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How weather conditions affect guest arrivals and duration of stay: An alpine destination case

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Abstract

Weather can be a major concern for travelers when choosing a destination, preparing their trip and during their stay. Existing publications focus on explaining the role of weather based on one, or at most, a few parameters and usually for one season. This paper proposes a new approach covering all four seasons by connecting daily data from meteorological stations to tourists' registration information. This approach allows for an understanding of travel volumes based on actual travel data and not on perceptions or desired outcomes. The results suggest a clear impact of weather on the number and duration of short-term trips for all seasons. There was no clear indication that weather forecasts played a significant role in the structure of mid or long term trips.

KEYWORDS

climate change, destination choice, destination marketing, holiday climate index (HCI), travel decision, weather

1 | INTRODUCTION

“How was the weather?” is a frequently asked question when people exchange their holiday experiences. Recent results from the annual German travel analysis, a representative survey among 7500 Germans (FUR, 2019), report that the most frequently listed positive memory of the last main holiday trip was neither landscape (70%), nor regional food and beverage (68%), nor the atmosphere (65%). It was good weather (73%). Also, extreme weather remains a part of traveler's memories: a study of Gössling, Abegg, and Steiger (2016) showed that people still report weather related events that took place while on holiday even after 10 years.

Weather and climate are destination attributes and therefore linked with destination choice (Decrop, 2010) and competitiveness (Crouch, 2011). They are part of the destination image for the cognitive and affective dimension (Tasci & Gartner, 2007). The cognitive role is closely linked to the activities and expected experiences during a stay (Karl et al., 2015). A destination which cannot provide the needed climate for a preferred activity (e.g., sun-bathing, hiking, winter skiing), will be excluded from the consideration set of prospective travelers. People do not differentiate that clearly between climate and weather when planning a holiday trip which will take place some months later (Scott & Lemieux, 2010). Analyzing the climate table of a destination they assume that they can expect the weather to be as the table shows. These tables show the monthly average of weather parameters, based on data taken over a longer time period of several years. It is important to note that average is simply a mathematical smoothing of weather variance in a destination. Even though average is not “normal” it is assumed to be a prospect of what one can expect during a particular time period. When the travel date comes nearer the forecast of the actual weather gains importance. Hamilton and Lau (2005) structure the information search about climate conditions and weather in three phases: First, travelers include the climate expectation of destinations in the destination choice process before actual trip planning (Goh, 2012). Second, during the decision and concrete planning phases they analyze different climate and weather information sources (e.g., destination website, meteorological services of the destination country, travel blogs) also depending on the remaining span until departure. This allows for activity planning and travel routing (Scott & Lemieux, 2010). Third, after the destination choice is made and in the last few days before departure, they look at the destination weather forecast for what they can expect. Zirulia (2016) reported that 76% of Italians consult the weather forecast before leaving for holidays. This may be done for something as simple as to decide which clothes to pack or more importantly as to which attractions to choose.

The above three phases, where climate and weather are considered during the travel decision and preparation process, lead to the question, "how strong a correlation is there between travelers' expectations of the activities to be engaged in during the trip and forecasted weather conditions?". Oppewal et al. (2015) showed in a choice experiment the influence of the sequence of either selecting first the experience type and then the destination or vice versa. This is a simple choice with significant implications. Does activity influence destination choice or does destination influence activity choice? Of course, this question has no clear answer. It depends on the individual and their travel goals. However, by studying trip decisions made with respect to expected weather conditions it becomes clear whether some destinations have the strength to overcome poor weather conditions which in this case would make them the dog wagging the tail. But if visitor numbers decline in times of unpleasant weather the destination becomes the tail being wagged by the activity (dog). Destination stakeholders that understand how weather affects their bottom line are in a much better competitive position as they know what to expect, allowing them to adjust variables they have control over such as pricing (Saló et al., 2012). Yield management based on weather effects then becomes a tool that businesses can use to manage their bottom line.

One way businesses can deal with the vagaries of weather is through advanced booking. For an individual making a deposit, which is non-refundable or only partially refundable before traveling to the destination, increases his/her economic risk. For a business, the requirement that individuals provide a deposit ensures an income flow even in times of inclement weather, provided they can still supply the activity. For example, deep sea fishing may be a preferred activity option, but if the weather forecast calls for storms and high seas, a decision to fish in inland streams may be a better option, especially if the tourist suffers from sea sickness. However, if onshore fishing options are not available and payment has already been made, the traveler either goes deep sea fishing and possibly gets sick enough to regret it or foregoes his/her deposit and stays on land. Conversely, a tourist staying at a spa resort or being able to adapt his/her activities during the stay without any monetary loss, may have no concerns about weather forecasts as there would be little if any disruption to their activity caused by the weather, barring any major event. Furthermore, the behavior of people needing a specific weather situation for an activity varies significantly between nearby living visitors and tourist coming from far away. As an example, wave riding in New Zealand can be taken (Mach et al., 2020). Some places are outstanding and therefore visited by a global surfer community. Those surfers coming from far away organize their trips months before and stay a longer time to make sure that they will find perfect waves and weather conditions at least for some days. In contrast, domestic surfers decide just some days before leaving from home with view at the weather forecast.

The results that show that a majority of tourists review weather forecasts before embarking on their trip, allow us to assume that most travelers have a fairly clear idea of the weather they can expect at the destination before leaving their home. Travelers with a domestic destination have been most likely confronted daily with weather forecasts in all mass media, leading to a high level of familiarity with the weather conditions of the chosen region. However, it should not be assumed that weather concerns occur only pre-trip. Choi (2020) found in a study examining stressors experienced by Korean Americans in their pre-trip, travel to and on-site touristic experiences, that weather was not a pre-trip stressor, but it rose to the third rank during the travel to stage and became the dominant stressor experienced during the on-site phase of travel. If weather conditions cause stress for the traveler during or while at the destination, then it makes sense to assume that weather is a relevant factor when making decisions about where to go or what to do.

What is considered as personal ideal climate depends on preferences for weather conditions such as temperature, wind, precipitation or humidity. This preference profile significantly differs among destinations: guests with an affinity for beach holiday trips at the Caribbean consider a day temperature of 30°C as most favorable (Rutty & Scott, 2014), at Florida's beach side 27°C (Atzori et al., 2018) while summer guests in mountain areas prefer a day temperature of around 23°C (Steiger et al., 2016). Moreover, the personal activity profile plays an important role if weather conditions are judged to be excellent, normal or bad. If an activity needs specific weather conditions, such as wind for surfing (Mach et al., 2020) and sailing, snow for skiing, snowboarding and snowmobiling (Rutty & Andrey, 2014), or clear weather for taking a scenic flight across a glacier, other weather parameters are often of much lower importance. On the other hand, if weather prohibits guests from fulfilling their expected experience, they rate the weather to be unacceptable. Mountain summer guests accept 2.1 days of continuous rain during a 1 week stay before classifying the weather as unacceptable (Steiger et al., 2016), for a Florida beach holiday stay 1.5 h of daily rain is the threshold between still acceptable and unacceptable (Atzori et al., 2018). It can be assumed that for short trips, which are linked to a specific activity, the tolerance level is much lower than for longer vacations. There is always a chance that with a longer trip unacceptable weather will abate for a time allowing preferred activities to take place. Regardless of trip length there is always the recollection phase where an internal assessment occurs. Expectations versus reality are the essence of post trip assessments (del Bosque & Martín, 2008). Weather encountered, judged to be abnormal or what was expected, will affect future travel decisions with respect to the destination visited.

There exists a broad variety of publications analyzing the impact of weather and climate on tourism demand. When reviewing literature, we found mostly quantitative studies. There are only a few studies using qualitative methods. Table 1 shows some selected studies, most of them having been published in the last 20 years. After a pre-

TABLE 1 Weather as research topic in literature: A selection of publications

Research focus	Subtopic	Author(s) and year	Type of study/data: Qualitative	Quantitative	Tourism/ tourist data	Meterological data	Region/period/activity
Demand/consumer reaction on	Weather general	Steiger et al. (2016)		x	I	x	Alps, Southern Germany, August 2014, sports
		Atzori et al. (2018)		x	I	D	Florida US, July 2016, different activities
		Lindsey et al. (2020)		x	D	Q	Chicago, 2016–2018, hiking
		Bae and Nam (2020)		x	Q		Jeju Island, South Korea, 2004–2014, general holiday
	Summer season t = temp s = sunshine r = rainfall	Lise and Tol (2001) (t, r)	x	x	Y	Y	210 countries, 1980–1996, various activities
		Agnew and Palutikof (2006) (t, s, r)		x	M, Y	M, Y	UK, 1980–1996, various activities
		Rutty and Scott (2010) (t)		x	I	D, M	Mediterranean, beach and urban destinations, forecast
		Serquet and Rebetez (2011) (t, s)		x	M	D, M	Swiss Alps, 1997–2007 (June, July, August)
		Taylor and Ortiz (2009) (t, s, r)		x	M	M	UK, 1998–2004, general holiday
		Hübner and Gössling (2012) (t, s, r)		x	M	I	Martinique Caribbean, sun and beach April/May 2011
		Köberl et al. (2016) (t, r)		x		D, M	Sardinia (Italy) and Cap Bon peninsula (Tunisia), various activities, forecast
	Winter season sn = snow w = wind	Falk (2010) (t, sn)		x	Y	Y	Austria, winter season, 1986–2006, alpine skiing
		Hamilton et al. (2007) (t, sn)		x	D	D	New England, 1997–2006, alpine skiing
		Shih et al. (2009) (t, sn, w)		x	D	D	Michigan, 1985–2004, skiing, winter holidays
	Extreme events	Chen and Lin (2014)	x	x	M	M	Taiwan, Hotels, 2007–2009, general holiday
		Gössling et al. (2016)			I		Austria, Germany, Swiss, 2013/2014, general holiday
	Climate change	Berghammer and Schmude (2014)	x	x	D	D	Alpine ski resorts, skiing, forecast
		Damm et al. (2017)		x	M	M	Europe's ski tourism, skiing, forecast
Supply/destination	Image	Tavares et al. (2020)		x	I		Brazil, 10 most visited countries, 2016/2017, general holiday
	Choice	Hamilton (2004)		x	M	M	German tourists, 1997, beach and general holiday
	Visitor info	Matzarakis (2014)		x		D	Greece, Thessaloniki, 1971–2001, sustainable tourism
	Vulnerability	Toubes et al. (2017)		x	A	A	Galicia, Spain, beach tourism, forecast
	Risk management	Tanana et al. (2019)	x	x		Y	Buenos Aires, Argentina, 2005–2015, beach and general holiday
		Ballotta et al. (2020)		x		D	Austrian Alps, 1959–2016, alpine skiing
Consumer/traveler	Informing	Rutty and Andrey (2014)		x	I		Ontario, Canada, 2012, skiing, snowboard, snowmobile
	Perception	Denstadli et al. (2011)	x	x	I	D	Scandinavia, summer 2009, summer holiday

TABLE 1 (Continued)

Research focus	Subtopic	Author(s) and year	Type of study/data: Qualitative	Quantitative	Tourism/ tourist data	Meterological data	Region/period/activity
		Stewart et al. (2012)	x	x	I	D	US, 2006, general holiday
		Jeuring (2017)		x	I		Netherlands, summer 2015, general holiday
		Bujisic et al. (2019)		x	D		Florida, US, 2010/2011, general holiday
	Well-feeling	Rutty and Scott (2015)		x	I	D	Caribbean, 2012, sun and beach tourism
	Reporting	Jeuring and Peters (2013)	x	x	A		Dutch tourists, 2011, general holiday
	Activities	Chen and Lin (2019)	x	x	M	M	Taiwan, 2004–2011, whale-watching
		Mach et al. (2020)		x	I	I	Globally/Costa Rica, 2015–2017, surfing
		Rantala et al. (2011)			A		Lapland, Finland, 2006–2009, guided wilderness trips
	Risk perception	Szalai and Rátz (2006)		x	I		Budapest, 2006, general holidays
	Accommodation	Pan and Yang (2017)		x	W	W	Charleston South Carolina, Hotels, 2006–2015, hotel occupancy forecast
Climate index	Summer tourism	Mieczkowski (1985)		x		M	World climate for int. tourism, general holiday
		de Freitas et al. (2008)		x			Climate index for tourism, summer holiday
	Winter	Prettenthaler and Kortschak (2015)		x	M	M	Alpine skiing in Europe, forecast
	Multiple seasons	Scott et al. (2016)		x	M	M, D	Inter-comparison of Holiday Climate Index and Tourism Climate Index in Europe
	Holiday	Rutty et al. (2020)		x	M	M, D	Caribbean, 2008–2017, beach tourism
	Camping and parks	Ma et al. (2020)		x	D	D	US, 2007–2016, camping
		Matthews et al. (2019)		x	M, D	M, D	Ontario, Canada, 2000–2010, beach parks
		Hewer et al. (2015)		x	I		Ontario, Canada, August/September 2010, camping

Note: Time series data: daily (D), weekly (W), monthly (M), quarterly (Q) or yearly (Y) data. In-situ survey (I) and alternative data (A) as photography, blogs or vulnerability data.

selection by Scopus using the filter terms "weather" and "tourism" the methodology section of the papers was analyzed. Afterwards, frequently cited publications using different types of data, analysis methods and touristic activities were listed to show the large variety of research approaches. The articles were grouped by demand, supply, consumer/travelers' behavior and climate index methodology. Table 1 shows that during the last 10 years, many of these publications have been discussing a mix of the impact of weather on tourism and related activities. Many papers focus on destination development as well as on how climate change will modify weather conditions and therefore those for specific activities. The quantitative studies are either based on in-situ surveys among visitors of a destination or they connect statistical data describing arrivals or overnight stays with some meteorological parameters. Many different approaches and time scales (yearly, monthly, daily) can be found among them. Most publications focus exclusively on one season, mainly summer or winter. Furthermore, a great diversity of regions and destination types from different climate zones can be found. Case studies have a certain dominance among the found papers. In our extensive literature search publications that combined daily weather data with daily destination statistics (i.e., number of arrivals and average duration of stay) could not be found (compare Table 1). That is the gap this paper intends to fill.

A specific approach within this group, is the tourism climatic index proposed by Mieczkowski (1985), later called "tourism climate index" (TCI). A second generation of a climate index for tourism (CIT) was proposed by de Freitas et al. (2008) which integrated thermal, esthetic and physical facets of weather and used the statistics of travelers' ratings of weather conditions for 3S (sun, sea and sand) holidays. Over the years many variations and adaptations of this approach have been developed. In attempts to consider types of tourism other than sun and beach, Kubokawa et al. (2014) focused on climate zones, while Ma et al. (2020) focused on seasonality or specific types of accommodation (e.g., camping). Nevertheless, this approach has been criticized due to the lack of normative thresholds, especially with respect to thermal comfort (Dubois et al., 2016), but also because general doubts of applicability to all types of tourism have been expressed. The early indices were designed to rate climate conditions of regions as one of several criteria when assessing their tourism development potential. Later the discussion was widened to develop indices which are easily interpreted by tourists but also precise for a scientific comparison with existing climate indices for leisure tourism. The holiday climate index (HCI) is the most recent evolution proposed by Scott et al. (2016). It aims at overcoming its critics by using variable rating scales and tourists' stated climatic preferences considering the destination type (e.g., urban, beach; Rutty et al., 2020; Scott et al., 2016). The HCI approach is based on daily weather data and therefore considers not only averages but also monthly variability of weather. By looking at variability it provides a risk assessment for each month that travelers will find unfavorable to dangerous weather conditions. The assessment of the HCI quality, in comparison to other climate indices, is based on monthly data of arrivals or overnight stays for representatives of the destination type.

This study concentrates on the influence of weather conditions on tourist arrivals and their duration of stay at the destination level. For each day of the calendar year the weather condition will be analyzed as a factor influencing tourist arrivals as well as duration of stay. Therefore, this study does not analyze the general weather conditions and their impact on destination image, choice and competitiveness as do some of the publications listed in Table 1. Rather, it focuses on the impact of weather conditions on arrivals and the duration of stay at the destination level.

The term "weather condition" in this paper is used in the sense of how people judge the weather based on short-term, mid-term or long-term information sources they consult. The conceptualization of the weather condition will be explained in the methodology section in more detail. Our hypotheses suppose that the weather condition influences the decision making of travelers before the trip (e.g., leaving now/choose another destination/staying at home/ other date for trip) as well as during it (e.g., earlier return/extension of stay) based on the information for the next few days. As an outcome of these decisions made by travelers the following effects formulated as hypotheses at the destination level might be observable:

H1. *The weather condition influences the number of arriving guests.*

H2. *The weather condition influences the duration of stay.*

Hypothesis H1 is related to the situation where the forecast for the weather condition is clearly deviating from the usual and expected, therefore potentially increasing or decreasing the number of arrivals. This hypothesis is supported by the research about tourism and climate indexes noted above. Hypothesis H2 covers situations where the weather condition during a stay is deviating for longer time than expected which might cause an earlier departure, or an extension of the stay. It is based on the results of earlier studies by Denstadli et al. (2011), Gössling et al. (2016), Hewer et al. (2015) and Steiger et al. (2016) reporting that very good weather increases the probability that people extend a holiday stay whereas very bad weather might cause an earlier return.

2 | DATA AND METHODOLOGY

The presented analysis is based on a case study of Oberstdorf, one of the most frequently visited alpine towns in the Bavarian Alps. Yearly about 1.7–2.0 million overnight stays in commercial accommodation occur (BayLfSt, 2020) and a further 400,000–500,000 stays take place in private accommodations. Oberstdorf is a leading German Alpine holiday destination. Analyzing the attractions and related activities promoted by the Oberstdorf's destination website www.oberstdorf.de it can be seen that the main focus attracting guests is on sports and outdoor activities in winter and summer. Most popular activities in summer are hiking and biking (Sawicki, 2015) while in winter alpine skiing, cross country skiing and taking a walk in the snow covered landscape are preferred (Hallmann et al., 2015). Thus, guests' expectations of a visit in Oberstdorf are linked to activities which are highly weather dependent all year around. Oberstdorf is a destination attracting primarily domestic guests (winter 2018/2019: 92.0%, summer 2019: 94.7% (BayLfSt, 2020)). The weather dependency of the main activities as well as the proximity of the source markets, which allows people to travel spontaneously to Oberstdorf, were the reasons for the selection of this destination for our study. Looking at the seasonal structure of the arrivals in Oberstdorf, two high season peaks and two low season periods are evident. The first high season period is in winter, including daily maximum values at Christmas and New Year's Eve as well as the traditional 10-day period of carnival, mostly in February. A second high-season period can be found from June to September. Low seasons are spring and autumn whereby many accommodation facilities are closed during April as well as November. These two high-demand and two low-demand periods suggest a separate analysis for each season. Figure 1 shows the typical seasonal structure for the years 2016–2019, which has been the norm for more than five decades (BayLfSt, 2020).

For the analysis, the destination management organization of Oberstdorf provided daily data from guests' registration over the last 8 years from January 1, 2012 to December 31, 2019 representing 3.4 million registrations. These registrations contained arrival date, departure date and accommodation type allowing the calculation of the number of guest arrivals per accommodation category per day as well as the duration of stay of each registered guest. For further analysis the accommodation categories of hotel, B&B hotel, inns, boarding and guest houses, private hosts and holiday flats were used. Camping, a category which can be considered as weather dependent (Hewer et al., 2015) could not be included because of data omissions concerning daily guest registration. Health-related accommodations such as rehab hospitals, health clinics or sanatoriums were excluded as it can be assumed that weather has no influence on the selection of the date of arrival and duration of stay. Furthermore, registrations regarding group accommodation, which frequently is used for school field trips, were not considered as such trips are planned in the long term and take place regardless of weather conditions. The seasons were defined from a guest perspective as winter (15.12–14.3.), spring (15.3–14.6), summer (15.6–14.9) and autumn (15.9–14.12). Summer is corresponding with the school holidays period in Germany, spread among the federal states. The date 29th February in leap years was ignored due to statistical reasons.

Finally, 2.78 million guest arrivals with a total of 14.9 million overnight stays were included in the analysis. Table 2 shows the daily average arrivals per accommodation category by season and the empirical distribution of overnight stays by duration of stay. The seasonality for hotels is less pronounced than for the other accommodation types and accounts in spring and autumn for half of the arrivals compared to the high seasons. Other accommodation types showed much more variability of bookings during the shoulder or low use seasons. While in winter, spring and autumn about two thirds of all guests stay a maximum of seven nights, in summer more than half of the guests (50.9%) stay eight or more days with 42.1% between 8 and 14 nights. Autumn is the season with the highest share (20.5%) of short trips with three overnight stays or less.

Daily weather data for Oberstdorf are collected, controlled and provided by the Deutscher Wetterdienst DWD (Germany's National Meteorological Service). These data are published by an open data portal of the climate data center (DWD Deutscher Wetterdienst, n.d.). The local meteorological station of Oberstdorf (ID 3730) is located at 806 m at the bottom of the valley. Available parameters of the station P_0–P_{13} are listed in Table 3.

To describe and analyze the daily weather during the period 2012–2019 as well as to compare it with past weather people remember as usual of the last years, daily meteorological data from January 1, 2002 to December 31, 2019 were taken from the open data portal. In very few cases missing values coded by 999 could be found. These were replaced by a moving average of values before and after.

To decide which weather parameters shall be used for the main analysis, a basic preliminary analysis of the meteorological data from the weather data station of Oberstdorf was completed. Table 4 shows the monthly averages for the 13 parameters P_1–P_{13} from Table 3 for

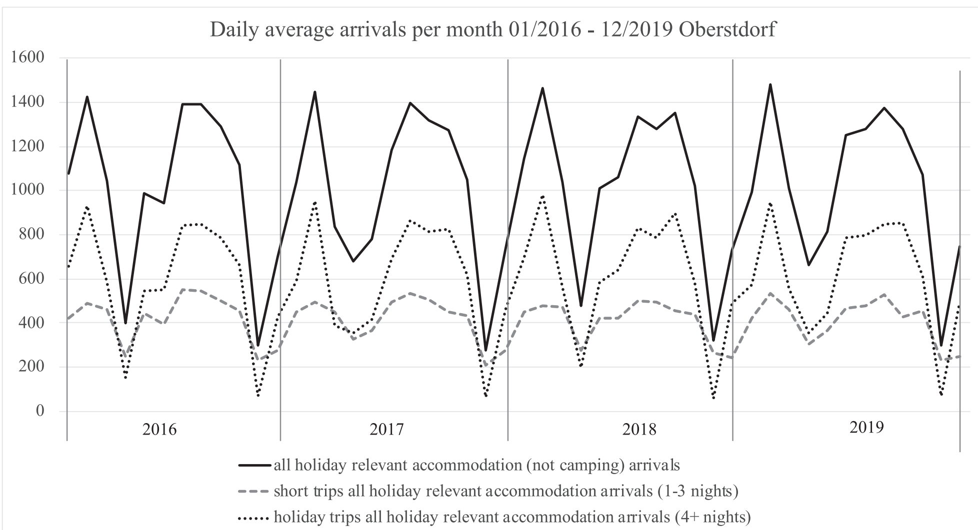

FIGURE 1 Oberstdorf seasonality of arrivals 2016–2019

the years 2010–2019. The longest sunshine durations and highest mean temperatures characterize the summer season, whereas snow and low average temperatures can be found during the winter season in Oberstdorf.

After compiling Oberstdorf weather data, we consulted frequently used online platforms offering current weather data, weather forecast and climate condition information (i.e., dwd.de [weather and climate], wetteronline.com, wetter.com, wetterkontor.com, wetterdienst.de, wetter24.de as well as the destination website) and examined the provided weather forecast information on the main pages. In addition, the public German broadcast channels ARD and ZDF were analyzed to document which parameters are always part of the weather forecast. It became clear that the focus of information is on the following parameters: temperature (max day, average day and minimum at night), sunshine, cloudiness, precipitation and finally wind. In winter the snow height is added frequently by a map; in the warm months information about humidity and/or dew point is provided by a text description.

It is quite obvious that some parameters are only of relevance for some destination types as for example the water temperature at the seaside or along larger lakes, or the snow height for mountain destinations. Therefore, we checked the relevance of each parameter from Table 3 for the destination Oberstdorf. Only for the wind parameters in our dataset we saw a lack of relevance in Oberstdorf. The weather station of Oberstdorf recorded average daily velocities of 1.99 m/s and average maximum velocities of 7.79 m/s for the period 2010–2019. Both values are relatively low using the Beaufort scale as 7.79 m/s is classified only as a moderate breeze on this scale and corresponds to four Beaufort. Looking at some percentages for the maximum daily wind speed 9.3 m/s (75%), 12.0 m/s (90%), 14.2 m/s (95%), 19.0 m/s (99%) and a maximum of 26.6 m/s were found. Only on 3 days within 10 years the wind speed reached level 10 on the

TABLE 2 Average daily arrivals by season and accommodation type

Average daily arrivals 2012–2019 by accommodation type							
Accommodation type	**Hotels**	**Holiday flats**	**Inns**	**B&B hotels**	**Boarding and guest houses**	**Private hosts**	**Total**
Winter	321	223	55	79	134	199	1012
Spring	235	126	31	49	80	109	629
Summer	341	216	68	86	161	204	1075
Autumn	246	111	30	44	69	95	596

	Share of overnight stays generated by arrivals with a duration of stay of 1, 2, 3, 4–6, 7, 11–14, 15–21 and 22–28 days								
Dur. stay	**1**	**2**	**3**	**4–6**	**7**	**8–10**	**11–14**	**15–21**	**22–28**
Winter	1.5%	5.4%	7.5%	25.0%	28.0%	13.1%	14.4%	4.4%	0.7%
Spring	2.1%	6.8%	10.6%	23.5%	22.4%	12.8%	16.0%	4.9%	1.0%
Summer	2.5%	4.1%	5.2%	15.4%	22.0%	14.0%	28.1%	7.7%	1.1%
Autumn	2.6%	8.1%	9.8%	24.0%	25.0%	11.7%	14.0%	4.0%	0.8%

TABLE 3 Weather parameters provided by Germany's National Meteorological Service at station ID 3730 Oberstdorf

P_j	Parameter	Description	Unit/scale
P_0	MESS_DATUM	Date of measurement	ddmmyyyy
P_1	FX	Daily maximum of wind	m/s
P_2	FM	Daily mean of wind velocity m/s	m/s
P_3	RSK	Daily precipitation height	mm
P_4	SDK	Daily sunshine duration	h
P_5	SHK_TAG	Daily snow depth	cm
P_6	NM	Daily mean of cloud cover	1/8
P_7	VPM	Daily mean of vapor pressure	hPa
P_8	PM	Daily mean of air pressure	hPa
P_9	TMK	Daily mean of temperature	°C
P_{10}	UPM	Daily mean of relative humidity	%
P_{11}	TXK	Daily maximum of temperature at 2 m height	°C
P_{12}	TNK	Daily minimum of temperature at 2 m height	°C
P_{13}	TGK	Daily minimum of temperature at 5 cm above ground	°C

TABLE 4 Climate conditions of the destination Oberstdorf based on data from 2010 to 2019

	P_1 max wind velocity m/s	P_2 mean of wind velocity m/s	P_3 mean precipitation height mm	P_4 mean sunshine duration h	P_5 mean snow depth cm	P_6 mean of cloud cover 1/8	P_7 mean of vapor pressure hPa	P_8 mean of air pressure hPa	P_9 mean of temperature °C	P_{10} mean of relative humidity %	P_{11} max of temp. at 2 m height °C	P_{12} min of temp. at 2 m height °C	P_{13} min temp. at 5 cm above ground °C
Jan	24.0	1.9	5.6	2.2	24	5.7	4.9	923	−1.9	88	16.9	−24.9	−29.8
Feb	17.5	1.8	2.7	3.4	30	5.3	4.6	922	−2.1	83	17.3	−29.4	−34.9
Mar	21.1	2.0	3.3	4.9	10	4.8	5.7	922	3.0	77	22.4	−17.1	−22.0
Apr	20.0	2.2	3.0	4.9	1	5.1	7.4	921	7.4	74	26.4	−10.1	−14.3
May	19.4	2.2	5.9	4.7	0	5.7	9.9	923	10.8	78	29.2	−5.4	−6.8
Jun	18.7	2.3	6.1	6.5	0	5.0	13.2	925	15.6	77	33.9	0.8	−0.6
Jul	22.9	2.2	5.3	6.6	0	4.7	14.7	926	17.2	77	35.6	2.1	1.0
Aug	26.0	2.1	5.8	6.1	0	4.7	14.8	926	16.6	80	33.0	3.0	2.0
Sep	22.8	1.9	5.1	4.7	0	5.0	11.9	926	12.3	84	27.6	−2.8	−4.3
Oct	26.6	1.8	4.2	4.0	0	5.1	9.5	925	8.5	85	27.2	−7.8	−9.9
Nov	21.0	1.6	3.2	2.6	1	5.7	6.8	922	3.2	88	20.5	−15.5	−21.5
Dec	21.8	1.9	4.1	2.6	9	4.7	5.3	927	−0.5	87	17.5	−20.5	−27.4

Beaufort scale (storm) and only on 13 days level 9 (strong/severe gale). Thus, we discussed with the destination management of Oberstdorf if wind is relevant factor for their guests and tourism stakeholders (e.g., the cable car companies). As result it was concluded that wind can be ignored as a relevant parameter because in many years the cable cars had to be stopped only for a few hours in summer and autumn, mainly because of short but heavy thunderstorms. Therefore, wind was excluded from the list of used weather parameters. Finally, the eight weather condition parameters from Table 5 were included in the empirical analysis.

The approach of this paper is based on how tourists use the weather condition information. From the perspective of a traveler who is just about to leave for a trip or planning an activity during a vacation, the weather condition at the destination is what the weather information systems tells him/her: current temperature, cloudiness, rainfall, sunshine, wind, and so on. Also, the weather condition forecasts are presented for the short-term (3 days), mid-term (5 days) and long-term (14 days). The term "weather condition" describes the overall evaluation of the weather the traveler expects to find when arriving at the destination and for the first 3–5 days after arrival. Precision of short-term weather information has improved considerably during the last few decades. Moreover, mid-term weather forecasts today improve year by year, even if they are still frequently imprecise (Weisheimer & Palmer, 2014). Thus, travelers have nowadays a solid basis to judge the type of weather most likely to be encountered upon arrival and for a few days after.

When describing the hypotheses H1 and H2, we used the terms "unusually good (bad) weather condition." This needs further conceptualization. The judgment "normal" indicates if the weather condition on a specific date is in all meteorological data near to the multi-annual mean. The normal weather for the period therefore is what has been observed in former years. However, if average is deemed to be normal it is entirely possible that normal does not exist. Averages are simply a smoothing out of the highs and lows. Nonetheless, the tendency is to equate average with normal. This is what we find in climate tables of destinations showing average values for some parameters. The weather condition from the guest perspective will be classified as normal if they see in the forecast what they expect from knowledge, former personal experiences or based on further information they gathered. Thus, the weather condition must be classified as unusual if it is heavily deviating from the average (i.e., normal) and thus from what the guests expect. In this study we therefore define a weather condition to be unusual by using weather data and statistics as explained below.

Our statistical approach differs from the climate index techniques, which are based on preference studies for specific types of tourism (e.g., 3S). Climate indexes are based on tourists' judgments about the weather for a destination such as thermal sensation using a thermal comfort scale, esthetic quality based on cloudiness and physical factors as wind and rain (de Freitas et al., 2008). These judgments from empirical studies can be applied to the meteorological data and finally aggregated from several parameters to one index value. This index is

TABLE 5 Weather condition parameters WS used for description of weather conditions

Season WS	RSK WS_1 precipitation	SDK WS_2 sunshine	SHK WS_3 snow height	NM WS_4 cloudiness	VMP WS_5 vapor pressure	TMK WS_6 temp average	TMX WS_7 temp max	TNX WS_8 temp min
Winter	x	x	x	x		x	x	x
Spring	x	x		x		x	x	x
Summer	x	x		x	x	x	x	x
Autumn	x	x		x		x	x	x

constructed on an ordinal scale and describes the proximity of the climate to the tourists' ideal. But it does not consider the aspect of short or mid-term variability of the weather parameters as well the seasonal change of the importance of weather parameters and their scales. For our research the climate indexes nevertheless were quite useful, as we could use the approach later to rank weather conditions from very pleasant to very unpleasant.

To cover all aspects of weather and its daily as well as seasonal variability this paper uses a new approach. It is based on weather conditions each described by multiple parameters. By this the method supports the analysis of the hypotheses as it uses for each day of the year its weather condition. We use the following calculations to describe the contribution of each weather parameter to the weather condition:

$$P_{j,d}^{y,m} = \frac{1}{m} \sum_{d=t}^{t+m-1} WS_{jd}^{y} \text{ for } \begin{array}{c} y \in \{2002,\ldots,2019\} \\ t \in \{1,\ldots,365\} \\ j \in \{1,\ldots,8\} \\ m \in \{3,5,14\} \end{array} \tag{1}$$

The moving averages of each parameter calculated for each day of the years 2002–2019 describe for $m = 3$ the short-term, $m = 5$ the mid-term and $m = 14$ the half month average parameter. The half month moving averages for the period January 1, 2012 to December 31, 2019 were then used to calculate a 10-year average from the 10 years before:

$$W_{j,d}^{y} = \frac{1}{10} \sum_{b=y-10}^{y-1} WS_{jd}^{y,14} \text{ for } \begin{array}{c} y \in \{2012,\ldots,2019\} \\ d \in \{1,\ldots,365\} \\ j \in \{1,\ldots,8\} \end{array} \tag{2}$$

The calculation is based on the data from 10 years over a 2 week period. This is equivalent to using 140 values for estimating the distribution parameters of the weather parameter for each day. Thus, in analogy to the mean we also estimated the standard deviation from the 10 years daily values as follows:

$$SW_{j,d}^{y} = \frac{1}{9} \sqrt{\left(\sum_{b=y-10}^{y-1} W_{j,d}^{y} - WS_{jd}^{y,14} \right)^{2}} \text{ for } \begin{array}{c} y \in \{2012,\ldots,2019\} \\ d \in \{1,\ldots,365\} \\ j \in \{1,\ldots,8\} \end{array} \tag{3}$$

The identification of unusual values of a weather parameter P_j for short-term and mid-term weather was then based on the following rules

$$I_{j,d}^{y,m} = \begin{cases} -1 & < W_{j,d}^{y} - c_{1-\alpha} \\ 0 \text{ if } P_{j,d}^{y,m} & \text{other} \\ 1 & > W_{j,d}^{y} + c_{1-\alpha} \end{cases} \tag{4}$$

with $c_{1-\alpha}$ being the lower respectively upper $1-\alpha$ confidence interval using the daily estimations W and SW for each weather parameter. For α we used 5% to find the daily thresholds for unusual values of weather parameters.

The 8 years have 2920 days, 728 in winter, 720 in spring, 744 in summer and 728 in autumn. Each day can be characterized by the indicators $I_{j,d}^{y,m}$. Using these indicators for cluster analysis, weather condition typologies for the next 3 days and the next 5 days can be derived for each season. A cluster analysis method, hierarchical clustering with squared Euclidian distance and Ward method from SPSS 25 was used.

The clusters, each representing a weather condition, were interpreted based on cluster centers of the indicator variables I. In the result Tables 6–8 presented later, the clusters C will be numbered by season (winter = 1, spring = 2, summer = 3, autumn = 4) and number of the described weather condition of clusters 1–7. As cluster analysis algorithms do not deliver a content-based logic order of the clusters, a ranking from most pleasant (1) to least pleasant (7) weather conditions was done. For the ranking of the clusters the approach of rating scales from the holiday climate index (HCI) concerning temperature, sunshine, cloud cover and precipitation were applied (Scott et al., 2016). The scales cannot be transferred 1:1, for example from HCI: urban to HCI: Alpine destination. Our clusters are based on the values of the indicator variables I from formula (4) above, indicating if a value of a parameter is significantly above (+1) or below (−1) the average. Thus, the direction of HCI: urban rating scales could be used for the spring, summer and autumn weather. All scales except temperature are linear, that is, no precipitation or no clouds are ranked best, and with an increase of these values the ranks decrease. Temperature has the highest rank for 23–25°C of day temperature for alpine summer destinations (Steiger et al., 2016), while temperatures below and above are ranked lower. As the analyzed case is an Alpine town, the average day temperature even in summer almost never reaches values above this level (see Table 4, mean of temperature and max temperature). Therefore, also for temperature a ranking from high to low was applied. As example the 3-day forecast for summer is used to illustrate the approach for the two best and the two weakest weather conditions. The weather condition {dry, very sunny and warmer} is ranked better

TABLE 6 Weather conditions derived from cluster centers of hierarchical clustering

Three-day forecast—Winter (C_{11} to C_{17} 3d)	N	Five-day forecast—Winter (C_{11} to C_{17} 5d)	N
Very cold and sunny	79	Very cold, bit more sun	75
Very sunny, average temperature	108	Very sunny, average temperature	80
Additional precipitation, plenty of snow, usual temp.	39	Unusually warm during the day	36
Usual 3 days winter weather	435	USUAL 5 days winter weather	493
cloudy, average precipitation, a bit colder	87	More precipitation, plenty of snow, usual temp.	42
Over-average precipitation, little sun, warmer	52	More precipitation, little sun, cloudy, average temp	88
Unusually high precipitation, little sun, average temp.	110	Unusually high precipitation	96
Three-day forecast—Spring (C_{21} to C_{27} 3d)	**N**	**Five-day forecast—Spring (C_{21} to C_{27} 5d)**	**N**
Very sunny, colder nights, day temperature normal	111	Very sunny, a bit warmer	122
Unusually sunny and warm	102	Warmer, a bit more rain	86
Unusually cold, all other normal	136	Usual 5 days spring weather	420
Usual 3 days spring weather	352	Bit colder, especially by night colder	52
Unusual amount of precipitation, average sun	56	Unusually colder, bit less sun, bit more rain	90
Unusually little sun, cloudy, temperature average	53	Unusually high precipitation, all other average	53
Wet, no sun, very cloudy cold	100	Wet, sparse sun, cloudy and colder	87
Three-day forecast—Summer (C_{31} to C_{37} 3d)	**N**	**Five-day forecast—Summer (C_{31} to C_{37} 5d)**	**N**
Dry, very sunny and warmer	108	Sunny and dry, temperature average	61
More sun, warmer, average precipitation	142	Very sunny and warm, over-average humidity	74
Colder, over-average sun	87	Warmer weather, over-average humidity	131
Usual 3 days summer weather	339	Usual 5 days summer weather	459
Very humid, bit warmer, warmer nights	55	Unusually high precipitation, all other average	63
Sparse sun, cloudy, bit more rain and colder	145	More precipitation, sparse sun, very cloudy, colder	104
Sparse sun, cloudy, very rainy and cold	54	Unusually cold, more precipitation, little sun, cloudy	38
Three-day forecast—Autumn (C_{41} to C_{47} 3d)	**N**	**Five-day forecast—Autumn (C_{41} to C_{47} 5d)**	**N**
Very sunny, no clouds, warmer	152	Very sunny, few clouds, warmer	86
Very sunny, higher max. day temp., all other average	59	Very sunny, no clouds, all other as usual	99
Much warmer—all other as average	106	Unusually warm, less sun, more precipitation	99
Usual 3 days autumn weather	317	Usual 5 days autumn weather	433
Unusually cold but a bit more sun, few clouds	73	No sun, cloudy, higher precipitation	71
Unusually high precipitation, all other average	67	Unusually high precipitation, all other average	66
Sparse sun, cloudy, more precipitation, temp. average	126	Unusually cold, all other average	46

than {more sun, warmer, average precipitation} because dry and very sunny are dominant and perceived better concerning the ranking scales. The condition {sparse sun, cloudy, bit more rain and colder} is better ranked than {sparse sun, cloudy, very rainy and cold} with the higher amount of rain and the lower temperature moving the latter to the last rank.

Concerning the ranking of winter weather conditions, the application of the temperature scale from HCI: urban must be seen as doubtful. Bausch and Unseld (2018) found for the German travel market, which is the main source market for Oberstdorf, that the experience of real winter weather with cold and icy weather are a main motive for a winter holiday stay in the Alps. Furthermore, the same study showed that sunshine has a very high weight among travel motives. Therefore, the ranking of winter weather conditions follows the HCI: urban concerning precipitation and cloudiness, but weights sunshine higher and uses an inverted temperature scale: cold weather is ranked better than warmer weather. Among the seven types of winter weather conditions derived by cluster analysis we found two clusters with cold, and sunshine mainly differing in temperature. We ranked the colder weather better than the average temperature weather, supposing, that the wish for real winter atmosphere comprises cold temperatures. This is an assumption and might differ in reality. In later analyses the ranking played only a role for comparing the two most pleasant with the two most unpleasant weather conditions. The ranking of the best two weather situations can be changed without effecting the findings.

Based on the recorded weather conditions, our two hypotheses were analyzed by combining the daily short-term forecast of weather condition with guest arrivals and the duration of stay using ANOVA. Additionally, we analyzed separately short-trips with a maximum

TABLE 7 Comparison of short-term weather conditions using ANOVA and t-test

Daily arrivals and their duration of stay: One-way ANOVA and two groups independent *t*-test short-term (3d)														
	All holiday relevant	Seasonal mean							ANOVA			*t*-Test two indep. groups		
Winter	accommodation	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	F-ratio	Probab.	Effect η^2	*t*-Value	Sig. two-tailed	Cohen's *d*
Arrivals	All trips	1125	1219	961	1158	1241	1061	1108	0.876	0.512	0.007	1.077	0.282	0.125
	Short trips (1–3 nights)	465	373	378	418	430	402	403	0.582	0.746	0.005	0.149	0.881	0.017
	Holiday trips (4+ nights)	659	847	582	741	811	659	705	1.157	0.327	0.010	1.112	0.267	0.129
Duration of stay	All trips	4.73	5.38	4.95	5.08	5.00	5.04	5.17	1.412	0.207	0.012	0.007	0.994	0.001
	Short trips (1–3 nights)	2.10	2.13	2.15	2.17	2.14	2.07	2.17	0.934	0.470	0.008	−0.549	0.583	−0.064
	Holiday trips (4+ nights)	667	6.96	6.93	6.91	6.69	7.13	6.98	1.023	0.409	0.008	−1.265	0.207	−0.147
Spring		C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}						
Arrivals	All trips	755	779	671	724	845	713	706	0.770	0.594	0.064	0.859	0.391	0.102
	Short trips (1–3 nights)	390	359	294	318	384	266	279	1.742	0.109	0.015	2.567	0.011**	0.290
	Holiday trips (4+ nights)	366	420	377	406	462	447	427	0.533	0.784	0.004	−0.885	0.377	−0.105
Duration of stay	All trips	4.32	4.54	4.74	4.74	4.85	5.09	5.10	3.383[a]	0.003***	0.027	−4.238	0.000***	−0.505
	Short trips (1–3 nights)	2.12	2.05	2.11	2.08	2.03	2.07	2.07	0.564	0.760	0.005	0.236	0.814	0.028
	Holiday trips (4+ nights)	6.72	6.88	6.94	7.11	7.13	7.22	7.30	2.768[b]	0.011**	0.023	−3.489	0.001**	−0.416
Summer		C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	C_{37}						
Arrivals	All trips	1334	1252	1106	1245	1351	1211	1133	1.025	0.408	0.008	1.273	0.204	0.136
	Short trips (1–3 nights)	496	475	403	477	508	415	412	2.528[c]	0.020**	0.020	3.024	0.003***	0.323
	Holiday trips (4+ nights)	838	776	703	769	843	796	721	0.396	0.882	0.003	0.346	0.73	0.037
Duration of stay	All trips	5.35	5.30	5.44	5.40	5.52	5.60	5.55	0.522	0.792	0.004	−1.662	0.097*	−0.178
	Short trips (1–3 nights)	1.91	1.91	1.90	1.88	1.86	1.91	1.86	0.499	0.809	0.004	0.464	0.643	0.050
	Holiday trips (4+ nights)	7.88	7.83	7.85	7.98	8.18	8.06	8.11	1.617	0.139	0.013	−2.334	0,020**	−0.249
Autumn		C_{41}	C_{42}	C_{43}	C_{44}	C_{45}	C_{46}	C_{47}						
Arrivals	All trips	778	742	596	626	555	845	807	2.889[d]	0.009***	0.024	−0.667	0.505	−0.077
	Short trips (1–3 nights)	405	385	327	324	264	278	295	2.517[e]	0.020**	0.021	3.495	0.001***	0.407
	Holiday trips (4+ nights)	373	357	269	301	291	567	512	4.518[f]	0.000***	0.037	−2.456	0.015*	−0.282
Duration of stay	All trips	3.87	3.78	3.75	3.73	4.08	4.58	4.39	6.140[g]	0.000***	0.049	−3.871	0.000***	−0.445
	Short trips (1–3 nights)	2.05	2.10	2.02	2.06	2.08	2.02	1.99	0.984	0.435	0.008	1.647	0.101	0.191
	Holiday trips (4+ nights)	6.28	6.15	6.28	6.15	6.43	6.74	6.62	4.466[h]	0.000***	0.036	−3.549	0.000***	−0.411

Note: Significances below 0.01 are marked by three ***, below 0.05 by two ** and below 0.1 by one * star.
[a]Post-hoc test: C1 & C7.
[b]Post-hoc test: C1 & C7.
[c]No sig. differences.
[d]No sig. differences.
[e]No sig. differences.
[f]Post-hoc test: C3 & C6, C7 and C4 & C6, C7.
[g]Post-hoc test: C1 & C6 and C3 & C6, C7 and C4 & C6, C7.
[h]Post-hoc test: C4 & C6, C7.

TABLE 8 Comparison of mid-term weather conditions using ANOVA and t-test

Daily arrivals and their duration of stay: One-way ANOVA and two groups independent t-test mid-term (5d)														
		Seasonal mean							ANOVA			*t*-Test two indep. groups		
Winter	All holiday relevant accommodation	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	F-ratio	Probab.	Effect η^2	*t*-Value	Sig. two-tailed	Cohen's *d*
Arrivals	All trips	1137	1266	949	1179	942	1173	1067	1.483	0.181	0.012	1.081	0.281	0.130
	Short trips (1–3 nights)	504	379	255	419	404	424	403	2.017[a]	0.061*	0.017	0.520	0.603	0.063
	Holiday trips (4+ nights)	633	887	694	760	538	749	664	1.659	0.128	0.014	0.926	0.355	0.111
duration of stay	All trips	4.67	5.31	6.08	5.07	4.92	5.03	4.95	3.895[b]	0.001***	0.031	0.262	0.793	0.032
	Short trips (1–3 nights)	2.10	2.12	2.14	2.16	2.13	2.18	2.14	0.515	0.797	0.004	−1.185	0.237	−0.143
	Holiday trips (4+ nights)	6.74	6.92	8.40	6.83	6.98	6.83	6.75	8.994[c]	0.000***	0.070	0.384	0.701	0.046
Spring		C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}						
Arrivals	All trips	715	730	748	678	701	795	693	0.332	0.920	0.003	−0.247	0.805	−0.031
	Short trips (1–3 nights)	334	361	333	256	289	363	288	0.923	0.478	0.007	0.541	0.589	0.067
	Holiday trips (4+ nights)	381	369	414	422	412	432	405	0.230	0.967	0.002	−0.844	0.399	−0.105
Duration of stay	all trips	4.48	4.53	4.70	5.09	4.78	5.02	5.01	2.308[d]	0.033**	0.019	−3.175	0.002***	−0.394
	Short trips (1–3 nights)	2.07	2.07	2.06	2.04	2.12	2.15	2.12	0.977	0.439	0.000	−1.406	0.161	−0.174
	Holiday trips (4+ nights)	6.77	6.90	7.11	6.93	6.94	7.31	7.25	2.367[e]	0.028**	0.019	−3.312	0.001***	−0.411
Summer		C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	C_{37}						
Arrivals	All trips	1232	1293	1321	1238	1264	1155	1089	0.682	0.664	0.006	1.300	0.195	0.177
	Short trips (1–3 nights)	463	517	449	475	463	394	416	2.069[f]	0.055*	0.017	3.177	0.002***	0.433
	Holiday trips (4+ nights)	770	777	873	763	801	761	673	0.500	0.809	0.004	0.329	0.742	0.045
Duration of stay	All trips	5.35	5.17	5.59	5.40	5.33	5.64	5.42	0.819	0.556	0.007	−1.651	0.100*	−0.225
	Short trips (1–3 nights)	1.89	1.91	1.88	1.89	1.90	1.90	1.89	0.166	0.986	0.001	−0.070	0.944	−0.010
	Holiday trips (4+ nights)	7.88	7.80	7.87	8.00	7.83	8.18	7.92	1.729	0.111	0.014	−2.461	0.015**	−0.336
Autumn		C_{41}	C_{42}	C_{43}	C_{44}	C_{45}	C_{46}	C_{47}						
Arrivals	All trips	840	635	711	657	733	728	605	1.074	0.377	0.009	0.653	0.514	0.092
	Short trips (1–3 nights)	405	349	342	318	283	335	256	1.483	0.181	0.012	1.821	0.070*	0.255
	Holiday trips (4+ nights)	435	286	370	338	450	392	349	0.879	0.509	0.007	−0.208	0.836	−0.029
Duration of stay	All trips	4.00	3.78	4.00	3.85	4.31	4.03	4.22	1.445	0.195	0.012	−1.220	0.224	−0.171
	Short trips (1–3 nights)	2.08	2.03	2.04	2.05	2.01	2.02	2.08	0.369	0.898	0.003	0.311	0.756	0.044
	Holiday trips (4+ nights)	6.19	6.33	6.36	6.25	6.49	6.48	6.67	1.518	0.169	0.013	−2.158	0.032**	−0.302

Note: Significances below 0.01 are marked by three ***, below 0.05 by two ** and below 0.1 by one * star.

[a]Post-hoc test: C1 & C3.

[b]Post-hoc test: C3 & C1, C4, C5, C6, C7.

[c]Post-hoc test: C3 & C1, C2, C4, C5, C6, C7.

[d]No sig. differences.

[e]No sig. differences.

[f]No sig. differences.

duration of stay of three nights and long-trips with four and more overnight stays. This was based on the work of Karl et al. (2020) who showed significantly different travel decision making when short trips (3 days) were compared to long trips (>4 days) by travelers from the German source market. As the arrivals and duration of stay are metric data, we used a univariate ANOVA. Further, we grouped the two most pleasant and the two most unpleasant weather conditions and compared them using *t*-test for independent groups. For short trips we analyzed the influence of each weather parameter on the arrivals using decision trees. Decision trees are an efficient nonparametric method that is frequently used in machine learning (Alpaydn, 2010). As a white box machine learning method, they are easy to interpret and identify a hierarchical structure of the most influential predictor variables. Nuzzo (2014) as well as Wasserstein and Lazar (2016) encourage the use of multiple methods on the same data set in order to improve the understanding of the underlying relationships. Thus, we compliment traditional statistical methods with an alternative algorithm from artificial intelligence. CHAID (Song & Lu, 2015) from SPSS 25 was used to estimate the trigger points.

3 | FINDINGS

The weather conditions we found using cluster analysis based on the 3-day and 5-day indexes from formula 4 for each season can be found in Table 6. Following the elbow criteria, we found for each season seven clusters. The usual weather condition, characterized by all indicator variables with values zero, was always the largest cluster. The short description of the weather condition is based on the averages of the indicator variables. In case the average value of an indicator of a weather condition parameter for a cluster is zero or near to zero, no or nearly no significant deviations from the multi-annual two weak average were found and therefore the result was interpreted as "usual." Average values of indicator variables of weather condition parameters close to -1 were interpreted as unusual and under average while close to $+1$ were considered unusual and above average.

Our hypotheses H1 and H2 were tested for each season and in separate steps for the short-term which was set at 3 days (Table 7) as well as the mid-term set at 5 days (Table 8) weather condition. First, we identified significant differences of daily arrivals and duration of stay for the seven clusters C, each representing a different type of weather condition per season. Further, we analyzed short-trips (max. three overnights stay) and long-trips (four and more overnight stays) using univariate ANOVA. The results can be found in Tables 7 and 8 in the columns F-ratios, probabilities and eta-squared effect. Further, a comparison of the daily arrivals and the duration of stay for the two most pleasant weather conditions (C_{s1} and C_{s2} for each season $s = 1, \ldots, 4$) with the two most unpleasant (C_{s6} and C_{s7} for each season $s = 1, \ldots, 4$) using *t*-tests for two independent groups was done. These results are shown in the Tables 7 and 8 in the columns *t*-value, Sig. (two-tailed) and the effect by Cohen's *d*.

TABLE 9 Influence of weather condition and season type on duration of stay

Dependent Var.: Duration of stay	Three-day weather forecast						Five-day weather forecast					
Source	Type III sum of squares	*df*	Mean square	*F*	Sig.	Partial eta square	Type III sum of squares	*df*	Mean square	*F*	Sig.	Partial eta square
Corrected model	286.114[a]	3	95.371	45.629	0.000	0.099	175.082[b]	3	58.361	30.118	0.000	0.085
Intercept	2.93 E04	1	2.93 E04	1.40 E04	0.000	0.919	2.21 E04	1	2.21 E04	1.14 E04	0.000	0.921
Pleasant/unpleasant weather cond.	37.739	1	37.739	18.056	0.000	0.014	139.482	1	139.482	71.981	0.000	0.069
Season low/high	225.109	1	225.109	107.699	0.000	0.080	12.858	1	12.858	6.636	0.010	0.007
Pleasant/unpleasant w. × Season low/high	15.944	1	15.944	7.628	0.006	0.006	4.529	1	4.529	2.337	0.127	0.002
Error	2.88 E03	1.24 E03	2.09 E03				1.89 E03	975	1.94 E03			
Total	9.48 E07	1.25 E03					2.45 E04	979				
Corrected total	4.29 E07	1.25 E03					2.06 E03	978				

[a] R-squared = 0.099 (Adjusted R-squared = 0.97).
[b] R-squared = 0.085 (Adjusted R-squared = 0.082).

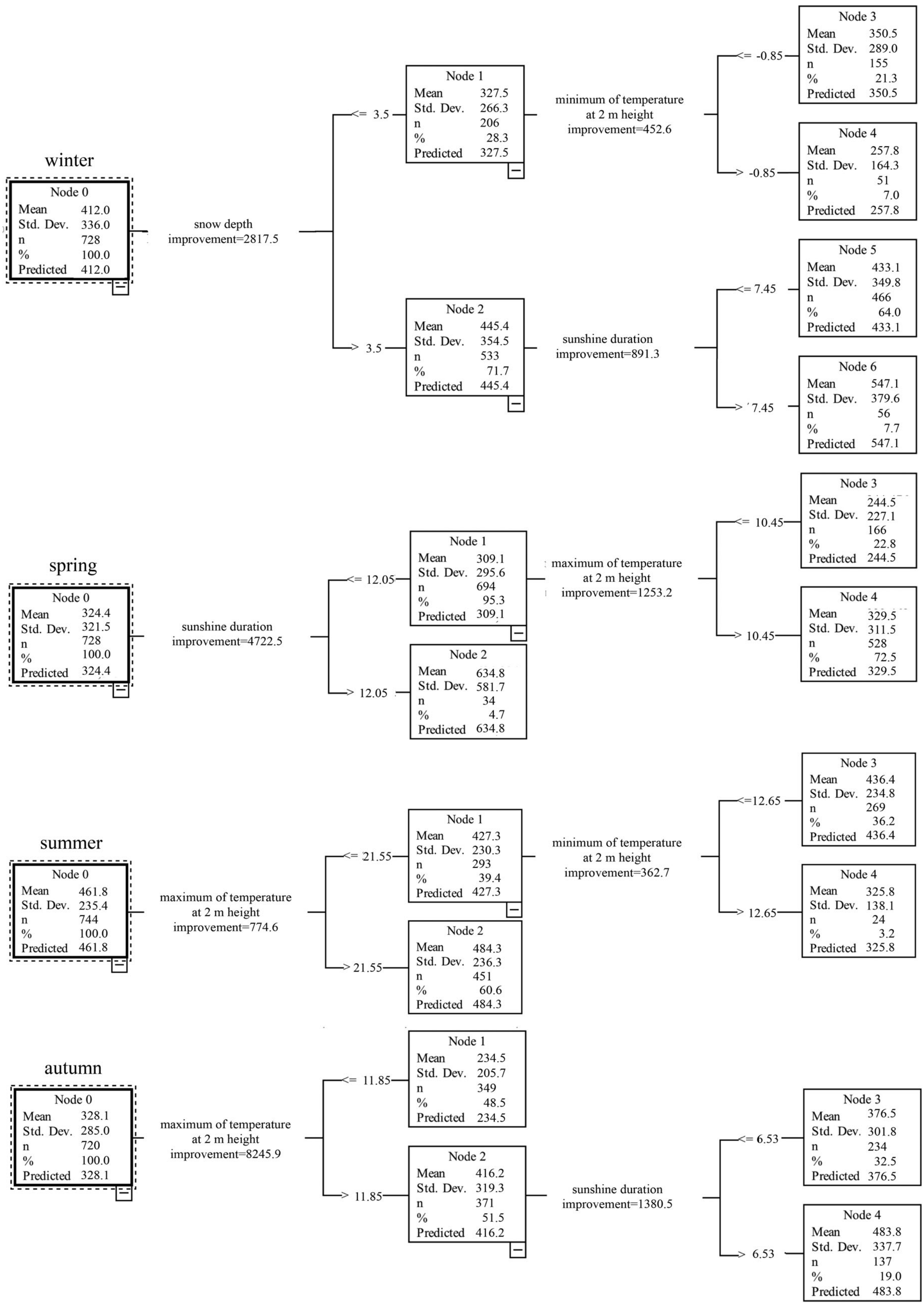

FIGURE 2 Decision trees for each season using the weather condition parameters from Table 5

Hypothesis H1 can be confirmed for short trips in summer as well as in autumn for the 3 days weather conditions (Table 7) by ANOVA as well as for the pleasant/unpleasant weather conditions using the *t*-test. Better weather conditions lead to significantly higher short trip daily arrivals in summer and autumn with a small to medium effect size. Moreover, for spring we see a significant influence with a small effect size when comparing the pleasant/unpleasant weather conditions with the *t*-test, but the ANOVA is only close to 0.1 probability but not below.

Looking at the arrivals in Table 8 (mid-term weather forecast), the influence of the weather forecast is much lower compared to the -short-term weather forecast. Using ANOVA to compare all seven 5-day weather conditions for each season, we detected significant differences comparing daily winter and summer arrivals for short trips at lower significance levels (α between 5% and 10%). Furthermore, t-tests indicate significant differences with small effect size of short-trips again for summer but this time not for winter. Instead, we noticed that autumn short trips were likely to show more variability. Spring is the only season we do not find any significant differences for arrivals of short-trip guests among the seven weather condition clusters C_{21} to C_{27} neither with ANOVA nor *t*-test. A further result is that daily arrivals of guests with long trips lasting at least four nights are robust against the mid-term weather conditions.

Rahman et al. (2018) showed that temporal booking decisions vary depending on the risk preferences of travelers which result in either a gain or loss in monetary return to the individual. During high seasons the risk for a gain increases as the chance a destination is nearly booked out increases, while the opportunities for a bargain decreases in case of a late booking. Thus, we can assume individuals engage in different booking and related travel behavior between low and high seasons. For example, a stretch of pleasant or unpleasant weather might cause different effects during the high season versus those that may occur during the low season. We analyzed the influence of both factors, the weather condition (pleasant/unpleasant) and the season type (high/low), on the duration of stay by using a generalized linear model (see Table 9).

Comparing high and low seasons we see for high seasons an average duration of 5.42 days in summer, 5.08 days in winter, but for low seasons only 4.73 days in spring and 3.94 days in autumn. When analyzing the influence of both factors, the weather condition (pleasant/unpleasant) and the season type (high/low), on the duration of stay (see Table 9), the results confirm a significant influence with small to medium effect size based on type of season. Furthermore, the interdependency of both factors is statistically significant. This shows the influence of both variables and their interaction term on duration of stay. Finally, we did a cross-check of the findings for short trips assumed by the above mentioned literature to be the most weather condition sensitive ones for daily arrivals. We used the daily weather condition parameters from Table 5 as input for the decision trees. We limited the number of hierarchy levels to two in order to find the most important weather condition parameters per season. Figure 2 shows the results for all four seasons and the arrivals per day (a/d).

The decision trees show that in winter the most important parameter is snow depth, splitting into a high-demand group (445 a/d) above a value of 3.5 cm and a low-demand group (328 a/d) below or equal to 3.5 cm of snow depth. Next, sunshine duration splits the high-demand group with the first split at a value above 7.45 h per day in the top high-demand group (547 a/d) and below in a modest high-demand group (433 a/d). The low-demand group splits again by the minimum day temperature near 0°C (−0.85). Colder weather, which means real winter atmosphere, finds a higher demand (351 a/d) than the warmer winter days without decent snow (258 a/d).

For the other seasons, we see in spring at the first level the sunshine duration as a very dominant factor (split value 12.1 h) splitting into a small group with 635 a/d and a large one with 309 a/d. This large group splits again by the maximum day temperature of 10.4°C (higher temperature 330 a/d, lower 245 a/d). In summer at the first hierarchy level, the maximum day temperature splits in high demand (484 a/d) for values above 21.55°C. The lower demand group (427 a/d) again is divided by the minimum temperature at a level of 12.65°C, whereby lower minimum temperatures are preferred (436 a/d against 326 a/d). Finally, for autumn we see as in summer the maximum day temperature at the first level splitting at 11.85°C and above into a high demand group (416 a/d). Temperatures below this threshold lead to a much lower level of daily arrivals (234 a/d). The high-demand group again splits by sunshine duration at a value of 6.53 h per day. Longer sunshine in autumn makes the destination attractive for short trip visitors (484 a/d).

4 | DISCUSSION

As shown by the literature review, destination climate and weather are very important concerns for most travelers. This applies to the early stage of destination choice by considering its climate conditions, by the preparation of the trip after having chosen the destination, and also to the on-site stay and related activities at the destination based on the weather forecast. Our focus was on the latest phase of the travel process chain when travelers take final decisions about visiting a destination including duration of their trip. From the perspective of the destinations these decisions lead to arrivals and overnight stays. Most of the studies we found are based either on yearly or monthly data. In a few cases researchers were using daily data, but almost solely from one or a few weather parameters (Agnew & Palutikof, 2006; Hamilton et al., 2007; Shih et al., 2009). Moreover, most studies analyzed just one season, either summer or winter. Our study analyses the impact of weather on tourism for all four seasons by using daily data from travelers visiting a destination in combination with the daily data from the local weather station. Furthermore, the study is based on a longitudinal approach combining traveler data from 2012 to 2019 and weather data from 2002 to 2019. By this new approach, the presented study delivers a more general understanding of the role of destination climate and weather across the entire seasonal cycle of a destination.

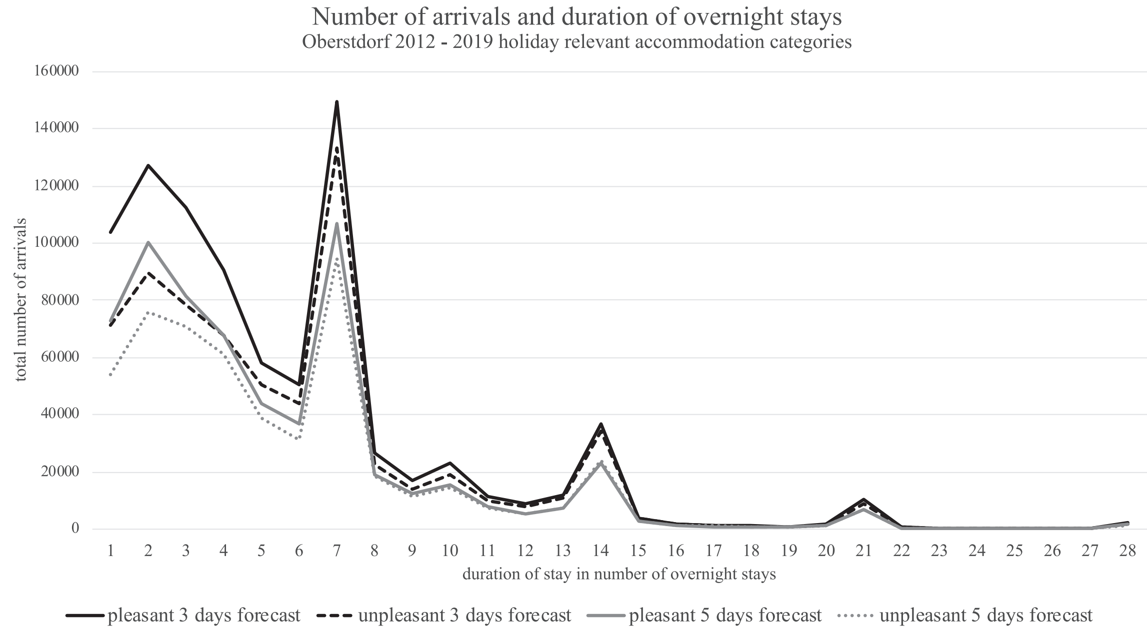

FIGURE 3 Empirical distributions of arrivals and duration of overnight stays

Our first hypothesis H1 expresses the assumption that weather conditions influence the number of arriving guests. Generally, we would expect that favorable weather conditions increase the number of daily arrivals whereas unfavorable weather reduces the number of arriving guests. As shown by Table 7 we could confirm this hypothesis for spring, summer and autumn. Only in winter, we do not see any significant influence of the short-term weather forecast on arrivals, neither for total nor for short- or long-trips. One plausible explanation could be that traditional holiday trips such as over Christmas or New Year's Eve are based on the calendar and not on any particular weather condition. These are trips which are organized months before and take place regardless of the weather conditions, because they occur during a period with many bank holidays and very high demand in traditional winter destinations. People who want to be sure to find good conditions for skiing might shift their trip from Christmas to a later date (Berghammer & Schmude, 2014), but these are not short term decisions.

We could not confirm the H1 hypothesis, for mid to long term stays, for any of the seasons using ANOVA or the *t*-tests. This result underlines the aforementioned assumption that people having planned and organized a long trip, they accept the weather condition as it is. Many people have to ask their employer for permission to leave for a week or longer or they have to use a fixed date during the school holiday periods. A further reason that might explain this finding is that the booking might have been fixed with a refunding option in case of cancelation. We did not examine booking policies for all the properties in Oberstdorf to determine if this is the case.

The second hypothesis H2 asks whether the weather condition influences the duration of stay. We would expect that unfavorable weather might cause an early departure whereas extraordinary good weather conditions could trigger an extension of the holiday. Our ANOVA and *t*-tests both revealed a significant influence of weather conditions for all four seasons as well for short-term 3 days and mid-term 5 days planning horizons on the duration of stay. However, looking at the observed durations for the identified weather conditions we see data contrary to what we expected. While the duration of short-trips does not show any significant influence resulting from the weather condition, the long-trips extend significantly in cases of bad weather conditions for all seasons. This is similar to the result we found for arrivals in autumn for C_{41} to C_{47}. A comparison of the distributions of the duration of stay for the groups of pleasant and unpleasant weather conditions for the period 2012–2019 using a Mann–Whitney *U* test for independent variables shows significant differences for $\alpha = 1\%$ for the 3 days as well as for the 5-day forecast horizon. Looking at the graph of the empirical frequency distributions for 1–28 overnight stays which is presented in Figure 3, a clear picture emerges.

The significant differences in the distributions are caused by a much higher level of arrivals for pleasant weather conditions (3 and 5 days) for shorter trips with a duration of up to 6 days. We see higher level of arrivals during pleasant weather conditions compared to unpleasant weather. In contrast, the short-term and mid-term forecast for pleasant or unpleasant weather condition does not have any more influence on the distribution for long trips. This explains the higher average duration of stay during an unpleasant weather forecast as the share of short stays is much lower and thus the average duration of stay rises. It is clear that pleasant weather triggers more travel to the destination of the short stay variety and much less during unpleasant weather. The apparent contradictions noted above are simply based on numbers of arrivals and have little to nothing to do with weather occurring after arrival.

Splitting the data from Figure 3 by season a further phenomenon becomes visible. In winter the quotient of the number of arrivals for pleasant and unpleasant weather conditions is for all durations of stay from 1 day to 2 weeks nearly balanced (pleasant/unpleasant between 1.00 and 1.29). In contrast, for autumn we record a positive quotient for short trips from 1 to 3 days (1.16, 1.46, 1.3), but for all long trips with a duration of stay between 4 days and 2 weeks a quotient between 0.93 and 0.49 is found. In autumn, short-trip travelers obviously are more weather sensitive whereas long stay travelers accept the autumn weather even if it is unfavorable. As a result, the number of short trip arrivals drops sharply during poor weather conditions in autumn, whereas long-term trip arrivals are very stable and do not react negatively to bad weather conditions. This phenomenon explains the longer duration of stay as well as the higher arrivals in autumn even though the weather is relatively bad. This finding reinforces our explanation in the preceding paragraph.

Looking at the results, we can in general confirm hypothesis H2. However, our data do not explain if pleasant weather conditions cause extensions of stays in general or unpleasant weather conditions cause an earlier return. We see a higher number of arrivals for shorter trips with a duration of up to five overnight stays, which might be seen as an indicator that a very good weather forecast stimulates people to have short trips lasting more than one or two overnight stays. For longer stays, there might be other effects. Our methodology of looking at time horizons of 3 and 5 days does not enable us to interpret the results for the longer stays of, for example, 2 weeks duration.

On a descriptive basis, we found a trend for more additional trips with a duration of 4–6 days in case of good weather conditions. This could have two reasons. Either it could be caused by additional longer trips to the destination or by the extension of shorter to longer stays. Equally, for long trips we can neither confirm nor reject a statistically significant extension by good or shortening by bad short-term or mid-term weather condition forecasts at the beginning of the trip. This would need further analysis looking at the weather condition during the entire stay in combination with data about individual behavior as earlier departure or prolongation of a stay. These data were not available, thus by our analysis these effects could not be analyzed.

A more general finding of the study deals with the correlation of the length of trips and the influence of weather conditions. To many travelers the weather condition is an important factor for the potential fulfillment of their expectations as their planned activities require a certain weather condition at the destination. When taking travel decisions, they need during the early stage of trip planning information about the weather they can expect upon arrival and for a few days after. By analyzing our findings, first from the perspective of the traveler regarding what is available to them for decision making, we arrived at a new understanding of how to analyze the impact of weather condition on travel decisions. Weather forecasts provide detailed information on the short-term and more generally on the mid-term and thus create an expectation as regards the current weather condition. Longer forecasts, for example, for a 2-week period are still very inaccurate. For a longer stay, travelers have to trust the information from the past either through their own experience or by looking at average weather parameters for the time period in question. This derived perception was formalized to describe the weather condition judged to be "usual." This result is coherent to the findings of Tang et al. (2021), who reported a low influence of weather after booking on the duration of stay but a strong influence on activities during the trip.

In case of a trip lasting only one or a few days, travelers can expect a good reliability of the forecast. Thus, in case of a weather forecast heavily differing from what their expectations are they can rapidly change their plans. This is what we found for all seasons: in the case of very good weather conditions, the arrivals from people doing a short trip increase significantly and the opposite occurs for bad weather. On the contrary, trips of longer duration show a high robustness regardless of expected weather conditions. Travelers only have relatively reliable weather information for the next 3–5 days. The cancelation of a 10-day or 2-week trip because of a short-term bad weather forecast seems to be very unlikely. Longer-trips need higher organizational efforts very often in combination with the booking of accommodation or transportation long before leaving. Our results suggest that the importance of the short-term and mid-term forecast for a change of an already scheduled trip declines by each additional day of the duration of trip. This is supported by the comparison of the number of arrivals and duration of overnight stays for pleasant and unpleasant weather conditions as shown in Figure 3.

A further general finding concerns the different level of influence of weather conditions by season. The findings underline that analyzing the seasons separately is essential, as the expectations for the trip and related activities and therefore the preferable weather condition change by season. What tourists wish for in summer is different than in winter. The seasonal typology approach considers these changing expectations and judgments of travelers concerning pleasant and unpleasant weather conditions. Moreover, this new methodology considers not only the seasonal demand structure of destinations but also their product focus per season. In our case of a town in the Bavarian Alps we found snow during the winter season to be an important but not a dominant weather parameter. But this has to do with the product and relative positioning among alpine winter destinations. A large share of the German winter holiday market consists of non-skiers or people who ski occasionally (Bausch & Unseld, 2018; Witting & Schmude, 2019). Thus, an additional and more general result of the study is that the role of climate and weather must always be seen in the context of each destination's individual profile for each season.

5 | CONCLUSIONS

There are a number of considerations that arise from this analysis. A first conclusion can be drawn with regard to adequacy of the methodology used in research of consumer perception of and reaction to destination weather conditions. Looking at typical weather forecasts in print, broadcast and online media, we can assume people form their view of the weather condition on the basis of the entire set of information they receive (Demuth et al., 2011). This is what the different tourism climate indexes try to achieve: to aggregate a combination of several climate parameters. But this assumes also that travelers use identical weights for each parameter in the aggregation formula. However, the studies of thermal climate comfort showed that the temperature people personally prefer has a large range and depends on their destination preferences. Thus, the aggregation of a set of parameters to one single value goes hand in hand with a high loss of information and therefore is not suitable to explain the complex choice decision of travelers. Our findings support the results of Scott et al. (2016) to discontinue the TCI. But we also see attempts to replace the TCI by alternative types of aggregation to just one index as, for example, the proposed HCI as not less critical. The general deficit of each index value, even if it tries to consider preferences of travelers concerning thermal, esthetic and physical aspects, is subject to a high loss of information by aggregation. Instead, we proposed in this paper to work with destination weather condition typologies. We characterized the short and mid-term weather condition by variables indicating for each weather parameter on a daily basis if it differs for a 3- or 5-day period significantly from the 2-week average values during the last decade. This is what people do: looking at the forecast they check the most prominent weather parameters like maximum and minimum day temperature, sunshine or cloudiness, amount, type and duration of precipitation and relate these to their trip goals they hope to realize during their stay at the destination. Future research about travelers' reactions on destination weather therefore should connect the travelers' specific activities intentions and the short- and mid-term weather conditions supporting them.

Further, climate is not weather, but they are related. Over time as climate changes daily weather conditions will also change. This may not be a big deal for destinations not overly weather dependent for tourism, but it is for those that are reliant on outdoor activity for their livelihood. Our findings showed a dramatic reduction of arrivals when the snow height fell below 3.5 cm in Oberstdorf. Climate change scenarios for the Bavarian Alps show a high dynamic decline of snow reliability (Weber et al., 2016). Thus, destinations with such a constellation are facing a potential dramatic change of guest arrivals if they do not change what they offer. Bausch and Gartner (2020) examined tourists activity preferences for Alpine destinations and found that many of the preferences were not as weather dependent as others. However, when examining destination promotional efforts, the activities receiving the most attention were those that were weather dependent (e.g., alpine skiing). One recommendation was that in the age of climate change destinations most at risk from changing weather patterns should complement their promotional efforts by those activities not as heavily dependent on daily weather or long-term climate predictions. This would allow for a buffer or hedge against simply trying to attract traditional clients that only visit if weather conditions have made it possible to pursue their preferred activity. As some of the climate change studies suggest daily weather patterns are likely to become more variable (Schroeer & Kirchengast, 2018), our findings lead us to believe those destinations most at risk from climate change would also experience more variability around daily bookings due to inclement weather conditions. This is something that should factor into strategic planning for at risk destinations.

This brings up another important and general point about weather conditions and its relationship to tourism. If weather conditions are such that it makes it difficult, or not ideal, to engage in a preferred activity how many tourists will change or cancel their plans? This is dependent on a number of factors such as sunk time or monetary costs. If an individual has to select days in advance for holiday leave and this decision cannot be revoked at the last minute, it becomes a sunk time cost and the individual is most likely to go ahead with the planned trip even if the weather conditions are not ideal. This decision becomes even more problematic if it is accompanied by sunk monetary costs that occur when deposits for rooms or other services are not refundable or refundable at a cost. It will also depend on seasonality. During high season tourists may have no other option but to reserve in advance and pay a non-weather dependent deposit. During low season with limited demand reservation policies may be more liberal. Further exacerbating this issue is the type of organized trip the tourist has selected. As mentioned above, fully organized trips are characterized by limited flexibility with respect to length of stay.

All of the above factors come into play when trying to figure out weather related effects on trip initiation and length. If this is the situation and the tourist experiences less than ideal weather conditions that are not seen as highly unusual but more and more likely to reoccur, then a different booking decision in a different destination is most likely to be the outcome. Weather uncertainty can lead to destination substitution. For destinations that are short term trip dominant this may be even more problematic. It is therefore critical that destinations examine their weather vulnerability with respect to climate change to decide on coping strategies.

As we have found significant impacts of weather forecast on the volume of short-term trips, this finding appears to help address our question of how many people will change their mind as a result of an unfavorable weather forecast. To address this question more directly, we analyzed which weather parameters are the most powerful triggers for the four seasons. Generally, we found for our case, Oberstdorf, only emotional and functional positive weather parameters to be important. Neither high precipitation nor cloudiness or vapor pressure play a central role. This allows the formation of a hypothesis for further research that the promotion of destinations presenting the region through perfect weather pictures for each season influences the expected weather conditions of the travelers. The power of pictures showing a dream world under perfect weather conditions for all types of activities in a destination becomes a part of the destination's induced image. This might result in a positive bias toward expected weather conditions. In a time of climate change and daily weather increasingly fluctuating away from the norm this may be exactly the wrong strategy to use unless there exist sufficient numbers of renewal (i.e., first time) visitors to entice. Frequent (i.e., repeat) visitors will experience the change and make decisions in their best interest. If what an individual wants to do is more often compromised by poor weather, then choosing an alternative destination would be an expected outcome.

Setting aside long-term climate change effects, weather changes in the short run can have significant effects on visitation. The assessment of the weather condition leading to a visit decision, as we have shown, is based on the short and mid-term weather forecast. People look for the coming days comparing the forecast with their trip goals. This is especially critical for people heavily invested in a sport or recreation activity with expectations of what particular weather conditions may bring. For example, alpine skiers know that snow conditions vary throughout the season and they look for those conditions that bring them the most benefit during different time periods. Spring skiing brings different expectations than early winter skiing. The commitment someone has to a specific sport and the extent to which weather affects goal realization for engaging in that sport will play a role in whether one chooses to visit a destination at a particular time, chooses a different time to visit or selects an entirely different destination. Although we were not able to definitely say how many tourists will change their plans as a result of unfavorable weather conditions the answer is "it is situational" and depends on a number of factors. What we can say definitively from our study is that arrivals and duration of stay as a result of the travel decisions are affected by weather conditions for a segment of a destinations' visitors.

Weather conditions described by averages, such as used in this study, take into account all previously collected data regarding selected weather parameters. The downside of examining averages is that they are often based on long term statistical compilation and fluctuating weather in the short term, even though it appears to be happening more frequently, will take a long time to move any of those averages. However, the tourist who visits the destination regularly will probably feel the change before the averages significantly move.

This, as we have argued, is what our results tell us. What we have not uncovered is the impact on extent of stay based on weather. Our data did not lend itself to this analysis. Nonetheless it is an important topic to pursue in future research studies. If weather turns out to affect extent of stay as well as short term arrivals some destinations may be in more danger from loss of clientele than they realize.

Weather is not something humans have control over. Climate is something that we have some measure of control over albeit in the long run. Simply because we cannot control something in the short run does not mean it should be ignored. Destinations face a multitude of threats to their status as a tourism destination. Weather related factors on tourist decision making is one of them. Destinations should evaluate their prospective risk factors, weather possibly being one of them, and take decisions about their future. Options, such as developing and promoting new reasons to visit can range from providing a greater focus on non-weather-related reasons to such things as activities that will take place regardless of weather conditions. These types of changes are within the control of the service providers even if the prevailing weather conditions remain outside their control. Doing nothing has its own consequences with some of them being foreseeable. Acting before there exists a crisis situation does two very important things: One, it recognizes there is a problem that needs to be addressed and two, it puts the acting destination in a situation where it can control its destiny.

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REFERENCES

Agnew, M., & Palutikof, J. (2006). Impacts of short-term climate variability in the UKon demand for domestic and international tourism. *Climate Research*, *31*, 109–120. https://doi.org/10.3354/cr031109

Alpaydn, E. (2010). *Introduction to machine learning* (2nd ed.). MIT Press.

Atzori, R., Fyall, A., & Miller, G. (2018). Tourist responses to climate change: Potential impacts and adaptation in Florida's coastal destinations. *Tourism Management*, *69*, 12–22. https://doi.org/10.1016/j.tourman.2018.05.005

Bae, J., & Nam, S. (2020). An analysis of the effect of climate indicators on tourism demand: A case study of Jeju Island. *Journal of Policy Research in Tourism, Leisure and Events*, *12*(2), 185–196. https://doi.org/10.1080/19407963.2019.1585363

Ballotta, L., Fusai, G., Kyriakou, I., Papapostolou, N. C., & Pouliasis, P. K. (2020). Risk management of climate impact for tourism operators: An empirical analysis on ski resorts. *Tourism Management*, *77*. https://doi.org/10.1016/j.tourman.2019.104011

Bausch, T., & Unseld, C. (2018). Winter tourism in Germany is much more than skiing! Consumer motives and implications to alpine destination marketing. *Journal of Vacation Marketing*, *24*(3), 203–217. https://doi.org/10.1177/1356766717691806

Bausch, T., & Gartner, W. C. (2020). Winter tourism in the European Alps: Is a new paradigm needed? *Journal of Outdoor Recreation and Tourism*, *31*, 100297. https://doi.org/10.1016/j.jort.2020.100297

BayLfSt. (2020). Tables 445511.001z, 45511-012z and 45511—505z arrivals and overnight stays in Bavarian municipalities. Fürth. Retrieved from https://www.statistikdaten.bayern.de/genesis/online

Berghammer, A., & Schmude, J. (2014). The Christmas-Easter shift: Simulating Alpine ski resorts' future development under climate change conditions using the parameter "optimal ski day". *Tourism Economics*, *20*(2), 323–336. https://doi.org/10.5367/te.2013.0272

Bujisic, M., Bogicevic, V., Parsa, H. G., Jovanovic, V., & Sukhu, A. (2019). It's raining complaints! How weather factors drive consumer comments and word-of-mouth. *Journal of Hospitality and Tourism Research*, *43*(5), 656–681. https://doi.org/10.1177/1096348019835600

Chen, C.-M., & Lin, Y.-C. (2014). The effect of weather on the demand for rooms in the Taiwanese hotel industry: An examination. *Tourism Management Perspectives*, *12*, 81–87. https://doi.org/10.1016/j.tmp.2014.09.004

Chen, C.-M., & Lin, Y.-L. (2019). The weather and macroeconomic determinants of whale-watching tourism: A Markov regime-switching analysis. *Current Issues in Tourism*, *22*(4), 476–485. https://doi.org/10.1080/13683500.2017.1293620

Choi, A. (2020). *The interplay of leisure travelers' stress, coping, and acculturation strategies: A study of Korean immigrants*. University of Minnesota.

Crouch, G. I. (2011). Destination competitiveness: An analysis of determinant attributes. *Journal of Travel Research*, *50*(1), 27–45. https://doi.org/10.1177/0047287510362776

Damm, A., Greuell, W., Landgren, O., & Prettenthaler, F. (2017). Impacts of $+2^{\circ}C$ global warming on winter tourism demand in Europe. *Climate Services*, *7*, 31–46. https://doi.org/10.1016/j.cliser.2016.07.003

Decrop, A. (2010). Destination choice sets: An inductive longitudinal approach. *Annals of Tourism Research*, *37*(1), 93–115. https://doi.org/10.1016/j.annals.2009.08.002

del Bosque, I. R., & Martín, H. S. (2008). Tourist satisfaction a cognitive-affective model. *Annals of Tourism Research*, *35*(2), 551–573. https://doi.org/10.1016/j.annals.2008.02.006

Demuth, J. L., Lazo, J. K., & Morss, R. E. (2011). Exploring variations in people's sources, uses, and perceptions of weather forecasts. *Weather, Climate, and Society*, *3*(3), 177–192.

Denstadli, J. M., Jacobsen, J. K. S., & Lohmann, M. (2011). Tourist perceptions of summer weather in Scandinavia. *Annals of Tourism Research*, *38*(3), 920–940. https://doi.org/10.1016/j.annals.2011.01.005

Dubois, G., Ceron, J. P., Dubois, C., Frias, M. D., & Herrera, S. (2016). Reliability and usability of tourism climate indices. *Earth Perspectives*, *3*(1), 2. https://doi.org/10.1186/s40322-016-0034-y

DWD Deutscher Wetterdienst. (n.d.). CDC (Climate Data Center). Retrieved from https://www.dwd.de/EN/climate_environment/cdc/cdc_node.html

Falk, M. (2010). A dynamic panel data analysis of snow depth and winter tourism. *Tourism Management*, *31*(6), 912–924. https://doi.org/10.1016/j.tourman.2009.11.010

de Freitas, C. R., Scott, D., & McBoyle, G. (2008). A second generation climate index for tourism (CIT): Specification and verification. *International Journal of Biometeorology*, *52*(5), 399–407. https://doi.org/10.1007/s00484-007-0134-3

FUR. (2019). Selected first resultsof the 49th Reiseanalyse for the ITB 2019 (p. 8). Kiel: Forschungsgemeinschaft Urlaub und Reisen (FUR) (research group vacation and travelling). Retrieved from https://reiseanalyse.de/wp-content/uploads/2019/03/RA2019_First-results_EN.pdf

Goh, C. (2012). Exploring impact of climate on tourism demand. *Annals of Tourism Research*, *39*(4), 1859–1883. https://doi.org/10.1016/j.annals.2012.05.027

Gössling, S., Abegg, B., & Steiger, R. (2016). "It was raining all the time!": Ex post tourist weather perceptions. *Atmosphere*, *7*(1), 10. https://doi.org/10.3390/atmos7010010

Hallmann, K., Zehrer, A., & Müller, S. (2015). Perceived destination image: An image model for a winter sports destination and its effect on intention to revisit. *Journal of Travel Research*, *54*(1), 94–106. https://doi.org/10.1177/0047287513513161

Hamilton, J. M. (2004). Climate and the destination choice of German tourists (SSRN Scholarly Paper No. ID 504362). Rochester, NY: Social Science Research Network.

Hamilton, J. M., & Lau, M. A. (2005). The role of climate information in tourist destination choice decision making. In S. Gössling & C. M. Hall (Eds.), *Tourism and global environmental change* (pp. 229–250). Routledge.

Hamilton, L. C., Brown, C., & Keim, B. D. (2007). Ski areas, weather and climate: Time series models for New England case studies. *International Journal of Climatology*, *27*(15), 2113–2124. https://doi.org/10.1002/joc.1502

Hewer, M. J., Scott, D., & Gough, W. A. (2015). Tourism climatology for camping: A case study of two Ontario parks (Canada). *Theoretical and Applied Climatology*, *121*(3), 401–411. https://doi.org/10.1007/s00704-014-1228-6

Hübner, A., & Gössling, S. (2012). Tourist perceptions of extreme weather events in Martinique. *Journal of Destination Marketing and Management*, *1*(1–2), 47–55. https://doi.org/10.1016/j.jdmm.2012.09.003

Jeuring, J. H. G. (2017). Weather perceptions, holiday satisfaction and perceived attractiveness of domestic vacationing in The Netherlands. *Tourism Management*, *61*, 70–81. https://doi.org/10.1016/j.tourman.2017.01.018

Jeuring, J. H. G., & Peters, K. B. M. (2013). The influence of the weather on tourist experiences: Analysing travel blog narratives. *Journal of Vacation Marketing*, *19*(3), 209–219. https://doi.org/10.1177/1356766712457104

Karl, M., Reintinger, C., & Schmude, J. (2015). Reject or select: Mapping destination choice. *Annals of Tourism Research*, *54*, 48–64. https://doi.org/10.1016/j.annals.2015.06.003

Karl, M., Bauer, A., Ritchie, W. B., & Passauer, M. (2020). The impact of travel constraints on travel decision-making: A comparative approach of travel frequencies and intended travel participation. *Journal of Destination Marketing & Management*, *18*, 100471. https://doi.org/10.1016/j.jdmm.2020.100471

Köberl, J., Prettenthaler, F., & Bird, D. N. (2016). Modelling climate change impacts on tourism demand: A comparative study from Sardinia (Italy) and Cap Bon (Tunisia). *Science of the Total Environment*, *543*, 1039–1053. https://doi.org/10.1016/j.scitotenv.2015.03.099

Kubokawa, H., Inoue, T., & Satoh, M. (2014). Evaluation of the tourism climate index over Japan in a future climate using a statistical downscaling method. *Journal of the Meteorological Society of Japan*, *92*(1), 37–54. https://doi.org/10.2151/jmsj.2014-103

Lindsey, G., Qi, Y., Gobster, P., & Sachdeva, S. (2020). Population changes, weather, and congestion: Exploring declines in use of Chicago's elevated trail. *Journal of Park & Recreation Administration*, *38*(1), 127–140. https://doi.org/10.18666/JPRA-2019-10063

Lise, W., & Tol, R. S. J. (2001). Impact of climate on tourist demand. *Journal of material culture*, *16*(3), 285–300. https://doi.org/10.2139/ssrn.278516

Ma, S., Craig, C. A., & Feng, S. (2020). The camping climate index (CCI): The development, validation, and application of a camping-sector tourism climate index. *Tourism Management*, *80*, 104105. https://doi.org/10.1016/j.tourman.2020.104105

Mach, L., Ponting, J., Brown, J., & Savage, J. (2020). Riding waves of intra-seasonal demand in surf tourism: Analysing the nexus of seasonality and 21(st) century surf forecasting technology. *Annals of Leisure Research*, *23*(2), 184–202. https://doi.org/10.1080/11745398.2018.1491801

Matthews, L., Scott, D., & Andrey, J. (2019). Development of a data-driven weather index for beach parks tourism. *International Journal of Biometeorology*. https://doi.org/10.1007/s00484-019-01799-7

Matzarakis, A. (2014). Transfer of climate data for tourism applications—The climate-tourism/transfer-information-scheme. *Sustainable Environment Research*, *24*(4), 273–280.

Mieczkowski, Z. (1985). The tourism climatic index: A method of evaluating world climates for tourism. *The Canadian Geographer/Le Géographe Canadien*, *29*(3), 220–233. https://doi.org/10.1111/j.1541-0064.1985.tb00365.x

Nuzzo, R. (2014). Statistical errors. P values, the 'gold standard' of statistical validity, are not as reliable as many scientists assume. *Nature*, *506*(7487), 150–153.

Oppewal, H., Huybers, T., & Crouch, G. I. (2015). Tourist destination and experience choice: A choice experimental analysis of decision sequence effects. *Tourism Management*, *48*, 467–476. https://doi.org/10.1016/j.tourman.2014.12.016

Pan, B., & Yang, Y. (2017). Forecasting destination weekly hotel occupancy with big data. *Journal of Travel Research*, *56*(7), 957–970. https://doi.org/10.1177/0047287516669050

Prettenthaler, F., & Kortschak, D. (2015). The effects of climate change on alpine skiing tourism a European approach. Retrieved from https://pdfs.semanticscholar.org/4649/4c84f0051be03d36e508f3474cebdfc913b8.pdf

Rahman, A., Crouch, G. I., & Laing, J. H. (2018). Tourists' temporal booking decisions: A study of the effect of contextual framing. *Tourism Management*, *65*, 55–68. https://doi.org/10.1016/j.tourman.2017.09.016

Rantala, O., Valtonen, A., & Markuksela, V. (2011). Materializing tourist weather: Ethnography on weather-wise wilderness guiding practices. *Journal of Material Culture*, *16*(3), 285–300. https://doi.org/10.1177/1359183511413646

Rutty, M., & Scott, D. (2014). Thermal range of coastal tourism resort microclimates. *Tourism Geographies*, *16*(3), 346–363. https://doi.org/10.1080/14616688.2014.932833

Rutty, M., & Andrey, J. (2014). Weather forecast use for winter recreation. *Weather, Climate, and Society*, *6*(3), 293–306.

Rutty, M., & Scott, D. (2010). Will the Mediterranean become "too hot" for tourism? A reassessment. *Tourism and Hospitality Planning & Development*, *7*(3), 267–281. https://doi.org/10.1080/1479053X.2010.502386

Rutty, M., & Scott, D. (2015). Bioclimatic comfort and the thermal perceptions and preferences of beach tourists. *International Journal of Biometeorology*, *59*(1), 37–45. https://doi.org/10.1007/s00484-014-0820-x

Rutty, M., Scott, D., Matthews, L., Burrowes, R., Trotman, A., Mahon, R., & Charles, A. (2020). An inter-comparison of the holiday climate index (HCI:Beach) and the tourism climate index (TCI) to explain Canadian tourism arrivals to the Caribbean. *Atmosphere*, *11*(4), 412. https://doi.org/10.3390/atmos11040412

Saló, A., Garriga, A., Rigall-I-Torrent, R., Vila, M., & Sayeras, J. M. (2012). Differences in seasonal Price patterns among second home rentals and hotels: Empirical evidence and practical implications. *Tourism Economics*, *18*(4), 731–747. https://doi.org/10.5367/te.2012.0141

Sawicki, Z. (2015). Sport tourism in Oberstdorf—The Most important sport and tourism Centre in the Bavarian Alps. *Topical Issues of Tourism: Tourism & Its Impacts on Society*, *10*, 436–445.

Schroeer, K., & Kirchengast, G. (2018). Sensitivity of extreme precipitation to temperature: The variability of scaling factors from a regional to local perspective. *Climate Dynamics*, *50*(11), 3981–3994. https://doi.org/10.1007/s00382-017-3857-9

Scott, D., & Lemieux, C. (2010). Weather and climate information for tourism. *Procedia Environmental Sciences*, *1*, 146–183. https://doi.org/10.1016/j.proenv.2010.09.011

Scott, D., Rutty, M., Amelung, B., & Tang, M. (2016). An inter-comparison of the holiday climate index (HCI) and the tourism climate index (TCI) in Europe. *Atmosphere*, *7*(6), 80. https://doi.org/10.3390/atmos7060080

Serquet, G., & Rebetez, M. (2011). Relationship between tourism demand in the Swiss Alps and hot summer air temperatures associated with climate change. *Climatic Change*, *108*(1–2), 291–300. https://doi.org/10.1007/s10584-010-0012-6

Shih, C., Nicholls, S., & Holecek, D. F. (2009). Impact of weather on downhill ski lift ticket sales. *Journal of Travel Research*, *47*(3), 359–372. https://doi.org/10.1177/0047287508321207

Song, Y., & Lu, Y. (2015). Decision tree methods: Applications for classification and prediction. *Shanghai Archives of Psychiatry*, *27*(2), 130–135. https://doi.org/10.11919/j.issn.1002-0829.215044

Steiger, R., Abegg, B., & Jänicke, L. (2016). Rain, rain, go away, come again another day. Weather preferences of summer tourists in mountain environments. *Atmosphere*, *7*(5), 63. https://doi.org/10.3390/atmos7050063

Stewart, A. E., Lazo, J. K., Morss, R. E., & Demuth, J. L. (2012). The relationship of weather salience with the perceptions and uses of weather information in a Nationwide sample of the United States. *Weather, Climate, and Society*, *4*(3), 172–189. https://doi.org/10.1175/WCAS-D-11-00033.1

Szalai, K., & Rátz, T. (2006). Tourist perceptions of uncertainty and risk associated with extreme weather events. 3rd International Conference on "Tourism Future Trends", October, 6.

Tanana, A. B., Rodriguez, C. A., & Gil, V. (2019). Strategic tourism management to address natural hazards in coastal areas: Lessons from Buenos Aires, Argentina. *Tourism Review*, *74*(3), 503–516. https://doi.org/10.1108/TR-04-2018-0047

Tang, J., Wu, H., Ramos, V., & Sriboonchitta, S. (2021). The role of weather conditions on tourists' decision-making process: a theoretical framework and an application to China's inbound visitors. *Current Issues in Tourism*, 1–16. http://doi.org/10.1080/13683500.2021.1883555.

Tasci, A. D. A., & Gartner, W. C. (2007). Destination image and its functional relationships. *Journal of Travel Research*, *45*(4), 413–425. https://doi.org/10.1177/0047287507299569

Tavares, J. M., Xuan, T., & Pennington-Gray, L. (2020). Destination images of the ten most visited countries for potential Brazilian tourists. *Imagens de Destino Dos Dez Países Mais Visitados Para Potenciais Turistas Brasileiros*, *16*(2), 43–50. https://doi.org/10.18089/tms.2020.160205

Taylor, T., & Ortiz, R. A. (2009). Impacts of climate change on domestic tourism in the UK: A panel data estimation. *Tourism Economics*, *15*(4), 803–812. https://doi.org/10.5367/000000009789955161

Toubes, D. R., Gössling, S., Hall, C. M., & Scott, D. (2017). Vulnerability of Coastal Beach tourism to flooding: A case study of Galicia, Spain. *Environments*, *4*(4), 83. https://doi.org/10.3390/environments4040083

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA statement on p-values: Context, process, and purpose. *The American Statistician*, *70*(2), 129–133. https://doi.org/10.1080/00031305.2016.1154108

Weber, M., Bernhardt, M., Pomeroy, J. W., Fang, X., Härer, S., & Schulz, K. (2016). Description of current and future snow processes in a small basin in the Bavarian Alps. *Environmental Earth Sciences*, *75*(17), 1223. https://doi.org/10.1007/s12665-016-6027-1

Weisheimer, A., & Palmer, T. N. (2014). On the reliability of seasonal climate forecasts. *Journal of the Royal Society Interface*, *11*(96), 20131162. https://doi.org/10.1098/rsif.2013.1162

Witting, M., & Schmude, J. (2019). Impacts of climate and demographic change on future skier demand and its economic consequences—Evidence from a ski resort in the German Alps. *Journal of Outdoor Recreation and Tourism*, *26*, 50–60. https://doi.org/10.1016/j.jort.2019.03.002

Zirulia, L. (2016). 'Should I stay or should I go?': Weather forecasts and the economics of 'short breaks'. *Tourism Economics*, *22*(4), 837–846. https://doi.org/10.1177/1354816616654256

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