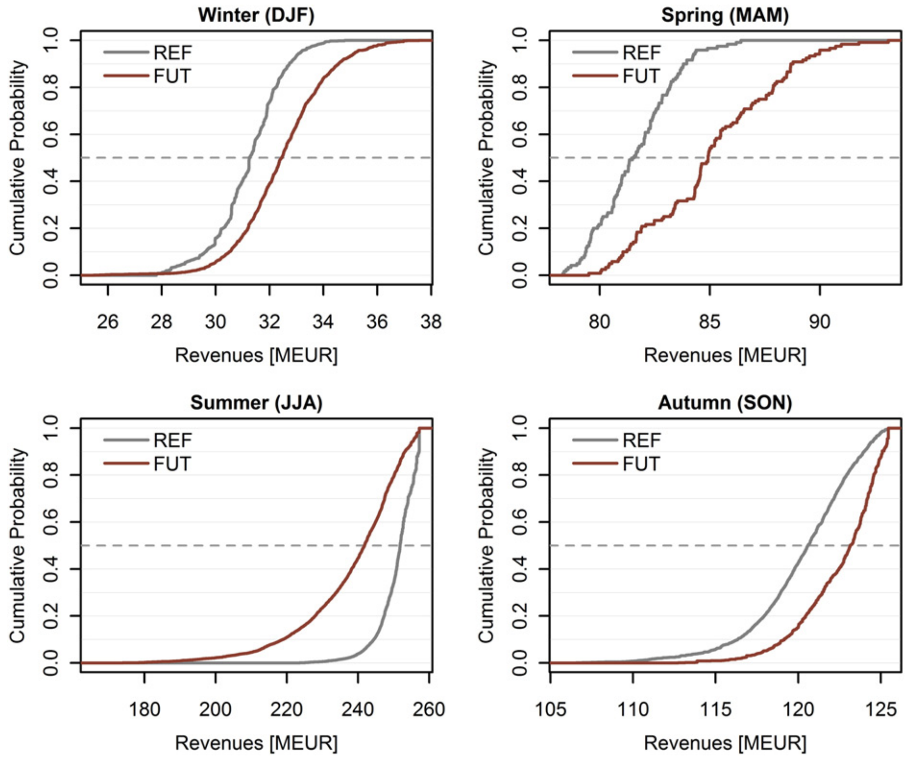

Fig. 5. Weather-dependent distribution of tourism revenues in Cap Bon under reference and future climatic conditions, considering four different climate scenarios.

losses, but also the chance for gains — compared to expected revenues. A shift of the whole curve to the right (left) indicates an overall increase (decrease) in tourism revenues due to climate change. However, shifts of the curves have to be interpreted with caution. As pointed out in Section 2.2, '*Approach A*' is likely to underestimate climate-induced changes in average tourism demand and revenues, i.e. shifts of the CDF, since the climate's influence on tourism seasonality is not taken into account. Moreover, only a limited number of observations were available for estimating the month-specific year-to-year weather sensitivity of tourism demand. Hence, results are rather uncertain, which is especially true for the case of Cap Bon.

In addition to the plots illustrating the weather-dependent distribution of tourism revenues, we explicitly point out the weather-related Value at Risk ('Weather-VaR') – i.e. the maximum loss expected from adverse weather conditions for a given level of confidence over a given period of time (Toeglhofer et al., 2012) – for two different return periods:

- Weather-VaR (0.8), i.e. a 1-in-5-year event
- Weather-VaR (0.9), i.e. a 1-in-10-year event

The concept of Weather-VaR is applied to the CDF of tourism revenues under both, reference ('REF') and future ('FUT1') climatic conditions. Additionally, a third indicator is pointed out, expressing the future risk of tourism revenue losses for the selected return periods relative to the revenues expected under average weather conditions of the reference period ('FUT2').

As illustrated in the top left plot of Fig. 4 and outlined in Table 4, the risk of weather-related tourism revenue losses in Sardinia during winter season is rather small, both measured in absolute and relative terms. Given the climatic conditions of the reference period, 'adverse' weather conditions as statistically occurring every five years lead to revenue losses of about 0.3 million euros or 1.3% compared to tourism revenues under average weather. Results further suggest that the risk of weather-induced revenue losses will remain more or less the same under future climatic conditions.

Given reference climatic conditions, tourism revenues during summer season face weather-induced risks of similar relative size as tourism revenues during wintertime. However, the risk of weather-induced losses during summertime is expected to increase considerably under future climatic conditions, particularly due to a rise in the probability of occurrence of 'too hot days'. As illustrated in the bottom left plot of Fig. 4, the weather-dependent CDF becomes flatter due to climate change. Hence, weather-induced variability in tourism revenues increases, which means that both, the risk for losses and the chance for gains rise, with the former being somewhat more pronounced. In addition, there is a slight decrease in the revenues expected under average weather conditions, which is reflected by higher Weather-VaR estimates for 'FUT2' than 'FUT1'.

Spring and autumn show the largest fraction of tourism revenues at risk from 'adverse' weather conditions, as occurring every five or ten years under reference climatic conditions. Weather-VaR estimates for future climatic conditions ('FUT1') however indicate the weather-related revenue risks in both seasons to decrease, at least for the return periods outlined in Table 4. Besides changes in the slopes of the weather-related CDFs, results additionally suggest a considerable overall shift to the right. Hence, under future climatic conditions tourism

Table 4
Weather-VaR (α) of tourism revenues in Sardinia (residents & foreigners) under reference (REF) and future (FUT) climatic conditions, separated by season.

	Winter (DJF)		Spring (MAM)		Summer (JJA)		Autumn (SON)	
	[MEUR]	[%]	[MEUR]	[%]	[MEUR]	[%]	[MEUR]	[%]
$\alpha = 0.80$								
REF	0.3	1.3	3.9	3.5	9.4	1.3	4.5	2.3
FUT1	0.3	1.4	3.5	2.9	26.5	3.6	2.5	1.2
FUT2	0.3	1.3	–	–	31.6	4.3	–	–
$\alpha = 0.90$								
REF	0.5	1.9	6.0	5.4	15.1	2.0	8.0	4.0
FUT1	0.5	2.1	5.2	4.4	40.7	5.5	3.9	1.9
FUT2	0.5	2.0	–	–	45.8	6.2	–	–

Table 5
Weather-VaR (α) of tourism revenues in Cap Bon under reference (REF) and future (FUT) climatic conditions, separated by season.

	Winter (DJF)		Spring (MAM)		Summer (JJA)		Autumn (SON)	
	[MEUR]	[%]	[MEUR]	[%]	[MEUR]	[%]	[MEUR]	[%]
α = 0.80								
REF	1.0	3.1	1.7	2.0	4.5	1.8	2.6	2.2
FUT1	1.3	3.9	3.0	3.6	13.9	5.7	2.7	2.2
FUT2	0.1	0.2	–	–	23.9	9.5	0.1	0.1
α = 0.90								
REF	1.6	5.2	2.1	2.6	7.4	2.9	4.2	3.5
FUT1	1.9	6.0	3.7	4.4	23.0	9.5	4.0	3.5
FUT2	0.7	2.4	0.3	0.4	33.0	13.1	1.4	1.2

revenues in spring and autumn are expected to exhibit an overall increase compared to reference conditions (see right plots in Fig. 4). This overall rise in average tourism revenues is likely to even exceed revenue losses related to a 1-in-5 or a 1-in-10-year event under future climatic conditions. That is why no Weather-VaR figures are outlined in case of 'FUT2'.

In contrast to Sardinia, the largest fraction of tourism revenues at risk from 'adverse' weather conditions, as occurring every five or ten years under reference climatic conditions in Cap Bon, is found for wintertime followed by autumn (see Table 5). Weather-VaR estimates for future climatic conditions ('FUT1') suggest the weather-related revenue risks in all seasons but autumn to rise, at least for the return periods outlined in Table 5. As regards winter and spring, this increase in the risk of weather-induced losses is however over-compensated by an overall increase in tourism revenues, i.e. an overall shift of the respective weather-dependent CDFs to the right (see Fig. 5). Hence, expressed relative to the revenues expected under average reference climatic conditions (i.e. 'FUT2') the revenues at risk from 'adverse' weather conditions turn out smaller than expressed relative to the revenues expected under average future climatic conditions (i.e. 'FUT1'). The weather-dependent CDF of tourism revenues during autumn as well faces an overall shift to the right. During summertime, rising weather risks are in contrast accompanied by an overall decrease in tourism revenues, i.e. an overall shift of the weather-dependent CDF to the left. Hence, taking the change in average summer tourism revenues into account intensifies the rise in the Weather-VaR estimates from reference to future climatic conditions.

3.2. 'Approach B'

Tables 6 to 8 summarize the interim results following the first step of '*Approach B*', i.e. the estimation of tourism demand models where all months of the year are considered within one and the same regression model. Models were estimated using two different versions of the 'Simple Beach Index' to represent meteorological conditions. Tables with the results on the second SBI version can be found in Appendix A. Each table outlines the estimated unstandardized OLS coefficients ("Estimate") along with the OLS standard errors ("Std. error"), p-values

Table 6
Regression analysis results for residential overnight stays in Sardinia, using SBI_1.

Variable	Estimate	Std. error	Betas	p-Value	SC_{OLS}	SC_{HAC}
Constant	4.139	1.279		0.001	**	**
SBI1	−0.015	0.001	−0.501	0.000	***	***
DEPyear (−12)	0.059	0.059	0.100	0.000	***	***
Jun.	0.868	0.093	0.200	0.000	***	***
Jul./Aug.	1.576	0.092	0.488	0.000	***	***
Sep.	1.013	0.089	0.233	0.000	***	***
Easter	0.442	0.442	0.101	0.000	***	***

Dependent variable: natural logarithm of monthly residential overnight stays in Sardinia; adj. $R^2 = 0.9481$; n = 245.
***Significant at 0.1%, **significant at 1%, *significant at 5%.

Table 7
Regression analysis results for foreign overnight stays in Sardinia, using SBI_1.

Variable	Estimate	Std. error	Betas	p-Value	SC_{OLS}	SC_{HAC}
Constant	2.922	0.694		0.000	***	***
SBI_1	−0.020	0.001	−0.511	0.000	***	***
DEPyear (−12)	0.076	0.005	0.268	0.000	***	***
LowSeason	−1.509	0.074	−0.467	0.000	***	***
CPIratio	−20.290	11.100	−0.030	0.059	°	°
$\ln XRT_{GBP\_EUR}$ (−1)	1.448	0.879	0.026	0.091		°
$\ln XRT_{USD\_EUR}$ (−1)	1.330	0.930	0.022	0.154		°
ln(GDP)	2.410	1.488	0.025	0.124		

Dependent variable: natural logarithm of monthly foreign overnight stays in Sardinia; adj. $R^2 = 0.9487$; n = 244.
***Significant at 0.1%, **significant at 1%, *significant at 5%, °significant at 10%.

and significance codes ("SC_{OLS}"). Additionally, standardized coefficients ("Betas") and significance codes based on autocorrelation and heteroscedasticity consistent standard errors ("SC_{HAC}") are presented. All final models exhibit normally distributed residuals according to the Anderson–Darling test (Anderson and Darling, 1954) and/or the Kolmogorov–Smirnov test (Kolmogorov, 1933; Smirnov, 1948) at a confidence level of 10%.

Table 6 presents the regression results of the model explaining residential overnight stays in Sardinia and using version 1 of the SBI to represent the monthly share of days with unacceptable temperature or precipitation conditions for beach holidays. The coefficients of all variables selected to enter the final model are statistically significant and exhibit the expected sign. As illustrated by the standardized beta coefficients, the SBI shows the biggest effect on monthly overnight stays among the variables included in the model. When using version 2 of the SBI instead, its explanatory power regarding variations in monthly residential overnight stays seems somewhat smaller (see Table A.1 in Appendix A). As illustrated by the standardized beta coefficients in Table A.1, the SBI then only exhibits the second biggest effect on monthly overnight stays behind the dummy for July/August, the two months with the highest fraction of non-school days in Italy.

When modelling foreign overnight stays a low-season dummy ("LowSeason"), indicating the time between November and March, was included to ensure normally distributed residuals. Table 7 illustrates the regression results of the model using version 1 of the SBI. The coefficients of all variables selected to enter the final model show the expected sign. Similar to the model explaining residential overnight stays, SBI_1 shows the biggest effect among all variables included. When using version 2 of the SBI instead, its explanatory power regarding variations in monthly foreign overnight stays even increases (see Table A.2 in Appendix A). As indicated by the standardized beta coefficients in Table A.2, the SBI thus remains to show the biggest effect on monthly overnight stays among all variables included.

Table 8 shows the regression results of the model explaining total overnight stays in Cap Bon and using version 1 of the SBI. Apart from lagged annual overnight stays, denoted by DEPyear (−12), the coefficients of all variables selected to enter the final model are statistically significant and show the expected sign. As illustrated by the standardized

Table 8
Regression analysis results for overnight stays in Cap Bon, using SBI_1.

Variable	Estimate	Std. error	Betas	p-Value	SC_{OLS}	SC_{HAC}
Constant	18.548	3.402		0.000	***	***
SBI_1	−0.016	0.001	−0.758	0.000	***	***
DEPyear (−12)	−0.033	0.022	−0.053	0.133		
Jul.	0.503	0.091	0.185	0.000	***	***
Aug.	0.748	0.089	0.275	0.000	***	***
9/11	−0.218	0.061	−0.129	0.001	***	***
Easter	0.269	0.086	0.099	0.000	**	***

Dependent variable: natural logarithm of monthly overnight stays in Cap Bon; adj. $R^2 = 0.8616$; n = 137.
***Significant at 0.1%, **significant at 1%, *significant at 5%.

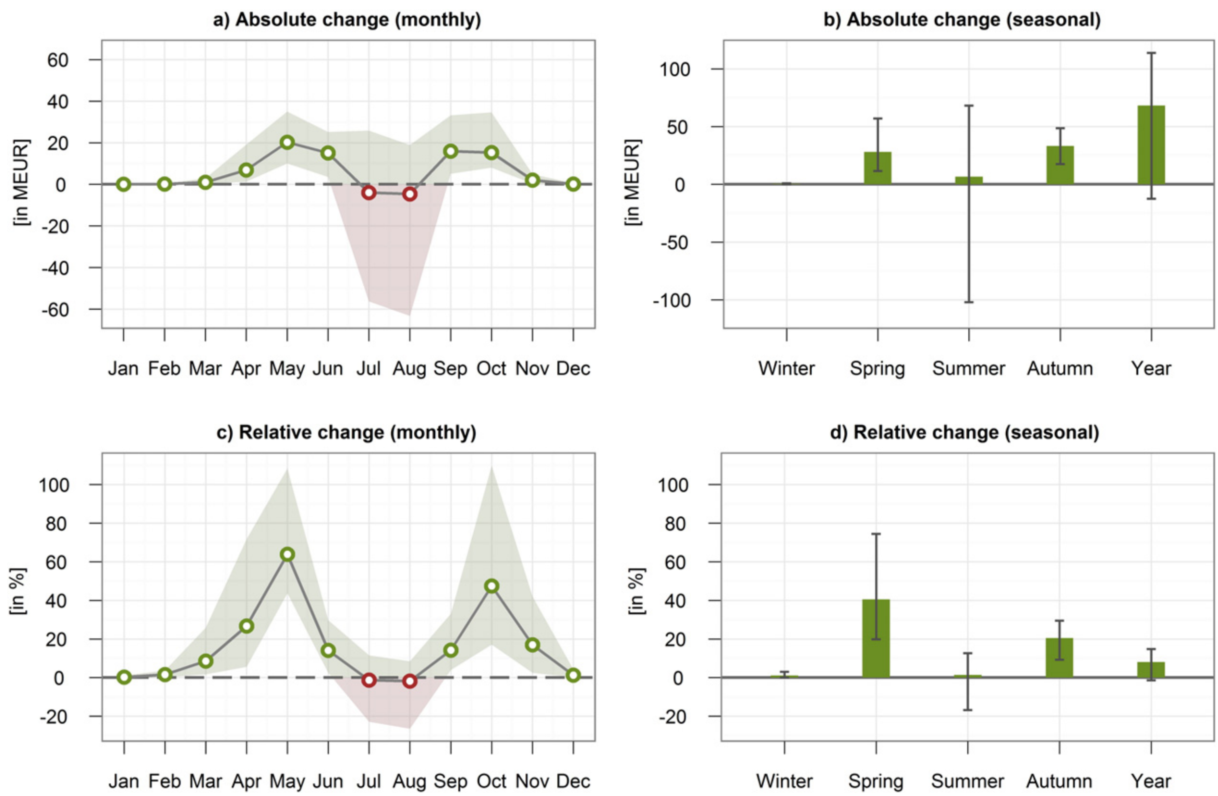

Fig. 6. Average change in tourism revenues in Sardinia due to a change from reference (1971–2000) to future (2041–2070) climatic conditions. Shaded areas and error bars represent the uncertainty resulting from the consideration of four different climate models and two different versions of the SBI, whereas circles and bars indicate the mean of the eight different simulation results.

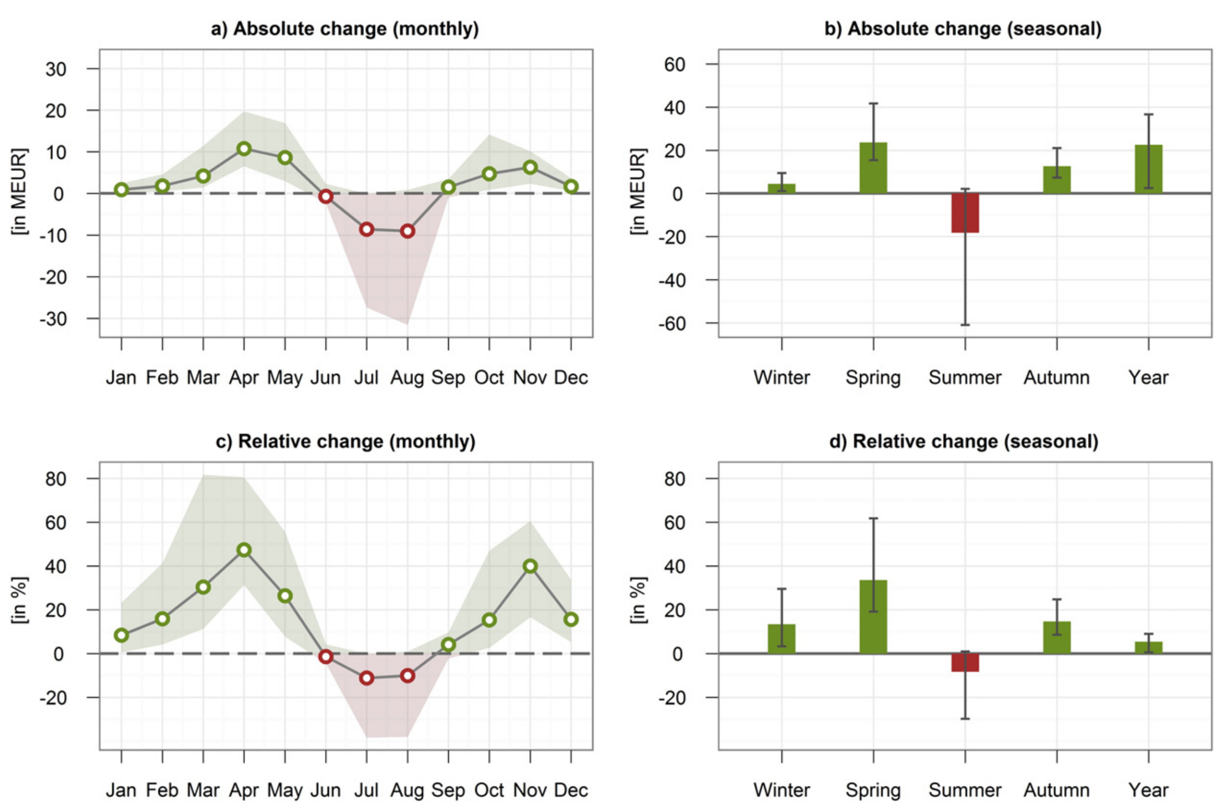

Fig. 7. Average change in tourism revenues in Cap Bon due to a change from reference (1971–2000) to future (2041–2070) climatic conditions. Shaded areas and error bars represent the uncertainty resulting from the consideration of four different climate models and two different versions of the SBI, whereas circles and bars indicate the mean of the eight different simulation results.

Table 9
Average percentage change in tourism revenues due to a change from reference to future climatic conditions (multi-simulation mean) — comparison of '*Approach A*' and '*Approach B*'.

	Winter (DJF)	Spring (MAM)	Summer (JJA)	Autumn (SON)	Year
Sardinia					
Approach A	+1.0%	+6.6%	−1.2%	+3.1%	+0.5%
Approach B	+1.1%	+40.5%	+1.4%	+20.5%	+8.1%
Cap Bon					
Approach A	+4.0%	+4.3%	−5.0%	+1.9%	−1.2%
Approach B	+13.3%	+33.6%	−8.4%	+14.6%	+5.4%

beta coefficients, the SBI shows the by far biggest effect on monthly overnight stays among all variables included. When using version 2 of the SBI instead, its explanatory power regarding variations in monthly overnight stays remains more or less the same (see Table A.3 in Appendix A). Hence, as indicated by the standardized beta coefficients in Table A.3, the SBI remains the variable with the by far biggest effect. In contrast to the model using SBI_1, the variable Easter is however not chosen to be included in the final model by the BIC.

The plots in Fig. 6 illustrate the final results of '*Approach B*' for Sardinia by showing the average change in tourism revenues due to a change from reference to future climatic conditions. Impacts on foreign and residential tourism are already summed up within Fig. 6, but presented separately in Appendix A (see Figs. A.1 and A.2). Outcomes are illustrated on a monthly and a seasonal resolution as well as in absolute and relative, i.e. percentage, terms. Shaded areas and error bars indicate the uncertainty range resulting from the consideration of four climate models and two different versions of the SBI, whereas circles and coloured bars represent the mean of the altogether eight different simulation results. Overall, the outcomes suggest potentials for climate-induced gains in tourism demand and revenues during current shoulder seasons (spring and autumn), but also the threat of losses during the current peak season (July/August) due to increases in the frequency of 'too hot', and hence 'unacceptable', days. However, uncertainty is high, particularly in case of the summer months July and August, where – depending on the climate model applied – positive as well as negative impacts may arise. As indicated by the last bar in the seasonal plots of Fig. 6, annual net impacts are nevertheless suggested to be positive by the majority of model versions.

Results for Cap Bon suggest potentials for climate-induced gains in tourism demand and revenues during current shoulder seasons (spring and autumn) and to a smaller extent also during current low season (winter) (see Fig. 7). The summer months June to August are, by contrast, expected to face the threat of climate-induced losses due to increases in the frequency of 'too hot', and hence 'unacceptable' days. As indicated by the last bar in the seasonal plots of Fig. 7, annual net impacts are nevertheless suggested to be at least slightly positive by all model versions.

3.3. Result comparison

As stated in Section 2.2, '*Approach A*' may underestimate climate-induced shifts in average tourism demand and revenues due to ignoring the climate's potential influence on tourism seasonality. Table 9 compares the average percentage change in tourism revenues due to a change from reference to future climatic conditions as indicated by '*Approach A*' and '*Approach B*'. The reported values represent the mean over all simulation runs. Apart from two exceptions, results of both approaches agree on the impact direction indicated for each season. As regards summer season impacts in Sardinia, note that despite the divergent impact direction indicated by the multi-simulation means, three of the altogether eight simulation runs of '*Approach B*' show negative impacts on tourism revenues, as do all simulation runs of '*Approach A*'. Overall both approaches result in rather similar conclusions: potentials for climate-induced gains in tourism revenues especially during spring and autumn (and also winter in case of Cap Bon) as well as threats of losses during summer. However, compared to '*Approach B*' absolute values of impacts as indicated by '*Approach A*' tend to be (considerably) smaller. This is particularly true for the spring and autumn season. In case of Cap Bon, the comparative underestimation of the positive impacts in winter, spring and autumn by '*Approach A*' causes annual impact directions to diverge between the two approaches applied.

3.4. Potential implications for water management

Water shortages form an issue of high relevance in both case study regions. Already today, water resources are scarce and hydrological modelling results of the CLIMB project suggest even more pronounced water stress due to climate change (Ludwig et al., 2013). Being both "*dependent on fresh water resources and an important factor in fresh water use*" (Gössling et al., 2012, p. 4), the tourism sector is not only affected by, but also contributes to water shortages. Especially the concurrence of peak tourist season and dry season aggravates water management issues. In a peak season day, tourists – including those lodging in non-official structures – raise the population in Sardinia, for instance, by a factor higher than 20 compared to local inhabitants (Statzu and Strazzera, 2009). In some Sardinian regions, the tourist impact factor even exceeds the value of 80. Tourists tend to use more water when they are on holiday than when they are at home (Eurostat, 2009) and hence typically consume relatively more water than local residents (Holden, 2000). Moreover, many tourism establishments are highly water intensive, including, among others, swimming pools, wellness & spa facilities as well as golf courses (Eurostat, 2009). Especially in periods of drought, water consumption needs of the tourism sector aggravate conflict potentials with alternative water users – including local residents, industry and agriculture – in both case study regions (Gafsi and Ben-Hadj, 2010; Statzu and Strazzera, 2009).

According to the results of our analysis, climate change may help to somewhat relax the currently pronounced seasonality of tourism and relieve some of the pressure exerted on water resources during midsummer. On the other hand, total water availability in both case study regions is likely to decrease due to climate change, with significant reductions expected particularly for spring and autumn (Ludwig et al., 2013), i.e. for those times of the year, when climatic conditions for 3S tourism are indicated to further improve and provide potentials for tourism demand gains. Hence, the pressure on water resources and the potential for water conflicts may increase especially during spring and autumn.

As pointed out by Roson and Sartori (2014), increases in tourism demand however not necessarily exacerbate water management problems in already water stressed regions like the Mediterranean: A rise in incoming tourists alters an economy's productive structure, which may lead, among others, to a contraction of the highly water intensive agricultural sector. Related reductions in the water demands of the agricultural sector may in turn outweigh the increased water demands of the tourism sector. Whether this effect also holds true for tourism demand increases in Sardinia and Cap Bon however represents a topic for future research.

3.5. Limitations and uncertainties

The approaches applied in this paper to assess the potential impacts of climate change on tourism in Sardinia and Cap Bon exhibit a range of uncertainties and limitations. First of all, a limited set of four RCMs and one emission scenario was employed to explore climate uncertainties. Although this already gives an idea of the impact range spanned due to climate model uncertainty, considering additional scenarios in future studies – especially as regards the underlying emission scenario – could provide further insights on the robustness of the outcomes.

Second, some climate indices included in the tourism demand models (SBI, TXH, TXC, TXU) are based on the climate preferences of young northern European tourists. Since other tourist segments may differ in their climatic perceptions, using alternative threshold levels in creating the respective indices may better reflect the climatic perceptions of the regions' actual tourist mix. Moreover, climate preferences and hence the sensitivity of tourism demand towards weather and climate may change over time (see e.g. Rosselló and Santana-Gallego, 2014). This is not accounted for in the approaches applied.

Third, in our analyses, we mainly concentrate on the currently dominant tourism type, i.e. 3S tourism. However, as for instance in the case of Sardinia, there has been a noticeable increase in culture-, trekking-, mountain-biking- and agrotourism in recent years. With 3S tourism tendentially requiring higher temperature ranges than the mentioned alternative tourism types, potentials for general tourism demand gains in late autumn, winter and early spring may be underestimated by the present paper.

Fourth, it is far from clear if tourists will actually be flexible and willing enough to considerably change the season of travelling. Flexibility and willingness regarding the travelling season however represents one of the non-climatic factors co-determining the scale of actual climate change impacts a destination will face. Assume for instance that the majority of people visiting Cap Bon were highly flexible with respect to their travelling date and highly loyal towards their destination, then the expected increase in 'unacceptable' climatic conditions during summertime is likely to just shift parts of tourism demand to those seasons, for which climate is expected to become more suitable. If however the majority of tourists are inflexible in their travelling date, the expected increase in unacceptable climatic conditions during summertime is likely to shift parts of tourism demand to other destinations instead of other seasons. Hence, in case of high temporal inflexibility – e.g. due to institutional settings or personal preferences – the potentials due to improving climatic conditions in current shoulder and off-peak seasons would not be realized. Given the ageing population in Europe, there are nevertheless reasons to expect some increase in travel date flexibility (Amelung and Moreno, 2012).

Fifth, climate change in sending countries and competing destinations has not been taken into account in our analyses. If climatic conditions for 3S tourism in sending countries improved relative to the climatic conditions in our case study regions, more tourists would possibly spend their holidays in their own countries, which would intensify negative and dampen positive direct climate change impacts on tourism demand in the case study regions. A similar argumentation holds true for climate change in competing destinations. If climatic conditions for 3S tourism in competing destinations improved (worsened) relative to the climatic conditions in our case study regions, positive direct climate change impacts on tourism demand in the case study regions would likely be dampened (intensified) and negative direct climate change impacts intensified (dampened).

Sixth, we focused on potential direct impacts of climate change on tourism demand. However, indirect impacts via climate-induced alterations in tourism relevant environmental factors may also be of significant scale. There is a range of environmental resources co-determining the attractiveness of the case study regions that might be negatively affected by climate change, including sea water quality, sea level, biodiversity, and landscape aesthetics. In addition, climate change is also likely to affect the regions' tourism industries by altering their operating costs, including cooling and water costs. With total available water expected to further decrease in future, the price for water is likely to rise. Possible measures for the tourism industry to adapt to decreasing water availability include water conservation, recycling of wastewater and desalination. Whereas measures related to water conservation may bring about cost savings, recycling of wastewater and desalination pose additional costs on the tourism industry and hence diminish its profits.

Last, but not least, the quality of data used is partly questionable. Hence, especially in case of Cap Bon results should be interpreted with caution.

4. Conclusions

Two different regression approaches were employed to assess the potential direct impacts of climate change on tourism in Sardinia (Italy) and Cap Bon (Tunisia). Results suggest the climatic conditions for the dominant 3S tourism type to improve in shoulder seasons (spring and autumn), but deteriorate in the summer peak season (especially in July and August) due to increased heat stress. Hence, based on the currently observed relationship between tourism demand and climatic conditions, there is the potential for climate-induced revenue gains in the shoulder seasons and the threat of climate-induced revenue losses in the summer months. Annual net impacts are however expected to be (slightly) positive in both case study regions. Provided enough temporal flexibility of tourists as regards their travelling dates, climate change may hence help to somewhat relax the currently pronounced seasonality in tourism and relieve some of the pressure exerted on water resources during midsummer. On the other hand, pressure on water resources may increase during current shoulder seasons, for which total available water is projected to decrease significantly.

Overall, results have nevertheless to be interpreted with some caution since they are subject to various uncertainties and limitations, including changing tourism preferences, data limitations, climate change in sending countries and competing destinations as well as climate scenario uncertainty.

Acknowledgements

This study has been developed within the project CLIMB (Climate Induced Changes on the Hydrology of Mediterranean Basins: Reducing Uncertainty and Quantifying Risk through an Integrated Monitoring and Modelling System, http://www.climb-fp7.eu), funded by the European Commission's 7th Framework Programme. We would like to acknowledge the formal and informal inputs from members of the CLIMB consortium during the three years of the project. We also acknowledge the E-OBS dataset from the EU-FP6 project ENSEMBLES (http://ensembles-eu.metoffice.com) and the data providers in the ECA&D project (http://www.ecad.eu).

Appendix A

Table A.1
Regression analysis results for residential overnight stays in Sardinia, using SBI_2.

Variable	Estimate	Std. error	Betas	p-Value	SC_{OLS}	SC_{HAC}
Constant	3.865	1.190		0.001	**	*
SBI_2	−0.012	0.001	−0.421	0.000	***	***
DEPyear (−12)	0.059	0.008	0.099	0.000	***	***
Jun.	1.062	0.077	0.244	0.000	***	***
Jul./Aug.	1.860	0.070	0.576	0.000	***	***
Sep.	1.229	0.073	0.283	0.000	***	***
Easter	0.393	0.060	0.090	0.000	***	***

Dependent variable: natural logarithm of monthly residential overnight stays in Sardinia; adj. $R^2 = 0.9547$; n = 245.
***Significant at 0.1%, **significant at 1%, *significant at 5%.

Table A.2
Regression analysis results for foreign overnight stays in Sardinia, using SBI_2.

Variable	Estimate	Std. error	Betas	p-Value	SC_{OLS}	SC_{HAC}
Constant	3.912	0.647		0.000	***	***
SBI2	−0.025	0.001	−0.634	0.000	***	***
DEPyear (−12)	0.068	0.005	0.241	0.000	***	***
LowSeason	−1.054	0.104	−0.326	0.000	***	***
CPIratio	−30.12	11.244	−0.045	0.006	**	**
$lnXRT_{GBP\_EUR}$ (−1)	1.445	0.818	0.026	0.102	°	
Easter	0.232	0.104	0.040	0.092	*	°

Dependent variable: natural logarithm of monthly foreign overnight stays in Sardinia; adj. $R^2 = 0.9547$; n = 245.
***Significant at 0.1%, **significant at 1%, *significant at 5%, °significant at 10%.

Table A.3
Regression analysis results for overnight stays in Cap Bon, using SBI_2.

Variable	Estimate	Std. error	Betas	p-Value	SC_{OLS}	SC_{HAC}
Constant	18.564	3.662		0.000	***	***
SBI_2	−0.016	0.001	−0.760	0.000	***	***
DEPyear (−12)	−0.033	0.024	−0.055	0.170		
Jul.	0.418	0.101	0.154	0.000	***	***
Aug.	0.590	0.100	0.217	0.000	***	***
9/11	−0.232	0.066	−0.137	0.001	***	***

Dependent variable: natural logarithm of monthly overnight stays in Cap Bon; adj. $R^2 = 0.8340$; n = 137.
***Significant at 0.1%, **significant at 1%, *significant at 5%.

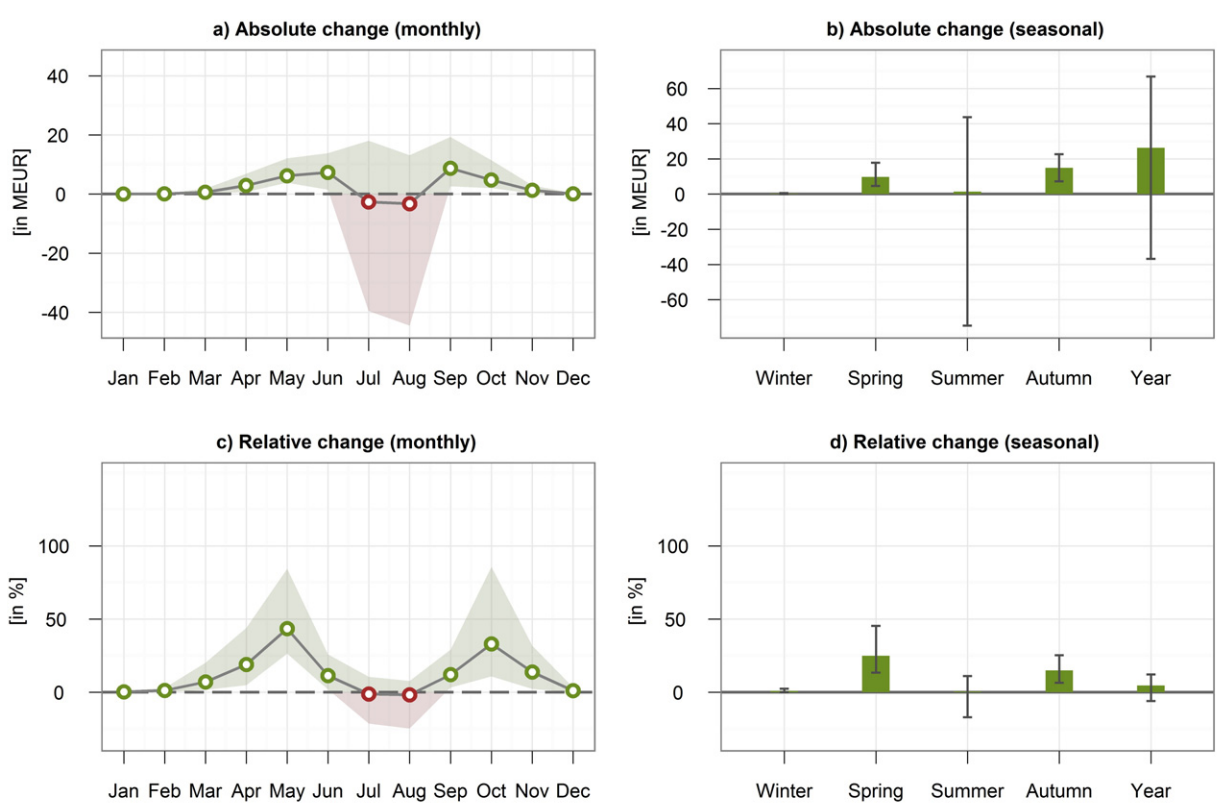

Fig. A.1. Average change in revenues from residential tourists in Sardinia due to a change from reference (1971–2000) to future (2041–2070) climatic conditions. Shaded areas and error bars represent the uncertainty resulting from the consideration of four different climate models and two different versions of the SBI, whereas circles and bars indicate the mean of the eight different simulation results.

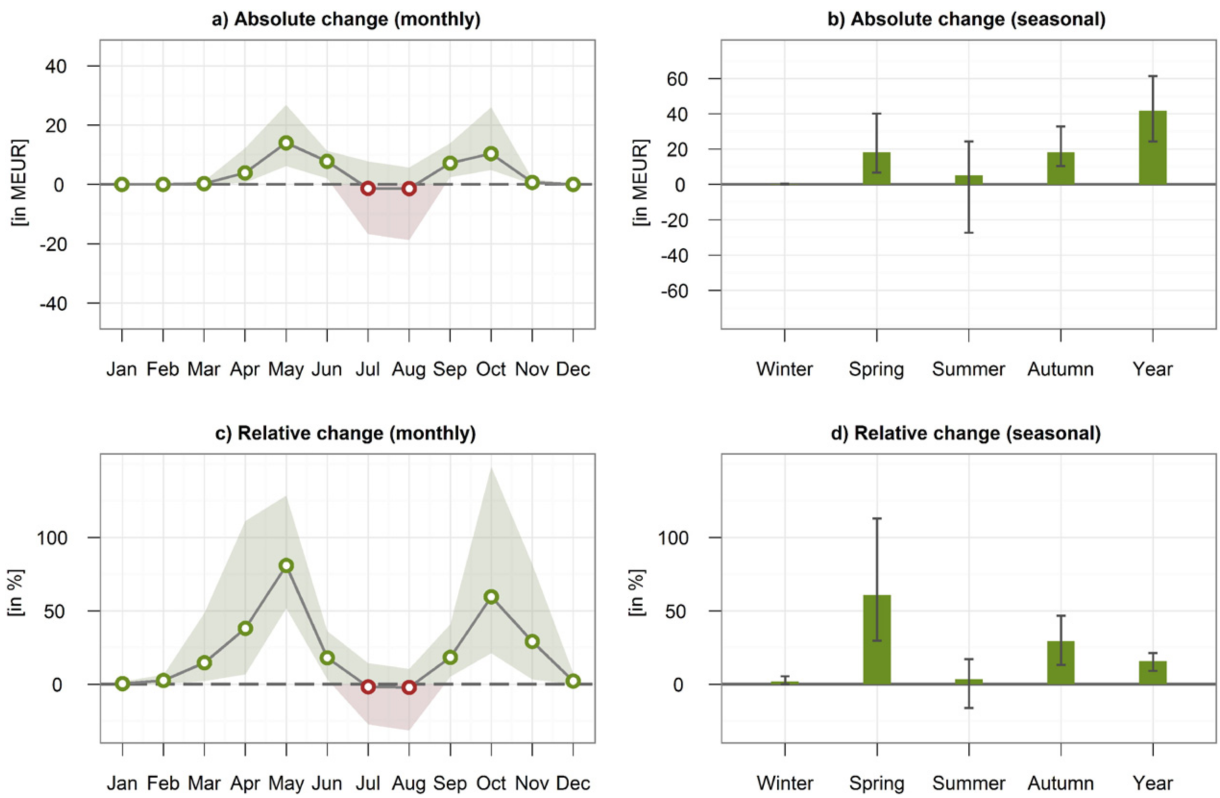

Fig. A.2. Average change in revenues from foreign tourists in Sardinia due to a change from reference (1971–2000) to future (2041–2070) climatic conditions. Shaded areas and error bars represent the uncertainty resulting from the consideration of four different climate models and two different versions of the SBI, whereas circles and bars indicate the mean of the eight different simulation results.

Appendix B. Abbreviations

3S tourism	'sea, sand and sun' tourism
BCI	Beach Climate Index
BIC	Bayesian Information Criterion
DJF	December, January, February
ECA&D	European Climate Assessment & Dataset
(E) CDF	(empirical) cumulative distribution function
E-OBS	a European daily high-resolution gridded dataset of surface temperature and precipitation
FUT	future period, i.e. 2041–2070
GDP	gross domestic product
GRP	gross regional product
INS	Tunisian National Institute of Statistics
ISTAT	Italian National Institute of Statistics
JJA	June, July, August
MAM	March, April, May
MEUR	million euros
OLS	ordinary least squares
ONTT	Tunisian National Tourism Authority
PoO	probability of occurrence
REF	reference period, i.e. 1971–2000
RCM	regional climate model
SBI	Simple Beach Index
SON	September, October, November
sq. km	square kilometre
TAW	total available water
TCI	Tourism Climate Index
%-points	percentage points

References

Agnew, M.D., Palutikof, J.P., 2006. Impacts of short-term climate variability in the UK on demand for domestic and international tourism. Clim. Res. 31, 109–120. http://dx.doi.org/10.3354/cr031109.

Amelung, B., Moreno, A., 2012. Costing the impact of climate change on tourism in Europe: results of the PESETA project. Clim. Chang. 112, 83–100. http://dx.doi.org/10.1007/s10584-011-0341-0.

Amelung, B., Viner, D., 2006. Mediterranean tourism: exploring the future with the tourism climatic index. J. Sustain. Tour. 14, 349–366. http://dx.doi.org/10.2167/jost549.0.

Anderson, T.W., Darling, D.A., 1954. A test of goodness of fit. J. Am. Stat. Assoc. 49, 765–769. http://dx.doi.org/10.1080/01621459.1954.10501232.

Becken, S., 2013. Measuring the effect of weather on tourism: a destination- and activity-based analysis. J. Travel Res. 52, 156–167. http://dx.doi.org/10.1177/0047287512461569.

Bigano, A., Goria, A., Hamilton, J., Tol, R.S.J., 2005. The effect of climate change and extreme weather events on tourism. Working Paper No. 2005.30. Fondazione Eni Enrico Mattei.

Cai, M., Ferrise, R., Moriondo, M., Nunes, P.A.L.D., Bindi, M., 2011. Climate change and tourism in Tuscany, Italy: what if heat becomes unbearable? SSRN Scholarly Paper No. ID 1942347. Social Science Research Network, Rochester, NY

Canales, P., Pardo, Á., 2011. Assessing weather risk in sun and sand destinations. Environ. Econ. 2, 50–61.

Canova, F., Hansen, B.E., 1995. Are seasonal patterns constant over time? A test for seasonal stability. J. Bus. Econ. Stat. 13, 237. http://dx.doi.org/10.2307/1392184.

Castellani, M., Mussoni, M., Pattitoni, P., 2010. Air passengers and tourism flows: evidence from Sicily and Sardinia. Working Paper Series. The Rimini Centre for Economic Analysis.

Corsale, A., 2011. Environmental conflicts and sustainable water policies in the Mediterranean region: the case of Sardinia. Coll. Geogr. 9, 121–130.

Deidda, R., Marrocu, M., Caroletti, G., Pusceddu, G., Langousis, A., Lucarini, V., Puliga, M., Speranza, A., 2013. Regional climate models' performance in representing precipitation and temperature over selected Mediterranean areas. Hydrol. Earth Syst. Sci. 17, 5041–5059. http://dx.doi.org/10.5194/hess-17-5041-2013.

ECA&D, 2011. E-OBS Gridded Data Set Version 5.0.

ECA&D, 2012. Indices dictionary [WWW document]. URL, http://eca.knmi.nl/indicesextremes/indicesdictionary.php (accessed March 2012).

Eurostat, 2009. MEDSTAT II: "Water and Tourism" Pilot Study.

Gafsi, H., Ben-Hadj, S., 2010. Destinations Developpement de strategies pour un tourisme durable dans les nations mediterraneennes Tunisie: Rapport Final.

Gössling, S., Scott, D., Hall, C.M., Ceron, J.-P., Dubois, G., 2012. Consumer behaviour and demand response of tourists to climate change. Ann. Tour. Res. 39, 36–58. http://dx.doi.org/10.1016/j.annals.2011.11.002.

Hadwen, W.L., Arthington, A.H., Boon, P.I., Taylor, B., Fellows, C.S., 2011. Do climatic or institutional factors drive seasonal patterns of tourism visitation to protected areas across diverse climate zones in Eastern Australia? Tour. Geogr. 13, 187–208. http://dx.doi.org/10.1080/14616688.2011.569568.

Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones, P.D., New, M., 2008. A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. J. Geophys. Res. Atmos. 113, D20119. http://dx.doi.org/10.1029/2008JD010201.

Hein, L., 2007. The impact of climate change on tourism in Spain. CICERO Work. Pap. 2007.

Holden, A., 2000. Environment and Tourism. Psychology Press.

ISTAT, 2010. Statistiche del turismo.

ISTAT, 2012. Conti economici regionali.

Kolmogorov, A.N., 1933. Sulla determinazione empirica di una legge di distribuzione. G. Ist. Ital. Attuari 4, 83–91.

Kutner, M., Nachtsheim, C., Neter, J., 2004. Applied Linear Regression Models. 4th edition. McGraw-Hill/Irwin, Boston; New York.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? J. Econ. 54, 159–178. http://dx.doi.org/10.1016/0304-4076(92)90104-Y.

Lohmann, M., Kaim, E., 1999. Weather and holiday destination preferences image, attitude and experience. Tour. Rev. 54, 54–64. http://dx.doi.org/10.1108/eb058303.

Ludwig, R., Soddu, A., Duttmann, R., Baghdadi, N., Benabdallah, S., Deidda, R., Marrocu, M., Strunz, G., Wendland, F., Engin, G., Paniconi, C., Prettenthaler, F., Lajeunesse, I., Afifi, S., Cassiani, G., Bellin, A., Mabrouk, B., Bach, H., Ammerl, T., 2010. Climate-induced changes on the hydrology of Mediterranean basins: a research concept to reduce uncertainty and quantify risk. Fresenius Environ. Bull. 19, 2379–2384.

Ludwig, R., Roson, R., Zografos, C., 2013. Climate Change Impacts on Water and Security in Southern Europe and Neighbouring Regions: A Summary for Policymakers from the CLIWASEC Cluster of Projects.

Mieczkowski, Z., 1985. The tourism climatic index: a method of evaluating world climates for tourism. Can. Geogr. 29, 220–233. http://dx.doi.org/10.1111/j.1541-0064.1985.tb00365.x.

Moreno, Á., 2010. Climate Change and Tourism: Impacts and Vulnerability in Coastal Europe. (PhD Dissertation). University of Maastrich, The Netherlands.

Moreno, A., Amelung, B., 2009. Climate change and tourist comfort on Europe's beaches in summer: a reassessment. Coast. Manag. 37, 550–568. http://dx.doi.org/10.1080/08920750903054997.

Morgan, R., Gatell, E., Junyent, R., Micallef, A., Özhan, E., Williams, A.T., 2000. An improved user-based beach climate index. J. Coast. Conserv. 6, 41–50. http://dx.doi.org/10.1007/BF02730466.

OECD, 2012. OECD. Stat. Organisation for Economic Co-operation and Development, Paris.

ONTT, 2014. Le Tourisme Tunisien en Chiffres.

Perch-Nielsen, S.L., Amelung, B., Knutti, R., 2010. Future climate resources for tourism in Europe based on the daily Tourism Climatic Index. Clim. Chang. 103, 363–381. http://dx.doi.org/10.1007/s10584-009-9772-2.

Prettenthaler, F., Köberl, J., Bird, D.N., 2015. "Weather value at risk": a uniform approach to describe and compare sectoral income risks from climate change. Sci. Total Environ. http://dx.doi.org/10.1016/j.scitotenv.2015.04.035.

Regione del Veneto, 2009. Statistical Report 2009 — the Veneto: sharing and comparing facts. Chapter 10: Tourism and Tourism Flows.

Roson, R., Sartori, M., 2014. Climate change, tourism and water resources in the Mediterranean. Int. J. Clim. Chang. Strateg. Manag. 6, 212–228. http://dx.doi.org/10.1108/IJCCSM-01-2013-0001.

Rosselló, J., Santana-Gallego, M., 2014. Recent trends in international tourist climate preferences: a revised picture for climatic change scenarios. Clim. Chang. 124, 119–132. http://dx.doi.org/10.1007/s10584-014-1086-3.

Rutty, M., 2009. Will the Mediterranean Become "Too Hot" for Tourism? A Reassessment. (Master's Thesis). University of Waterloo, Canada.

Rutty, M., Scott, D., 2010. Will the Mediterranean become "too hot" for tourism? A reassessment. Tour. Hosp. Plan. Dev. 7, 267–281. http://dx.doi.org/10.1080/1479053X.2010.502386.

Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat. 6, 461–464. http://dx.doi.org/10.1214/aos/1176344136.

Scott, D., Lemieux, C., 2010. Weather and climate information for tourism. Procedia Environ. Sci., World Climate Conference — 3 1, pp. 146–183. http://dx.doi.org/10.1016/j.proenv.2010.09.011.

Serquet, G., Rebetez, M., 2011. Relationship between tourism demand in the Swiss Alps and hot summer air temperatures associated with climate change. Clim. Chang. 108, 291–300. http://dx.doi.org/10.1007/s10584-010-0012-6.

Smirnov, N., 1948. Table for estimating the goodness of fit of empirical distributions. Ann. Math. Stat. 19, 279–281. http://dx.doi.org/10.1214/aoms/1177730256.

Song, H., Witt, S.F., 2000. Tourism demand modelling and forecasting. Advances in Tourism Research. Pergamon, Amsterdam.

Statzu, V., Strazzera, E., 2009. Water Demand for Residential Uses in a Mediterranean Region: Econometric Analysis and Policy Implications.

Toeglhofer, C., Mestel, R., Prettenthaler, F., 2012. Weather value at risk: on the measurement of noncatastrophic weather risk. Weather Clim. Soc. 4, 190–199. http://dx.doi.org/10.1175/WCAS-D-11-00062.1.

UNWTO-UNEP-WMO, 2008. Climate Change and Tourism: Responding to Global Challenges. UNEP/Earthprint.