ISLANDS
ERASMUS MUNDUS RESEARCH MASTER

Microclimate Injustices across an Island Resort:

The Case of Maspalomas/Playa del Ingles, Gran Canaria, Spain

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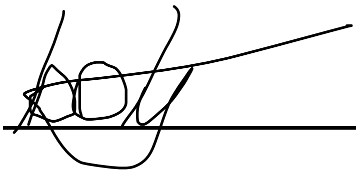

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Abstract

The growth of resort tourism in the 20th century has led to the transformation of various rural coastal and island regions into new specialised built up resort zones. This is typically in destinations fitting the Three S's of sun, sea, and sand. One such area where this transformation has been felt acutely is Maspalomas/Playa del Inglés, located on Gran Canaria's southern coastline. However the consequences of such development on regional microclimates is relatively unknown. This article utilises remote sensing data from the LandSat 8 satellite to map the regional distribution of surface temperatures within Maspalomas/Playa del Inglés. In this way temperature disparities are identified between cooler built up neighbourhoods dense with tourism related activities, and hotter built up neighbourhoods on the peripheries typically housing local residents and workers in the tourism sector. To explain why, links are drawn between the Tourism Area Life Cycle model and the concept of resortification to argue that, across resort regions, landscaping and environmental amenities are prioritised for touristic spaces over their non-touristic counterparts, thus causing a heat disparity. This article asserts that this constitutes a spatial injustice, and points to a broader reality of marginalisation and segregation for residents of resortified regions. To address such injustices, this article argues that resort areas must establish a *Right to the Resort* for residents, empowering these communities with greater democratic say over planning decisions and ensuring better provision of vital neighbourhood investment.

Key Words

Resorts, Resortification, Climate Inequality, Remote Sensing, Urban Heat, Landscape Cooling, Tourism

1. Introduction

From the mid 20th century onwards, with the growth of the *mass tourism* model of low costs and high capacity (Cantillon, 2018; Chong, 2020; Goodwin, 2017; Weaver, 2001), the sector has established itself as the dominant industry in a host of both urban and rural regions, particularly within hotspots such as the Mediterranean, the Caribbean, and Maraconesia (Hernández Martín et al., 2021; Kizos et al., 2017; Lagarias & Stratigea, 2023; Leka et al., 2022; Weaver, 2001). Yet, mass tourism growth has also been linked to harmful consequences for affected regions, through threatening biodiversity (Hall, 2010), contributing to inflation (Shaari et al., 2018), and squeezing the local housing markets (Biagi et al., 2015), amongst other impacts. Furthermore, through establishing a building footprint of hotels, resorts, attractions, and other associated businesses, mass tourism can cause dramatic landscape transformations through either rapid redevelopment of existing urban spaces towards centring tourism or the construction of entirely new specialised resort zones on top of previously rural areas (Blaxell, 2010; Cantillon, 2018; Jauze, 2013). Understanding in detail the consequences, both positive and negative, of this spatial element to tourism is critical to help the sector to adapt to growing demands for tougher environmental and social responsibility. Such demands are particularly acute in areas that have been most affected by mass tourism, with there being growing political discontent and resistance to the sector (Nixon, 2015; Pettas et al., 2022; Suarez, 2024).

One such consequential impact of tourism development is the effects upon local microclimates. Here microclimate denotes small scale, human level climatic conditions such as humidity and temperature, in cities often being shaped by the fabric of local urban features (Erell et al., 2011). Regional climate is considered a key determinant of destination building, and as such tourism development may be more acute in regions exhibiting "desirable" year round climates (Scott et al., 2016). However, altering a landscape's surface through anthropogenic actions such as building hotels, new housing, attractions, and general landscaping can distort the local microclimate (Lin et al., 2020; Rizwan et al., 2008). Some of these impacts may be intentional, particularly as in some destinations without efforts at localised cooling such as planting street trees for shade, local climates could become excessively hot and thus threaten tourism desirability. Nonetheless, these impacts could also be unintentional side effects of developing tourism amenities such as irrigated parks, lakes, and swimming pools, as these features have also been linked to local climate alternation through spillover cooling effects (Lin et al., 2020; Peña, 2008).

Yet, in tourism dense areas such as resort regions, land value is often tied to tourism desirability (Cantillon, 2018; Liu & Wall, 2009). This means that there is potential for spatial and social segregation (Musterd, 2005) between the desirable areas allocated for tourists and those left on the peripheries for regional residents/workers in the sector. These non-touristic neighbourhoods may exhibit different spatial properties and receive less volumes of development investment. Combined such a situation could cause non-touristic neighbourhoods to have a less favourable microclimate compared to touristic areas. In this regard tourism development, particularly in resort regions, could produce concerning environmental disparities. Given a context of global climate change and rising criticism directed at the sector (Nixon, 2015; Suarez, 2024), examining if and how tourism can be identified as producing such microclimate inequalities, is thus a salient and pressing research agenda.

2. Theory and Literature

When analysing tourism development and its environmental impact, it may be important to specify what type of area is tourism growth occurring. This entails separating tourism growth into a typology of urban and rural developments, with potentially the most dramatic environmental alterations being in the latter category whereby tourism can transform sparsely populated rural landscapes into new specialised economic zones/resort areas. To understand how environmental inequalities can emerge within these resort areas, this study employs the concept of *resortification*, which denotes a specific process of landscape transformation from rural to concentrated tourism development through hotels, amenities, new business etc. (Blaxell, 2010; Jauze, 2013; Tade, 2004 as cited in Blaxell 2010). As a concept, resortification covers the particular market pressures, political decisions, destination brand management, and stakeholder influences that shape this transformation.

A multitude of interrelated factors combine to determine the desirability of a particular rural destination for resortification, including but not limited to, the aforementioned favourable climates for tourism (Scott et al., 2016; Szuster et al., 2023), proximity to attractive landscape/coastal features such as sandy beaches (Cantillon, 2018; Lagarias & Stratigea, 2023), access to transportation links (Lohmann & Duval, 2011; Prideaux, 2000), availability of affordable land and labour (Andriotis, 2003; Joppe, 2012), encouraging regional planning agendas (Alvarez León, 2012; Cantillon, 2018), and potentially other clustering incentives for resorts, such as the Hotelling Model (Rodríguez-Victoria et al., 2017). Emphasising the importance of climate and location, destinations most favourable for resort development have been thought of as embodying the “Three S’s of Sun, Sand, and Sea” (Aguiló et al., 2005; Cantillon, 2018; Szuster et al., 2023).

Efforts to model resortification and more general the process of area transformation into tourism destinations have led to the formation of theoretical frameworks, most notably Butler's Tourism Area Life Cycle/TALC model (Butler, 1980, 2004).

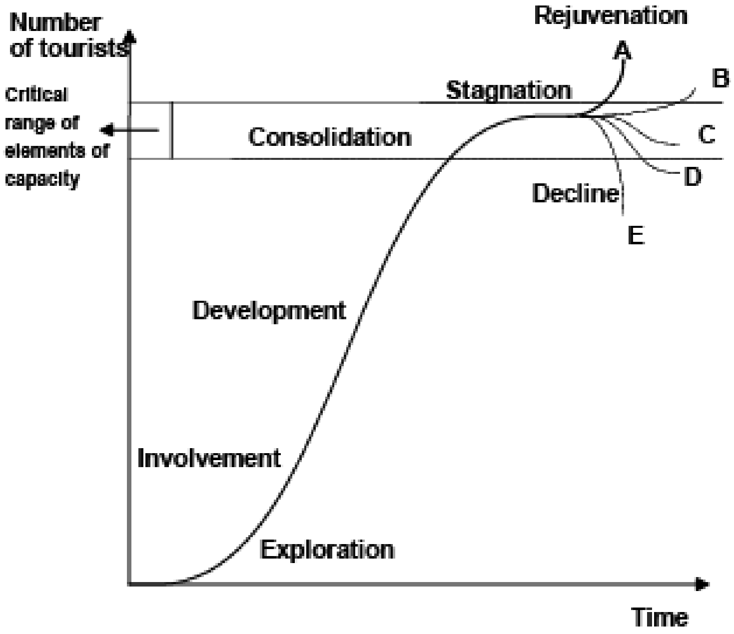


Figure 1: “A tourism area cycle of evolution” (Butler, 2004)

Although the TALC model has some drawbacks, such as not separating rural and urban tourism development, relevant for this article is Butler’s identification of a period of rapid growth within tourism area transformation referred to as the *Development Stage* (Butler, 1980, 2004). Butler defines this stage as being often following a top down planning agenda to construct and expand tourism in a given region. For resortification, it is in this stage where total landscape transformation towards a resort region is felt most acutely, and where the speed of this development may entail a lack of careful planning due to market pressures to quickly capitalise upon rising demand from tourists to visit. The speed and totality of this Development Phase, may partially explain identifiable commonalities between many resort areas globally – features identified within a subfield of tourism studies termed “Resort Morphology” (Liu & Wall, 2009). For coastal resorts, these features include tourism businesses clustering near desirable environmental features such as the beaches or the coastline, forming an area defined as the Recreational Business District or RBD (Andriotis, 2003; Liu & Wall, 2009). Furthermore, expanding out from the RBD in these coastal resort areas, due to endless rising tourism demand of the Development Stage, there may be the construction of ever larger hotels with desirable and distinguishing features such as expansive swimming pools and carefully maintained surrounding gardens (Butler, 1980).

In the Development Stage intensive landscaping is made possible by rising profits to both to reshape the resort region into one more visually appealing, and provide new pull factors such as the construction of attractions such as golf courses. Further for resorts in hot arid regions, such landscaping efforts may also be directed at cooling the area's climate into one more hospitable to tourists. In pursuit of this goal resort planners may incorporate irrigated additional green features (on top of golf courses and hotel lawns) such as urban parks and trees as methods of cooling resort microclimates (Arshad et al., 2021; Peña, 2008). The resulting urban cooling effect from green areas is partly attributable to plant life having a higher albedo compared to artificial surfaces, due to evapotranspiration, where heat energy is absorbed and utilised in the photosynthesis process (Qiu et al., 2013, 2017). Furthermore, trees, in particular, provide canopies for shade, further lowering local daytime temperatures (Erell et al., 2011; Gomez-Muñoz et al., 2010).

Another design feature that may have the added effect of cooling is the incorporation of artificial water features, such as ponds, lakes, or pools, which may absorb heat and, through evaporation, increase local humidity, which could lead to cooling breezes, however their effectiveness is debatable (Jacobs et al., 2020; Lin et al., 2020). Additionally, altering the colour of surfaces, notably by painting buildings white, increases the surface albedo of structures so that they reflect more sunlight than they absorb. Often associated with traditional architectural styles of the Mediterranean, this style of painted buildings is sometimes referred to as "Pueblos Blancos"/"White Villages"' in the Andalusia region of Spain (Periáñez, 2017) Finally, designing lower-density neighbourhoods for resorts allows for air flow, which in turn can also mitigate excess heat. Combined these interventions could transform more touristic areas of resortified spaces into Urban Heat Sinks (UHS) whereby these spaces are cooler relative to surrounding areas (Fan et al., 2017; Mohamed et al., 2018).

However, this process could mean resortification causes urban heat inequality across resortified regions. This is because, as well as the construction of new hotels and attractions, within the Development Stage of resortification there is an increase in the demand for a regional workforce to staff new amenities and hotels (Andriotis, 2003; Cantillon, 2018). This in turn causes a need for neighbourhoods to house workers and a growing non-tourist resident population. However, given that throughout resortification, land value is tied to tourism desirability (Andriotis, 2003; Cantillon, 2018), the spaces reserved for residents and non-touristic neighbourhoods may be an afterthought, pushed to the fringes of a resort region in cramped overcrowded spaces. Moreover, within these non-touristic spaces there is a lower to non-existent financial incentive for the same scale of landscaping development and provision of amenities as seen in nearby touristic areas. This could result in dramatic and visible differences in the built environment between touristic and non-touristic areas, as well as there being clear segregated dividing lines between neighbourhood types. Furthermore, this spatial segregation could form the basis for a host of environmental inequalities, such as disparities in urban cooling, air pollution, green space access etc.

This principle of spatial segregation and environmental marginalisation caused by resortification has been observed globally, particularly by researchers working within the field of Resort Morphology (Andriotis, 2003; Liu & Wall, 2009). For instance, in the example of resort developments on the Greek island of Crete, outside of the primary touristic areas, there exists periphery spaces of residences for "locals and the seasonal immigrant workforce" (Andriotis, 2003, p. 71). These areas have a noticeable lack of infrastructure investment such that "Roads are very narrow, pavements almost non-existent, and parking spaces scarce making locals' life difficult" (Andriotis, 2003, p. 72). In hot regions, such cramped spaces, lacking green surfaces, can trap heat and cause elevated temperatures (Giridharan et al., 2004; Rizwan et al., 2008). Compared to the cooling of more touristic areas therefore, this study argues that resident spaces are at greater risk of exhibiting features typically associated with the contrasting Urban Heat Island (UHI) effect (Arshad et al., 2021; Equere et al., 2021; Fan et al., 2017; Giridharan et al., 2004; Rizwan et al., 2008, 2008; Son et al., 2017). This denotes the phenomenon of cities and towns experiencing noticeable rises in temperatures relative to surrounding areas, tied to the development practices of their urbanisation.

Against a backdrop of global urbanisation and climate change, the UHI effect has been the subject of extensive contemporary analysis examining the scale of heat islands and the harmful effects they could cause for city populations (Arshad et al., 2021; Equere et al., 2021; Fan et al., 2017; Lin et al., 2020; Nuruzzaman, 2015). Regarding some key features and considerations, the UHI effect is often most intense during the evening/night time because urban surfaces absorb heat during the day, which is then released at night when air temperatures drop relative to surfaces (Rizwan et al., 2008; Sobstyl et al., 2018). Importantly, within many cities the distribution of urban heat has been identified as mirroring more broader spatial marginalisation, reflecting the enduring legacy of oppressive planning practices such as redlining (Li et al., 2022; Wilson, 2020) and slum development (Wang et al., 2019).

Resortification thus may risk causing such disparity in urban temperatures across a resort region, particularly in hotter and drier destinations that could require significant landscaping investment to be made hospitable. This is due to the following theorised process: (1) Hot arid coastal areas, despite being conducive to resort development, require some degree of landscaping to create attractive and comfortable microclimates for tourists. (2) In the *Development stage* (Butler, 1980, 2004) of resortification, the subsequent investment into irrigation, green spaces, and water features may be largely restricted to resort areas, with the quality and safety of housing for locals and workers being comparatively marginalised and pushed to the peripheries. (3) The result is a spatial inequality in heat distribution, with touristic areas exhibiting an urban cooling/UHS and non-touristic areas experiencing a urban heating/UHI effect. An abstract spatial model of a resort region that has undergone this process looks as follows:

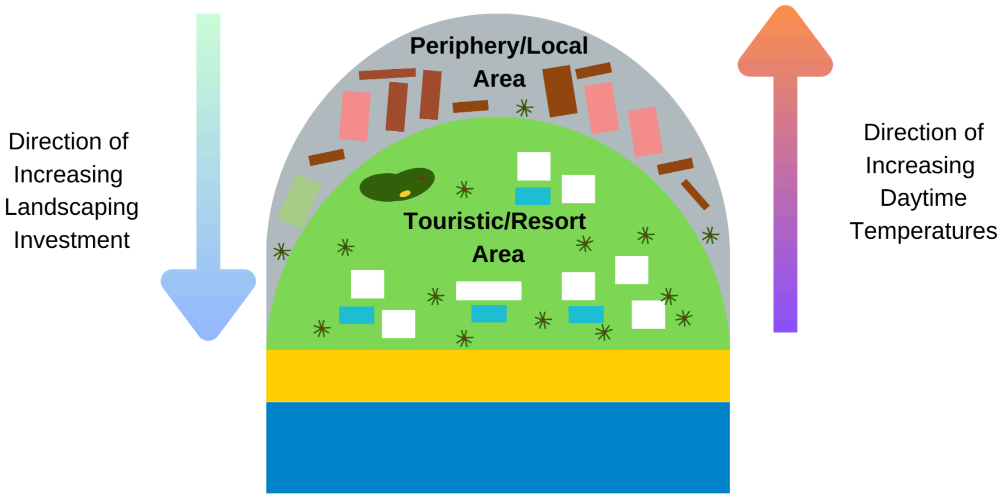


Figure 2 - Spatial Model of Resortified Region and Heat Inequality

Furthermore, in a wider perspective, these hypothesised links between resortification and microclimate inequality constitutes a potentially important spatial injustice. This is because a sizable disparity in temperature and any urban cooling effect could cause significant harm for those living in non-touristic areas. Concerningly, excess urban heat has been linked to increased health risks for urban residents, such as instances of heatstroke and dehydration (Lee et al., 2017; Milojevic et al., 2011; Taylor et al., 2015). Further the UHI potentially leads to higher use of air conditioning and water resources during heat waves, putting strain on local infrastructure (Hartz et al., 2006; Radhi & Sharples, 2013). Additionally, the UHI effect has been linked to the Urban Pollution Island (UPI) effect, whereby the concentration of harmful air pollutants is elevated in built up areas (Ulpiani, 2021). Although there is an ongoing debate regarding the direction of causality between urban heat and urban air pollution, urban heat is thought to contribute to increases in surface level ozone, with hotter surfaces increasing local ozone generation (Shi et al., 2023; Ulpiani, 2021). For residents exposed, pollutants such as surface level ozone can cause worsening health outcomes, increasing the risk of conditions such lung infections and respiratory diseases (Kim et al., 2020). Moreover, urban heat is associated with greater car usage as opposed to walking (Aboelata & Sodoudi, 2020), potentially leading to further local air pollution and additional heat from exhausts fumes.

Efforts at mapping heat distribution thus could shed light on the theorised marginalisation of residents compared to tourists. Microclimate inequality in resort areas could therefore be important evidence of how resident needs are sidelined by market forces during resortification. Linking this disempowerment to broader theoretical discussions, heat disparity and microclimate injustice may highlight a diminished *Right to the City* afforded to residents of non-touristic areas in resort regions (Harvey, 2012, 2013). In this regard, the process of resortification can be critiqued overlooking the need for a community voice. Moreover, due to rising temperatures globally, unequal access to safe and resilient microclimates threatens goals of sustainability and conflicts with international targets outlined in Sustainable Development Goal 11 (United Nations, 2018) and commitments detailed in the Sendai Framework for Disaster Risk Reduction (United Nations, 2015).

3. Research Question

Central to this study therefore is the following research question:

To what extent does resortification cause microclimate injustice between touristic and non-touristic neighbourhoods?

Hypotheses

To establish causality between the decisions shaping resortification and subsequent localised climate injustices, this study examines a transitive causal logic involving the distribution of intermediary environmental variables. Each step of causality is thus framed as a testable hypothesis.

Specifically, this study first examines the influences of coastal proximity, irrigated green spaces, and water features on cooling an area.

H1: Across a given resort region in a dry arid climate zone, green irrigated spaces, water features such as swimming pools, and coastal proximity will cause localised decreases in daytime temperatures.

Furthermore, this study will then analyse if these features are higher in frequency within touristic areas, as opposed to non-touristic areas, interrogating the theorised difference in landscape investment.

H2: Across resort regions, touristic areas will have greater density of green irrigated land, water features such as swimming pools, and will be closer to the coast.

This study will then examine if there is a subsequent daytime cooling effect experienced by touristic/resort areas.

H3: Between touristic areas and residential areas, there will be a disparity in distribution of daytime temperatures, with touristic areas experiencing a greater cooling effect.

Finally, in linking empiricals findings to established theory and literature, this study will examine if the subsequent climate disparities can be accurately described as an urban injustice, being evident of spatial segregation and of the inability of residents from exercising the *Right to the City*.

H4: Climate disparities in a resort area are evident of wider segregation and demonstrate residents' lack of a *Right to the City.*

The above logic and hypotheses are an example of the transitive network of causality (Johnson & Ahn, 2015), with the hypothesised link between resortification and microclimate inequality having identifiable and measurable intermediaries in the form of the deliberate distribution of environmental features. Focusing on the intentional placement of green spaces, water features, and the types of neighbourhoods closer to the coast across resort areas, this study examines the broader consequences of the choices made to benefit the tourist experience in the region. The hypotheses are formatted to test the impact of these decisions on local temperatures, comparing areas where such features have been implemented against those without them. By analysing these disparities, this study aims to demonstrate how the magnitude and distribution of any artificial oasis effect observed in touristic areas are both determined by the specifics of the resortification process, rather than being coincidences or correlations. This approach will help us better understand the causal impact of resort development choices on environmental and social conditions, highlighting the role of resort planners in creating spatial disparities.

4. Materials and Methods

This study utilises a combination of remote sensing (U.S. Geological Survey, 2023) and crowdsourced geospatial data (OpenStreetMap contributors, 2024) to empirically examine the validity of Hypotheses 1-3 across a specific resortified area. From these sources, various environmental and spatial features are determined, such as crucially Land Surface Temperature (LST), Building Concentration, Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Swimming Pool Concentration, Coastal Proximity and Tourism Industry Concentration. With these metrics various analytical methods are utilised to test the first three hypotheses.

Overview of Study Area

This article focuses its analysis on a specific resort region on the island of Gran Canaria. As an island Gran Canaria has a resident population of around 862,893 as of 2023 (Instituto Nacional de Estadística (INE), 2023), a total landmass of around 1,560 km^2, and is situated at around 28°N, 16°W. This makes Gran Canaria the second most populated and third largest landmass of the Canary Islands. Following their conquest in the 15th century, the economy of the Canary Islands has changed significantly, from being traditionally dominated by primary industries such as agriculture and fisheries, to more recently, from the 1960s onwards, a rapid transformation to mass tourism centred economy (Hernández Martín et al., 2021). Like many island chains globally, the contemporary Canary Islands is now a hotspot for mass tourism, with estimates placing the contribution of the tourism industry in the overall GDP of the islands at between 50% and 80% (Garín-Muñoz, 2006). In terms of numbers, in 2019, around 14 million people visited the Canary Islands, with around 4 million of these visiting Gran Canaria specifically, making it the second most popular destination in the Canary Islands after Tenerife (García-Romero et al., 2023). However, this model of mass tourism is not without growing controversy. In Spring 2024, large protests erupted across Gran Canaria and the wider archipelago over perceived negative impacts of tourism on local communities (Suarez, 2024). Notably, tourism was argued to have contributed to driving up the price and accessibility of housing, goods, services, and critical resources such as water, as well as contributing to environmental harm. This discontent is with the economic backdrop of the Canary Islands being one of the poorest regions of Spain with an estimated GDP per capita of €24 000 in 2022 (Eurostat, 2024).

Figure 3 - Protest Signs from Spring Anti-Tourism Protests in Las Palmas de Gran Canaria (Holland 2024)

Furthermore, as a result of the growing dominance of mass tourism, much of the rural and urban landscape of Gran Canaria has dramatically transformed in the past 60 years, with investors responding to increased tourism demand by aggressive development of hotels and resorts both in existing urban areas such as Las Palmas and Agaete, and new custom built resort regions on previously rural areas. Regarding the latter, these new resortified regions are concentrated in the southern rain shadow coast of the island, being attracted to the consistent cloud free weather, high temperatures, and a sandy coastline. Thus, the south of Gran Canaria is an example of the aforementioned "Three Ss" of sun, sand and sea (García-Romero et al., 2023; Szuster et al., 2023) that make a location conducive to mass tourism and resortification. This rapid tourism driven development has likely contributed to Gran Canaria having the highest proportion of its landscape classed as "anthropization" of all the Canary Islands (Ferrer & Quesada, 2024).

This article locates its analysis within the heavily touristic resort combined areas of Playa del Inglés and Maspalomas, located in the municipality of San Bartolomé de Tirajana, which has a resident population of 54,668 as of 2023 (Instituto Nacional de Estadística (INE), 2023). This region is confined to the north by Pilancones Natural Park, to the east and south by the Atlantic Ocean, and to the west by igneous breccia from the island's volcanic history. The area's most distinguishing feature is the Maspalomas Dunes, a sandy desert area and national landmark. The region has a BWh Köppen climate classification (Meteorología (AEMET), 2021), indicating scarce natural water and limited vegetation.

Since the 1960s this area has undergone significant urbanisation away from its traditional use for tomato cultivation and seasonal habitation by agricultural workers. This was wholly driven by the development of tourism. Famously, a 1961 urban planning contest named the "International Bid of ideas for Maspalomas Costa Canaria" led to the adoption of a master plan developed by the French based ATEA and SETAP consortium (Alvarez León, 2012). This process echoes the Bulter's TALC model, with the rapid *Development Stage* of the region having preceding public-private collaboration and top-down planning agendas (Butler, 1980, 2004). Thus, it can be considered a strong example of a resortified area. In the years since, the urban landscape of the area has continued to develop, resulting in a reduction of the overall dune area and general anthropogenic alteration of the remaining natural landscape (Cabrera-Vega et al., 2013).

Regarding the culture and demographics of tourism within Maspalomas and Playa del Inglés, there are important considerations. For the Canary Islands as a whole, Northern European tourists from countries such as the UK, the Netherlands, and Germany are the dominant national grouping, with Spanish tourists only accounting for around 11% of the total (Hernández Martín et al., 2021). These tourist groups have had a noticeable impact on the built up landscape of resortified areas, with there being a host of businesses such as German Bars located across the region and many of the street signs and advertisements are trilingual being in English, Spanish, and German. The prevalence of specifically German tourists has been so intense and long standing that as early as 1971 a Canary Island satirical magazine published a map with Maspalomas labelled "Neue Germania" and the rest of the island designated an "Aboriginal Reserve" - an illusion to the colonial undertones of resort tourism (Domínguez-Mujica et al., 2011).

Notably, there is a prevalence of queer tourism in the region, centred around the Yumbo Centrum shopping plaza, where there is a cluster of LGBTQ+ bars and businesses (Melián-González et al., 2011; Valcuende et al., 2023). As a result, the region is renowned as a safe and popular destination for queer tourists globally and hosts notable events and festivals such as a Winter Pride and a Summer Pride. To illustrate the scale of queer tourism over 300,000 people attended Summer Pride 2024 (Canarias7, 2024), making it one of the largest in the European Union. This dimension of queer tourism may be an important ethical dimension to consider as many tourists visiting the study region may also experience marginalisation in other contexts, and thus may seek travel as a means for escapism from oppressive structures (Collins, 2015). As a result, research of this area should take precautions to not contribute to excessive stigmatisation of the tourism community as a whole, as this may play lip service to negative stereotypes for LGBTQ+ people. One example of such research is a recent paper that was initially criticised by advocacy groups for its portrayal of gay male tourists in the region (García-Romero et al., 2022; Marcus, 2021).

Figure 4 – Study Area on 10th May 2023 (ESA, 2024)

Looking at the spatial design of the resort area, closer to the coast and the dunes are located most of the resorts and estates, in the localities of Meloneras, Playa del Inglés, and Campo International.. These resort hotels often contain typical features of pools and surrounding irrigated green land. Furthermore, there are two golf courses situated in proximity to Meloneras, Campo International, and the dune area. On the outskirts of the resort areas are two periphery localities centred around housing island locals, mirroring the observations made by resort morphologists (Andriotis, 2003; Cantillon, 2018; Liu & Wall, 2009). These are El Tablero, situated atop a hilltop in the North West and San Fernando, built along the GC-1 highway. These areas are designed much more typically for Canary Island townships, featuring tighter streets, less green spaces, multistorey apartment blocks, and irregular terrace housing.

Data Acquisition and Processing

Across this study area a variety of spatial data was collected to form the basis for empirical modelling. For data sourced from remote sensing, this study employed the LandSat 8 satellite (U.S. Geological Survey, 2023). Imagery from LandSat 8 has a resolution of 30m x 30m. The study area comprises around 33,000 such squares. LandSat 8 was chosen in favour of the higher resolution Sentinel 2 satellite, due to the fact that, unlike Sentinel 2, LandSat 8 captures Long Range Infrared bands, which is necessary for the calculation of Land Surface Temperature (LST). The LandSat 8 satellite passes over the study area at around 11:29am, thus close to midday. To capture a general understanding of environmental variables throughout the year, across the study area, six cloudfree timestamps spaced roughly 60 days apart throughout 2023 were utilised. This brought the total amount of data points to 200,000.

NDVI and NDWI

Foremost, for each of these timestamps the distribution of the Normalised Vegetation Difference Index and the Normalised Water Difference Index was calculated using the following formulae using the LandSat 8 Bands NIR (Near Infrared), SWIR (Short Wave Infrared), Red, and Green (Equere et al., 2021; Sahu, 2014):

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

$$NDWI = \frac{Green - SWIR}{Green + SWIR}$$

The mean results for each timestamp is presented in the table below. Here there is less variation in the year round changes to monthly mean NDVI versus the NDWI. To this end NDWI appears to follow seasonal trends, with there being drier surfaces in Summer as opposed to Winter. A potential explanation for the lack of seasonal changes in NDVI in the Maspalomas/Playa del Inglés region than other locations could be due to the consistent sun and the potential influence of irrigation of green spaces.

Day	**Mean NDVI**	**Mean NDWI**
5th January	0.11	-0.03
20th March	0.11	-0.06
18th May	0.11	-0.07
24th July	0.11	-0.07
12th September	0.10	-0.04
13th November	0.09	-0.05

Albedo

Again using LandSat 8 data, the surface albedo was determined (Equere et al., 2021). This represents the reflectivity of a surface, on a scale of 0-1. This denotes the fraction of the light that is reflected, with 1 indicating total reflectance and 0 indicating total absorption. The formula for calculating surface albedo using LandSat 8 is:

$$\alpha = \frac{0.356 \cdot \mathrm{Blue} + 0.0130 \cdot \mathrm{Red} + 0.373 \cdot \mathrm{NIR} + 0.085 * \mathrm{MIR} + 0.072 \cdot \mathrm{SWIR} - 0.0018}{1.016}$$

Daylength

For each 6 time stamps, the approximate day length in each period was calculated. This enables the inclusion of seasonality in the modelling. This was achieved using the “geosphere” package for R (Hijmans, 2021). To calculate day length, the Solar Declination/tilt of the earth away from the sun was determined using the following formula:

$$P = \arcsin(0.39795 \cos(0.2163108 + 2 \arctan(0.9671396 \tan(0.0086 \cdot (Day - 186)))))$$

This was then converted to solar hours and then hours of daylight using the following formulae, where “lat” represents the local latitude (in this case 27.75 degrees North) :

$$a = \frac{\sin(0.8333 \cdot \frac{\pi}{180}) + \sin(\mathrm{lat} \cdot \frac{\pi}{180}) \cdot \sin(P)}{\cos(\mathrm{lat} \cdot \frac{\pi}{180}) \cdot \cos(P)}$$

$$DL = 24 - \frac{24}{\pi} \cdot \cos^{-1}(a)$$

This resulted in the following output for estimated daylight hours for each timestamp:

Day	**Hours of Daylight**
5th January	10.44
20th March	12.09
18th May	13.56
24th July	13.61
12th September	12.44
13th November	10.86

Land Surface Temperature

Calculating Land Surface Temperatures was slightly more complex than these control variables. Here a similar process detailed in several prior studies on urban heat and remote sensing was utilised (Arshad et al., 2021; Equere et al., 2021; Son et al., 2017). Foremost, the values/DN in the Long Range Infrared Band of LandSat 8 was converted to Top of Atmosphere Spectral Radiance/L_λ values. This process uses input units found in the LandSat 8 metadata/MLT file (U.S. Geological Survey, 2023). These values are the Radiance Multiplicative Band /M_L (0.00038) and the Radiance Additive Band /A_L (0.1). The formula for this conversion was the following:

$$L_\lambda = M_L \cdot DN + A_L$$

The second step was to use these values to calculate the Radiance to At-Sensor Temperature/BT. This converts the Spectral Radiance into temperature values or Brightness Temperature in Kelvin. This process requires two constants related to the Long Range Infrared Band's specific thermal conversion constants, found again in the metadata file. These are and $K1$ (799.0284), and $K2$ (1329.2405).

$$BT = \frac{K2}{ln(\frac{K1}{L}_\lambda + 1)}$$

The above metric alone could be used for study of heat distribution, however it does not account for the variation caused by surface level emissivity. Emissivity denotes how much infrared a surface will absorb or reflect, often determined by the relative proportion of different surface types such as soil or vegetation. The relative values of emissivity scale from 0 to 1. NDVI is used to determine emissivity, through the fractional vegetation factor P_v. This was calculated with the following formula:

$$P_v = \left(\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}}\right)^2$$

From this the surface emissivity $e\lambda$ is approximated. This uses two constants relating to the relative emissivity of soil $\epsilon s\lambda$ (0.964) and the emissivity of vegetation $\epsilon v\lambda$ (0.984), as well as a surface roughness metric $C\lambda$ (0.005).

$$\epsilon\lambda = \epsilon \mathrm{v}\lambda + \epsilon \mathrm{s}\lambda \cdot (1 - \mathrm{P}_v) + \mathrm{C}\lambda$$

Combining these building blocks with the general the wavelength of the emitted radiance for Landsat 8, λ (0.00000010895), the adjusted LST, T_s is determined using the following formula (converting from Kelvin to Celcius).

$$T_s = \frac{BT}{1 + (\frac{\lambda BT}{\rho} \cdot ln(\epsilon\lambda))} - 273.15$$

Where ρ is a correction constant incorporating the speed of light *c*, Planck's constant *h*, and Boltzmann's constant σ.

$$\rho = \frac{c \cdot h}{\sigma}$$

This process was repeated for across the 33,000 squares of the study area for each timestamp. In total, this means that, for approximately 200,000 30m x 30m squares at a point in time, the surface temperature was determined. The table below shows the mean value for each timestamp.

Month	Mean LST (ºC)
5th January	34.78
20th March	42.89
18th May	46.76
24th July	37.37
12th September	40.29
13th November	34.83

Below is also an example raster of land surface temperature for July 2023:

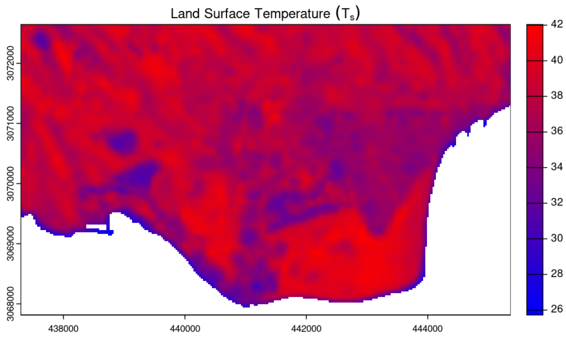


Figure 5: LST for July 2023

Coastal Distance, Buildings, Tourism, and Swimming Pools

Concurrent to the remote sensing data, OpenStreetMap was employed to extract data regarding spatial and built up features of the area (OpenStreetMap contributors, 2024). One such example is distance from the coast in kilometres. Furthermore, the spatial distribution of touristic businesses such as hotels and resorts was also mapped, as well as the general building footprint of the region.

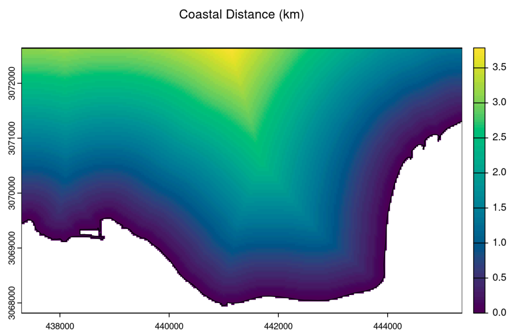


Figure 6: Distance from Coast in Study Area

To convert the vector data (the tourism points and building footprint) to a 30m x 30m raster grid that aligns with the LandSat layers, a Gaussian kernel transformation was applied, with a kernel radius of 400 cells. The result is a heat map of "Building Concentration" and "Tourism Exposure" as scaled variables ranging from -1 upwards.

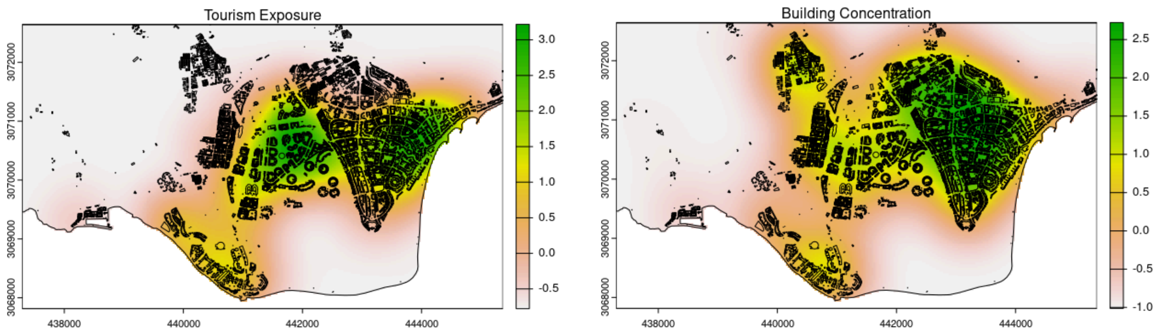


Figure 7: Tourism Concentration and Building Concentration (Overlaying Building Footprint)

The usage of Building Concentration and the OSM building footprint data (OpenStreetMap contributors, 2024) as opposed to Normalised Difference Built-Up Index (NDBI) is due to the resulting NDBI raster layer having large swaths of the sand dunes return high values, thus being mistaken for anthropogenic features. Thus, the NDBI was not used in this study. Whilst there are potentially some drawbacks to this approach, such as some buildings not being included within OSMs dataset and lack of any temporal changes to building footprint the data (so construction projects starting in 2023 were potentially omitted), ultimately compared to NBDI's weaknesses in a sandy environment, constructing and utilising such a Building Concentration heatmap was determined to be more accurate.

Finally, due to the 30m x 30m resolution of the LandSat 8 Imagery, many swimming pools might be excluded from NDWI calculations, although NDWI may still have value for measuring seasonal variation in surface wetness and features such as lakes or ponds. As a result, as well as NDWI this study also utilised OSM data on the distribution of swimming pools, again formatted in a similar fashion to Building Concentration and Tourism Concentration to 30m x 30m a heatmap using a Gaussian kernel of 400 cells.

Elevation

Finally, for elevation, this study employs NASA's Shuttle Radar Topography Mission data for the area (NASA, 2013). Again this is at a resolution of 30m x 30m squares. Incorporating elevation within studies of urban heat has some precedence, notably with Equerre et al.'s utilisation of topographic information and Advanced Neural Networks to construct predictive models of LST across a built up region of the Greater Chicago Metro Area (2021).

Analytical Modelling

In the formation of inferences from the relationships between the above is variables, as well as testing Hypotheses 1-3, a variety of statistical approaches were utilised. In this way potential causal links between key factors such as environmental features such as water, greenery, and coastal proximity and urban heat across the built up landscapes of Maspalomas/Playa del Inglés was empirically explored using tools such as linear regression. This thus tests Hypothesis 1. Furthermore, to test if planners deliberately prioritised the needs and desires of touristic areas and differentiated them from non-touristic areas, means testing between the distribution of identified cooling environmental features across the area is employed. In this way Hypothesis 2 is addressed. Finally, combining this analysis into a comprehensive modelling approach, means testing, linear, and polynomial regression was utilised to examine if there are detectable differences in urban heat between touristic areas and non-touristic areas. Moreover this more complex modelling was used to explore if there are differences in the relationship between increased anthropogenic development and the direction and intensity of changes to local microclimates. Therefore Hypothesis 3 is also empirically tested.

Exploratory Inferences and Testing Hypothesis 1

Foremost, a Pearson Correlation matrix between all variables is considered to examine both the possibilities of multicollinearity and make initial exploratory inferences. From this, Ordinary Least Squares (OLS) linear regression model building was employed to examine the validity of H1. This is that environmental features such as green spaces, inland water, and coastal proximity can cause generalised declines in daytime temperatures. The resulting formula is for this model is:

$$LST_i = Albedo_i + NDVI_i + NDWI_i + CoastDistance_i + Daylight_i + Elevation_i + SwimmingPools_i + \epsilon$$

Furthermore, for further exploratory purposes, six more similar models are constructed - one for each monthly timestamp (thus omitting the Daylight variable due to a lack of seasonality). This enabled analysis of any variation in cooling effect from environmental features across a year. The formlae for these monthly regression models is a follows:

$$LST_i = Albedo_i + NDVI_i + NDWI_i + CoastDistance_i + Elevation_i + SwimmingPools_i + \epsilon$$

From analysing the effects of NDVI, NDWI, and Coastal Proximity on temperatures, this validity of H1 can be interrogated, thus highlighting the relative importance of these anthropogenic and environmental design features in affecting daytime microclimates.

Testing Hypothesis 2

For analysing H2, means testing was employed. Foremost, the data covering the study area was filtered to cover a more limited space, specifically where the Building Concentration metric exceeds 0. This restricted analysis to purely built up areas. This area was then split into two land use types, one where Tourism Concentration exceeds 0 and the other where Tourism Concentration falls below 0. These represent touristic and non-touristic areas respectively. Between these two areas, Hypothesis 2 predicts that touristic areas have greater concentration of environmental cooling features.

To test this, Mann-Whitney U tests were utilised looking at the distribution of mean yearly NDVI, mean yearly NDWI, Swimming Pool Concentration, and Coastal Proximity between the two area types. This is to examine if there are statistically significant differences between the two area types. From analysing the results of this test, inferences can be drawn on the distribution of cooling features between touristic and non-touristic areas. For touristic areas, statistically significant higher mean values for NDVI, NDWI, and Swimming Pools, as well as statistically significant lower means values for Coastal Distance, indicate support for H2.

Testing Hypothesis 3

Regarding the third hypothesis, this study used a variety of different statistical methods. The first, similar to the analysis of H2, entailed splitting the data into two subsets of touristic and non-touristic areas (again using the Tourism Concentration Value of 0 as the threshold). Between these two subsets, Mann-Whitney U tests are again utilised to examine the distribution of Land Surface Temperatures. Following this two OLS regression models were constructed, with Land Surface Temperature as the dependent variable. Crucially, this is to examine the influence of Building Concentration on Land Surface Temperature between the two groups. This is because, H3 postulates that there exists a potential artificial oasis/cooling effect caused by resortification driven building development in the area, however, this effect may be more pronounced in touristic areas as opposed to non-touristic areas. The formula for these two models is as follows:

$$LST_i = Buildings_i + Albedo_i + NDVI_i + NDWI_i + CoastDistance_i + Daylight_i + Elevation_i + SwimmingPools_i + \epsilon$$

By comparing the influence of building concentration on Land Surface temperature between the two models, inferences can be made concerning any potential differences in urban cooling or heating. However, it may be that the effect is more complex that linear regression allows analysis. This can be seen in the scatter plot below looking at mean Land Surface Temperatures and Building Concentration (for Building Concentrations exceeding 0):

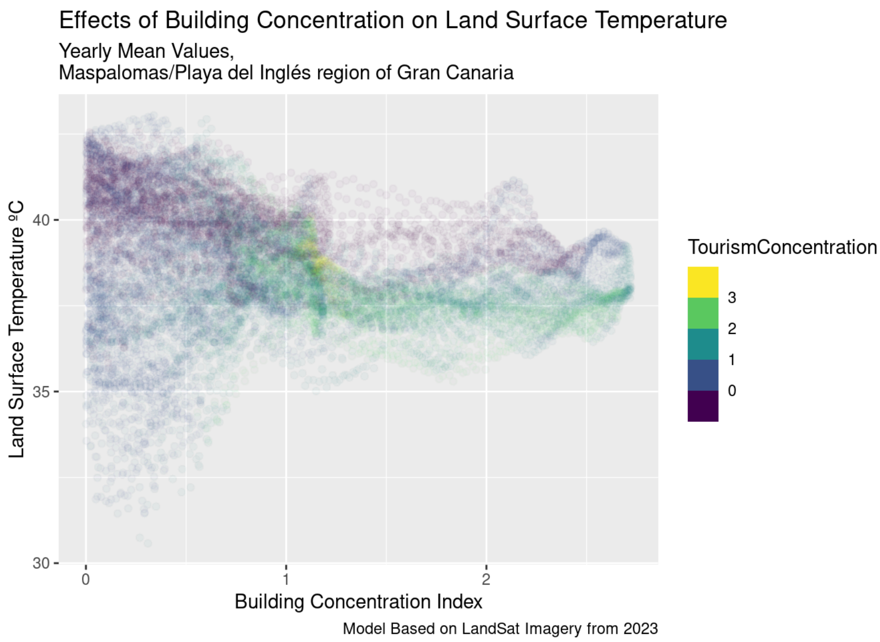


Figure 8: Mean LST throughout 2023

Three initial observations can be made from this graph. (1) There does appear to be some behavioural differences between touristic areas (in yellow and green) and non-touristic areas (in purple and blue) with regards to a potential urban cooling effect (2) A general decline in the spread/variability of LST values is observed as Building Concentration increases. This may be linked to non-built up areas varying considerably, from the heat of the sandy dunes to cooler elevated land (3) The relationship between Building Concentration and LST does not appear to be wholly linear. Efforts to address these concerns necessitated a more complex modelling approach in the form of a Polynomial Interaction Model looking at the relationship between LST, Building Concentration and Tourism Concentration, as well as other control variables. This allows for more detailed modelling through the inclusion of a polynomial term, as well as interaction effects between control variables. This strengthens the model in the face of potential multicollinearity, and heteroskedasticity which together can weaken more linear modelling. The formula for this comprehensive modelling approach is as follows:

$$
\begin{aligned}
\mathrm{LST}_i = {} & \mathrm{Buildings}_i + \mathrm{Buildings}_i^2 + \mathrm{Tourism}_i + \mathrm{Tourism}_i^2 \\
& + \mathrm{Albedo}_i + \mathrm{NDVI}_i + \mathrm{NDWI}_i + \mathrm{CoastDistance}_i + \mathrm{Elevation} \\
& + \mathrm{Daylight}_i + \mathrm{Pools}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{Tourism}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{Albedo}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{NDVI}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{NDWI}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{CoastDistance}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{Elevation}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{Daylight}_i \\
& + \mathrm{Buildings}_i \cdot \mathrm{Pools}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{Albedo}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{NDVI}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{NDWI}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{CoastDistance}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{Pools}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{Daylight}_i \\
& + \mathrm{Tourism}_i \cdot \mathrm{Pools}_i \\
& + \epsilon_i
\end{aligned}
$$

5. Results

In this results and discussion section, the output from the statistical analysis is presented sequentially, going from an initial exploration of the relationship between the multitude of variables in this analysis, towards the comprehensive modelling approaches outlined for testing Hypothesis 3. Following the validity of the theorised network of causality, the three empirical hypotheses are thus examined sequentially.

Exploratory Inferences and Regression Matrix

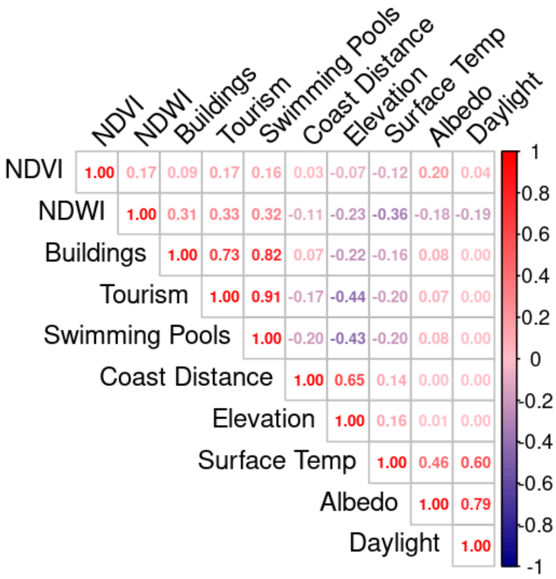


Figure 9 - Pearson's Regression Matrix

Looking at the above regression matrix, several initial exploratory inferences can be made. These represent approximations of the relationships between the spatial features of the study area. For instance, there is a strong correlation between Tourism Concentration and Building Concentration, with the two producing a bivariate regression coefficient of 0.73. This suggests that a significant portion of the built-up area can be associated with tourism activities. Looking at the influence of spatial features on surface temperatures, NDVI, NDWI, and Swimming pools all have some degree of negative relationship with LST, as well as Coastal Distance having a weak positive relationship with LST. This gives some initial support to Hypothesis One. Also, the effect of Daylight Hours has a fairly strong positive relationship with LST. This indicates that seasonality does influence temperatures. Tourism Concentration and Building Concentration both have positive relationships with NDVI and NDWI. This indicates that these environmental features may be the result of deliberate landscaping and planning decisions in the region, and not naturally occuring, this could give some initial support to Hypothesis 2. Finally, Tourism Concentration and Building Concentration also have negative relationships with LST. This suggests some initial support for the urban cooling effect and Hypothesis 3.

Effect of Environmental Cooling Features

	Year Round LST	January LST	March LST	May LST	July LST	September LST	November LST
(Intercept)	11.004***	34.071***	41.196***	45.197***	35.981***	37.530***	31.827***
	(0.089)	(0.062)	(0.086)	(0.099)	(0.086)	(0.103)	(0.082)
Albedo	0.000***	0.000**	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NDVI	−6.395***	−3.618***	−8.409***	−10.099***	−9.883***	−5.962***	−7.107***
	(0.106)	(0.081)	(0.110)	(0.124)	(0.110)	(0.135)	(0.109)
NDWI	−15.154***	−13.190***	−16.252***	−15.230***	−11.025***	−8.705***	−16.225***
	(0.153)	(0.122)	(0.160)	(0.182)	(0.162)	(0.195)	(0.148)
Swimming Pools	−0.546***	−0.604***	−0.713***	−0.493***	−0.509***	−0.310***	−0.742***
	(0.009)	(0.006)	(0.010)	(0.012)	(0.010)	(0.011)	(0.009)
Coastal Distance	0.563***	0.294***	0.409***	0.606***	0.522***	0.806***	0.817***
	(0.012)	(0.008)	(0.013)	(0.014)	(0.012)	(0.014)	(0.011)
Elevation	−0.001***	0.001***	−0.002***	−0.009***	−0.008***	0.007***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Daylight	2.206***						
	(0.011)						
Num.Obs.	198516	33086	33086	33086	33086	33086	33086
R2	0.456	0.570	0.520	0.450	0.445	0.400	0.650
R2 Adj.	0.456	0.569	0.520	0.449	0.445	0.400	0.650
AIC	1070974.1	94166.5	126133.1	131991.5	124041.2	130255.9	116795.4
BIC	1071065.9	94233.7	126200.3	132058.7	124108.5	130323.1	116862.7
Log.Lik.	−535478.056	−47075.241	−63058.533	−65987.744	−62012.603	−65119.929	−58389.711
RMSE	3.59	1.00	1.63	1.78	1.58	1.73	1.41

Looking at the results from the above regression table and several inferences relating to the validity of Hypothesis 1 are possible. NDVI, NDWI, and Swimming Pool Concentration all have statistically significant year round negative effects on LST. Examining the magnitude of these effects and they appear quite dramatic. However, this is due to the scaled nature of NDVI and NDWI values which range between -1 and 1. This means that a 0.1 point rise in NDVI would correlate to a year round difference of approximately -0.64ºC in Land Surface Temperature. These cooling effects substantiate the validity of Hypothesis 1.

Furthermore, Coastal Distance has a positive effect on LST. This therefore indicates that the further a location is from the coast, the hotter the resulting temperatures. This also supports Hypothesis 1, with a year-round relationship of every one kilometre distance from the coast leading to around 0.57ºC temperature rise. The strength of this effect varies throughout the year. The least dramatic relationship is January and the most is in November. Finally, looking at the influence of seasonality, one hour extra of daylight seems to cause around a 2.2ºC rise in surface temperatures across the region. Taken together, these results support the position of Hypothesis 1 and therefore the null hypothesis that environmental features don't affect land surface temperatures can be rejected.

Differences in Environmental Cooling Features

Variable	Mean Touristic	Mean Non-Touristic	Mann-Whitney U p-value
NDVI	0.129	0.085	< 0.001
NDWI	-0.025	-0.054	< 0.001
Pool Concentration	1.274	-0.201	< 0.001
Coastal Distance	1.284	2.264	< 0.001

Examining the above results of hypothesis testing on the distributions of NDVI, NDWI, Pool Concentration, and Coastal Distance, there are some key inferences to be drawn that relate Hypothesis 2. Foremost, Touristic Built-Up Areas have statistically significant higher average levels of vegetation, surface water, and concentration of swimming pool. Given that these were identified as cooling features in the above analysis, this finding supports the hypothesis that, in terms of landscape cooling investment, there is greater allocation for touristic areas within a resort region as compared to their non-touristic counterparts. Furthermore, touristic areas have a statistically significant lower mean coastal distance than non-touristic areas - the mean proximity to the coast for touristic areas is about one kilometre closer than non-touristic areas. This finding also supports Hypothesis 2 and this study's abstract spatial model of resortification (Figure 2.2), whereby touristic areas cluster and outcompete non-touristic areas for coastal proximity. This also mirrors the observations made by several key resort morphologists. All in all therefore,, by examining the distribution of these key environmental features, support can be given for the position of Hypothesis 2. Therefore, the null hypothesis that there is no significant difference in the distribution of identified cooling features between touristic and non-touristic areas can be rejected.

Differences in Heat Distribution

Land Use and Surface Temperatures

Variable	Mean Touristic	Mean Non-Touristic	Mann-Whitney U p-value
Land Surface Temperature	38.15ºC	39.88ºC	< 0.001

As an initial analytical step, the results of the above Mann-Whitney U test comparing the distributions of surface temperatures between Touristic and Non-Touristic built-up areas can be said to support Hypothesis 3. On average Touristic Areas are around 1.75ºC cooler compared to Non-Touristic areas when it comes to surface temperatures. This difference is statistically significant. This finding suggests that any urban cooling effects caused by resortification in dry arid regions are felt more acutely in touristic areas than non-touristic areas, potentially forming the basis of a noteworthy environmental inequality.

Land Use Linear Regression Results

	Touristic LST	Non-Touristic LST
(Intercept)	7.870***	9.305***
	(0.172)	(0.282)
Building Concentration	−0.391***	−0.519***
	(0.038)	(0.042)
Albedo	0.000***	0.000***
	(0.000)	(0.000)
NDVI	−7.365***	−3.535***
	(0.191)	(0.509)
NDWI	−9.885***	−6.908***
	(0.252)	(0.482)
Coastal Distance	0.674***	−0.186***
	(0.021)	(0.052)
Elevation	0.011***	0.006***
	(0.002)	(0.002)
Pool Concentration	−0.156***	−0.591***
	(0.031)	(0.054)
Daylight	2.536***	2.752***
	(0.020)	(0.034)
Num.Obs.	60294	24120
R2	0.457	0.450
R2 Adj.	0.457	0.450
AIC	322581.4	127839.8
BIC	322671.4	127920.7
Log.Lik.	−161280.690	−63909.908
RMSE	3.51	3.42

Looking at the results of Linear Regression analysis of two models - one based on toursitic built up areas and one based on non-touristic built up areas, there are some notable differences. Foremost, non-touristic areas have a higher intercept than touristic, indicating that the baseline temperature difference is around 2ºC. That being said, in non-touristic areas, there appears to be a more dramatic negative relationship between building concentration and the cooling of surface temperatures, indicated by a steeper slope for the effect of building concentration upon land surface temperatures within non-touristic areas compared to touristic areas. This seems to partially challenge the hypothesis that the urban cooling effect is more pronounced in tourist areas as opposed to non-touristic areas. However, looking closer at the results of the two regression models, we can see that the combined effects of NDVI and NDWI appears to cause more significant cooling in touristic areas than in non-touristic areas. This suggests that the integration of greenery and water features may be more effective in touristic areas. Interestingly however, ,the concentration of pools seems to have a more impactful effect in non-touristic areas.

Furthermore, the effects of coastal distance seem to be negative in non-touristic areas and positive in touristic areas. This positive relationship in tourist areas suggests that those areas closer to the ocean experience a cooling effect. However, for non-touristic areas, the negative effect suggests that the relationship is inverse, with areas closer to the coast being hotter. Potentially, this is due to spatial features such as the GC-1 highway, which for residential neighbours such as San Fernado represents a southern boundary line and therefore the closest point to the coast. The elevated temperatures from anthropogenic boundary features like highways (Fan et al., 2017) could be contributing to this reversed direction, similarly so could elevation. Nonetheless, looking at the results from regression analysis for Hypothesis 1, the general overall regional effect of coastal proximity is negative on surface temperatures.

To visualise the implications of these models a predictive graph of these can be made of the two models. This is achieved by holding all other variables at their mean values, creating a theoretical dataset where building concentration increases sequentially from 0 to 3, and running this data through the model parameters. This produces the following graph, in which the higher initial position yet a slightly more dramatic slope for non-touristic areas as opposed to touristic areas can be seen. These models thus add some nuances to validity of Hypothesis 3 and, alone, cannot be used to reject the null hypothesis that there is no difference in urban cooling between area types.

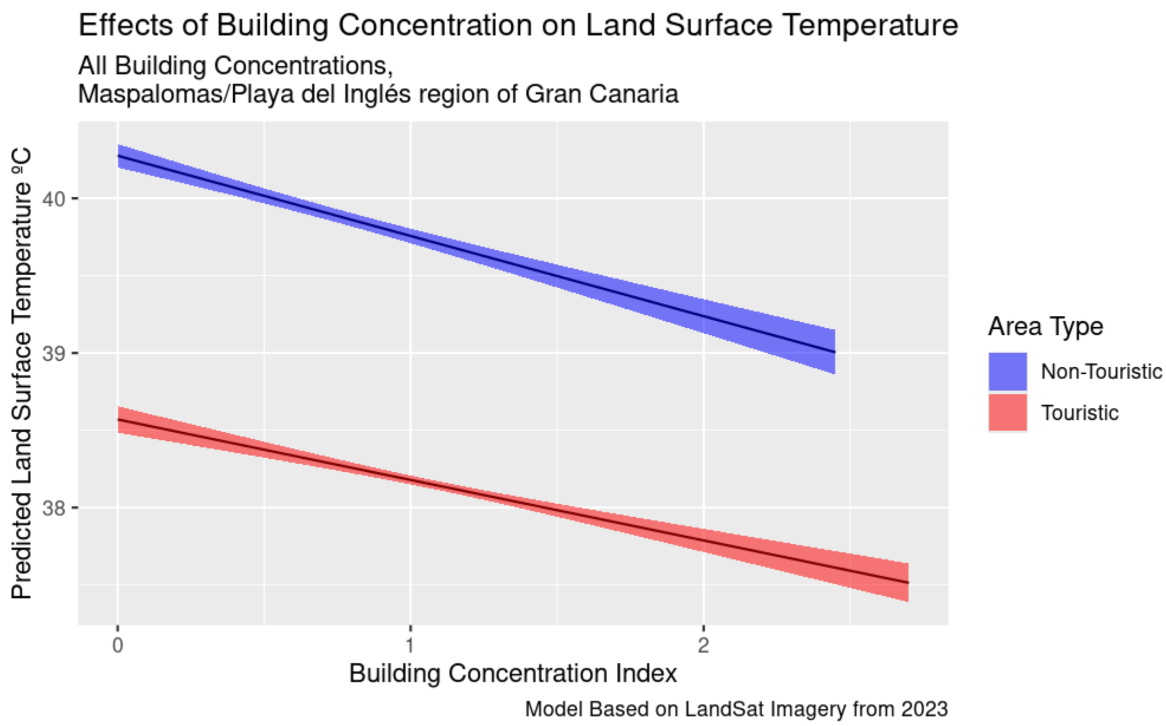


Figure 10: Comparative Linear Regression Predictive Graphs.

Taken together, the findings from this linear regression analysis (which looks purely at built-up areas) illustrate a relationship that is more complex than prior analysis suggested. Based on this analysis alone, therefore the null hypothesis, that is that touristic areas do not experience a more intense urban cooling effect than non-touristic areas, cannot be rejected. However, looking at the initial regression matrix, it's likely that within these models there is a considerable degree of multicollinearity, which could affect the validity of the results and any subsequent causal inferences. Yet, as shown by the R^2 values, both models do account for more than 45% of the variance in land surface temperatures within their respective regions, so these models should not be easily dismissed. Nonetheless, potentially a more comprehensive modelling approach is needed to fully understand the relationships between the spatial distribution of the tourism industry, the concentration of buildings, environmental features, and surface temperatures within this study region. Furthermore, as mentioned in the Method's section, it is possible that the relationship between buildings and surface temperatures may not be linear. Therefore, a more complex models could be required to fully interrogate Hypothesis 3

Combined Polynomial Regression Results

	Year Round LST
(Intercept)	10.896***
	(0.094)
Building Concentration	−1.219***
	(0.155)
I(Building Concentration^2)	−0.118***
	(0.021)
Tourism Concentration	−1.632***
	(0.150)
I(Tourism Concentration^2)	−0.034
	(0.026)
Albedo	0.000***
	(0.000)
NDVI	−6.401***
	(0.116)
NDWI	−13.912***
	(0.159)
CoastDistance	0.534***
	(0.016)
Elevation	0.006***
	(0.001)
Daylight	2.233***
	(0.011)
PoolConcentration	−0.519***
	(0.045)
Building Concentration × Tourism Concentration	−0.373***
	(0.051)
Building Concentration × Albedo	0.000***
	(0.000)
Building Concentration × NDVI	1.544***
	(0.232)
Building Concentration × NDWI	7.474***
	(0.234)
Building Concentration × Elevation	0.006***
	(0.001)
Building Concentration × CoastDistance	−1.059***
	(0.035)
Building Concentration × Daylight	0.369***
	(0.017)
Building Concentration × PoolConcentration	−0.141**
	(0.047)
Tourism Concentration × Albedo	0.000***
	(0.000)
Tourism Concentration × NDVI	−1.364***
	(0.220)
Tourism Concentration × NDWI	−2.174***
	(0.223)
Tourism Concentration × Elevation	0.013***
	(0.001)
Tourism Concentration × CoastDistance	0.732***
	(0.027)
Tourism Concentration × Daylight	−0.040*
	(0.017)
Tourism Concentration × PoolConcentration	0.499***
	(0.036)
Num.Obs.	198516
R2	0.467
R2 Adj.	0.467
AIC	1066922.0

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The above regression table provides the results of this study's attempt to produce a more comprehensive approach across nearly 200,000 observations. This model examines the interactions between building concentration, the concentration of the tourism industry, environmental features that could influence urban cooling, and the interaction between the tourism industry and building concentration. Furthermore, this model incorporates polynomial terms to examine if the relationship between key predictor variables of

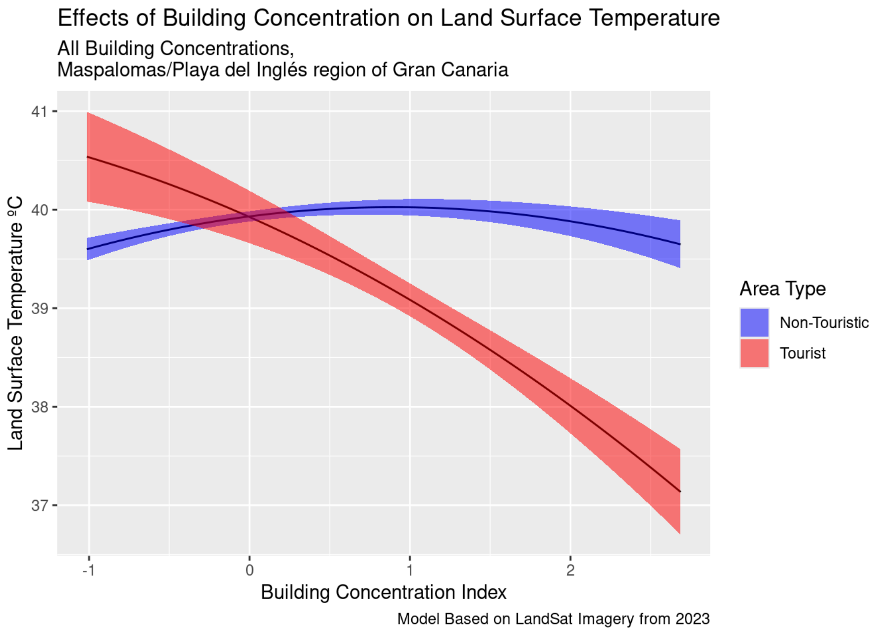
Tourism Concentration, Building Concentration, and the response variable of Land Surface Temperature is nonlinear. Examining the fit of the model, it accounts for between 46% and 47% of the variation in LST across the study area for 2023.

Looking at the coefficients from the model, building concentration overall has a statistically significant net negative effect on land surface temperature. The coefficient for the polynomial term of building concentration is also statistically significant, indicating that the relationship is not linear. The relationship between the concentration of the tourism industry and land surface temperature is also significant and negative . However, the coefficient for the polynomial term of tourism concentration is not significant, which indicates perhaps the relationship between the tourism industry's spatial distribution and urban temperatures is more linear than the overall impact of development. Additionally, multiplying building concentration with the concentration of the tourism industry in an interaction term produces a statistically significant negative coefficient, This indicates a stacking effect between tourism concentration and building concentration, wherein a densely built-up area that is also a tourist area will have a multiplicative effect on lowering surface temperatures, resulting in an bonus cooling/oasis effect. This may overall cause touristic areas to cool more substantially than non-touristic areas as building concentration increases.

Furthermore, the interaction effects between building concentration and vegetation and water are statistically significant positive correlations, whereas, in the interactions with tourism concentration, the relationship is significant and negative. This supports the inference from the prior regression model that the cooling effects of vegetation and water are more pronounced in tourism areas. In non-touristic areas, the presence of vegetation and water does not seem to provide the same cooling effect. This suggests important morphological differences in the way in which vegetation and water features are integrated and utilised into tourist and non-touristic areas. Additionally, there is again a difference in the effect of coastal distance. This is between the negative direction of coastal distance overall when interacting with building concentration versus the positive direction of coastal distance when interacting with tourism concentration, plus the standalone effect of coastal distance also being positive (similarly to the initial regression modelling).

To visualise the predicted relationship between tourism, buildings, and temperatures, predictive graphing can again be made of this more comprehensive model. This is between theoretical areas of low tourism (-0.5

Tourism Concentration) and high tourism (a value of 2 Tourism Concentration) This produces the following graphs.



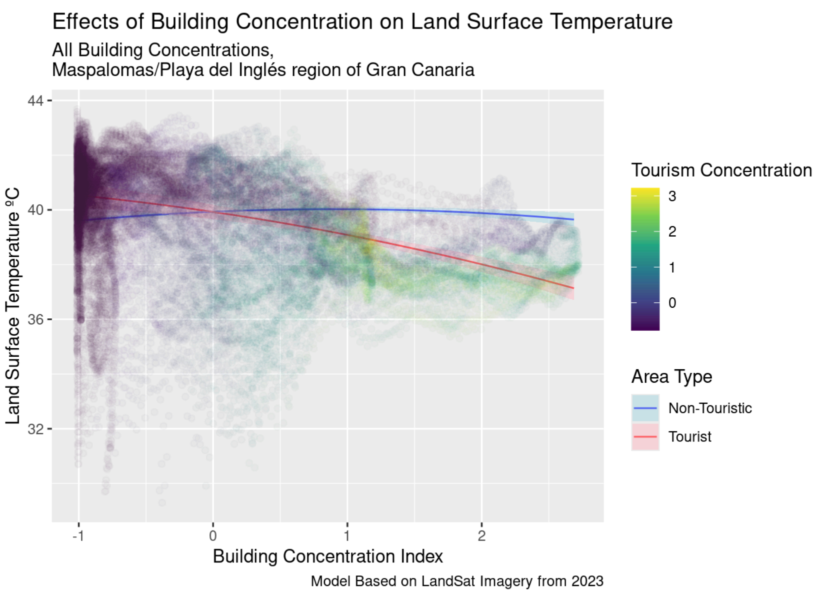


Figure 11: Polynomial Regression Predictive Graphing

From analysing these graphs, it appears that, when controlling and interacting with environmental variables, there seems to be no conclusive urban cooling effect for residential non-touristic areas in this study location. In contrast, for touristic areas, there does seem to be a strong urban cooling effect as the area is developed from an arid desert landscape. Thus, this more complicated model does support Hypothesis 3. Furthermore, when examining the interactions between tourism concentration and key environmental cooling, the effects of these key features are amplified in touristic areas. This suggests a difference in design philosophy, with touristic areas having more quality-controlled microclimates. Nonetheless, there are some caveats to these conclusions. Notably, the model accounts for just under half of the variation in land surface temperatures across the year. This implies that other factors could be important or that the resolution (30m x 30m) of this analysis might be too abstract to fully understand some of the more micro influences on land surface temperature.

Establishing Causality

Looking at these empirical results and how they can shed light upon the relationship between the tourism industry and subsequent uneven microclimates across a given resortified region, there is an inequality between tourist areas and non-touristic areas regarding year-round surface temperatures. However, concluding that the tourism industry alone causes an extra urban cooling/oasis effect may be an oversimplification, as there are likely intermediary factors.

Thus, when examining the distribution of environmental features across this specific arid resortified area, there are higher levels of vegetation, surface water, and swimming pools, within touristic areas. Furthermore touristic areas are typically closer to the coast. These features are all identified in modelling as having a year-round cooling effect upon land surface temperatures - a finding that is replicated in other studies analysing urban heat. These features being more common in touristic areas may be evidence of greater investment in landscaping within touristic areas and the prioritisation of tourism development in more desirable locations. Interestingly, the more complex modelling suggests that the cooling effect itself of these features is more pronounced in touristic areas relative to non-touristic, suggesting further disparity in the quality and implementation of cooling features. Together, these disparities cause touristic areas to have additional cooling compared to surrounding neighbourhoods. Thus, when comparing touristic areas to non-touristic areas there is a clear disparity in microclimate comfort and urban cooling. This chain of causality mirrors the hypothesised links in the study's conceptual model. Therefore, the study concludes that across this specific resortified area of Maspalomas/Playa del Inglés, there is empirical evidence to support the claim that the outcomes of resortification cause detectable year round climate disparities between touristic and non-touristic areas. As a chain of causality, this model looks as follows:

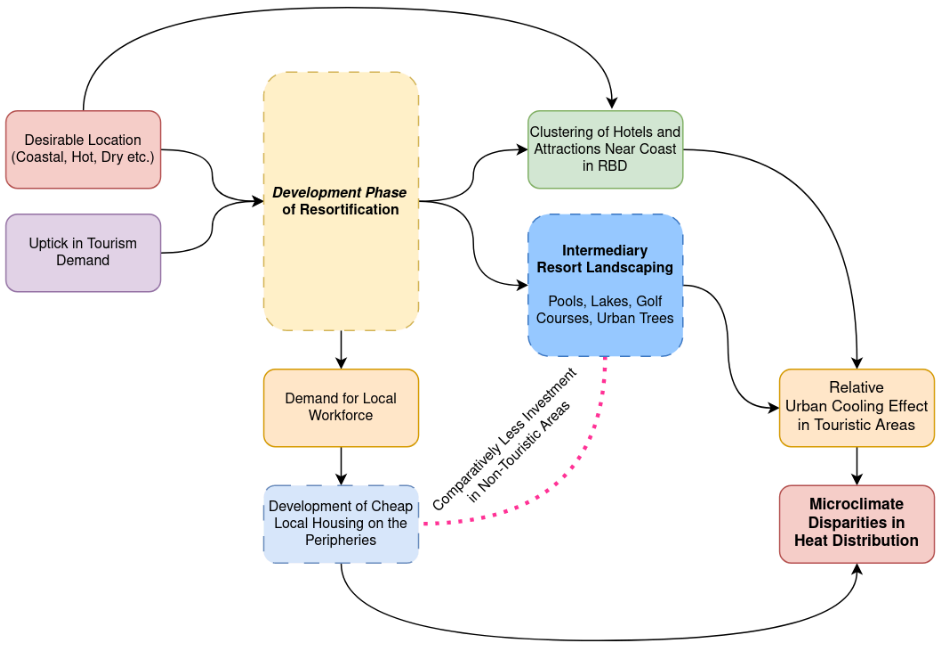


Figure 12: Network of Transitive Causality.

6. Discussion and Conclusion

To answer this article's research question, the identified causal network between resortification and urban heat disparities shows that there is at least a resortification-driven microclimate difference between touristic and non-touristic areas in Maspalomas/Playa del Inglés. However, concluding that this constitutes an *injustice* requires a broader theoretical discussion. In this way, Hypothesis 4 can be addressed. To this end, the empirical results from testing Hypotheses 1 to 3 are contextualised within a broader discussion of how they indicate segregation and harm attributed to resortification and microclimate disparity. This discussion is followed by an assessment of the Right to the City afforded to residents of non-touristic peripheral areas of resort regions, making the case that various political and institutional forms may be necessary to address potential grievances. Finally, following this analysis, the potential shortcomings of this article's methodology are identified, and avenues for future research are explored.

Resort Segregation

A key consideration that could indicate that this microclimate inequality constitutes an injustice is that it is evident of broader segregation across the resort area. In this context, social segregation between tourists and non-tourists is conceptualised as "the spatial separation of the population according to their social or socio-economic position"

(Musterd, 2005, p. 333). In the book "Resort Spatiality" Cantillon explores spatial consequences of resortification through an in-depth comparative qualitative analysis of several resort towns globally, including Cancun, Ibiza, and Miami (2018). Within these settings Cantillon examines spatial tensions that exist between locals and tourists. Drawing attention to significant discrepancies in land use between tourists and locals, it suggested that locals suffer a form of ghettoisation or segregation in many resort areas. This contributes to tourist areas being better maintained and having more greenery, conclusions that are echoed by this article's findings. Furthermore in some cases, resorts are constructed in a manner that makes them difficult for locals to navigate and access (through the implementation of physical barriers such as walled neighbourhoods). As one extreme example, in Cancun, the development of segregated shanty towns for locals or *colonias* on the periphery for residents/workers, was deliberately hidden by intentional landscaping from the beginning of the resortification process and carried on throughout the Development Phase of the resort region (Azcárate, 2011; Cantillon, 2018; Castellanos, 2010).

Linking the results from empirical testing of Hypotheses 1-3 to Cantillon's observations, the Maspalomas/Playa del Inglés region may be described as exhibiting similar properties of segregation and spatial marginalisation as other resort regions. Specifically, the clustering of touristic neighbourhoods in more desirable areas and the evidence of increased urban cooling for touristic developments suggest that, across this study area, the location of non-touristic neighbourhoods such as El Tablero and San Fernando are spatially sidelined and hidden in the margins, lacking access to key amenities and landscaping investment. This outcome of spatial separation could be argued to be a deliberate and almost unavoidable feature of resortification due to a planning agenda prioritising resort tourism. Emphasising the notion that locals and their living conditions are hidden from resorts, Cantillon explains that for tourists, a desirable resort exists "outside of the routines and responsibilities that dominate their everyday lives'' (2018, p. 90). In this regard, the spatial segregation of workers or locals to be out-of-sight and out-of-mind is to save visiting tourists from witnessing the class realities of resortified regions - resort segregation is not a mistake but a feature.

However, there are some potential critiques of this conclusion of segregation and marginalisation in specifically Maspalomas/Playa del Inglés. Due to working in the hotel areas throughout the day, many locals are exposed to and could be said to benefit from the cooling effect of touristic areas. Furthermore, since the passing of Spain's Ley 22/1988 de Costas, national regulations dictate that coastal features such as beaches cannot be privately owned (España, 1988), meaning locals can legally access at least some of the amenities of touristic areas even if they cannot afford housing close to them. Indeed, compared to more rigid examples of resort segregation from less regulated regions, across Maspalomas/Playa del Inglés, the physical, social, and financial barriers between touristic and non-touristic space may be more porous. The notion of more subtle spatial marginalisation may explain why, in her interviews, Cantillon reports a sizable degree of apathy from locals towards the tourism sector, with the sector often portrayed by residents as "a necessary evil" (2018, pp. 174–177).

Microclimate Disparities as an Injustice

Yet, emphasising recent population discontent around the tourism sector on the Canary Islands (Suarez, 2024), it seems unrealistic to argue that similar ambivalence is the consensus amongst Canarian locals exposed to resortification in the archipelago. Moreover, the concept of the barriers between touristic and non-touristic areas being porous could even exacerbate these negative sentiments through spatial comparisons of social welfare, purchasing power, and living standards. Within resorts, workers are constantly exposed to tourists that are seemingly exempt from labour, thus allowed to spend the days enjoying themselves in comfortable resorts with hospitable microclimates. At the extreme end of the comparative spectrum, this could echo Veblen's Theory of the Leisure Class, whereby workers in some resort regions are in close proximity to a rotating population of elites engaging in what Veblen describes as "conspicuous" leisure and consumption (Veblen, 2017). That being said this is potentially not the case in Maspalomas/Playa del Inglés due to the tourism demographic within this region often being from arguably marginalised backgrounds. Nonetheless, exposure to inequality, coupled with the physicality of the unequal distribution of important quality of life-enhancing features (including the disparity in climate comfort), may mean that even if residents in more non-touristic neighbourhoods are supported economically by the tourism sector, their relative status as less fortunate is ever present. This can negatively impact local population's mental wellbeing, and, within the Canary Islands, contribute to the aforementioned political tension between the tourism industry and locals.

In addition to the political and psychological impacts caused by comparative differences, it is pertinent to emphasise that the identified resortification-driven microclimate disparity can cause physical health inequalities in the study region. This is because hotter areas and hotter microclimates negatively impact the health outcomes of the residents living within them. This can manifest in a broad range of direct health risks, such as elevated cases of heat stroke, heat exhaustion, and stress. Given that heat and heat waves are considered “by far the largest cause of mortality related to extreme weather events” (Achebak et al., 2024, p. 1) in high income hot countries such as spain., these concerns are quite pertinent for policymakers to consider. Even without a heat wave event, across the study area where non-touristic built-up areas were found to routinely reach excessively high surface temperatures upwards of 40ºC. Furthermore, due to the links between pollution and urban heat (Ulpiani, 2021), common dangerous air pollutants, such as surface-level ozone, may cluster in hot urban areas. This could further worsen health outcomes, such as lung disease and bronchitis.

To summarise, the empirical results from this article can be used to criticise the development practices of resortification. Relevant to Hypothesis 4, the results suggest that across the study area there is identifiable segregation between touristic and non-touristic areas. This segregation aligns with the theorised spatial model of a resortified region. Furthermore, resort segregation may drive environmental disparities between areas, specifically in this case the differences in urban heat. This may also be evidence of the spatial marginalisation of non-touristic groups, such as workers in the tourism industry and their families. Such marginalisation could be contributing to the growing dissatisfaction with the mass tourism model in the Canary Islands. Moreoveover this marginalisation could cause harm through both the stress of exposure to comparative differences in living standards and negative health consequences of high microclimate temperatures. These harms mean that, in the case of Maspalomas/Playa del Inglés, urban heat disparities can be conceptualised as a microclimate injustice.

Right to the Resort

However, the injustices resulting from resortification and microclimate disparity may also be evidence of a violation of locals' right to determine the functioning of the city in which they live. Famously, the geographer David Harvey labels this right as the *Right to the City* ((Harvey, 2012, 2013). Harvey asserts that residents deserve a say in the shaping and development of their urban surroundings. However, resortification may be a textbook example of a region ignoring the needs and desires of its resident population in favour of market forces and ever-increasing returns on investment. In resort regions, the dominant capital power of the tourism industry likely sidelines the needs of the resident population, keeping them in a low socio-economic status and a position of marginalisation.

A critique of this case is that residents of a resort region shouldn't expect anything different from their current status. If they have moved to an area seeking work in the hotel and tourism industry, they therefore consented to living in a resortified region, despite its potentially negative and marginalising aspects. This criticism thus asserts that locals cannot effectively exercise a legitimate right to push back against the tourism industry. However, this may be a flawed and counterproductive point when considering that often workers in the industry are migrant labourers or individuals with limited economic options (Andriotis, 2003; Castellanos, 2010), thus they are disempowered in the face of capital forces, meaning that they may have no other viable choices than work in tourism. This position means they lack economic power and thus are stripped of the voice to determine their spatial surroundings and pushed into potentially less hospitable periphery neighbourhoods and living conditions.

In the current context of global climate change and rising discontent against the mass tourism industry, this lack of empowerment for tourism workers and their spatial marginalisation, evidenced by their neighbourhoods not benefiting from urban cooling, underscores a need for urgent reform. It is crucial to empower the resident population with democratic decision-making over the development of resortified regions. Adapted from Harvey (2012, 2013), this article terms this concept the *Right to the Resort*. Referring back to the context of Masplomas/Playa del Inglés, establishing this right is especially pertinent for the Canary Islands, as various climate models have noted that areas such as the south of Gran Canaria may become too hot for tourism to function effectively (Carrillo et al., 2022). On a micro level, this will likely affect neighbourhoods such as El Tablero and San Fernando more severely than resort regions due to their lack of cooling techniques. Empowering these neighbourhoods and investing in them now to build microclimate resilience is essential. Potential avenues to achieve include mandating that resort developers set aside land for subsidised housing for workers in the tourism industry, affording them similar amenities as those provided to tourists, as well as implementing a tourism tax to fund resilience building and equitable development across the region.

Concluding Remarks

This article contributes to the ongoing discussions and debates surrounding the benefits and challenges of tourism and resort development, both locally in the Canary Islands and globally. By employing quantitative spatial methods, it demonstrates a clear microclimate inequality within a given resort region. Furthermore, this methodology can be replicated in other similar resort areas with freely accessible data (NASA, 2013; OpenStreetMap contributors, 2024; U.S. Geological Survey, 2023), provided there are enough cloud-free days. In addressing the research question, across the Maspalomas/Playa del Inglés resort region of Gran Canaria, touristic areas are generally cooler and benefit more from anthropogenic cooling efforts than non-touristic areas. Consequently, these touristic zones are more resilient to climate change. Various modelling techniques applied within a theorised transitive model of causality indicate that microclimate disparity results from resortification, especially during the *Development Phase* (Butler, 1980, 2004) of the region's transformation into a resort area. Temperature disparities are linked to the unequal distribution of key spatial cooling features such as greenery, swimming pools, and coastal proximity. Moreover, these temperature disparities constitute a spatial injustice, given the health risks posed by excess heat and the mental strain from continual exposure to the comparative differences between touristic and non-touristic areas.

This injustice suggests a broader spatial segregation and marginalisation of residents in non-touristic areas, who are often workers in the tourism industry and their families. A significant aspect of this marginalisation is the disempowerment of residents in shaping the development of their urban space may be a fundamental feature of resortification, which prioritises market demands for desirable land and tourism development. This also pushes residents to the peripheries away from attractive features such as beaches. To address this marginalisation, this article advocates for the establishment of a *Right to the Resort* for residents. Such a right would grant them democratic control over future resort development. Additionally, it calls for increased investment in non-touristic neighbourhoods to enhance their climate resilience amidst rising temperatures in regions like southern Gran Canaria.

Regarding potential limitations of this article's methodology, there are notable shortcomings to consider. Primarily, to triangulate conclusions about injustice and marginalisation, it may be important to integrate qualitative research into the study, forming a mixed-methods approach. Such qualitative methods could be invaluable in fully contextualising the phenomena of environmental inequality and microclimate disparities, thereby strengthening the argument that they constitute an injustice. Cantillon's research, which utilised qualitative methods (though not specifically on climate differences across a resort region), found a certain level of ambivalence from locals towards the harms caused by tourism development (2018). If a similar apathy were detected in Maspalomas/Playa del Inglés, it could weaken claims of disempowerment.

Moreover, even if a *Right to the Resort* were established, apathy could cause residents to be reluctant to exercise it, viewing the harms of resortification as necessary compromises.

Additionally, the methodology's key response variable of surface temperature might not fully represent urban heat distribution. Other studies employ field work derived atmospheric readings to gauge air temperature, which, although linked to surface temperature, could more accurately reflect the harmful effects of uneven heat distribution. Thus, incorporating air temperature measurements into quantitative modelling might be a more valuable approach. Furthermore, the use of LandSat 8 data, with its resolution of 30m x 30m, might be too broad to capture finer landscape details and their impact on microclimate temperature. For this reason, this article utilised crowdsourced workarounds such as swimming pool distribution. An alternative datasource could be the Sentinel 2 satellite with its resolution of 10m x 10m (ESA, 2024). However, it lacks the necessary bands for surface temperature calculations. Some studies have attempted to align Sentinel 2 spatial data with equivalent LandSat 8 layers, laying the groundwork for predictive upscaling of LandSat 8 derived metrics such as temperature, however these approaches may lack utility for subsequent modelling as the resulting 10m x 10m temperature layer is ultimately a estimation.

Addressing these limitations could form the basis for future studies on the relationship between resortification and microclimate injustices. Integrating interviews and adopting a comparative perspective across different resort areas in various climate zones may provide more concrete and relevant insights into the consequences of resortification. Additionally, combining on-the-ground sensing tools with remote sensing satellite data could enhance the accuracy and relevance of microclimate measurements. Advances in modelling, such as using neural networks to examine the relative importance of various spatial variables on urban microclimates, could further interrogate the validity of the transitive model of causality presented in this article. This approach could compensate for potential statistical limitations caused by multicollinearity and non-normality within the datasets. Lastly, a temporal study using historical data from remote sensing sources could offer valuable insights into the *Development Phase* (Butler, 1980, 2004) within resort regions, enabling the tracking of potential spatial segregation and subsequent environmental injustices.

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Appendix

RMarkdown

In this appendix section is a comprehensive overview of the raw R code employed for the empirical modelling and graphing used for this article. By presenting the code in its entirety, the transparency and reproducibility of the research is upheld. It is hoped that this will be particularly useful for researchers and practitioners interested in replicating the methodology or applying similar techniques to other resort regions.

Remote Sensing and LST - Example Month July 2023

````
# Introduction

Here the LST and NDVI from LandSat 8 at 30m resolution is calculated for July
2023.

```{r, message=FALSE}
# load packages
library(tidyverse)
library(terra)
library(RColorBrewer)
library(sf)
library(leaflet)
library(osmdata)
```

## Loading Rasters

These rasters denote different bands of EM radiation captured by the LandSat 8
satellite over the south of Gran Canaria at 11:29am on the 24th July 2023. These
bands cover most of the visible light spectrum as well as the infrared spectrum.
Combined in various was they can be used to calculate various measures such as the
NDVI (normalised difference vegetation index) and the LST (land surface
temperature).

First lets plot and load the rasters

```{r}
# function to plot raster with a label and custome colour scale
plot_rast = function(raster, label, colors) {
  terra::plot(raster, col=colorRampPalette(colors)(100))
  mtext(text=label, side=3, line=2)
}
````
````

````
# define the bounding box epsg:4083
bbox = ext(c(437292.6282,445376.8775,3067829.6809,3072637.1023))

# load each raster, crop to bounding box, and plot with label
b2 = crop(rast("landsat_july/B2.TIF"), bbox)
b3 = crop(rast("landsat_july/B3.TIF"), bbox)
b4 = crop(rast("landsat_july/B4.TIF"), bbox)
b5 = crop(rast("landsat_july/B5.TIF"), bbox)
b6 = crop(rast("landsat_july/B6.TIF"), bbox)
b7 = crop(rast("landsat_july/B7.TIF"), bbox)
b10 = crop(rast("landsat_july/B10.TIF"), bbox)
```

## Loading Coast Shapefile

Using OSM Data to first extract a coastline of the island

```{r, warning=FALSE}
# query osm
gran_canaria_query = opq(bbox = "Gran Canaria") %>%
  add_osm_feature(key = "place", value = "island") %>%
  osmdata_sf()
# extract the coast data
gran_canaria_sf = gran_canaria_query$osm_multipolygons

# make spatial vector
gran_canaria_vect = st_transform(gran_canaria_sf, crs(b2)) %>%
  vect()
```

## Masking Ocean Values

```{r}
b2 = mask(b2, gran_canaria_vect)
b3 = mask(b3, gran_canaria_vect)
b4 = mask(b4, gran_canaria_vect)
b5 = mask(b5, gran_canaria_vect)
b6 = mask(b6, gran_canaria_vect)
b7 = mask(b7, gran_canaria_vect)
b10 = mask(b10, gran_canaria_vect)
```

## Calculating NDVI

```{r, warning=FALSE}
# calc and plot ndvi using bands 5 and 4
ndvi = (b5-b4)/(b5+b4)

plot_rast(ndvi,
            "Normalised Difference Vegetation Index (NDVI)",
````

```
            c("brown", "green"))
```

Calculating NDBI

```{r}
ndbi = (b6-b5)/(b6+b5)

plot_rast(ndbi,
            "Normalised Difference Built Index (NDBI)",
            c("lightgreen", "black"))
```

Calculating NDWI

```{r}
# calc and plot
ndwi = (b3-b7)/(b3+b7)

plot_rast(ndwi,
            "Normalised Difference Water Index (NDWI)",
            c("yellow", "blue"))
```

Calculating Surface Albedo

```{r}

# calc and plot
albedo = (0.356*b2+0.0130*b4+0.373*b5+0.085*b6+0.072*b7-0.0018)/1.016

plot_rast(albedo,
            expression(paste("Surface Albedo (", alpha,")")),
            c("pink", "blue"))
```

Calculating LST

Top of Atmosphere Spectral Radiance

```{r}
# define metadata values
mult_b10 = 3.8e-04
add_b10 = 0.1

# calc and plot
l = (mult_b10*b10+add_b10)

plot_rast(l,
            expression(Spectral~Radiance~(L[lambda])),
```

````
            c("brown", "yellow"))
```

### At-Sensor Temperature

```{r}
# add effective wavelength of landsat b10
k1 = 799.0284
k2 = 1329.2405

# calc and plot
bt = (k2/log(k1/l+1))

plot_rast(bt,
            expression(Brightness~Temp~(BT)),
            c("blue", "red"))
```

### Surface Level Emissivity

#### Fractional Vegetation Factor

```{r}
# define min and max ndvi
min_ndvi = global(ndvi, fun=min, na.rm=TRUE) %>%
  as.numeric()
max_ndvi = global(ndvi, fun=max, na.rm=TRUE) %>%
  as.numeric()

# calc and plot vegetation factor
pv = ((ndvi-min_ndvi)/(max_ndvi-min_ndvi))^2

plot_rast(pv,
            expression(Fractional~Vegetation~Factor~(P[v])),
            c("maroon", "green"))
```

#### Emissivity

```{r}
# soil emissivity
es = 0.964

# veg emissivity
ev = 0.984

# calc and plot emissivity
e =  ev*pv+es*(1-pv)+0.005

plot_rast(e,
````

````
            expression(Emissivity~(epsilon*lambda)),
            c("yellow", "darkgreen"))
```

### Correction Constant

```{r}
# speed of light
c = 2.997925e8

# planck's constant
h = 6.626070e-34

# boltzmann's constant
sigma = 1.380649e-23

# calc and output correction constant/rho
rho = c*h/sigma
rho
```

### Land Surface Temperature

```{r}
# wavelength
wl = 10.895e-6

# calc and plot
ts = bt/(1+(wl*bt/rho)*log(e))-273.15

plot_rast(ts,
            expression(Land~Surface~Temperature~(T[s])), c("blue", "red"))
```

#### Leaflet Visualisation of LST

Using the Leaflet Package for R, we can visualise the resulting raster

```{r}
plet(ts,
      col=(c("darkblue","pink")),
      legend="bottomright",
      main="LST (Cº)",
      tiles=c("Esri.WorldImagery"))

```

## Stack and Export

Export July data as a csv
````
````

````
```{r}
stack = c(ndvi, ndbi, ndwi, albedo, ts)

data_df = na.omit(as.data.frame(stack, xy=TRUE))

data_df$month = "july"

names(data_df) = c("X", "Y",
                  "NDVI","NDBI",
                  "NDWI", "Albedo", "TS",
                  "Month")

write_csv(data_df, "july.csv")
```
````

Seasonality and Daylight Hours

````
``{r}
library(tidyverse)
library(geosphere)
```
```{r}
# create a vector with the day numbers through the year
day_numbers = c(5, 79, 138, 205, 255, 316)

# convert the vector into a tibble
day_numbers_tibble = tibble(Day_Number_Through_Year = day_numbers)

dl = daylength(27.749997, day_numbers) %>% round(2) %>% as_tibble()
names(dl) = "Daylight"
dl$Month = c("january", "march", "may", "july", "september", "november")
dl %>% write_csv("daylight.csv")
```
````

OSM and Control Variables

````
# Introduction

Here the various control variables are determined

```{r, message=FALSE}
# load packages
library(tidyverse)
library(terra)
library(RColorBrewer)
library(sf)
library(leaflet)
````

````
library(osmdata)
```

## Loading Data

```{r}
# load one raster, for use as crs
b2 = rast("landsat_july/B2.TIF")
```

### Loading Coast Shapefile

```{r, warning=FALSE}
# query osm
gran_canaria_query = opq(bbox = "Gran Canaria") %>%
  add_osm_feature(key = "place", value = "island") %>%
  osmdata_sf()
# extract the coast data
gran_canaria_sf = gran_canaria_query$osm_multipolygons

# make spatial vector
gran_canaria_vect = st_transform(gran_canaria_sf, crs(b2)) %>%
  vect()
```

### Loading Tourism Shapefile

```{r}
# query osm
osm_tourism = opq(bbox = bbox_osm) %>%
  add_osm_feature(key = "tourism") %>%
  osmdata_sf()

# extract tourism points
tourism_vect = st_transform(osm_tourism$osm_points, crs(b2)) %>%
  vect()

plot(tourism_vect)
```

### Loading Pool Shapefile

```{r}
osm_pool = opq(bbox = bbox_osm) %>%
  add_osm_feature(key = "leisure", value = "swimming_pool") %>%
  osmdata_sf()

pool_vect = st_transform(osm_pool$osm_polygons, crs = st_crs(b2)) %>%
  vect()
````

````
osm_pool$osm_polygons
# Plot the water features
plot(pool_vect)
```

### Loading Building Shapefile

```{r}
# query osm
osm_building = opq(bbox = bbox_osm) %>%
  add_osm_feature(key = "building") %>%
  osmdata_sf()

# extract building polygons
building_vect = st_transform(osm_building$osm_polygons, crs(b2)) %>%
  vect()

plot(building_vect)
```

## Calculating Distance from Ocean

```{r}
# create blank template
bbox = ext(c(437292.6282,445376.8775,3067829.6809,3072637.1023))
template = crop(rast("landsat_july/B1.TIF"), bbox)

# crop sp by bbox
gran_canaria_vect = crop(gran_canaria_vect, bbox)

# create land raster
sea_mask = rasterize(gran_canaria_vect,
                        template,
                        NA,
                        background=1)


# calc distance and plot
coastdistance = distance(sea_mask) %>%
  mask(gran_canaria_vect) / 1000
terra::plot(coastdistance, col = hcl.colors(100))
plot(gran_canaria_vect, add = TRUE)
mtext(text="Coastal Distance (km)", side=3, line=2)
```

## Calculating Tourism Exposure

Furthermore, there the effect of exposure to tourism, modelled here using a
heatmap, again calculated using OSM data.
````
````

````
```{r}
# create tourism raster
tourism_mask = rasterize(tourism_vect,
                        template,
                        1,
                        background=NA)

# create heatmap
tourism_kernal = focalMat(tourism_mask, 400, "Gauss")
tourism_heat = focal(tourism_mask, tourism_kernal,
                  fun = sum, na.rm = TRUE)
tourism_heat[is.na(tourism_heat)] = 0
tourism_heat = tourism_heat %>%
  mask(gran_canaria_vect) %>%
  scale()

# plot
plot(tourism_heat)
plot(gran_canaria_vect, add = TRUE)
plot(building_vect, add = TRUE)
mtext(text="Tourism Exposure", side=3, line=2)
```

## Calculating Building Footprint Heatmap

```{r}
# create buidling raster
building_mask = rasterize(building_vect,
                        template,
                        1,
                        background=NA)

# create heatmap
building_kernal = focalMat(building_mask, 400, "Gauss")
building_heat = focal(building_mask, building_kernal,
                        fun = sum, na.rm = TRUE)
building_heat[is.na(building_heat)] = 0
building_heat = building_heat %>%
  mask(gran_canaria_vect) %>%
  scale()

building_heat
plot(building_heat)
plot(gran_canaria_vect, add = TRUE)
plot(building_vect, add = TRUE)
mtext(text="Building Concentration", side=3, line=2)
```

## Calculating Swimming Pool Heatmap
````

````
```{r}
# create buidling raster
pool_mask = rasterize(pool_vect,
                        template,
                        1,
                        background=NA)

# create heatmap
pool_kernal = focalMat(pool_mask, 400, "Gauss")
pool_heat = focal(pool_mask, pool_kernal,
                        fun = sum, na.rm = TRUE)
pool_heat[is.na(pool_heat)] = 0
pool_heat = pool_heat %>%
  mask(gran_canaria_vect) %>%
  scale()

plot(pool_heat)
plot(gran_canaria_vect, add = TRUE)
plot(pool_vect, add = TRUE)
mtext(text="Swimming Pool Concentration", side=3, line=2)
```

## Calculating Elevation

Load in 30m resolution from STRM project. The processing steps here are just to
plot and visualise it with a custom colour scale.

```{r}
# load elevation raster, resample, and crop
strm = rast("strm/strm.tif") %>%
  project(crs(b2)) %>%
  resample(b2, method = "bilinear") %>%
  crop(bbox) %>%
  mask(gran_canaria_vect)

# plot
plot(strm)
plot(gran_canaria_vect, add = TRUE)
plot(building_vect, add = TRUE)
mtext(text="Elevation (m)", side=3, line=2)
```

## Stack and Export

```{r}
control_stack = c(coastdistance, tourism_heat, building_heat,
                  road_heat, strm, pool_heat)

data_df = na.omit(as.data.frame(control_stack, xy=TRUE))
````
````

````
names(data_df) = c("X", "Y",
                  "CoastDistance","TourismConcentration",
                  "BuildingConcentration", "RoadConcentration", "Elevation",
                  "PoolConcentration")

write_csv(data_df, "control_variables.csv")
```
````

Analysis and Model Building

````
# Introduction

Training a variety of models predicting and understanding TS using LandSat 8 at
30m resolution.

```{r, message=FALSE}
# load packages
library(tidyverse)
library(terra)
library(RColorBrewer)
library(sf)
library(leaflet)
library(osmdata)
library(modelsummary)
library(ggnewscale)
library(nnet)
library(car)
library(corrplot)
library(nortest)
library(car)
```

# Loading and Binding

```{r}
jan = read.csv("january.csv")
march = read.csv("march.csv")
may = read.csv("may.csv")
july = read.csv("july.csv")
sept = read.csv("september.csv")
nov = read.csv("november.csv")

# bind together
total_data = rbind(jan, march, may, july, sept, nov)

# load control data and join
controls = read.csv("control_variables.csv")
total_data = left_join(total_data, controls,
````

````
                        by = c("X" = "X",
                              "Y" = "Y"))
# load daylight and join
daylight = read.csv("daylight.csv")
total_data = left_join(total_data, daylight,
                        by = c("Month" = "Month"))

# calc average ndvi, ndwi, albedo, TS
mean_data = total_data %>%
  group_by(X, Y) %>%
  summarise(NDVI = mean(NDVI),
            NDWI = mean(NDWI),
            Albedo = mean(Albedo),
            TS = mean(TS),
            .groups = "drop")
mean_data = left_join(mean_data, controls,
                        by = c("X" = "X",
                              "Y" = "Y"))

builtup_data = total_data %>% filter(BuildingConcentration > 0)
```

# Monthly Tables

```{r}
total_data %>%
  group_by(Month) %>%
  summarise(NDVI = round(mean(NDVI), 2),
            NDWI = round(mean(NDWI), 2),
            TS = round(mean(TS), 2))
```

# Hypothesis Tests

## H2

```{r}
touristic_data = mean_data %>% filter(TourismConcentration > 0 &
BuildingConcentration > 0)
non_touristic_data = mean_data %>% filter(TourismConcentration < 0 &
BuildingConcentration > 0)
# Calculate means for each variable in both groups
touristic_means <- touristic_data %>%
  summarize(
      Mean_NDVI = mean(NDVI, na.rm = TRUE),
      Mean_NDWI = mean(NDWI, na.rm = TRUE),
      Mean_PoolConcentration = mean(PoolConcentration, na.rm = TRUE),
      Mean_CoastDistance = mean(CoastDistance, na.rm = TRUE)
  )
````

````
non_touristic_means <- non_touristic_data %>%
  summarize(
      Mean_NDVI = mean(NDVI, na.rm = TRUE),
      Mean_NDWI = mean(NDWI, na.rm = TRUE),
      Mean_PoolConcentration = mean(PoolConcentration, na.rm = TRUE),
      Mean_CoastDistance = mean(CoastDistance, na.rm = TRUE)
  )

# Perform Mann-Whitney U tests
ndvi_mann_whitney <- wilcox.test(touristic_data$NDVI, non_touristic_data$NDVI)
ndwi_mann_whitney <- wilcox.test(touristic_data$NDWI, non_touristic_data$NDWI)
pool_mann_whitney <- wilcox.test(touristic_data$PoolConcentration,
non_touristic_data$PoolConcentration)
distance_mann_whitney <- wilcox.test(touristic_data$CoastDistance,
non_touristic_data$CoastDistance)

results_table <- data.frame(
  Variable = c("NDVI", "NDWI", "PoolConcentration", "CoastDistance"),
  Mean_Touristic = round(c(touristic_means$Mean_NDVI, touristic_means$Mean_NDWI,
touristic_means$Mean_PoolConcentration, touristic_means$Mean_CoastDistance), 3),
  Mean_Non_Touristic = round(c(non_touristic_means$Mean_NDVI,
non_touristic_means$Mean_NDWI, non_touristic_means$Mean_PoolConcentration,
non_touristic_means$Mean_CoastDistance), 3),
  p_value = round(c(ndvi_mann_whitney$p.value, ndwi_mann_whitney$p.value,
pool_mann_whitney$p.value, distance_mann_whitney$p.value), 3)
)

# Print the results table
print(results_table)

```


## H3

```{r}

# Check for normality using Anderson-Darling test
ad.test(touristic_data$TS)
ad.test(non_touristic_data$TS)
mean(non_touristic_data$TS)
mean(touristic_data$TS)
wilcox.test(touristic_data$TS, non_touristic_data$TS)
```


# Pearson Regression Matrix

```{r}
matrix_data = total_data %>%
  select(TS, TourismConcentration, BuildingConcentration, Albedo, NDVI,
      NDWI, CoastDistance, Daylight, Elevation, PoolConcentration)
````

````
names(matrix_data) = c("Surface Temp", "Tourism", "Buildings",
                        "Albedo", "NDVI", "NDWI",
                        "Coast Distance", "Daylight",
                        "Elevation", "Swimming Pools")

cor_matrix = cor(matrix_data, use = "complete.obs")
corrplot(cor_matrix, method = "number", type = "upper", order = "hclust",
      tl.col = "black", tl.srt = 45, number.cex = 0.6,
      col=colorRampPalette(c("darkblue","pink","red"))(100))
```


# General Linear Models

## H1

```{r}
# h1 models
models_h1 = list(
"Year Round" = lm(TS ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation +
                        Daylight,
            data = total_data),
"January" = lm(TS ~
                        Albedo +
                        NDVI +
                        PoolConcentration +
                        NDWI +
                        CoastDistance +
                        Elevation,
            data = total_data %>% filter(Month == "january")),
"March" = lm(TS ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation,
            data = total_data %>% filter(Month == "march")),
"May" = lm(TS ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation,
````

```
            data = total_data %>% filter(Month == "may")),
"July" = lm(TS ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation,
            data = total_data %>% filter(Month == "july")),
"September" = lm(TS ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation,
            data = total_data %>% filter(Month == "september")),
"November" = lm(TS ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation,
            data = total_data %>% filter(Month == "november")))

modelsummary(models_h1, stars = TRUE)
` ` `

## H2

` ` `{r}
# h2 models
ols_h2a = lm(TourismConcentration ~
                        Albedo +
                        NDVI +
                        NDWI +
                        PoolConcentration +
                        CoastDistance +
                        Elevation,
            data = mean_data %>% filter(BuildingConcentration > 0))

modelsummary(ols_h2a, stars = TRUE)

summary(ols_h2a)
` ` `

## H3

### Split Models
```

````
```{r}
# split the dataset
high_tourism = subset(builtup_data, TourismConcentration > 0)
low_tourism = subset(builtup_data, TourismConcentration < 0)

# fit separate models for high and low tourism Concentration areas
split_models = list(
"Touristic LST" = lm(TS ~ BuildingConcentration + Albedo + NDVI + NDWI +
CoastDistance + Elevation + PoolConcentration + Daylight, data = high_tourism),
"Non-Touristic LST " = lm(TS ~ BuildingConcentration + Albedo + NDVI + NDWI +
CoastDistance + Elevation + Daylight  + PoolConcentration, data = low_tourism))

# compare summaries
modelsummary(split_models, stars = TRUE)
```

### Polynominal Interaction Modeling

```{r}
model_poly_interaction = lm(TS ~
                              BuildingConcentration + I(BuildingConcentration^2) +
                              TourismConcentration + I(TourismConcentration^2) +
                              Albedo + NDVI + NDWI +
                              CoastDistance + Elevation + Daylight +
                              PoolConcentration +
                              BuildingConcentration:TourismConcentration +
                              BuildingConcentration:Albedo +
                              BuildingConcentration:NDVI +
                              BuildingConcentration:NDWI +
                              BuildingConcentration:Elevation +
                              BuildingConcentration:CoastDistance +
                              BuildingConcentration:Daylight +
                              BuildingConcentration:PoolConcentration +
                              TourismConcentration:Albedo +
                              TourismConcentration:NDVI +
                              TourismConcentration:NDWI +
                              TourismConcentration:Elevation +
                              TourismConcentration:CoastDistance +
                              TourismConcentration:Daylight +
                              TourismConcentration:PoolConcentration,
                        data = total_data)

# summary of the polynomial model with interactions
modelsummary(model_poly_interaction, stars = TRUE)
summary(model_poly_interaction)
```

# Graphing
````

```
## Mean LST

```{r}
scatterplot = ggplot() +
  geom_point(data = mean_data %>% filter(BuildingConcentration > 0),
             aes(x = BuildingConcentration,
                 y = TS,
                 colour = TourismConcentration),
             alpha = 0.03) +
  scale_color_viridis_c(name = "Tourism Concentration") +
  labs(title = "Effects of Building Concentration on Land Surface Temperature",
       subtitle = "Yearly Mean Values,
Maspalomas/Playa del Inglés region of Gran Canaria",
       caption = "Model Based on LandSat Imagery from 2023",
       x = "Building Concentration Index",
       y = "Land Surface Temperature ºC")
scatterplot
```

Land Use Features

```{r}
# plotting tourism concentration vs NDVI
ggplot(mean_data %>% filter(BuildingConcentration > 0), aes(x =
TourismConcentration, y = NDVI)) +
  geom_point() +
  geom_smooth(method = "lm") +
  ggtitle("Tourism Concentration vs. NDVI")

# plotting tourism concentration vs NDWI
ggplot(mean_data %>% filter(BuildingConcentration > 0), aes(x =
TourismConcentration, y = NDWI)) +
  geom_point() +
  geom_smooth(method = "lm") +
  ggtitle("Tourism Concentration vs. NDWI")

# plotting tourism concentration vs pools
ggplot(mean_data %>% filter(BuildingConcentration > 0), aes(x =
TourismConcentration, y = PoolConcentration)) +
  geom_point() +
  geom_smooth(method = "lm") +
  ggtitle("Tourism Concentration vs. Pool Concentration")


# plotting tourism concentration vs coast
ggplot(mean_data %>% filter(BuildingConcentration > 0), aes(x =
TourismConcentration, y = CoastDistance)) +
  geom_point() +
  geom_smooth(method = "lm") +
  ggtitle("Tourism Concentration vs. Coastal Distance")
```
```

````
```

## Land Use Regression Plots

```{r}
tourism_dense = tibble(
  NDVI = mean(high_tourism$NDVI),
  BuildingConcentration = seq(min(high_tourism$BuildingConcentration),
                          max(high_tourism$BuildingConcentration),
                          by = 0.05),
  Albedo = mean(high_tourism$Albedo),
  NDWI = mean(high_tourism$NDWI),
  Daylight = mean(high_tourism$Daylight),
  CoastDistance = mean(high_tourism$CoastDistance),
  PoolConcentration = mean(high_tourism$PoolConcentration),
  Elevation = mean(high_tourism$Elevation)
)

tourism_sparse = tibble(
  NDVI = mean(low_tourism$NDVI),
  BuildingConcentration = seq(min(low_tourism$BuildingConcentration),
                          max(low_tourism$BuildingConcentration),
                          by = 0.05),
  Albedo = mean(low_tourism$Albedo),
  NDWI = mean(low_tourism$NDWI),
  Daylight = mean(low_tourism$Daylight),
  CoastDistance = mean(low_tourism$CoastDistance),
  PoolConcentration = mean(low_tourism$PoolConcentration),
  Elevation = mean(low_tourism$Elevation)
)

# predict values
tourism_dense_predictions = predict(
  split_models$`Touristic LST`,
  newdata = tourism_dense,
  se.fit = TRUE,
  interval = "confidence") %>%
  as.data.frame() %>%
  bind_cols(tourism_dense) %>%
  select(c("fit.fit", "fit.lwr", "fit.upr", "BuildingConcentration"))
tourism_dense_predictions$area = "Touristic"

tourism_sparse_predictions = predict(
  split_models$`Non-Touristic LST `,
  newdata = tourism_sparse,
  se.fit = TRUE,
  interval = "confidence") %>%
  as.data.frame() %>%
````

````
  bind_cols(tourism_sparse) %>%
  select(c("fit.fit", "fit.lwr", "fit.upr", "BuildingConcentration"))
tourism_sparse_predictions$area = "Non-Touristic"

# bind into toplot
toplot = rbind(tourism_dense_predictions,
            tourism_sparse_predictions)

# comparison plot

all_density_plot = ggplot(data = toplot,
                        aes(x = BuildingConcentration,
                              y = fit.fit,
                              ymin = fit.lwr,
                              ymax = fit.upr,
                              fill = area)) +
  geom_line(alpha = 2) +
  geom_ribbon(alpha = 0.5) +
  scale_fill_manual(values = c("Non-Touristic" = "blue", "Touristic" = "red"),
name = "Area Type") +
  labs(title = "Effects of Building Concentration on Land Surface Temperature",
      subtitle = "All Building Concentrations,
Maspalomas/Playa del Inglés region of Gran Canaria",
      caption = "Model Based on LandSat Imagery from 2023",
      x = "Building Concentration Index",
      y = "Predicted Land Surface Temperature ºC")

all_density_plot
```


## Polynominal Plots

```{r}
# all building concentrations, polynominal
tourism_area = tibble(
  TourismConcentration = 2,
  NDVI = mean(total_data$NDVI),
  BuildingConcentration = seq(min(total_data$BuildingConcentration),
                        max(total_data$BuildingConcentration),
                        by = 0.05),
  Albedo = mean(total_data$Albedo),
  NDWI = mean(total_data$NDWI),
  Daylight = mean(total_data$Daylight),
  PoolConcentration = mean(total_data$PoolConcentration),
  CoastDistance = mean(total_data$CoastDistance),
  Elevation = mean(total_data$Elevation)
)

residence_area = tibble(
  TourismConcentration = -0.5,
````

```
  NDVI = mean(total_data$NDVI),
  BuildingConcentration = seq(min(total_data$BuildingConcentration),
                          max(total_data$BuildingConcentration),
                          by = 0.05),
  Albedo = mean(total_data$Albedo),
  NDWI = mean(total_data$NDWI),
  Daylight = mean(total_data$Daylight),
  PoolConcentration = mean(total_data$PoolConcentration),
  CoastDistance = mean(total_data$CoastDistance),
  Elevation = mean(total_data$Elevation)
)

# bind together
scenario = rbind(tourism_area, residence_area)

# predict values
area_predictions = predict(
  model_poly_interaction,
  newdata = scenario,
  se.fit = TRUE,
  interval = "confidence"
)

# make tibble
area_predictions = area_predictions$fit %>%
  as_tibble()

# make toplot
toplot = bind_cols(scenario,
                  area_predictions)

toplot = select(toplot, c("fit", "lwr", "upr",
                          "BuildingConcentration",
                          "TourismConcentration"))

toplot$area = ifelse(toplot$TourismConcentration == -0.5, "Non-Touristic",
                  "Tourist")

# plot polynominals

poly_density_plot_lines = ggplot(data = toplot,
                              aes(x = BuildingConcentration,
                                    y = fit,
                                    ymin = lwr,
                                    ymax = upr,
                                    fill = area)) +
  geom_line(alpha = 2) +
  geom_ribbon(alpha = 0.5) +
  scale_fill_manual(values = c("Non-Touristic" = "blue", "Tourist" = "red"),
                          name = "Area Type") +
```

```
  labs(title = "Effects of Building Concentration on Land Surface Temperature",
      subtitle = "All Building Concentrations,
Maspalomas/Playa del Inglés region of Gran Canaria",
      caption = "Model Based on LandSat Imagery from 2023",
      x = "Building Concentration Index",
      y = "Land Surface Temperature ºC")

poly_density_plot_points = ggplot() +
  geom_line(data = toplot,
            aes(x = BuildingConcentration,
                  y = fit,
                  colour = area),
            alpha = 2) +
  geom_ribbon(data = toplot,
            aes(x = BuildingConcentration,
                  y = fit,
                  ymin = lwr,
                  ymax = upr,
                  fill = area),
            alpha = 0.5) +
  scale_colour_manual(values = c("Non-Touristic" = "blue", "Tourist" = "red"),
                        name = "Area Type") +
  scale_fill_manual(values = c("Non-Touristic" = "lightblue", "Tourist" = "pink"),
                        name = "Area Type") +
  new_scale_color() +
  geom_point(data = mean_data,
            aes(x = BuildingConcentration,
                  y = TS,
                  colour = TourismConcentration),
            alpha = 0.01) +
  scale_color_viridis_c(name = "Tourism Concentration") +
  labs(title = "Effects of Building Concentration on Land Surface Temperature",
      subtitle = "All Building Concentrations,
Maspalomas/Playa del Inglés region of Gran Canaria",
      caption = "Model Based on LandSat Imagery from 2023",
      x = "Building Concentration Index",
      y = "Land Surface Temperature ºC")

poly_density_plot_lines
poly_density_plot_points
```