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The effects of climate change on summer beach tourism and possible implications for adaptation

Franz Prettenthaler[1] Kortschak Dominik[1]

Abstract: In this paper we consider the effects of climate change to beach tourism in Europe for the period (2035-2065). We are especially interested in spatial and temporal reallocation of overnights stays under a changed climate and the influence of adaptation measures. Similar to other papers we find that for the period (2035-2065) impacts of climate change on beach tourism are relatively modest. Further we show that successful adaptation of some areas has negative effects for areas that do not adapt.

Keywords: beach tourism, overnight stays, climate change, adaptation

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[1] Joanneum Research, Centre for Climate Energy & Society, Graz, Austria

1 Introduction

In Europe tourism contributes more than 5% to GDP while the share is higher in the Mediterranean countries where tourism contributes more than 10 % to GDP (EEA 2012). In the Mediterranean area tourism is mainly concentrated at coastal areas (Magnan et al 2013). Tourism in general and in particular beach tourism is an industry that is highly dependent on climate resources. With a change in climate, the distribution of these resources is expected to change (compare e.g. Higham and Hall (2005) and Amelung and Moreno (2012)). For touristic regions it is important to know how climate resources will evolve compared to other combatting regions to adequately adapt to implications of a changed climate to tourism demand. More specific this paper is concerned with the question of how touristic flows will change under a changed climate and how possible adaptation measures will change these flows. To measure touristic flows we will use overnight stays. We call this type of analysis, with an associated tool-box and data base for weather or climate sensitivities Weather Driven Demand Analysis (WEDDA). For this specific task, in which we are interested, how the relative distribution of tourists among the different European destinations will evolve due to climate change, we built the WEDDA-Regional Distribution Model (RDM) described below. The WEDDA-RDM is a multi-destination and multi origin model for the estimation of shifts in overnight stays under a changed climate. In this paper we will discuss with the example of beach tourism, how the WEDDA-RDM can be used to analyse the effects of supply site adaptation measures as well as demand side adaptation measures under different climate change scenarios.

Maybe the most important step in estimating the effects of climate change on tourism is to find a suitable climate index that describes climate preferences of tourists for a considered type of tourism. Indices can range from single weather indices like annual mean temperature to more complex indices combining several physical indices.

The most often used climate index is the TCI from Mieczkowski (1985). This index is made out of expert knowledge and is indented to describe the utility of a given climate situation for light outdoor activities (used in e.g. Amelung, B. und Moreno A. (2012), Hein et al. (2009), Nicholls & Amelung, (2008); Amelung et al., (2007), Perch-Nielsen et al. (2010)). However this index cannot be used for beach tourism since when considering beach tourism, optimal temperatures are much higher than for other types of tourism. Based on questionnaires of beach tourists, Morgan et al. (2000) developed a variant of the TCI especially suited for beach tourism. This index is used for example in Amengual et al. (2014) as well as in Moreno and Amelung (2008). Both indices are criticized because they do not account for overriding effects (e.g. pleasant thermal conditions can be overridden by precipitation). To incorporate overriding effects, de Freitas (2008) developed an index that takes into account different aspects of weather (thermal, physical and aesthetical).

Beside studies that consider the generation of climate indices, other studies (Rutty and Scott (2010), Scott et al. (2008) and Ceron et al. (2013)) use surveys to investigate tourist perception of different weather situations. In this paper we will use results of Rutty and Scott (2010) to construct a beach climate index for beach tourism.

Beside the choice of a climate index, it is also important to relate a climate index to touristic demand. First there are papers that consider the effects of climate change for individual regions, but do not account for substitution effects between different regions. For example Maddison (2001) and and Lise and Tol (2002) use temperature and precipitation to study the effect of climate change to overnight stays. Barrios and Rivas (2013) use TCI and a hedonic price index to measure the effects of climate change on overnights stays. Beside this type of papers, there are also papers that try to compensate for the substitution effects between different destinations regions. For example Hamilton et al (2005), use a log linear model including temperature as explanatory variable to estimate the arrivals of tourists in countries. Under changed climate, arrivals of tourists from a given origin country are distributed according to the new estimated demand. Hamilton and Tol (2007) downscale the results of Hamilton et al (2005) to NUTS1 and NUTS2 regions in Germany, Ireland, UK. Hein et al. (2010) uses TCI to forecast touristic flows for seven destination regions (five Spanish regions, north-western Europe, other Mediterranean), but does not provide a description of the used method. Amelung and Moreno (2012) use TCI as climate index on a log linear model to estimate monthly overnight stays for NUTS2 regions. Under changed climate tourists are than distributed according to the new estimated demand. Amelung and Moreno (2012) do not consider tourists from different origin countries.

Finally, adaptation measures for the tourism sector are discussed in Scott et al. (2009). Adaptation can be separated into demand side adaptation strategies and supply side adaptation measures. The highest adaptation capacity is attributed to the tourists. While Scott et al. (2009) provides a good overview of different adaptation measures, to our knowledge there are no empirical studies that consider the effects of supply side adaption strategies to overnights stays. The effects for demand side adaptation strategies are investigated in Amelung and Moreno (2012) for general tourism in Europe.

To evaluate spatial and temporal redistribution of overnight stays, the WEDDA-RDM has the following improvements over existing models and methods. The WEDDA-RDM uses NUTS3 regions as spatial resolution and month as time resolution. It defines different type of destination regions. Climate dependence of overnight stays depends on the type of destination region. The estimation of the climate dependence uses only regions that can be associated with the considered type and were reliable data of the monthly number of overnight stays is available. This is different from e.g. Amelung and Moreno (2012) and Barrios and Rivas (2013) which concentrate on monthly overnight stays of NUTS2 regions but use yearly data of a region and monthly data of the country to develop their models. WEDDA-RDM will use a new climate index based on results of Rutty and Scott (2010). The index is evaluated using daily weather data. The use of daily weather data to estimate a monthly index is also used in Perch-Nielsen et al. (2010). To study the effect of different adaptation strategies of tourists, we will use a comparable method to Amelung and Moreno (2012). Further we will show how supply side adaptation can be incorporated in WEDDA-RDM.

The rest of the paper is structured as follows: In section 2 we provide details of the used model, and how it is applied to evaluate future distribution of tourists. Further we provide details of underlying data. In Section 3 we provide the results of WEDDA-RDM for beach tourism. Section 4 adds concluding remarks. Finally in the appendix we provide more details on monthly data of overnight stays.

2 Used Method and Data

2.1 MODEL DESCRIPTION

In this paper we want to predict the effects of a changed climate on overnight stays related to beach tourism therefore we will use the WEDDA-RDM. The WEDDA-RDM is based on a multinomial logit model. The impact of climate conditions on overnight stays is estimated using the different climate conditions in different months. Using different climate conditions in different months to estimate a model is for also used in Hein et al. (2010).

2.1.1 WEDDA-RDM

For a set of destination regions I, a set of months M and a set of origin countries O, the WEDDA-RDM predicts the shifts of overnight stays from a set of current climate indices C to a new climate index $\hat{C}$, where the number of overnight stays $ov_{i,m,o} = ov_{i,m,o}(C)$ are known under current climate C. The model is based on climate utility functions $RT_{i,m,o}(C)$ that depend on the destination country i, the month m and the country of origin o. In the model it is assumed that the probability that a tourist of origin country o spends an overnight stay in a region i and month m conditioned that it spends the overnight stay in a region out of the set of regions I and a month out of the set of month M is given by

$$p_{i,m,o}(C) = \frac{\exp(RT_{i,m,o}(C))}{\sum_{j\in I}\sum_{n\in M}\exp(RT_{j,n,o}(C))}.$$

Under a changed climate $\hat{C}$ the WEDDA-RDM predicts that overnight stays from origin country o are distributed according to $p_{i,m,o}(\hat{C})$ among the chosen set of destination regions I and months M, i.e

$$ov_{i,j,o}(\hat{C}) = \frac{p_{i,m,o}(\hat{C})}{p_{(i,m,o)}(C)} \cdot ov_{i,j,o}(C).$$

The utility function in the model is defined as

$$RT_{i,m,o}(C) = g_{i,m}(C) + \epsilon_{i,m,o} + N_{i,o},$$

where $\epsilon_{i,m,o}$ is a parameter that describes the attractiveness of a specific month m for the destination region i for tourists of origin o, $N_{i,o}$ is the attractiveness of the region for tourists of origin country o. $g_{i,m}(\cdot)$ is the climate dependent part of the utility which will be explained later in more detail, and is referred to as impact function. While $g_{i,m}(\cdot)$ can be seen as external variable, $\epsilon_{i,m,o}$ and $N_{i,o}$ are chosen such that the probability that a tourist of origin country o spends an overnight stay in a region i and month m conditioned that it spends the overnight stay in a region out of the set of regions I and a month out of the set of month M is the share of overnight stays of observed overnight stays for the destination region and month, i.e.

$$p_{i,m,o}(C) = \frac{ov_{i,m,o}}{\sum_{j\in I}\sum_{n\in M} ov_{j,n,o}}.$$

Note that shifting from climate C to $\hat{C}$ the utility changes by $RT_{i,m,o}(\hat{C}) - RT_{i,m,o}(C) = g_{i,m}(\hat{C}) - g_{i,m}(C)$.

2.1.2 The climate dependence

The WEDDA-RDM uses different impact functions $g_{i,m}(C)$ for different types of destination regions and season. Currently the WEDDA-RDM uses four types of destinations regions: city regions, beach regions, ski regions and other regions (details on how the regions are allocated to the different destination types are given in section 2.2.2). Further the model distinguishes between the summer season (May to October) and the winter season (November to April). In this paper we concentrate on beach tourism, hence we will only describe in more detail how this impact function is estimated for the summer season and beach regions.

For beach regions in the summer season WEDDA-RDM Model uses the impact function $\mathrm{g_i(C)} = \mathrm{g_i}(\mathrm{BCIR_{i,m}}) = \mathrm{B} \cdot \mathrm{BCIR_{i,m}}$, where B is a parameter and $BCIR_{i,m}$ is a beach climate index (see 2.2.1 for an exact definition). The parameter B is estimated from a set of estimation regions $\tilde{I}$ and the month of the summer season $\widetilde{M}$ (May-October). We use a set of estimation regions $\tilde{I}$ and not all beach regions for the estimation of the parameter since we do not have reliable data on monthly overnight stays for all regions. The data was obtained from the corresponding National Statistical Institutes, this also means that the exact definition of overnight stays differs between different regions; further the size of the considered regions can vary significantly. This means that the absolute number of overnight stays of different regions is not directly comparable. Hence we decided to use only the share of overnight stays in a month $s_m^i = \frac{ov_{i,m}}{\sum_{n \in \widetilde{M}} ov_{i,n}}$ compared to other month in the season for the estimation of the impact function, i.e. we assume that

$$s_m^i \approx \frac{\exp(B\ BCIR_{i,m} + \epsilon_{i,m})}{\sum_{n \in \widetilde{M}} \exp(B\ BCIR_{i,n} + \epsilon_{i,n})}$$

Note that $\epsilon_{i,m}$ is not known. If we set $\epsilon_{i,m} = 0$ for the estimation, we would assume that there are no common patterns in the distribution of overnight stays for all destination regions. This might not be true, since for a given origin country there might be preferences to make holidays in a certain month independent of the climate in the destination regions (e.g Ferragosto in Italy). In the estimation of B we compensate for these effects by replacing $\epsilon_{i,m}$ with the term $A \cdot log(ROV_{i,m})$ where A is a parameter and $ROV_{i,m}$ is an index that relates to the attractiveness of the month for holidays (see section 2.2.2 for more details). For estimation of A and B we use the maximum likelihood method i.e we choose A and B to maximize.

$$\sum_{i \in I} \prod_{m \in \widetilde{M}} (s_m^i)^{\frac{\exp(A \cdot log(ROV_{i,m}) + \mathrm{B} \cdot \mathrm{BCIR_{i,m}})}{\sum_{n \in \widetilde{M}} \exp(A \cdot log(ROV_{i,n}) + \mathrm{B} \cdot \mathrm{BCIR_{i,n}})}}.$$

This defines the impact function.

For other types of regions and seasons (with the exception for ski regions in the winter season) we use the same method for estimating the impact function $g_{i,m}$, but with different climate indices.

2.1.3 Application of the model

To apply the WEDDA-RDM we have to choose a set of origin countries O, a set of destination region I and a set of month M.

As origin countries we use the countries AT, BE, BG, CH, CY, CZ, DE, DK, EE, EL, ES, FI, FR, HU, IE, IS, IT, LT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK, UK, RU, US, CN and JP. In the results section we will only present the total number of overnight stays, therefore we assume that the relative change in total number of overnight stays is the same as for the sum of overnight stays from the considered origin countries.

The actual choice of sets I and M determines how we assume that tourists behave under a changed climate, or in other word determines how the tourists adapt to a changed climate in the model. So the choice of sets I and M can also be interpreted as adaptation strategy of tourists towards a changed climate. In general the set I will consist of a set of comparison region and the considered region. Note that with this method we can also provide changes to regions that are not in I.

We have the following options to choose the set of destination regions I:

- We can choose I as only the considered region, meaning that tourists do not change the destination region (location conservatives).
- We can choose I as the regions with the same type this means that tourists might change the destination but will not change the type of their holidays, e.g. beach tourism is not exchanged with city tourism (activity conservatives).
- We can choose I can be chosen to consist of regions of any type, this means that when climate condition change tourists might also consider changing the type of their holidays, e.g from city to beach (type flexible).

For choosing the set of month M we have the following options:

- We can choose as M only the considered month m. This means that tourists will not consider to change the timing of their holidays (time conservatives).
- We can choose M as the considered season, meaning that tourists consider shifting their holidays inside the season but do not for example consider to change from summer holidays to winter holidays (season conservatives).
- We can choose M as all month of the year (time flexible)

In this paper we will not present results for all possible sets I and M we will rather concentrate on two different sets.

As comparison regions we use beach regions plus the regions ITH59 (Rimini) and ITH35 (Venice) (see Figure 2.1). This is motivated by the observation that for all considered type of regions there are regions with improving and with deteriorating climatic conditions, so it is reasonable to assume that tourists do not change the type of tourism, since they can always find alternatives of the same type. As set of month we either consider the considered month or the summer season. So we neglect the possibility of changing a summer holiday to a winter holiday.

This means that we assume that tourists adapt to a changed climate by either only changing the destination regions, or by changing the destination region and or the timing of the holidays. We should note when we choose M to be the summer season, this does not mean that we assume that the preferences of tourists for a given month changes (e.g. because of a change in the holiday structure). If we want to incorporate such a change we would have to change the attractiveness of a month $\epsilon_{i,m,o}$ for all considered destination regions. Further note that climate change might also change the popularity of a month for holidays, this would also have an impact on the attractiveness of individual months $\epsilon_{i,m,o}$.

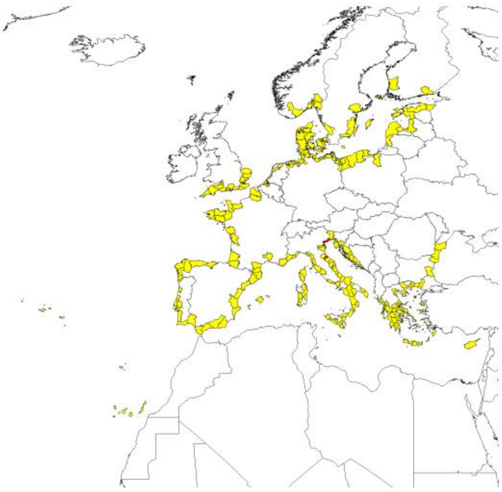

Figure 2.1 The set of regions I that are used for the estimation of the effects of climate change for beach tourism.

With the choice of sets I and M we can study the effects of different adaptation strategies of tourists on overnight stays. In this paper we also want to analyse the effects of supply side adaptation measures on overnight stays. Therefore we have to integrate the effects of supply side adaptation in WEDDA-RDM. We will describe two possibilities of integrating the effects of supply side adaptation measures. First there are adaptation measures which increase the general attractiveness of a region or a month (e.g. improved infrastructure, special offers in the off season), this corresponds to an increase of $N_{i,o}$ respectively $\epsilon_{i,m,o}$. Second there are adaptation measures that lessen the effects of changed climate (e.g. shading). Since for beach regions and the summer season the attractiveness changes with $B(BCIR_{i,m} - \widehat{BCIR}_{(i,m)})$, a possibility to integrate this type of adaptation measure is to change the parameter B when the difference between $BCIR_{i,m} - \widehat{BCIR}_{(i,m)}$ is negative, i.e we replace $g_i(\widehat{BCIR}_{i,m}) = B\ \widehat{BCIR}_{i,m}$ with

$$g_i(\widehat{BCIR}_{i,m}) = \begin{cases} B\ \widehat{BCIR}_{i,m}\ if\ \widehat{BCIR}_{i,m} - BCIR_{i,m} \geq 0 \\ B\ BCIR_{i,m} + B_1(\ \widehat{BCIR}_{i,m} - BCIR_{i,m})\ if\ \widehat{BCIR}_{i,m} - BCIR_{i,m} < 0 \end{cases}$$

Where B_1 measures how successful the applied adaptation measure is. In this paper we will use $B_1 = 0.5 \cdot B$ (adaptation is to 50% successful) or $B_1 = 0$ (adaptation is complete successful).

In this paper we will only consider the second type of adaptation measures, since improving the general attractiveness of a destination region, can be done independent from climate resources, and hence might not be seen as adaptation to a changed climate.

2.2 DATA

2.2.1 Climate data

To calibrate our model, we use two sources of daily weather data. For precipitation we use E-OBS data (gridded from weather station observations across Europe, Haylock et al. 2008). We only use grid cells at the coastline of the considered region. For temperature, humidity, cloud cover and sea surface temperature we use ERA-interim reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (a global re-analysis product). We only use grid cells at the coastline of the considered region and the values for 12:00 UTC. Note that this incorporates some bias in the model since we are considering regions with different geographical longitude. ERA-interim data is also used in (Amengual et al 2014) for the assessment of weather suitability for touristic purposes. With this index we calculated the daily BCIR and aggregated it to monthly values. For the calibration of the model parameters we use the average for the period 1990 to 2011. We use the period 1990-2011 since ERA-interim data is only available to us for the time span 1990 to 2013 and we did not consider the years 2012 and 2013 for the calibration since data of overnights stays were only available to us up to the year 2011 for a reasonable set of origin countries.

For weather data under climate change scenarios we use data from the Euro-CORDEX initiative. We use the outcome of the two CMIP5 global climate models HadGEM2-ES and CNRM-CM5, downscaled with the regional climate model RCA4. For more details on the chosen climate model we refer to (ToPDAd Deliverable 2.1). For the two climate models we calculated the relative change in BCRI for the base period (1979-2009) to the climate change period (2035-2065) and multiply it with the observed BCRI for the period (1990- 2011) to get BCIR for the climate change period. We use a different period than for the estimation since for climate signals at least a time span of 30 years should be used.

The BCIR index is defined through three sub-indices. First, we use a score for temperature that has a maximal value of 100 and is proportional to $\phi(t|\mu,\sigma)$, $\mu = 29.5$ and $\sigma = 4.31$, where ϕ denotes the density of the normal distribution and t the heat index (Steadman 1979) on the considered day. The parameters of the normal distribution are chosen to approximately match the green bars in Figure 4.3 of Rutty (2009). The second sub index is a score for precipitation with value 100 for less than 0.1mm of precipitation, 50 for a precipitation between 0.1 mm and 5 mm and 0 for more than 5 mm of precipitation. The last sub index is a score for sunshine, it evaluates to $100 * (1 - \frac{\min(cloud\ cover - .25, 0)}{0.75})$ where cloud cover is the percentage of cloud cover. BCIR is then the geometric weighted average of the three scores with weights 4.3, 4.4 and 4.6 (compare Rutty 2009 Table 4.4)

Since we use daily data and a geometric average, the whole index evaluates to 0 if one sub index evaluates to 0. This means that precipitation has a quite strong influence on the index. This fact is in accordance with findings of (Ceron et al. 2013).

2.2.2 Socio economic data

For the number of monthly overnight stays we use data from different National Statistical Institutes. For BG, CY, DK, EE, EL, ES, FR, HR, IT and SE we have the monthly number of overnight stays in NUTS3 regions. For NL, PL and PT we have the monthly number of overnight stays in NUTS2 regions. For Germany we have the monthly number of overnights stays in “Reisegebiete” (statistical areas of a size between NUTS2 and NUTS3). This data is mainly used for the estimation of the model. For the estimation of the model we use the average of all years with data.

For the application of the model we need the number of overnight stays for each considered region i, month m and origin country o. Since this data is not available to us, we combine data from different sources to get an estimate of the number of overnight stays in a NUTS3 region and month with origin information. We combine data from three sources: From Eurostat we use monthly number of overnight stays with origin information for countries, yearly number of overnight stays for NUTS2 regions, and yearly number of beds for NUTS3 regions. From UNWTO we use yearly number of overnight stays with origin information. Further we use the data from the National Statistic Institutes. More details are provided in the appendix. We derive the number of overnight stays for the years 1996 to 2011. Note that also Amelung and Moreno (2012) combine data from different spatial levels to get monthly distribution of tourists for NUTS2 regions.

Type of regions and other derived quantities

WEDDA-RDM uses different types of destination regions. We use the following procedure to identify the destination type of a NUTS3 region. A city region, is a region where more than 60 % of overnights are reported in cities or if there is no data on overnight stays for the cities in the region if at least 60 % of population lives in cities. For the overnight stays in cities we use URBAN audit data from Eurostat and for the number of overnights in the region we use the combined data as described above.

Beach regions are all NUTS3 regions that have a coastline, except for the following regions:

- city regions
- regions which have ski areas of at least 70 km combined slope length and are located in Finland, Norway, Sweden or United Kingdom
- regions where the maximal sea temperature (at 12 UTC) between 1990 and 2013 does not exceed 16°C. 16 °C is the lower bound for “neither warm nor cold bathing water temperature” in Table 1 of (Morgan et al. (2000))
- regions that lie too far north, i.e. in the NUTS2 regions Northern and Eastern Finland (FI1D), North Sweden (SE3),UK North East (UKC),UK North West (UKD), or Scotland (UKM).

Ski regions are regions which include ski areas of at least 70 km cumulative slope length and are not beach regions or city regions

Other regions are regions that are neither ski regions, beach regions nor city regions.

For the estimation of the impact function we only want to use regions that can be associated with tourism. Therefore we define touristic regions. We say that a NUTS3 region is a touristic region if two out of the following three criteria are fulfilled:

- The region has more tourists than the average NUTS3 region.
- The region has more overnight stays per inhabitant than Europe.
- The region has more tourists than the average region in the same country.

For regions that are not NUTS3 regions we say that the region is a touristic region, respectively of a specific type, if the majority of beds in NUTS3 regions associated with the region are in a touristic region, respectively in a NUTS3 region of the specific type.

As estimation set $\tilde{I}$ we use beach regions that are also touristic regions and we have data on overnight stays from the corresponding National Statistical Institute. The regions that we use for estimation are depicted in Figure 2.2.

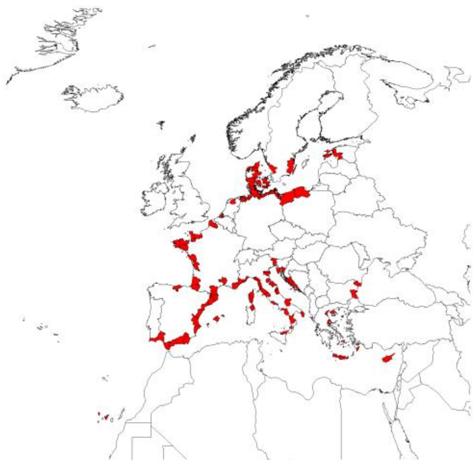

Figure 2.2 Regions $\tilde{I}$ that are used for estimating the impact function $g_{i,m}(C)$ for beach regions and the summer season.

For the estimation of the impact function $g_{i,m}(C)$ we use an index $ROV_{i,m}$, that is a measure of the attractiveness of a month independent of climatic factors in the destination region. The idea behind $ROV_{i,m}$ is that if for example the sum of overnight stays in all destination regions is higher in August than in July, than we expect that for tourists from the considered origin country it is more attractive to make holidays in August than in July. For the calculation of $ROV_{i,m}$ we will only consider overnight stays from two origin countries: Domestic overnight stays, and overnight stays from the country which has the biggest share of foreign overnight stays in the considered destination country (the country in which the considered region is located). For both origin countries we calculate the share of overnight stays (in all destination regions) in the considered month. $ROV_{i,m}$, is the weighted average of these two shares normalized to the summer season (May-October). The weight is the share of foreign tourists in the NUTS2 region in which the considered region is located.

Finally, to get an estimate for the number of future overnight stays for a given origin country, we use the above derived data to calculate the yearly number of overnight stays per inhabitant for the years 2000-2011. We relate this data to GDP per capita of a country. Since with a growing number of overnight stays per inhabitant the rate of growth of overnight stays might slow down, we assumed that the elasticity of overnight stays (per inhabitant) with respect to GDP (per capita) is decreasing with the number of overnight stays per inhabitant. With projections of GDP and population taken from the IIASA Database on SSP, we forecast future number of overnight stays for a given country. The increase in overnight stays is than distributed evenly among all regions and months, i.e. all regions are multiplied with the same factor, providing us with an estimate for the number of overnight stays under current climate.

In this paper we are interested in relative results, i.e. the change in overnight stays compared to a world without climate change. While the estimation of $\mathrm{N_{i,o}}$, $\epsilon_{\mathrm{i,m,o}}$ and the future number of overnight stays have significant impact on the absolute values of future overnights stays in a given region or month, the influence on relative results are significantly smaller, i.e. they only influence the weights of different regions and months in the comparison to each other. So the actual values of $\mathrm{N_{i,o}}$, $\epsilon_{\mathrm{i,m,o}}$ and the future number of overnight stays will have less influence on the results in this paper than the changes in the climate indices.

3 Results

In this section we want to present numerical results of the applied procedure. In section 3.1 we provide some results that show how well we can explain the observed data. In section 3.2 we use WEDDA-RDM to show how climate change and different adaptation strategies might affect future touristic flows.

3.1 RESULTS OF CALIBRATION

After estimating the impact function $g_{i,m}(C)$ for beach regions in the summer season we basically obtain the coefficient relating the climate index BCIR to overnight stays. It is estimated to $B = 0.0122$ which means that a change of 1 in BCIR is related approximately to a 1.2% change in overnight stays.

We want to provide some information on how well the impact function can captures the observed overnight stays. Therefore we calculate the mean squared error of the estimated shares over the variance of the observed shares for regions and month that were used for the estimation, i.e.

$$\frac{\sum_{i\in\tilde{I},m\in\tilde{M}}\left(\frac{\exp\left(A\cdot log\left(ROV_{i,m}\right)+\mathrm{B}\cdot\mathrm{BCIR_{i,m}}\right)}{\sum_{n\in\tilde{M}}\exp\left(A\cdot log\left(ROV_{i,n}\right)+\mathrm{B}\cdot\mathrm{BCIR_{i,n}}\right)}-s_m^i\right)^2}{Var\left(s_m^i\right)}.$$

This measure corresponds to the R^2 in classical regression models and evaluates to 0.84.

For beach region that are also touristic regions we use the monthly utility $A\cdot log\left(ROV_{i,m}\right)+\mathrm{B}\cdot\mathrm{BCIR_{i,m}}$ to estimate the expected share of overnight stays for the summer season (May-October). In Figure 3.1 this expected share is plotted against the logarithm of the observed share of overnight stays. We can observe that there is a clear connection between observed and estimated share, although the variability of observed shares is relatively high. Note that for the estimated share we basically only used the climate index BCIR, and did not take other factors like size, population destination, reachability, quality, prices of hotels, etc of destination regions into account.

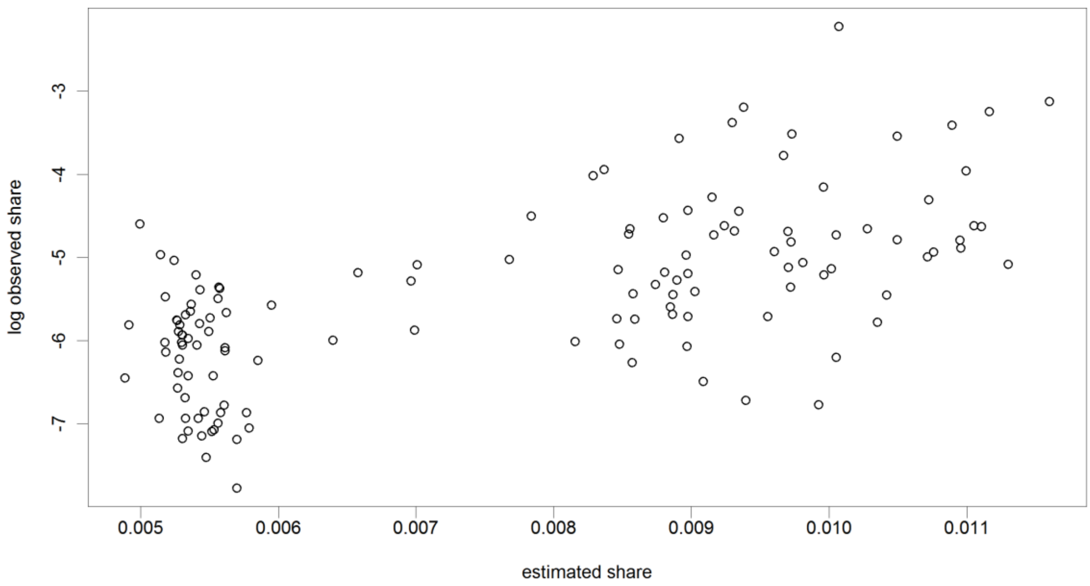

Figure 3.1 Estimated share vs log observed share for touristic beach regions

3.2 THE EFFECT OF CLIMATE CHANGE ON BEACH TOURSIM

In this section we want to show the impact of climate change on summer beach tourism. We will consider the period 2035-2065 and two Representative Concentration Pathways (RCP)/Shared Socio-economic Pathways (SSP) combinations namely RCP4.5/SSP4 and RCP8.5/SSP5. See ToPDAd Deliverable 2.1 for the reason why we have chosen this RCP/SSP combination.

In this paper we will consider the difference of a climate change scenario relative to a baseline scenario, i.e. for each region we compare the number of estimated overnight stays taking only socio economic changes into account against the number of overnight stays when taking also climate change effects into account. For the baseline we use the climate of the period 1979 to 2009.

Difference between different RCP/SSP scenarios: At first we want to consider differences between RCP4.5/SSP4 and RCP8.5/SSP5. For this comparison we use all month in the season as comparison months. At first we can observe that impacts on overnight stays are stronger for RCP8.5/SSP5 than for RCP4.5/SSP4 this is somehow expected because RCP8.5 is associated with a bigger warming than RCP4.5. Beside the difference in magnitude the spatial weather distribution is quite consistent, with the exception that the northern European countries are favoured more by RCP8.5/SSP5 than RCP 4.5/SSP4.

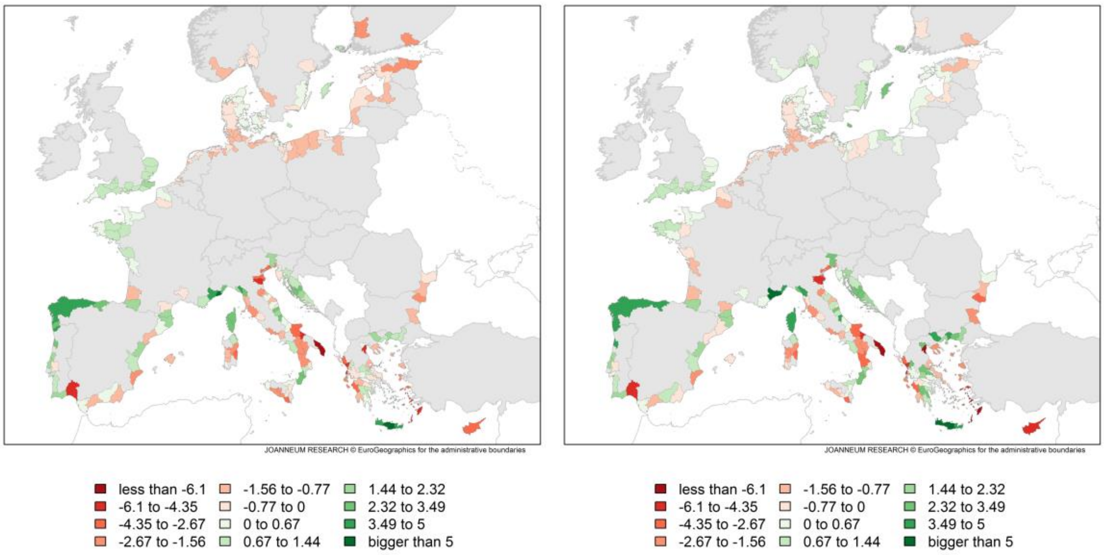

Figure 3.2 Change in overnight stays in [%] for period 2035-2065 compared to base line. RCP4.5/SSP4 (left) and RCP8.5/SSP5 (right) beach regions

Change between different touristic behaviours: In the rest of the paper we will only provide results for RCP4.5/SSP4. In Figure 3.3 we provide the results of two considered touristic adaptation strategies. In the left figure we provide the results when tourists are not changing the timing of holidays and in the right figure we provide the results when tourists can change timing of holidays. While there are differences for single beach regions, the overall picture is quite similar. This means that the choice of touristic adaptation strategies has only limited influence on the seasonal overnight stays for most beach regions. However the temporal distribution of overnight stays is different for the two considered adaptation strategies of tourists.

Figure 3.4 illustrates the change in summer overnight stays (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4, given that tourists do not change timing of holidays. There is a significant increase of overnight stays in colder regions in midsummer (July and August) and a reduction of tourists in the warmer region. The impact of climate change in the shoulder season is significantly smaller and more in favour of the warmer regions. Figure 3.5 illustrates the change in summer overnight stays (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4, given that tourists can change timing of holidays. We can observe that in this case warmer regions gain significant tourists in the shoulder season while they lose overnight stays in midsummer. Finally, for colder regions the gain in midsummer is less pronounced compared to when tourists cannot change timing of holidays.

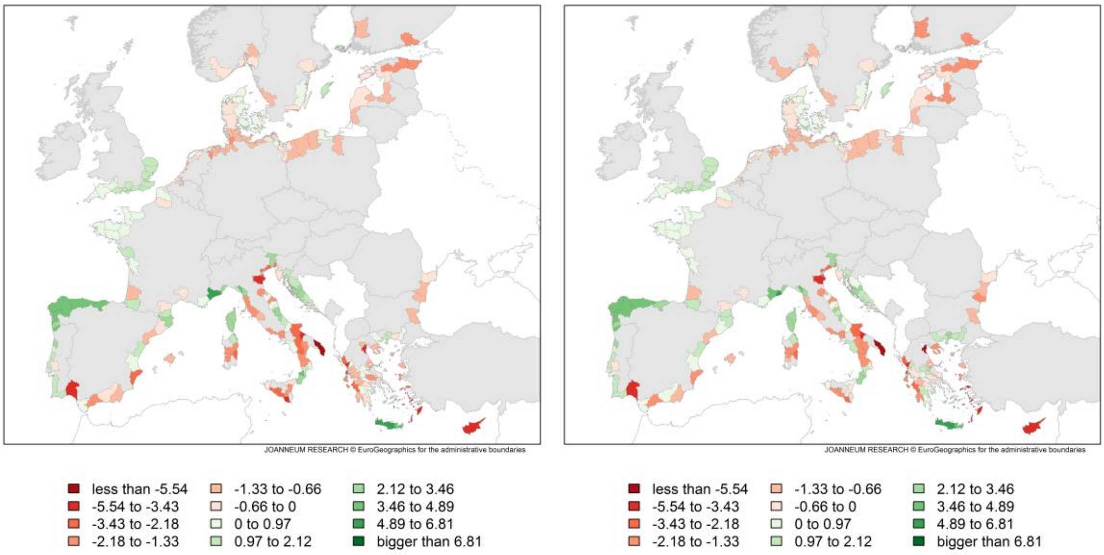

Figure 3.3. Change in summer overnight stays in [%] (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4, when tourists do not change timing (left) or can change timing (right); average over climate models

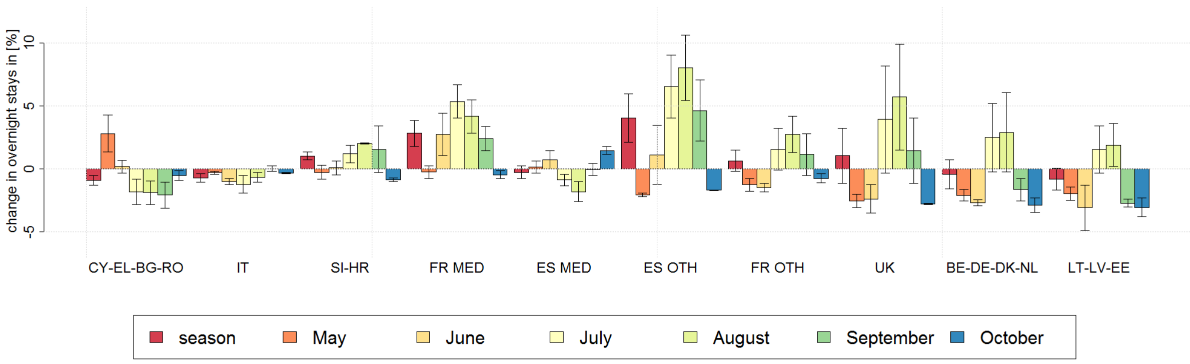

Figure 3.4 Change in summer overnight stays in [%] (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4 when tourists do not change timing; average over climate models (error bars indicate the range of climate scenarios)

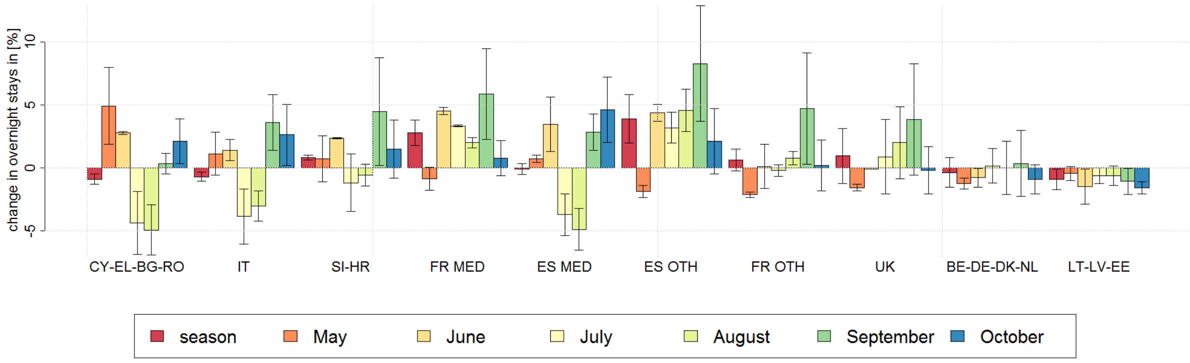

Figure 3.5 Change in summer overnight stays in [%] (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4 period 2035-2065 when tourists can change timing; average over climate models (error bars indicate the range of climate scenarios)

Difference between climate models: In Figure 3.4 and Figure 3.5 we can observe that there is a significant uncertainty stemming from the use of different climate models. Figure 3.6 shows the differences in climate change impacts resulting from these two climate models when tourists change timing for RCP4.5/SSP4. As illustrated by Figure 3.6, the predicted effects differ significantly. This is especially apparent for northern Europe. While the climate scenario based on HadGEM2 results in positive effects, the climate scenario based on CNRM results in negative impacts. Further positive and negative impacts are smaller for CNRM than for HadGEM2.

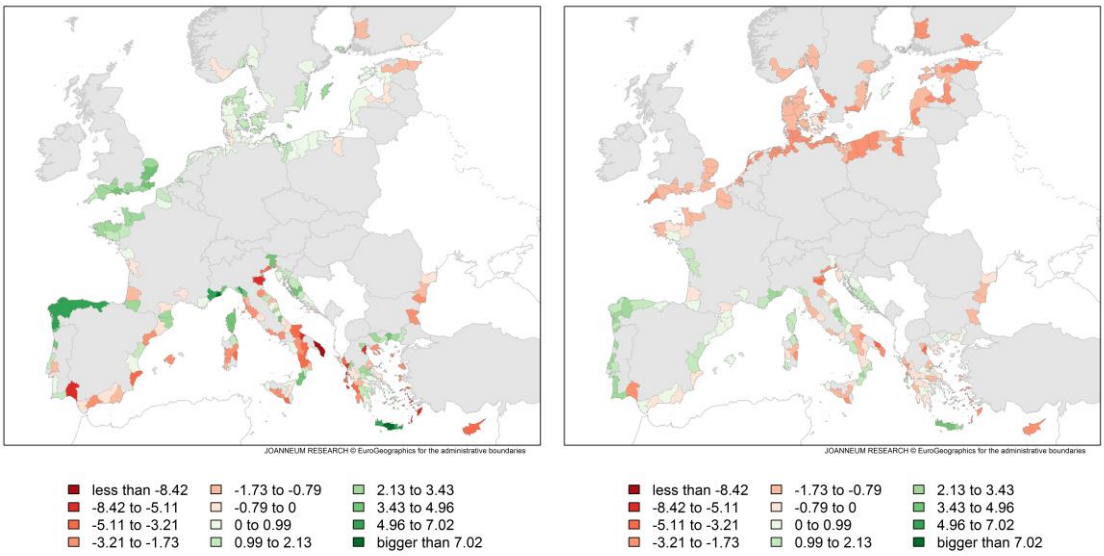

Figure 3.6 Change in summer overnight stays in [%] (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4, when tourists can change timing; climate model HadGEM2 (left) vs. CNRM (right)

Supply side adaptations: In Figure 3.7 and Figure 3.8 we provide results when supply side adaptation measures are considered. We assume that adaptations measures are implemented for beach regions and months with a monthly average heat index above 29. We assume that these adaptation measures are partly successful respectively successful (see above). We can observe that under this adaptation measures especially the south eastern European countries would lose significant less overnight stays in the core season, but also the gain due to overnight stays in the shoulder season is reduced. In addition, total losses are significantly reduced region might still lose overnight stays because of increased competition. Further we can observe that a successful adaptation for warm beach regions has negative effects for areas of other regions.

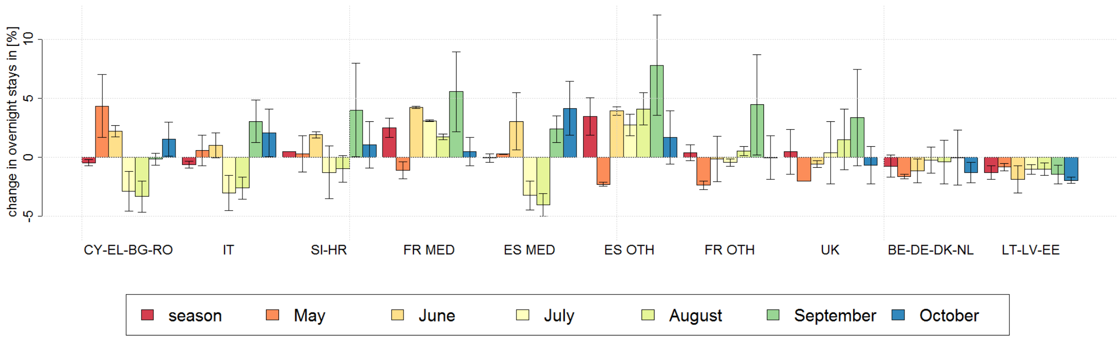

Figure 3.7 Change in summer overnight stays in [%] (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4 period 2035-2065 when tourists can change timing; average over climate models and adaptation is partly successful (error bars indicate the range of climate scenarios

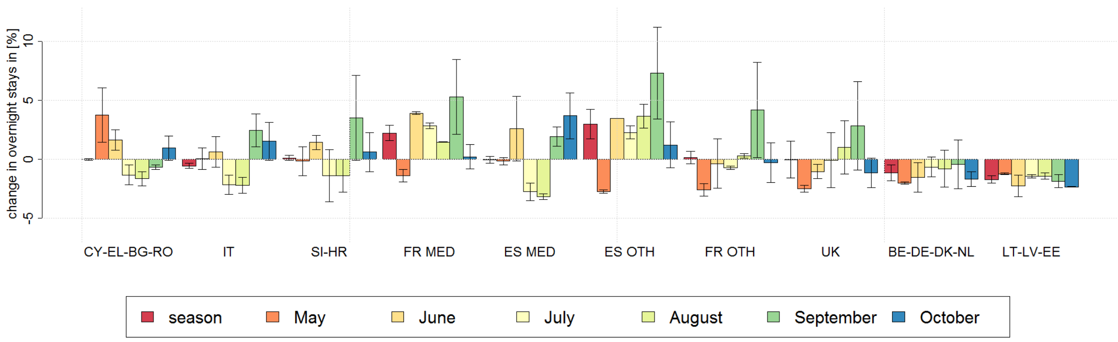

Figure 3.8Change in summer overnight stays in [%] (2035-2065 vs. baseline) in beach regions for RCP4.5/SSP4 period 2035-2065 when tourists can change timing and adaptation is successful; average over climate models (error bars indicate the range of climate scenarios

4 Conclusion and Discussion

In this paper we have used WEDDA-RDM to analyse the effect of climate change on beach tourism in Europe. The effects are quite modest, which confirms earlier studies like Moreno and Amelung (2009) that also use beach specific climate indices.

On average, over the considered climate models, the Mediterranean and some parts of northern Europe lose overnight stays, while northern Spain, France and the UK gain overnight stays. We have seen that different adaptation strategies of tourists have only limited effects on distribution of seasonal overnight stays, while they have significant effects on the inter-seasonal distribution of overnight stays. Furthermore we have seen that successful supply side adaptation can significantly reduce the losses in the core season but has negative effects on the shoulder season and for regions that do not adapt.

WEDDA-RDM can be generalized in various ways. Currently we use the same impact function for all origin countries, with more knowledge on the climate preferences of different origin countries, a different impact function for different origin countries can be used. Currently we have implemented four types of destination regions, and associated each region with one type. Since most NUTS3 regions offer different types of tourism one could split the number of tourists to the different types, but therefor one would need data on the types of tourism in the different regions. Further one could use more types of tourism if one can find corresponding impact functions.

Climate change is only represented as the change of climate variables and side effects like water scarcity or beach deterioration are not included in the model. Here more research is needed how these effects of climate change are affecting touristic demand in a region, and could then be added to WEDDA-RDM. In this paper we have shown how supply side adaptation measures could be implemented in WEDDA-RDM, but the actual applied method was rather ad hoc. For a better representation of adaptation measures in WEDDA-RDM, more research is needed to quantify the effects of a specific adaptation measure on touristic demand.

5 Appendix

For the analysis in this paper we need the monthly number of overnight stays for NUTS3 regions. Therefore we combine several data sources to obtain a best estimate of the data. We want to get data for the years 1996 to 2011 and for the NUTS3 regions of the countries AT, BE, BG, CH, CY, CZ, DE, DK, EE, EL, ES, FI, FR, HR, HU, IE, IS, IT, LI, LT, LU, LV, NL, NO, PL, PT, RO, SE, SI, SK, UK. For each considered NUTS3 region we want to obtain the total number of overnight stays and the number of overnight stays from the origin countries AT, BE, BG, CH, CY, CZ, DE, DK, EE, EL, ES, FI, FR, HU, IE, IS, IT, LT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK, UK, RU, US, CN and JP.

The principle idea is to use monthly number overnight stays with origin information for countries and first distribute the overnight stays with the yearly number of overnight stays for NUTS2 regions to the NUTS2 regions. In a second step the overnight stays from the NUTS2 regions are distributed among the NUTS3 regions with the number of beds in the NUTS3. Since for some NUTS3 respectively NUTS2 regions we have additional information on monthly overnight stays from the National Statistic Institutes, we also want to use this information.

A complication is that data from Eurostat is not complete and has possible outliers. An alternative data set is obtained from UNWTO. This data set provides yearly numbers of overnight stays with origin information. Therefore we first complete the yearly number of overnight stays and in a second step distribute them among the different month.

The first step is complete the monthly number of overnight stays with origin information for countries. As basis we take yearly data on overnight stays in hotels and similar establishments for a given country with origin information from Eurostat. When for a cell no data exists, we take the data of UNWTO, normalized by the median of the ratio between the data of UNWTO and Eurostat of the specific origin destination combination, if for the origin destination combination no data exists we use the median of the ratio of total tourists.

To get rid of possible outliers, we estimate for every origin destination combination a linear model on the logarithm of data from UNWTO and Eurostat if for a year the absolute value of the residual exceeds 0.01 and the year is detected as outlier by a Dixon test, we mark this point as possible outlier. We repeated this procedure until no further possible outliers is detected. For the possible outliers we use the value (UNWTO or Eurostat) that is closer to the geometric interpolation of two neighbouring points which are not declared possible outliers. Finally for Switzerland we use a geometric interpolation for the total number of tourists for the year 2004 as for this year no data from Switzerland is available to us. After applying this procedure we have a complete time series (for the years 1996-2011) of total number of overnight stays for the considered destination countries. For the number of overnight stays with origin information there is still missing data.

The next step is to complete the time series of the number of overnight stays with origin information. For origin countries with missing data and more than 6 data points we fit a general linear model with log link function and Poisson errors. As independent variables we take the total number of tourists and the year. For 6 or less data points we use the median of the ratio between total number of tourists and tourists from the considered origin country to estimate the number of tourists. An exception is Iceland (as origin and destination country). Fore Iceland we set the missing numbers from and too Iceland to zero.

After applying this procedure we have a complete time series of overnight stays with origin information for the years 1996 to 2011

The next step is to break down the annual data to monthly data. Therefore we use monthly number of overnight stays with origin information from Eurostat. We multiply the data for every year destination and origin combination such that we get the same number of tourists in that year as the annual data. Then we estimate missing data. Therefore, for every origin destination combination, we estimate the average distribution of tourist per Month (where possible we distinguishe between years with eastern in March or April) we assume that this distribution of yearly overnight stays to monthly overnight stays holds true for years with missing data. For the combination of Netherlands (destination) and Bulgaria (origin), we use the average of all monthly data as approximation for the number of tourists, as for this pair no complete year of data is available to us.

With the above described procedure it is possible that for a destination region, month and year combination the total overnight stays are less than the sum of overnight stays from the considered origin countries. In this case we multiply the number of overnight stays for all origin countries with a common factor such that the fraction between the number of overnights stays in the considered origin country and the total number of overnight stays in this month year combination is the same as the average for years where there is no contradiction.

This procedure provides us with monthly data of overnight stays including origin countries for 1996 to 2011 for all considered destination countries. Note that this time series (except for missing data) is available on Eurostat. Hence we consider this data is quite reliable.

Next, we break down the national data to NUTS3 regions.

At first we obtain for every NUTS3 region the yearly number of overnight stays without origin information. Therefore we use three data sources. First, data from Eurostat with the number of overnight stays in NUTS2 regions. Second, for some countries we even have the number of overnight stays for NUTS3 regions (from National Statistic Institutes, where type of accommodation depends on country). Third, we have the number of beds in NUTS3 regions from Eurostat.

The first step is to get the number of overnight stays for a NUTS2 region. Here we take the data from Eurostat. If for a year, the number of overnight stays from the National Statistical Institute exists, but not from Eurostat, then we use the data from the National Statistical Institute to prolong the data from Eurostat. For this year we use the median of ratios between the two time series to harmonize the data.

For all NUTS3 regions in a considered NUTS2 region we estimate the share of overnight stays for this region. If data from National Statistic institutes exists we use this data, else we use the number of beds. For years without data we use the median of the shares for each year with data. This provides us with a time series of overnight stays for NUTS3 regions. Still missing data is prolonged with the median ratio to the national data. National data is than distributed according to the time series of NUTS3 regions.

For Ireland – since no other data is available to us – we used the inhabitants to distribute the overnight stays to the different NUTS3 regions

The next step is to detect possible data errors. Whenever the absolute value of the log of the ratio of the overnight stays in one year and the year after is bigger than 0.5, we calculated the median fraction of the overnights in the NUTS3 region and the overnights in the whole country. We declared the ratio of the considered years that was farer away as outliers and replaced it by the median multiplied by the overnight stays.

Next we break down the yearly data for NUTS3 regions to monthly data for NUTS3 regions. If no data from National Statistical Institute regions exists we use the monthly data of the country to distribute the overnights to the different month.

If data from National Statistical Institute exists, we first break it down to NUTS3 regions by the number of beds. We calculate the share of overnight stays for each month. To prolong the time series to years without data, we fit a multinomial model with the following independent variables: the number of overnights of the country in the given month, the number of overnights in a given year, and a factor for the month. This provides us with an estimate for the monthly distributions of overnight stays. In a last step we multiply the monthly distribution with the number of yearly overnight stays in a NUTS3 region. Since in general for every year the overnight stays in a month for the sum of all NUTS3 regions does not match the predicted sum for the monthly overnight stays in the country, we have to adjust these numbers. We use the following procedure: We weight every NUTS3 region with the weighted sum of overnight stays over the months. As weights we use the absolute error of the month. We split the error of each month according to these weights to the individual NUTS3 regions. If after the split there were still NUTS3 regions and months with less than 0 overnight stays we used a different method: Here we split the months into months with too many and too few overnight stays. We distribute the errors in the months with too few overnight stays according to the minimal number of overnight stays of the NUTS3 regions. Further, we subtract values in the month where too much overnight stays are predicted, such that it is in accordance with the monthly distribution of overnights stays in the NUTS3 regions. This reduces the number of months with errors. This procedure is iterated.

Finally, we have to include origin information for the number of overnight stays in the NUTS3 regions. If origin information from the National Statistical Institute exists, the first step is to prolong the time series for origin countries with data. Therefore we use a glm (Binomial family) to link the fraction of overnights of a given country on the subnational level to the ratio for the country.

For origin countries that are not listed in the dataset from the National Statistical institute, we split the remaining overnight stays (Total minus countries with data) according to the ratios for the country.

Further we apply a similar method as for monthly data so that the sum on overnight stays for NUTS3 regions matches the sum for the country.

For regions where no data on NUTS3 regions exist, we use the same distribution as for the country.

So we have generated a 16 year (1996-2011) data series of monthly overnight stays with origin information.

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