Do Natural Amenities Promote Growth? Evidence from Surf Breaks

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Abstract

We investigate whether natural amenities can be a geographic determinant of growth. We combine data on spatial and temporal variation in the quality of over 5000 surf breaks globally with data on local economic performance, proxied by night-time lights. We document a strong association between natural amenity quality and local economic development in rural areas, but not in urban areas where they may be subject to over-exploitation. Gaining access to surfable breaks, whether due to newly discovered breaks or enhanced surfing technology, increases economic growth. High-quality waves generated during El Niño events also boost local economic activity. The effects are consistent with a tourism mechanism that is larger than can be attributed to surfers alone.

JEL codes: O13, O44, O47, Q26, Q51, Q56, R11, R12

Key words: Natural amenities, economic growth, new economic geography, natural advantages, tourism, surfing, night-time lights.

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1 Introduction

Geography has long been thought to play a role in economic growth, because some places enjoy natural advantages over others. These advantages may be direct, as rivers facilitate trade and rich soil makes farms more productive; or indirect, as nice environments make places more desirable to live. The indirect effects are "natural amenities", and there is no consensus on whether they are important for growth. This paper helps to address that gap.

The difficulties with studying natural amenities are in measurement and identification. Natural amenities like a nice view and clean air do not have a market price, so their quality is typically inferred from wages (Roback 1982, 1988) or house prices (Rosen, 1974, Chay and Greenstone, 2005). This is infeasible on a global scale. Even if an amenity's quality can be measured, it is difficult to identify its contribution to economic growth. For example, economies with a clement climate grow faster (e.g. Deller et al., 2001; Cheshire and Magrini, 2006; Wu and Gopinath, 2008; Glaeser and Gottlieb, 2009), but it is difficult to identify the role of climatic amenity versus other channels, like agriculture.[1] As a result, a review of the literature finds that "the evidence on any positive role of landscape amenities for local economic development... remains limited" (Waltert and Shlapfer, 2010).

Estimating the economic impact of natural amenities is important. It offers insight into a potential determinant of the location and pace of economic growth. It also allows us to properly assess the effects of changing natural amenities due to pollution, development, and climate change which have hitherto been difficult to pinpoint.

This paper uses three clean natural experiments to identify how a particular natural amenity contributes to economic growth... surf breaks.[2] Surf breaks are well-suited to this type of study because their quality is exogenously determined by a finely balanced combination of weather and sea-floor geography (bathymetry), both locally and at distance. Two locations may be metres apart but of vastly different appeal to surfers, which we can exploit for identification. We measure quality directly through an independently verified rating system from a unique global database of 5000+ locations, combined with data on El Niño

[1] In contrast, there is some evidence that endogenous amenities affect growth. For example, Cullen and Levitt (1999) find that crime drives urban flight, and Diamond (2016) finds that endogenous amenities like shops, transport, and the quality of schools and jobs have fuelled the sorting of skills in US cities.

[2] A note on terminology. A "surf break" is a location. The quality of a break is determined by geography and is generally stable over time, unless there has been some human intervention (see Section 5). A "wave" is an individual pulse of energy that propagates across the surface of the ocean, and which may be the fleeting subject of a surfer's sport. Groups of waves are "swells". A wave's quality depends on the wind at its source and end, and the break where it is ridden (see Section 2).

events and global wave heights.[3] As well as their convenience as an identification strategy, surf breaks are also a scarce and highly valuable amenity to more than 35 million surfers (The Economist, 2012) who are increasingly prosperous,[4] and who are growing in number as populous, wave-rich economies like Brazil and Indonesia consume more leisure.[5] They are regularly the subject of policymaker's attention as they are discovered (Noble, 2017), built (Dean, 2016) and destroyed (Section 5). They are also on the front line of climate change, as rising sea levels change how and where waves break.

We measure economic activity using two detailed and geographically disaggregated datasets on night-time lights and population. The first records the amount of light emitted at night around the globe at approximately a $1km^2$ resolution annually, from 1992-2013. This has been used by many recent studies as a geographically disaggregated proxy for economic activity (Chen and Nordhaus, 2011; Henderson et al., 2011; 2012; Donaldson and Storeygard, 2016); covering institutions (Michalopoulos and Papaioannou, 2013; 2014), political favouritism (Hodler and Raschky, 2014), infrastructure investment (Jedwab et al., 2015; Jedwab and Moradi, 2016) and poverty (Smith and Wills, 2016) amongst others. The second, from LandScan, records global population at a $1km^2$ resolution annually, by interpolating sub-national population counts using satellite images of buildings, roads and land-cover, amongst other things. To our knowledge this provides the first global, spatially detailed study of natural amenities.

The first experiment asks the question, "do places with high quality surf breaks grow faster than those with low quality breaks"? To answer this we exploit finely-grained cross-sectional variation in the quality of surf breaks. We find that lights in the 5km around rural 3-, 4- and 5-star breaks grew ~0.6 to 0.8 percentage points per annum faster than in the area around rural 1-star breaks from 1992-2013, after controlling for convergence and subnational zone fixed-effects. In contrast, illumination around urban 3-, 4-, and 5-star breaks grew less than urban 1-star breaks by -0.1 to -0.6 percentage points per annum from 1992-2013. This was not just a reallocation of activity from surrounding areas, as there were positive and diminishing spillovers out to 50km. We find no significant effect on the permanent population, so these results reflect changes in per capita economic activity. The results are robust to a variety of tests including omitted geographic variables, selection effects and spatial correlation. To interpret these findings we note that our data defines urban and rural areas by their population density. So, the findings are consistent

[3] Previous studies have estimated the economic impact of surfing at individual locations using travel costs (Coffman and Burnett, 2009), surveys (Lazarow, 2009), and hedonic pricing (Scorse et al., 2015).

[4] In 2013 Fortune Magazine noted, *"Surfing today is the Silicon Valley CEO. It's the brain surgeon. It's the super-athlete. It's dad, mom, and the kids"*, and that in 2010 \$6.3 billion was spent on surf accessories (boards, wetsuits, etc.) alone. Tony Abbott, the former Prime Minister of Australia, and Justin Trudeau, the current Prime Minister of Canada, are keen surfers.

[5] Brazil's emergence is seen in it winning the men's World Championship Tour for the first time in 2014, and again in 2015. Surfing will also appear at the Olympics for the first time in Tokyo, 2020.

with surf breaks being a finite resource that suffer diminishing marginal returns due to overcrowding. In rural, or less populated areas, the existence of a high quality surf break offers a natural resource that can be harnessed for the economic benefit of the local area. However, this finite natural amenity can become overcrowded in urban areas. If the areas around good surf breaks become specialised in surfing-related activities (e.g. tourism, surfing retail), then these diminishing marginal returns will extend to the surrounding economy.

We investigate tourism as a possible mechanism through which surf breaks boost economic activity in rural areas. Unfortunately high-quality, geographically-detailed data on tourism flows does not exist at a global scale. Instead we use official, geographically disaggregated data on tourist expenditure and activities from Australia, which has the most surf breaks in our database. We find that tourism expenditure in regions with better surf breaks grew significantly faster than in those without. Unsurprisingly this was true for the tourist visits that involved surfing. More interestingly it was also true for tourist visits that did not involve surfing. This is consistent with natural amenities creating a focal-point for specialised tourism, which creates spillovers to the broader tourism industry. For example, infrastructure may initially be built for intrepid surfers attracted to good breaks, which then lowers costs and creates service agglomerations that make it easier for other tourists to visit.

The second experiment asks, "does discovering a new surf break (or seeing one disappear) alter nearby economic growth"? We answer this using two approaches. The first conducts event studies on three surf break discoveries, due to competitions organised by Surfer Magazine and the World Championship Tour; and two rare disappearances, due to construction of a coastal road and dredging of a river-mouth. After the surf breaks were discovered we find that lights in the surrounding 50km grew by up to 3.1 percentage points per annum faster than they were beforehand. After the two surf breaks were destroyed, light growth in the surrounding area fell by up to -1.5 percentage points relative to the prior trend. Both results control for global changes in lights. The disappearances in particular are notable, because they were caused by investments that were intended to boost growth. The second approach conducts an event study around a technological discovery: Rip Curl's 2007 invention of battery-heated wetsuits. Prior to the invention, lights surrounding the 83 cold-water breaks above 55 degrees latitude were declining by -1.4% per annum on average, after controlling for global trends. After the invention the average rate of light growth increased by 4.3 percentage points. This suggests that discovering a new natural amenity, the technology to exploit it, or destroying an existing amenity, may have a large short-term effect on growth.

Finally, the third experiment asks, "what happens when the surf is good"? Generally, bigger waves are better, but they must be generated at long range to provide space for the swell to organize as it travels, and for the weather at the surf break to not be affected by the originating storm. To capture this we combine monthly data on wave heights with information on El Niño events, which produce famously good long-range swells in the Pacific. Using a triple-interaction approach we estimate the effect of large waves, during El Niño years, at high-quality breaks. We find that, during El Niño events, a one standard deviation increase in wave height increases light growth in the 50km surrounding 4-star and 5-star breaks by 5.6 and 3.9 percentage points, relative to 1-star breaks.

Collectively these three experiments show that natural amenities can promote local economic growth. Geography typically competes with institutions as the main driver of growth (North, 1989; 1990; Acemoglu et al., 2002). This adds to the existing evidence that supports the role of geography in economic growth via channels like agriculture (Marshall, 1890), natural-resource extraction[6], exposure to disease (Diamond, 1999; Sachs 2000, 2001), coastal access (Gallup and Sachs, 2000), and frequency of natural disasters (Hsiang and Meng, 2015).

We find evidence that the mechanism works via tourism. This mechanism is indirect, as natural amenities like surf breaks provide non-market services. Waltert and Shlapfer (2010) identify that natural amenities affect growth by augmenting either the productivity of physical capital, or of labour. An example of the first is tourism infrastructure: an investment in a beach road or a resort will be more productive if people want to go there. Examples of the second are nice locations attracting migrants with footloose incomes, workers willing to accept lower wages, and entrepreneurs willing to accept lower profits. As noted above we find that the permanent population is unchanged but tourist numbers increase near good surf breaks, which supports the tourism, rather than footloose worker, mechanism. Faber and Gaubert (2019) also find that tourism causes local economic gains, in a cross-sectional study of Mexican municipalities using sand colour and offshore islands as instruments for beach quality. We extend that work by directly measuring the quality of surf breaks,[7] on a global dataset,[8] in three experiments that exploit both temporal and spatial variation, at a finer resolution (up to 1x1 km^2).[9]

We also find evidence that that the economic benefits from natural amenities have diminishing returns. This adds to the "new economic geography" literature on the location of

[6]See Dell (2010), Aragon and Rud (2013), Caselli and Michaels (2013), Allcott and Kenniston (2014), Cavalcanti et al. (2019) and reviews by Cust and Poelhekke (2015) and van der Ploeg and Poelhekke (2016).

[7]The quality and location of surf breaks are independent of the onshore economy, while sand colour may be correlated with soil quality/agricultural productivity, and islands can contribute to economic activity by virtue of needing to be accessed from nearby coast.

[8]A global dataset allows us to investigate other importance questions, like whether the importance of natural amenities differs based on the stage of economic development, see Table 5.

[9]This resolution allows us to answer important questions on the impact of natural amenities in urban vs rural areas, and whether they cause displacement of economic activity (Table 14).

economic activity, which draws a distinction between “first-nature geography”, concerning natural advantages, and “second-nature geography”, concerning endogenous forces of agglomeration and dispersion[10]. We find that first-nature geography is important, as rural areas that are near good surf breaks grow faster than those that are not. We also find that second-nature geography matters, as good surf breaks in urban areas actually see less economic growth than other regions. This makes sense if the surrounding economy becomes specialised in a finite resource with diminishing marginal returns. Our findings present a message of caution: surf tourism may compete against other industries, and could potentially lead to worse economic outcomes if higher productivity activities are suffocated as a result. This points to the importance of sensible industrial policy and the sound management of natural resources. It should be added that our results do not say anything about the intrinsic natural value that these surf breaks offer, both to the ecosystems that depend on these coastal areas and to the people that enjoy them. Overall these findings suggest that the natural amenities can boost economic growth, but only if they are not over-exploited. Increasing the supply of the resource, for example through artificial wave parks, may help to achieve this.

Finally, we find evidence that natural amenities create spillovers to other forms of tourism. Rodrik (1996; 2004) argues that there is a coordination problem involved with locating sectoral clusters. High quality natural amenities may help to solve this. For example, a stretch of coast may have many beaches suitable for a tourism cluster. However, forming a cluster requires many independent public and private agents investing in the same location at the same time. A high quality surf break, patronised by intrepid surfers, can provide the focus for this investment. It can then grow to support a broader, non-surfing tourism industry as in Byron Bay (Australia), Jeffreys Bay (South Africa), and Taghazout (Morocco), which all started as small surfing towns.

The paper proceeds as follows. Section 2 introduces our identification strategy by explaining the very fine balance of factors that combine to produce a good surf break. Section 3 outlines the data and how it is used to measure economic activity near surf breaks. Section 4 exploits cross-sectional variation in the quality of surf breaks by asking the question “do good surf breaks contribute more to economic growth than bad breaks?”. Section 5 exploits temporal variation in surf break quality by asking, “does discovering a new break alter economic growth?”. It also considers breaks that have disappeared, and the effects of a discovery in wetsuit technology. Section 6 interacts both cross-sectional

[10]See Cronon (1991), Fujita et al. (2001) and Redding (2009, 2010). Natural advantages, like rivers, ports and resource endowments, cause agglomeration as they directly reduce trade and input costs (Ellison and Glaeser, 1997; 1999; Ellison et al., 2010; Redding, 2010; Redding and Rossi-Hansberg, 2016). Natural amenities, like coastlines, mountains and lakes, have also been found to anchor the location of high-income suburbs (Lee and Lin, 2015). Path dependence is important, as natural advantages have persistent effect after they become obsolete, like portage sites near rivers (Bleakley and Lin, 2012; 2015), and existing agglomeration can prevent natural advantages being exploited (Michaels and Rauch, 2016).

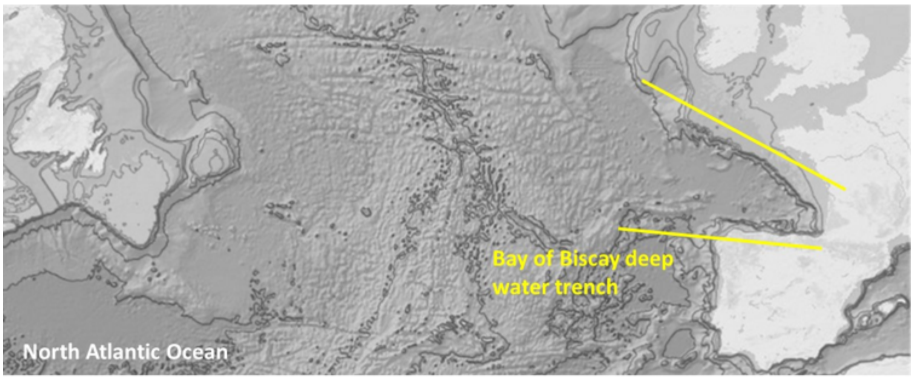

Figure 1: A deep trench in the Bay of Biscay allows waves generated in the North Atlantic to travel uninterrupted to the Basque region's coast, creating good surf breaks.

and temporal variation in quality by asking, "what happens when the surf is good?". Section 7 concludes by discussing policy implications and extensions.

2 What makes a good wave?

Waves are created by wind blowing across the surface of the ocean. The wind creates ripples known as swell lines, which propagate across large distances that can stretch up to 15,000km away from the originating low pressure system. During their travels the waves disperse, as longer wavelengths speed to the front; and group, as different wavelengths cancel and amplify one another. On their journey the waves warp and bend as they interact with the underwater topography (bathymetry), in a process called refraction. This can make the waves bigger, smaller, longer, shorter, faster, slower, fatter or hollower, depending on the bathymetry along the way. As waves approach the coast they break: the base slows as it interacts with the sea floor while the peak continues at speed. It is at the point of breaking that surfers draw off some of the waves' energy for their sport.[11] Ideally waves are only ridden by one surfer at a time, and so they are a finite resource. After the wave breaks it imparts energy to the shore, shaping sand bars which in turn affect breaking in a "self-organising system" (Butt and Russell, 2004).[12]

The quality of a surfing wave depends, broadly, on three characteristics: size, length and shape. The size of a wave is dictated by the strength, direction and duration of the originating winds, the area over which they act, the distance to where they are ridden, and the bathymetry in between (see Figure 1). Wave length is determined more locally by the angle at which the swell meets the shore, which in turn depends on the direction of swell,

[11]Surfers ride waves by balancing the force of water pushing the surfboard up the wave's face against gravity pulling it down.

[12]Butt and Russell (2004) provide an introduction to oceanography and coastal engineering with a focus on surfing.

how it refracts, and the shape of the coast. Wave shape depends on local bathymetry, swell period and wind direction. If the sea floor rises sharply then the base of the wave will slow abruptly, relative to the peak, and the wave will pitch to create a "barrel". This is exacerbated for long period swells, which travel faster; and offshore (from land to sea) winds, which hold up the wave and cancel out short-period windswell.

From this we see that the quality of a surf break is essentially random. Not only does it depend on the direction and strength of swell at its source, and wind and coastal characteristics locally, but it also depends on the bathymetry over the entire intervening distance, down to a very fine scale. Sand-bars, which dictate bathymetry for the sandy locations that account for over 50% of our sample, are formed "in a chaotic system, where imperceptibly small changes in input produce vastly differing outputs" (Butt and Russell, 2004). While some of these individual characteristics may be correlated with economic outcomes at a local level, the fine balance of many factors needed to produce good waves is unlikely to be.

3 Data and Measurement

We use two main datasets to study how surf breaks affect local economic growth. The first is a dataset containing the location and basic characteristics of over 5000 surf breaks. The second uses satellites to measure night time light emissions at a 1km^2 resolution. In addition we use data on population at a 1km^2 resolution, urban areas, Australian tourism, political/economic activity, atmospheric pressure, and wave heights.

3.1 Surf breaks

WannaSurf (www.wannasurf.com) is an online "world surf spot atlas". It records the location, quality, type, accessibility, coastal and oceanic characteristics of 5,288 surf breaks around the world, which we collect using Python (Figure 2). Of these we drop 91 for which the data on quality is either missing or rated 0 stars ("choss"), leaving 5,197 breaks in our dataset. These breaks are distributed across 146 countries, but are concentrated in Australia (888 breaks) and the US (874) (see Figure 3).

The main characteristics used in this study are surf break location and quality. The GPS coordinates of each break are provided using the WGS84 datum. Accuracy ranges from 3m-200m depending on the original datum used to record the location. Each break is assigned one of five quality ratings, which are verified by independent experts and range from "sloppy" (1-star) to "totally epic" (5-star) (see Figure 1). Quality describes the

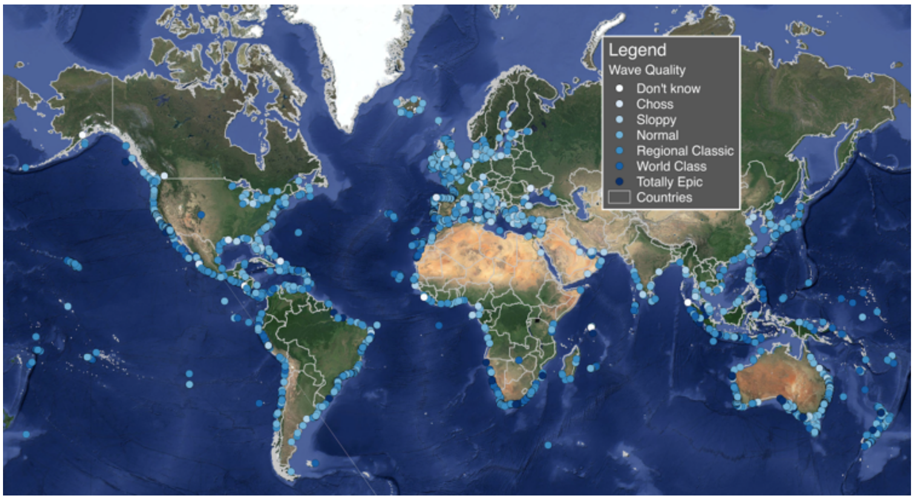

Figure 2: Overview of surf break locations in WannaSurf database.

Star Rating	Description	All		AU & US		Ex. AU/US	
		Count	Urban	Count	Urban	Count	Urban
1	Sloppy	384	62%	134	67%	250	59%
2	Normal	2041	59%	772	64%	1269	56%
3	Regional Classic	2141	54%	670	59%	1471	52%
4	World Class	464	44%	122	57%	342	39%
5	Totally Epic	167	39%	64	53%	103	30%
	Total	5197	55%	1762	61%	3435	52%

Table 1: Breakdown of WannaSurf surf breaks by quality.

average physical quality of the waves at the location, and in most cases is fixed over time (we study rare examples of changing qualities in Natural Experiment II). It does not capture crowds, ease of access, surrounding views, etc. We use a measure of quality that is relatively robust to measurement error because it is verified by independent experts.[13] In the first instance data on a new break is nominated by one of the website's 78,000 registered users. The data is then checked and monitored for accuracy by one or more WannaSurf Regional Correspondents. We ignore the additional poll-based "user rating" (see http://www.wannasurf.com/help/faq/index.html) which could be more subject to bias. For reference, of the eleven locations on the surfing World Championship Tour seven are 5-star, three are in popular surfing areas with a dense concentration of 4-star breaks, one is 3-star (in central Rio de Janeiro, to promote the sport), and crowds range from "empty" to "ultra-crowded".

WannaSurf records a variety of other characteristics for each break. These include variables on accessibility ("Distance", "Easy to find?", "Public access?", "Crowd"), difficulty

[13] Oceanologists are not yet been able to predict break quality using geographic and climactic models, due to the complex interactions that determine it at a metre-by-metre scale (though they do forecast wave heights relatively successfully, for example www.swellnet.com.au). Rather than using geographic variables to instrument for break quality, this paper has the advantage of measuring quality directly.

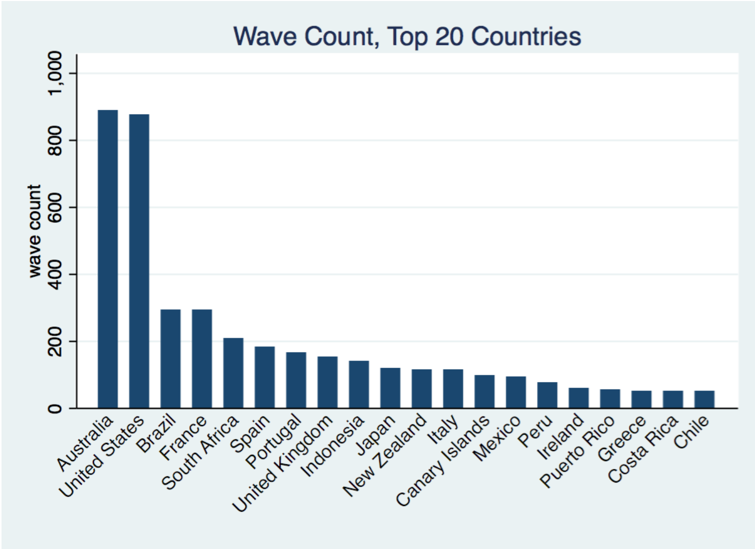

Figure 3: WannaSurf data covers 146 countries, though data on surf breaks is concentrated in Australia and the US.

Break Type	Count	Share	Avg Quality (stars)	Urban (%)
Beach-break	2,070	40%	2.29	58%
Reef-rocky	1,057	20%	2.96	54%
Point-break	670	13%	2.94	47%
Sand-bar	570	11%	2.41	63%
Reef-coral	453	9%	3.07	39%
Breakwater/jetty	132	3%	2.45	77%
River-mouth	120	2%	2.73	49%
Don't know	101	2%	2.44	61%
Reef-artificial	24	0%	2.96	79%
Total	5,197	100%	2.61	55%

Table 2: Breakdown of surf breaks by type.

("Experience"), the type of wave ("Frequency", "Type", "Direction", "Length", "Bottom", "Power") and oceanic conditions ("Good swell direction", "Good wind direction", "Swell size", "Best tide"). Of these we use the "Type" variable, which indicates whether the shoreline is a beach, a reef, a river-mouth, a headland (point-break) or a breakwater, to test whether other omitted geographic variables influence our results (see Table 2).

3.2 Night-time lights

The Defence Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) uses satellites to record the average annual night-time light intensity around the world, from 1992-2013 (Figure 5i.). The data is provided at a resolution of 30x30 arc-seconds (approximately 1 square kilometre near the equator), and ranges from 0 to 63. The data is constructed by overlaying all daily images over the course of a year, discarding

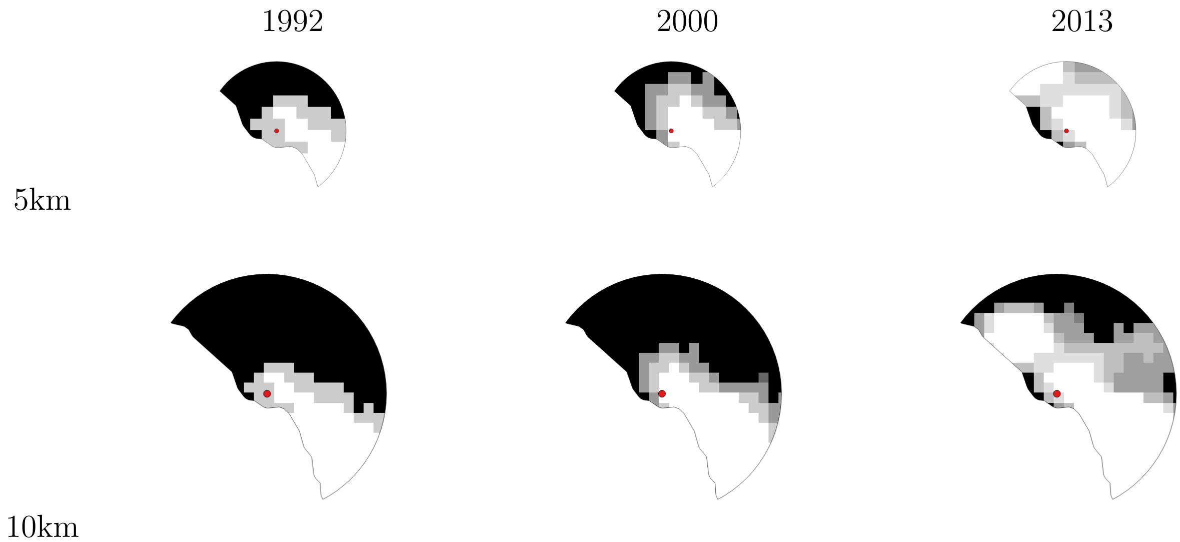

Figure 4: Example of illumination growth in the 5km and 10km surrounding Anchor Point, a “World Class” (4-star) break in southern Morocco, clipped along the coastline.

those that are obfuscated by cloud cover, lightning, aurora, etc. for a given pixel. There is a strong link between GDP growth and mean light intensity at a national level (Doll et al., 2006; Henderson et al., 2012; Michalopoulos and Papaioannou, 2014). We make use of the high spatial resolution of the data to study economic activity at a sub-national level, as has been done in a number of other studies (Chen and Nordhaus, 2011; Michalopoulos and Papaioannou, 2013; Hodler and Raschky, 2014; Jedwab et al., 2015; Jedwab and Moradi, 2016; Smith and Wills, 2016).

We measure illumination in the immediate vicinity of a break using concentric circles of various radii. We draw these circles at 5km, 5-10km and 10-50km around each break, clipped along the coastline (see Figure 4), and take the total illumination on the remaining land in each circle for each year. Coastlines are defined by a shape file from VDS Technologies, a private mapping firm, which may be subject to some small measurement error but it will be uncorrelated with break quality. Circles may overlap, so we include all overlapping areas in all breaks they are close to. This is the most conservative approach because high quality breaks will raise light growth around nearby low quality breaks, making the null hypothesis more difficult to reject. An alternative approach, based on treating individual pixels with the quality of nearby waves, is described in Appendix B.1.

Night-time light data is subject to some issues that are relevant for this study. First, “top-coding” refers to pixels with a light reading of 63, beyond which we cannot distinguish levels of economic activity. This is not important in our data as it occurs for less than five “novelty” breaks in the centre of cities, like a wave park in Kuala Lumpur and a river-wave in central Munich. Second, light data includes significant luminosity readings from gas flares, which do not reflect economic activity. To control for this we drop all cells with gas flare activity according to the provider of the lights data (the NOAA Earth Observation Group), and trim any observations over water. Third, light data is affected by overglow (or "blooming"), where light is recorded in pixels away from its origin, and is magnified over terrain like water and snow (Doll, 2008). Small et al. (2005) find that overglow is linearly proportional to lit area, which is consistent with a physical model for atmospheric scattering. We clip our observations around the coastline, and in Appendix A confirm that overglow changes linearly with light, so will not bias our study of light growth. Fourth, the satellites used to construct the data change in 1994 (F11), 1995 (F13), 1997 (F14), 2000 (F15), 2003 (F16), 2007 (F17), and 2010 (F18) - which we average in years with multiple satellites, and the effectiveness of the sensors diminishes over time. To control for this we use year fixed effects.

3.3 Population

Oak Ridge National Laboratory produces the LandScan dataset which provides annual mid-year spatial population counts at a 30x30 arcsecond resolution from 2000-2013 (Figure 5). It is similar to the Gridded Population of the World data from NASA's Socioeconomic Data and Applications Center (SEDAC), which measures population at a 30×30 arc second resolution in 1990, 1995 and 2000, and has been used by Dell (2010) and Alesina et al. (2015) amongst others. LandScan records estimates of the "ambient", or daily average, population in each grid cell. Importantly, this excludes intermittent population such as tourists or temporary relief workers, and may not reflect things like seasonal migrations or refugee movements. This allows us to focus explicitly on spillovers to the permanent population. The estimates are based on aggregate data for second order administrative units compiled by the International Programs Center of the US Bureau of Census. The aggregate data is distributed throughout the grid according to a likelihood model that uses inputs including data on elevation, land cover, roads, night lights, coastlines, settlements, and high resolution satellite imagery, among other sources.[14] It pays special attention to coastal features. To account for the dynamics of coastal change the LandScan model extends all coastal boundaries several kilometres seaward. This ensures that all shore and small island features are included within an administrative unit boundary.

This population data also has some shortcomings. Aggregate population is allocated spatially using a likelihood model. This is subject to model error. The census data is also not collected every year. Between census years it is based on annual mid-year national population estimates from the Geographic Studies Branch of the US Bureau of Census, so year-to-year population comparisons suffer from interpolation error. LandScan

[14] For further detail http://web.ornl.gov/sci/landscan/landscan_documentation.shtml

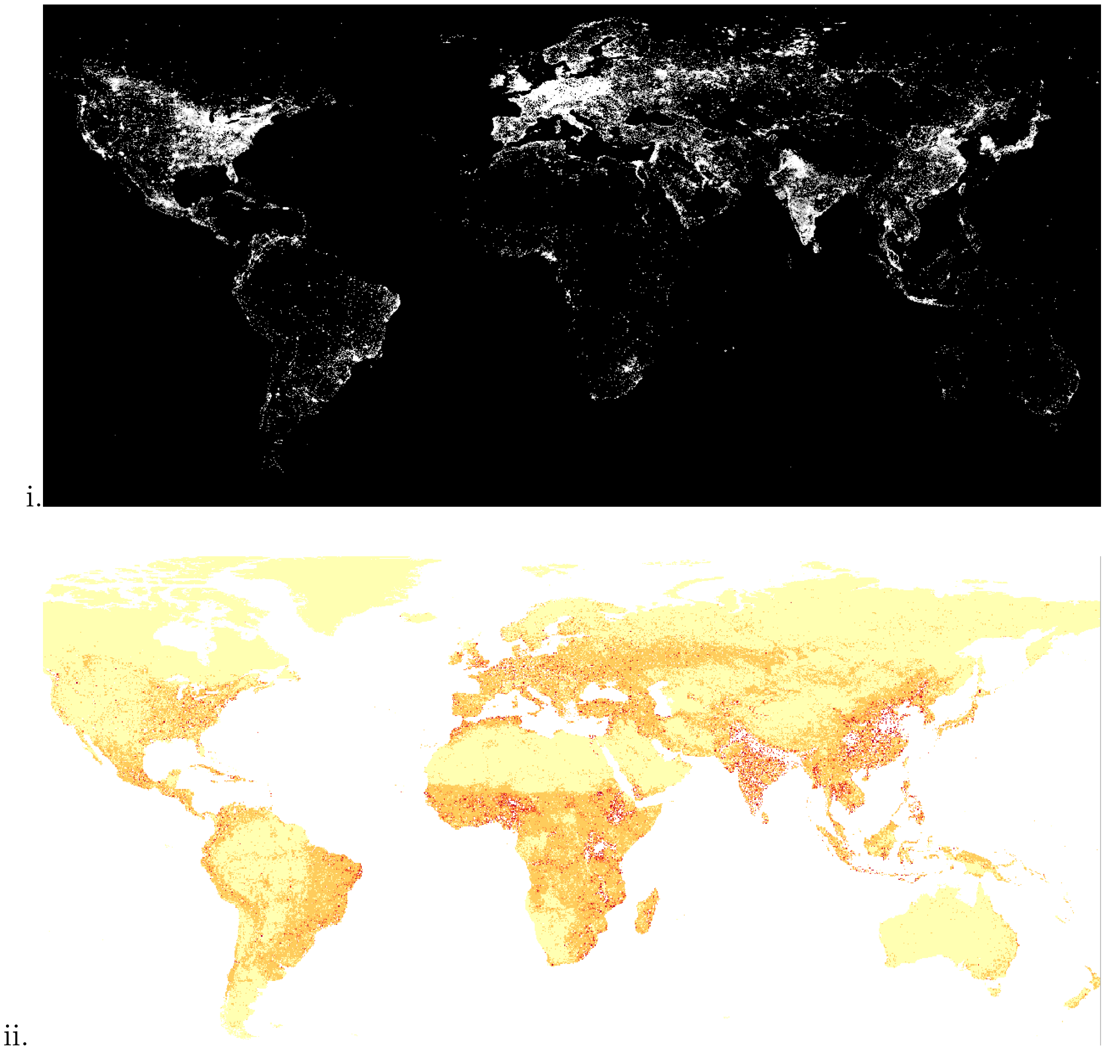

Figure 5: Data on i. night-time lights (DMSP-OLS) and ii. population (LandScan)

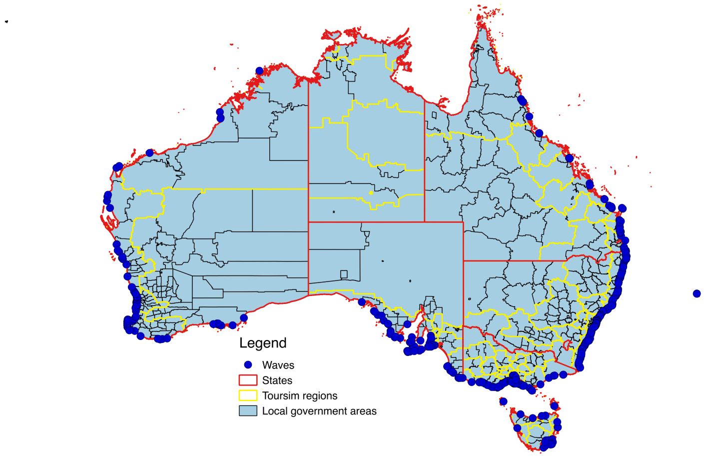

Figure 6: Australia's surf breaks, tourism regions and local government areas.

cautions against using the data for annual cell-by-cell migration comparisons. Therefore, we present all population changes in 5km to 50km circles, over a 13 year horizon which incorporates at least two censuses in most cases.

3.4 Urban and rural classification

SEDAC also provides an "Urban Extents Grid", from its Global Rural-Urban Mapping Project (GRUMP), which uses 1995 population estimates to classify each square of a 30x30 arc second global grid as either urban or non-urban (a.k.a. "rural"). The classification is based on contiguous lighted squares as of 1995 and settlements known to hold at least 5000 people, and agrees with urban extents based on DHS surveys (Dorelien et al., 2013). Table 1 shows that good quality surfbreaks tend to be less urban than bad quality breaks, particularly outside Australia and the US which have the most breaks in the database. We consider the possibility of a selection bias in Sections 4.3 and 4.4.

3.5 Tourism

Unfortunately high-quality global data on surfing tourism does not exist. However, Australia is the country with the largest number of surf breaks in our dataset (17% of sample), and Tourism Research Australia (TRA) is an Australian government body that collects official data on domestic and foreign tourism through the National and International Visitor Surveys. For domestic overnight tourists this includes official data on the activities that they participate in at each destination, including surfing. We use data on the total expenditure at the destination for all domestic overnight trips, and total expenditure at the destination for domestic overnight trips that involved surfing. This is available annually from 2004 to 2017 for the 109 Tourism Regions (TRs) in Australia, of which 38 TRs have surf breaks that appear in our database (see Figure 6). In the regions that contain surf breaks, surfing-related trips account for 4% of total domestic overnight tourist expenditure on average (ranging up to 79%).

3.6 UN Human Development Index

The UN compiles the Human Development Index (HDI) as a summary measure of a country's level of development. In our sample it ranges from 0.37 to 0.93 and is grouped into "Low" (<0.55), "Medium" (0.55-0.699), "High" (0.7-0.799) and "Very High" (>0.8) bands.

3.7 El Niño and Wave Heights

The National Oceanic and Atmospheric Administration records the monthly Southern Oscillation Index (SOI), based on the difference in the standardized sea level pressure between Tahiti and Darwin, Australia. An El Niño event is defined as any where $SOI \leq -0.7$ for three or more consecutive months, which gives events in 1992, 1993, 1994, 1997, 1998, 2002, 2006, 2009, and 2010.

Australia's Commonwealth Scientific and Industrial Research Organisation (CSIRO) provided data on the monthly mean significant wave height from its Centre for Australian Weather and Climate Research (CAWCR) Wave Hindcast on a global 24 arcminute grid, from 1992-2013 (Hemer et al., 2011). The mean significant wave height is defined as the average height (trough to crest) of the upper third of the waves in the wave-field. They also provided data on the monthly wave height anomaly, which is the deviation from the annual cycle at each grid point.

4 Natural Experiment I: Do good surf breaks contribute more to economic growth than bad breaks?

"Surfers are the trendsetters, then the other tourists follow"
- Tarik Senhaji, Director General, Moroccan Sovereign Wealth Fund (2016)

4.1 Identification

Surfing offers a clean natural experiment because the quality of surf breaks is exogenously determined by a careful calibration of climatic, bathymetric and geographic conditions. Section 2 described how this quality depends on a complex interaction between time-variant factors, like the strength, direction and duration of winds where the wave originates and breaks; and time-invariant factors, like the sea floor bathymetry over the distance the wave travels, and the shape of the coastline where it breaks.

An example may be helpful. In less than a mile along the north shore of Oahu, Hawaii, lie three of the world's most famous, 5-star reef-breaks: Backdoor, Pipeline and Sunset Beach (see Figure 7). Every December the world surfing tour concludes there, as champion surfers test themselves against long-range north Pacific swells that break against a succession of shallow reefs. In between Pipeline and Sunset lies Kammieland: another reef break on exactly the same beach, facing the same direction, and receiving the same swell, which is only rated 2-stars due to a complex interaction of water flowing over that reef and others. The rest of the breaks on this uninterrupted stretch of sand do not even warrant a name. Therefore, while a surf break's existence may be related to economic activity (due to trade advantages of coastlines, etc.) the quality of the break is essentially random. Natural Experiment I exploits this randomness to determine whether areas near high-quality waves grow faster than those near low-quality waves. The control group is areas near 1-star waves, which is a relatively high hurdle as they are also coastal and of sufficient interest to surfers to appear in the WannaSurf database. We also test the robustness of this identification strategy to issues like endogeneity, selection bias and measurement error.

The main selection issue that we are concerned about is that higher quality waves may be more likely to appear in our dataset in more remote areas than low quality waves. If areas with less lights grow faster than those with brighter lights, it would be possible to wrongly attribute light growth to wave quality instead of convergence. We deal with this selection issue by controlling for initial lights to capture convergence in all our specifications.

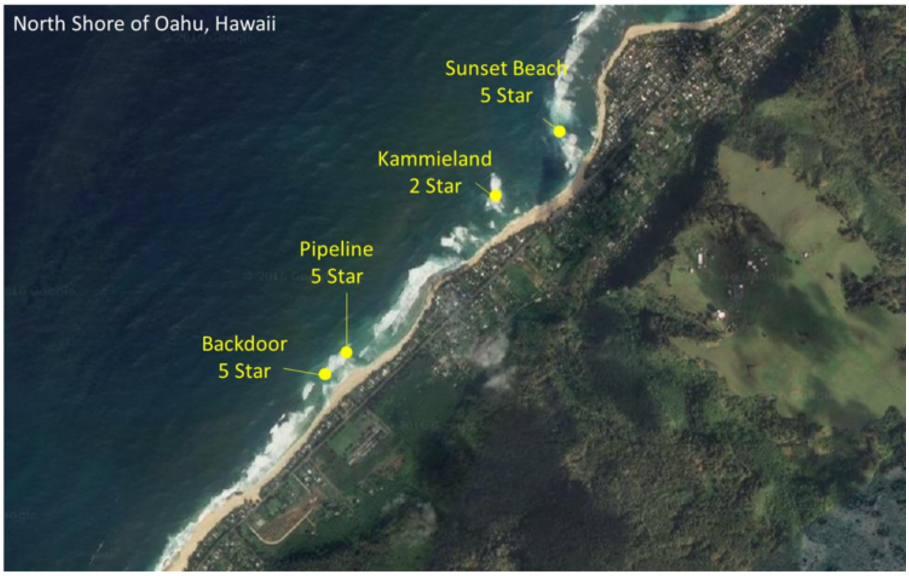

Figure 7: Satellite image of the North Shore of Oahu, Hawaii, showing how a single mile of beach can contain three 5-star breaks and one 2-star break, due to subtly detailed variation in bathymetry (Google Maps, 2016).

4.2 Estimating Equations

We exploit cross-sectional variation in the quality of surf breaks to estimate their effect on spatial outcomes using the following model:

$$\ln(Y^d_{i,2013}) - \ln(Y^d_{i,1992}) = \alpha + \beta_1 Q_i + \beta_2 U_i + \beta_3 (Q_i * U_i) + \kappa \ln(Y^d_{i,1992}) + F_z + \epsilon_{i,t} \quad (4.1)$$

where $Y^d_{i,t}$ is the total light (or population) within d kilometres of break i in year t, $Q_i \in [1, \ldots, 5]$ is the star quality rating of break i which we treat as both continuous and categorical, the urban indicator $U_i = 1$ if the break is in an urban area as defined in Section 3.4 and 0 otherwise, and F_z is zone[15] fixed effects. The counterfactual is the change in $\ln(Y^d_{i,t})$ from 1992-2013 for a 1-star non-urban break. This is a relatively high hurdle because 1-star breaks are on the coast and are sufficiently known by surfers to appear in WannaSurf, so our estimates are conservative. The initial level of lights for each break is included to control for the possibility of convergence: that places with low initial levels of economic activity grow faster than places with high activity.[16] Table 1 shows that high-quality waves tend to occur in more rural areas, and so including this term prevents convergence from biasing our results. We deal with potential spatial correlation by clustering the standard errors by zone, and using spatially-robust heteroskedastic-

[15] Zone is the largest subnational unit (e.g. the United States is comprised of eight zones).

[16] As we are using logs we exclude breaks with zero initial lights. So, our results estimate intensive growth effects.

and autocorrelation-consistent (HAC) standard errors following Conley (1999 and 2010; implemented using Hsiang, 2010 and Fetzer, 2014).[17]

To study tourism as a channel for how surf breaks affect growth we use data on Tourism Regions in Australia, described in Section 3.5. There are only 38 tourism regions with surf breaks in this data. So, to have sufficient power for our estimates we exploit the panel nature of this data by using a linear time trend model:

$$ln(Y_{i,t}) = \alpha + \beta_1 Q_i t + \beta_2 Q_i^U t + \kappa \ln(Y_{i,2004}) + Z_t + \epsilon_{i,t} \tag{4.2}$$

where $Y_{i,t}$ is the level of the dependent variable (either: total expenditure, total expenditure on trips that involved surfing, or total expenditure on trips that did not involve surfing), in tourism region i in year t (2004=0); Q_i is the measure of surf break quality (either mean or maximum) in that region; Q_i^U is the measure of surf break quality (mean or maximum) in only the urban areas of that region; and Z_t is year fixed effects. We include the initial level of the dependent variable to control for possible convergence effects, and use robust standard errors. So, the counterfactual is the level of lights each year in tourism regions with no surf breaks, and we test if the growth in lights is affected by the quality of a region's surf breaks overall (β_1), or in urban regions only ($\beta_1 + \beta_2$).

4.3 Results

Economic activity near high quality breaks grew faster than near low quality breaks in rural areas from 1992-2013, but the effect was reversed in urban areas. Activity in rural areas (proxied by night-time lights) increased overall, rather than simply being reallocated from nearby areas. There was no evidence of surf break quality affecting the permanent population, so the increase in economic activity represented an increase in per capita terms. Detailed data from Australia is consistent with tourism being a channel for this growth. The results are robust to a variety of controls including omitted geographic characteristics, overlapping breaks, wave-rich countries, and convergence.

4.3.1 Surfing and economic activity

Economic activity near high-quality breaks in rural areas grew significantly faster than near low-quality breaks from 1992-2013, but the effect was reversed in urban areas. In

[17] This applies a spatial weighting matrix to the standard errors that decays linearly out to 100km, and accounts for serial correlation at each location out to three lags non-parametrically.

	Total change in ln($lights^{5km}$) from 1992-2013			
	(1)	(2)	(3)	(4)
2 star	0.0188	0.0188	0.0871	0.0871
	(0.475)	(0.428)	(0.203)	(0.136)
3 star	0.0293	0.0293	0.146**	0.146***
	(0.252)	(0.209)	(0.0109)	(0.00653)
4 star	-0.000813	-0.000813	0.122	0.122*
	(0.979)	(0.979)	(0.102)	(0.0693)
5 star	-0.0333	-0.0333	0.175*	0.175**
	(0.426)	(0.410)	(0.0548)	(0.0380)
Urban			0.390***	0.390***
			(3.96e-10)	(2.02e-10)
2 star*Urban			-0.103	-0.103
			(0.183)	(0.108)
3 star*Urban			-0.180***	-0.180***
			(0.00334)	(0.00196)
4 star*Urban			-0.187**	-0.187**
			(0.0206)	(0.0108)
5 star*Urban			-0.307***	-0.307***
			(0.000670)	(0.00122)
ln($lights^{5km}_{1992}$)	-0.284***	-0.284***	-0.338***	-0.338***
	(0)	(0)	(0)	(0)
Constant	2.269***	2.269***	2.344***	2.344***
	(0)	(0)	(0)	(0)
Observations	4,289	4,289	4,289	4,289
R-squared	0.718	0.411	0.732	0.441
Sample	All breaks	All breaks	All breaks	All breaks
FE	Zone	Zone	Zone	Zone
SE	Zone	Conley	Zone	Conley

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: The effect of surf break quality on the change in $ln(lights)$ in the surrounding 5km, from 1992-2013, controlling for the initial level of lights. The effects are estimated in aggregate, (1)-(2), and distinguishing between urban and rural areas, (3)-(4). Fixed effects are at the subnational zone level. Standard errors are clustered at the zone level, or allow for spatial correlation within 100km, and autocorrelation to 3 periods (Conley).

rural areas, Table 3 shows that lights surrounding good quality (3- to 5-star) breaks grew by 0.122 to 0.175 log points more than 1-star breaks on average over our 21 year sample (~0.6 to 0.8 percentage points per annum; see columns 3-4). This result controls for convergence, and the average light growth within each subnational zone. While lights near 1-star breaks grew 0.39 log points more in urban than rural areas over our sample, the light near good quality urban breaks grew by -0.034 to -0.132 log points[18] less than 1-star urban breaks on average over the sample (-0.16 to -0.63 percentage points per annum). This effect increases in size and significance with the quality of surf break, and controls for convergence, average light growth in urban areas, and average light growth in each subnational zone. Economic activity near good breaks was not just redistributed from surrounding areas, because we find similar but diminishing effects out to 50km away (see Table 14).

Robustness

Are the results being driven by a selection bias? For example, in rural areas low quality breaks might be less likely to appear in the data than rare, high-quality breaks. If so, then high-quality breaks would benefit more from a convergence effect, due to their low initial level of lights. To control for this we include the initial level of lights in all our regressions.

Are these results being driven by an omitted geographic characteristic, that both increases the quality of surfing breaks and drives economic growth? For example, river mouths (2% of our sample) have a higher average quality rating than the rest of the sample (2.73 vs 2.61 stars), and may be associated with economic activities like fishing and trade which are unrelated to surfing. To control for this we add surfbreak-type fixed effects to the specification in equation 4.1. The omitted surfbreak-type is beachbreaks, which is the largest category and accounts for 40% of the sample. The results in Table 4 show that the effect of wave quality on light growth is virtually the same as Table 3, in both urban and rural areas. Rivermouths do not have a significantly different effect on light growth to beachbreaks in our sample. However, breakwaters saw more light growth than beachbreaks on average, while point-breaks (headlands) and rocky reefs saw less.

Are the results being driven by some countries more than others? Australia and the USA are large, developed countries and account for 17% of breaks each (see Figure 3). In Table 5 we report the results of equation 4.1 for Australia and the US only (1), and for everywhere except Australia and the US (2). We find the effects are larger and more significant in Australia and the US, though the convergence parameter κ is larger for the rest of the sample. We also split the sample into developed (UN HDI = "Very High")

[18]The net effect of the β_1 and β_3 terms in equation 4.1.

	Total change in ln($lights^{5km}$) from 1992-2013			
	(1)	(2)	(3)	(4)
2 star	0.0209	0.0209	0.0880	0.0880
	(0.453)	(0.394)	(0.211)	(0.141)
3 star	0.0400	0.0400	0.158***	0.158***
	(0.137)	(0.102)	(0.00890)	(0.00435)
4 star	0.0144	0.0144	0.131*	0.131*
	(0.673)	(0.657)	(0.0896)	(0.0606)
5 star	-0.0136	-0.0136	0.194**	0.194**
	(0.761)	(0.749)	(0.0398)	(0.0254)
Urban			0.391***	0.391***
			(7.11e-10)	(3.66e-10)
2 star*Urban			-0.0997	-0.0997
			(0.200)	(0.126)
3 star*Urban			-0.182***	-0.182***
			(0.00398)	(0.00218)
4 star*Urban			-0.177**	-0.177**
			(0.0284)	(0.0167)
5 star*Urban			-0.308***	-0.308***
			(0.000898)	(0.00133)
ln($lights^{5km}_{1992}$)	-0.286***	-0.286***	-0.340***	-0.340***
	(0)	(0)	(0)	(0)
Breakwater/jetty	0.0505**	0.0505*	0.0617**	0.0617**
	(0.0475)	(0.0540)	(0.0234)	(0.0191)
Don't know	-0.0479	-0.0479	-0.0831	-0.0831
	(0.770)	(0.754)	(0.612)	(0.584)
Point-break	-0.0465***	-0.0465**	-0.0396**	-0.0396**
	(0.00903)	(0.0214)	(0.0225)	(0.0475)
Reef-artificial	-0.0614	-0.0614	-0.0363	-0.0363
	(0.275)	(0.276)	(0.507)	(0.519)
Reef-coral	-0.0229	-0.0229	-0.00960	-0.00960
	(0.438)	(0.423)	(0.742)	(0.740)
Reef-rocky	-0.0370*	-0.0370*	-0.0349*	-0.0349*
	(0.0724)	(0.0639)	(0.0905)	(0.0741)
Rivermouth	-0.0318	-0.0318	-0.0266	-0.0266
	(0.598)	(0.588)	(0.656)	(0.642)
Sand-bar	-0.0310	-0.0310	-0.0338	-0.0338
	(0.176)	(0.151)	(0.146)	(0.116)
Constant	Yes	Yes	Yes	Yes
Observations	4,210	4,210	4,210	4,210
R-squared	0.716	0.414	0.731	0.443
FE	Zone	Zone	Zone	Zone
SE	Zone	Conley	Zone	Conley

Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4: The effect of surf break quality on the change in $ln(lights)$ in the surrounding 5km, from 1992-2013, controlling for the initial level of lights and surfbreak-type. The omitted surfbreak-type is beachbreaks, which account for 40% of the sample. The effects are estimated in aggregate, (1)-(2), and distinguishing between urban and rural areas, (3)-(4). Fixed effects are at the subnational zone level. Standard errors are clustered at the zone level, or allow for spatial correlation within 100km, and autocorrelation to 3 periods (Conley).

	Total change in ln($lights^{5km}$) from 1992-2013			
	(1)	(2)	(3)	(4)
2 star	0.0348	0.126**	0.0534	0.139
	(0.766)	(0.0318)	(0.425)	(0.218)
3 star	0.221**	0.111*	0.118*	0.155
	(0.0342)	(0.0549)	(0.0607)	(0.145)
4 star	0.288**	0.0492	0.204***	0.0215
	(0.0295)	(0.517)	(0.00967)	(0.863)
5 star	0.230	0.131	0.149	0.134
	(0.150)	(0.152)	(0.121)	(0.412)
Urban	0.455***	0.366***	0.374***	0.292***
	(0.000208)	(1.03e-08)	(8.95e-07)	(0.00906)
2 star*Urban	-0.0481	-0.151**	-0.0811	-0.0706
	(0.697)	(0.0261)	(0.270)	(0.568)
3 star*Urban	-0.248**	-0.155**	-0.158**	-0.108
	(0.0211)	(0.0179)	(0.0210)	(0.341)
4 star*Urban	-0.360***	-0.114	-0.282***	0.0167
	(0.00845)	(0.182)	(0.000798)	(0.899)
5 star*Urban	-0.411**	-0.224**	-0.298***	-0.165
	(0.0186)	(0.0298)	(0.00609)	(0.357)
ln($lights^{5km}_{1992}$)	-0.293***	-0.379***	-0.307***	-0.413***
	(1.20e-09)	(0)	(0)	(0)
Constant	1.819***	2.714***	2.054***	3.029***
	(0)	(0)	(0)	(0)
Observations	1,498	2,791	2,892	1,397
R-squared	0.384	0.500	0.389	0.577
Sample	AU & US	Ex. AU/US	HDI≥0.8	HDI<0.8
FE	Zone	Zone	Zone	Zone
SE	Conley	Conley	Conley	Conley

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The effect of surf break quality on the change in $ln(lights)$ in the surrounding 5km from 1992-2013, controlling for the initial level of lights and distinguishing between urban and rural areas. In column (1) the sample is restricted to Australia and the US only, and in column (2) it excludes Australia and the US. Column (3) restricts the sample to countries with a UN Human Development index above 0.8 ("Very High"), and Column (4) restricts the sample to countries with a HDI below 0.8 ("Low"/"Medium"/"High"). Fixed effects are at the subnational zone level. Standard errors allow for spatial correlation within 100km, and autocorrelation to 3 periods (Conley).

and developing (UN HDI $\in$ [“Low”, “Medium”, “High”]) countries in columns (3) and (4) respectively. We find that the effects are concentrated in developed countries, while the convergence parameter κ is notably larger for developing countries.

Finally, are the results affected by 5km circles that overlap for multiple surf breaks? As noted in Section 3.2 we address this by conservatively including overlapping areas in all nearby breaks making it more difficult to reject the null (as good breaks would increase lights at nearby bad breaks). In addition, we re-run our analysis using pixels, rather than breaks, as the unit of observation (see Appendix B.1). This allows us to treat each pixel individually with the maximum quality break within 5km, and we find similar results to the baseline specification.

4.3.2 Surfing and population

The permanent population near high-quality surf breaks did not grow significantly differently to the population near low-quality breaks from 1992-2013, in either urban or rural areas. We show this using the specification in equation 4.1 using population, rather than lights, as the dependent variable. The results are in Table 6. Similar results are found in for populations up to 50km away (Table 15). This analysis uses the LandScan data described in Section 3.3, which explicitly excludes tourists. We examine tourism next.

4.3.3 Surfing and tourism

High-quality data on tourism is not available with the same level of global breadth or geographical detail as the data on lights and population used above. Instead, we use tourism data for Australia, which has the most surf breaks in our dataset, and records official data on the total expenditure by domestic visitors to each tourism region in aggregate, and for the trips that involve surfing (see Section 3.5).

The Australian data reveals that there is a positive and significant effect of surf break quality on overall tourism expenditure. In Table 7, columns (1) and (2) show that adding 1 star to the average quality of surf breaks in a region (up to 5 stars) increased the growth in total tourism expenditure in that region by 0.0027 to 0.0048 log points per annum (0.27 to 0.48 percentage points per annum), after controlling for year fixed-effects. The effect was concentrated in non-urban surf breaks, and similar effects were found using the maximum quality of surf breaks in Table 16.

Unsurprisingly, surf break quality had a large and positive effect on surfing-related tourism expenditure. Columns (3) and (4) in Table 7 show that, as the average quality of surf

	Total change in $\ln(pop^{5km})$ from 1992-2013	
	(1)	(2)
2 star	-0.0808	-0.0808
	(0.541)	(0.486)
3 star	-0.143	-0.143
	(0.250)	(0.233)
4 star	-0.113	-0.113
	(0.451)	(0.455)
5 star	0.0344	0.0344
	(0.877)	(0.852)
Urban	0.836***	0.836***
	(1.80e-07)	(4.64e-10)
2 star*Urban	-0.0311	-0.0311
	(0.824)	(0.808)
3 star*Urban	-0.00751	-0.00751
	(0.958)	(0.954)
4 star*Urban	-0.200	-0.200
	(0.286)	(0.241)
5 star*Urban	-0.307	-0.307
	(0.253)	(0.141)
$\ln(population^{5km}_{1992})$	-0.265***	-0.265***
	(4.40e-06)	(0)
Constant	2.300***	2.300***
	(4.84e-08)	(0)
Observations	5,054	5,054
R-squared	0.468	0.148
Sample	All breaks	All breaks
FE	Zone	Zone
SE	Zone	Conley

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: The effect of surf break quality on the change in $\ln(population)$ in the surrounding 5km, from 1992-2013, controlling for the initial level of population. The effects distinguish between urban and rural areas. Fixed effects are at the subnational zone level. Standard errors are clustered at the zone level, or allow for spatial correlation within 100km, and autocorrelation to 3 periods (Conley).

	$\ln(Y_{i,t})$:					
	Exp_{Total}		Exp_{Surf}		$Exp_{NonSurf}$	
	(1)	(2)	(3)	(4)	(5)	(6)
t interacted with:						
AvgQual	0.00268**	0.00485**	0.0298***	0.0279**	0.00295**	0.00509**
	(0.0496)	(0.0105)	(0.00654)	(0.0134)	(0.0354)	(0.0104)
AvgQual_{urban}		-0.00465**		0.00378		-0.00457**
		(0.0212)		(0.559)		(0.0304)
$\ln(Y_{i,2004})$	1.043***	1.048***	0.842***	0.834***	1.045***	1.051***
	(0)	(0)	(0)	(0)	(0)	(0)
Constant	-0.501**	-0.568***	1.447***	1.516***	-0.534***	-0.599***
	(0.0136)	(0.00887)	(0.000208)	(0.000386)	(0.00973)	(0.00652)
Obs	1,218	1,218	423	423	1,218	1,218
R-squared	0.895	0.895	0.590	0.591	0.892	0.892
FE	Year	Year	Year	Year	Year	Year
SE	Robust	Robust	Robust	Robust	Robust	Robust

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: The effect of surf break quality on tourism activity in Australia. Tourism activity is measured by total expenditure at the destination of all trips (columns 1-2), trips that involved surfing (columns 3-4), and trips that did not involve surfing (columns 5-6) for each Tourism Region in Australia. Surf break quality is measured by the average quality in each Tourism Region, both in aggregate, or separating out urban areas. The results control for the initial level of tourism expenditure and year fixed effects, and use heteroskedasticity-robust standard errors.

breaks in a region increased by 1 star (up to 5 stars), the annual growth of surfing-related tourism expenditure in that region increased by 0.028 to 0.030 log points per annum (2.8-3.0 percentage points per annum). Similar effects were found using the maximum quality of surf breaks in each region in Table 16.

Less obviously, surf break quality also had a positive effect on tourism expenditure for trips that did not involve surfing. This was measured as the difference between total tourism expenditure to each region, and tourism expenditure on trips to that region that involved surfing. Non-surfing related tourism ranges from 21% to 100% of total tourism expenditure in each region. In Table 7, columns (5) and (6) show that increasing the maximum surf break quality in a region by 1 star (up to 5) increased non-surfing-related tourism expenditure by 0.003 log points per annum on average over our sample. This increased to 0.005 log points (or approximately half a percentage point) per annum for surf breaks in non-urban areas. This suggests that surf breaks generated positive spillovers to non-surfing related tourism.

4.4 Discussion

The results in this section show that, from 1992-2013, night-time lights near good surf breaks grew faster than those near bad surf breaks in rural areas, but not in urban areas. This is true after controlling for convergence, by including the initial level of lights in the regression, and controlling for subnational trends in light growth by including zone fixed effects. The results are not driven by redistribution of economic activity from nearby regions (up to 50km away), selection bias in rural areas, or by omitted geographic characteristics. We do, however, find evidence that the effects are concentrated in developed countries like Australia and the US. We find no evidence that the quality of surf breaks affect the permanent population living near them, so the changes in economic activity happened on a per capita basis. Using detailed Australian data we also find evidence that tourism expenditure grew faster in regions with better surf breaks in rural areas, but not in urban areas.

How can we explain this finding: that high quality surf breaks boost economic growth in rural areas but not in urban ones? In this analysis urban areas are defined by their population density. So, the findings can be re-written as: high quality surf breaks boost economic growth when the population density is low, but not when it is high. This makes sense if we think of the limited number of waves that arrive at a surf break each day, making it a finite resource that faces diminishing returns due to overcrowding. Good surf breaks in rural areas are not likely to suffer from the overcrowding constraint, while those in urban areas will. If urban areas near good surf breaks become specialised in surfing-related economic activity (e.g. tourism, surfing retail, etc.), these diminishing returns will extend to the surrounding economic activity. Surfers living near high-quality urban breaks may even actively oppose economic development to prevent further overcrowding. Bad urban surf breaks are less likely to suffer from this overcrowding, and are less likely to be specialised in surfing-related activity, so will not face the same diminishing returns. This does, however, suggest that surfing-related growth has its limits. Surf tourism, particularly in urban areas, may compete against other industries, and could lead to worse economic outcomes if the natural amenity becomes overcrowded, at the same time as other more sustainably productive activities are suffocated.

Why are the effects concentrated in developed countries like Australia and the US? In part it may be because surfing is a relatively expensive leisure activity, with surfboards costing ~US$300 to $1000, wetsuits US$100 to $500, transport and accommodation costs associated with staying near the coast, and the opportunity cost of leisure time. So, the effects of surfing are concentrated where people can afford to participate. It may also be due to a selection bias in our data, which leads the good quality breaks we observe to be more rural and start with less initial light, particularly in developing countries (see Table 1). The selection effect is consistent with surfers identifying and surfing high-quality breaks in isolated, rural areas, but not bothering to do so for isolated low-quality breaks. It is more pronounced in developing countries because they have fewer surfers and a smaller share of all possible surfbreaks listed in our database. This selection effect would cause the results in Table 5 to understate the effects of surfbreak quality on light growth, and overstate the importance of the convergence parameter, κ, especially in developing countries.

5 Natural Experiment II: Does discovering a new surf break alter economic growth?

"Four years ago, American surfer Brian Gable submitted Skeleton Bay as an entry to Surfing Magazine's 'Google Earth Challenge' competition, which he subsequently won. Shortly thereafter Cory Lopez was filmed in a ridiculously long barrel…Since then it's been documented by an increasing number of surfers to the point where each swell sees the beach lined with 4WDs and cameramen who've travelled from South Africa or even further afar." - Brokensha (2012)

5.1 Identification

Natural Experiment I compared how quickly lights grew near high-quality surf breaks, relative to low-quality breaks. Natural Experiment II uses a different counterfactual: areas with no surf breaks at all. To do this we use a series of event studies to understand how economic activity is affected by discovering a new surf break, seeing an existing one disappear, or gaining the ability to surf a new break because of technological innovation.

The first approach in Natural Experiment II uses a small sample of three discovery and two disappearance events, drawn from a survey of the surfing literature (see Table 8).[19] We require these events to have four characteristics. First, they must involve high-quality surf breaks. Second, discovered breaks must become known, and disappearances must have been known, to the global surfing community via mainstream media. Third, this must happen at a clearly defined time during our sample period, 1992-2013. Fourth, the event must be exogenous to local economic activity.

The first discovery comes from Surfer magazine's 2008 "Google Earth Challenge". Contestants were asked to pore over Google Earth and find a break that had never been surfed before. The winner was Skeleton Bay, off the coast of the Namibian desert. Since then the surfing world - amateur and professional alike - has descended into the desert to ride its 1500m long waves. We study whether economic growth followed.

The other two discoveries come from the first times the surfing World Championship Tour was held at a "secret spot": in 2006 at La Jolla, Oaxaca, Mexico;[20] and in 2007 at El

[19] The majority of breaks were discovered during the 1960s and 70s, when surfing first became a global phenomenon. Unfortunately our data does not go back that far and there is no official surfing body or archive that stores and maintains this kind of information.

[20] The effect is captured by this quote, "...the ASP [Association of Surfing Professionals world tour] arrived [at La Jolla] in full regalia and scored it at its peak, and the best surfers in the world rode the best waves they've ever seen. And now, the blitz is on. The world watched everything unfold as live

Break	Country	Discov/Disapp	Date	Quality	Source
La Jolla	Mexico	Discovery	2006	4 star	Rip Curl Search
El Gringo	Chile	Discovery	2007	4 star	Rip Curl Search
Skeleton Bay	Namibia	Discovery	2008	5 star	Surfer Magazine
Jardim do Mar	Madeira, Portugal	Disappearance	2005	4 star	www.savethewaves.org
Mundaka	Spain	Disappearance	2005	5 star	www.savethewaves.org

Table 8: Discoveries and disappearances of surf breaks.

Cold-Water Breaks			
Country	Break Count	Country	Break Count
Denmark	15	Latvia	2
Estonia	2	Lithuania	3
Faeroe Islands	1	Russia	3
Finland	2	Sweden	11
Iceland	14	United Kingdom	16
Ireland	9	United States	5
Total			83

Table 9: List of countries with surf breaks above +55 or below -55 degrees latitude.

Gringo, Arica, Chile.[21] Conversely, breaks disappeared in 2005 at Jardim do Mar, Madiera, Portugal, when a rock wall was built to protect a new coastal road; and in Mundaka, Biscay, Spain, when a rivermouth was dredged for boats leading to the cancellation of a 2005 world tour event. Both disappearances were by-products of local investment, making any estimates of economic decline very conservative.

The second approach in Experiment II uses Rip Curl's release of the first battery-heated surfing wetsuit in 2007, which made surfing in extremely cold waters much more accessible (Longman, 2016). We study whether this affected economic activity near cold-water surf breaks by treating 2007 as a discovery event for the 83 locations in our database at latitudes above 55 degrees north (none are below 55 degrees south; see Table 9).

5.2 Estimating Equations

For both approaches we study $\ln(Y_{i,t}^{50})$ - the log illumination in the 50km surrounding break i in year t (1992=0) - using the linear time trend model:

$$\ln(Y_{i,t}^{50}) = \alpha + \beta_i t + \gamma_i \max(t - t_i^D, 0) + W_i + Z_t + \epsilon_{i,t} \tag{5.1}$$

footage, beamed via satellite, flooded the web. The photos are everywhere. And even though the location remains, for now, a secret, every surfer in his right mind is frothing to find this quietly reeling point." (Surfer Magazine, 2006)

[21] Rip Curl hosted "Search" events on the world tour from 2005-2011, but the locations were only secret in 2006 and 2007.

We focus on 50km rather than 5km circles because of the relative isolation of the breaks of interest, and the small number of observations. On the right-hand side, t is the year, t_i^D is the year of the discovery/disappearance event for surfbreak i, W_i are fixed effects for each surfbreak, Z_t are fixed effects for each year, and the standard errors are clustered at the country or zone level. Therefore, we will be estimating the annual average light growth in each surf break before (β_i), and after ($\beta_i + \gamma_i$), the event in question. We control for the average level of lights in each year (Z_t), which captures factors like satellite sensitivity and global economic cycles. We also control for any time-invariant, break-specific characteristics (W_i), which captures factors like the initial level of lights. For the five discoveries and disappearances we estimate a pre- and post-event time trend for each break individually, due to the different event times. For the 83 breaks affected by the invention of battery-heated surfing wetsuits we estimate a pooled pre- and post-event time trend for all together.

5.3 Results - Discoveries and Disappearances

Table 10 shows that discovering a new 4- or 5-star surf break increased light growth in the surrounding 50km by up to 3.1 percentage points per annum, relative to the rate of light growth in the area prior to discovery. This controls for average light levels around the world using year fixed effects. All three discoveries saw a positive effect on light growth after the event, with two being statistically significant. Destroying a 4- or 5-star break caused light growth in the surrounding area to shrink by up to -1.5% per annum relative to the prior trend, which was statistically significant in both cases. The estimated disappearance effects are likely to be conservative because the road-building (Jardim do Mar) and river-dredging (Mundaka) that caused them were intended to raise growth. These results indicate that investing in infrastructure can lead to economically important side-effects from depleting natural amenities.

	Level of $\ln(lights^{50km})$
Baseline year (t):	
Skeleton Bay	0.0294***
	(0)
Jardim do Mar	0.0351***
	(0)
Mundaka	0.0238***
	(0)
La Jolla	0.00856***
	(5.99e-08)
El Gringo	0.0366***
	(0)
Post-event year ($\max(t - t_i^D, 0)$)*:*	
Skeleton Bay	0.0313***
	(0)
Jardim do Mar	-0.0150***
	(0)
Mundaka	-0.00893***
	(1.28e-05)
La Jolla	0.0125***
	(1.98e-08)
El Gringo	0.00338
	(0.158)
Constant	-51.24***
	(8.63e-07)
Observations	112,576
Number of breaks	5,173
R-squared	0.717
Sample	All
Break FE	Yes
Year FE	Yes
SE Cluster	Country

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: The effect of five surfbreak discovery/disappearance events on the level of lights in the surrounding 50km. Details of each event are given in Table 8. Time trends are estimated before and after the event for each break individually. The results control for fixed effects for each break and each year. Standard errors are clustered at the country level, due to the small number of observations at the zone level for some of the surfbreaks of interest.

Level of ln($lights^{50km}$)	
Baseline year (t):	
Cold-Water Surfbreaks	-0.0144***
	(0.00874)
Post-event year ($\max(t - t_i^D, 0)$*):*	
Cold-Water Surfbreaks	0.0425***
	(0.00247)
Constant	9.942***
	(0)
Observations	112,576
Number of breaks	5,173
R-squared	0.985
Sample	All
Break FE	Yes
Year FE	Yes
SE Cluster	Zone

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: The effect of the invention of battery-heated wetsuits on the level of lights in the 50km surrounding cold-water surf breaks. Details of the breaks of interest are given in Table 9. Time trends are estimated before and after the event for all cold-water surfbreaks collectively. The results control for fixed effects for each break and each year. Standard errors are clustered at the subnational zone level.

5.4 Results - Cold-Water Breaks

Prior to the invention of battery-heated wetsuits, average lights in the 50km surrounding cold-water surf breaks were declining by -1.5% per annum (see Table 11). After the invention of battery-heated wetsuits in 2007, light growth in these areas increased by 4.3 percentage points per annum. This result controls for global factors such as changing light sensitivity, or the global financial crisis, using year fixed effects.

Together the two approaches in Natural Experiment II show that being able to exploit a new, high-quality natural amenity for the first time can significantly raise growth in the short term. The large estimated effects can be reconciled with the smaller increment in growth found in Natural Experiment I, as the latter focused on longer term effects and used 1-star breaks as the counterfactual (rather than no surfing activity at all).

6 Natural Experiment III: What happens when the surf is good?

"Getting ready for swells is one thing, but getting ready for a season of swells, like El Niño, is a whole different thing. It's exciting to think that we might possibly score this year."

-Timmy Reyes, professional surfer (Surfer Magazine, 3 November 2015)

"Timmy Reyes' girlfriend even went as far as to say she hates El Niño after Timmy spent five months travelling to four countries on three continents, racking up more than 20,000 miles in an airplane and 10,000 miles in a car."
- (Surfing Magazine, 2 June 2016)

6.1 Identification

Experiment III studies whether economic growth near high-quality surf breaks is particularly strong in years with good waves. To do this we exploit unanticipated changes in the El Niño weather pattern which generate large, well-ordered (long period), long-range swells. In contrast to the previous experiments, this is a panel study that interacts temporal variation in wave heights (size) and El Niño patterns (period) with cross-sectional variation in break quality to isolate the effects of surf breaks on economic activity.

The El Niño Southern Oscillation (ENSO) fluctuates between El Niño and La Niña states every three to seven years (Butt, 2009).[22] In a typical year trade winds blow across the Central Pacific from east to west, pushing warm surface water towards Australasia. Here warm air rises, creating low air pressure and precipitation. The surface water is replaced with cool upwellings near Chile and Peru, which creates high pressure and dry conditions there. During a La Niña episode these trade winds are stronger than average, reinforcing the effects. During El Niño events the trade winds weaken, if not reverse. Warm surface water stays in the east, causing low-pressure systems in the far North Pacific to track much further south. Broadly, the result is larger waves in the North and Eastern Pacific (including California and Hawaii); and smaller waves in Australia and the North-West Atlantic (Butt, 2009; Housman, 2016). The advantage of El Niño swells, particularly

[22]Exogenous ENSO changes have been used as natural experiments in a range of economic studies on a variety of countries, sectors and commodities (e.g. Handler and Handler 1983; Brunner, 2002; Hsiang et al., 2011; Ubilava, 2012; Iizumi et al., 2014; Hsiang and Meng, 2015). Cashin et al. (2015) find El Nino events cause economic activity to fall in Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa, while the US and Europe benefit.

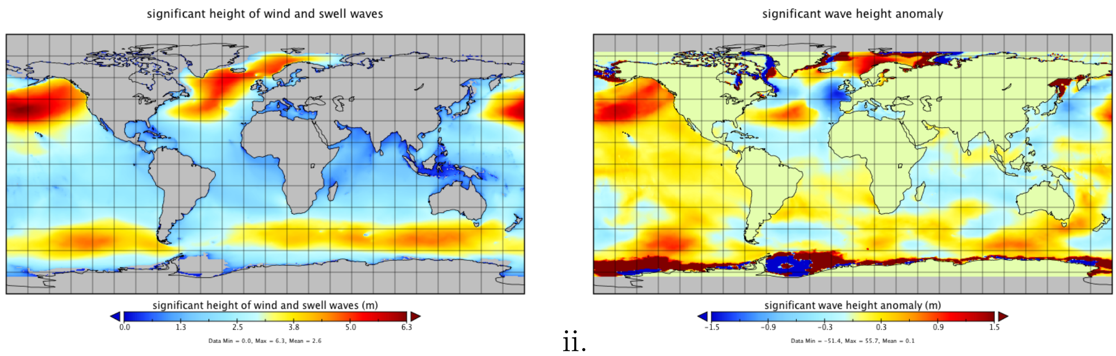

Figure 8: i. Significant wave heights (m) and ii. Significant wave height anomalies (m) during the January 1992 El Niño event.

for surfers in the North-East Pacific, is that they are generated far away and are often coupled with clement local conditions (Butt, 2009; Housman, 2016).

We use a triple-difference approach to estimate the effect of large waves, during El Niño years, at high-quality breaks. The interaction of all three variables is needed. Large waves alone are not sufficient for good surfing conditions, as they will be unruly if generated nearby and accompanied by strong winds and storms. El Niño events produce long-range swells and good weather in some parts of the world, but reduce wave heights in others (see Figure 8ii.). They also affect the economy through other channels, like weather and climate (Cashin et al., 2015). Finally, neither large waves nor good weather will matter if the break itself is low quality and cannot accommodate large swells.

6.2 Estimating Equations

We conduct this experiment using a triple-difference specification:

$$\begin{aligned} \Delta \ln(Y_{i,t}^d) \quad = \quad & \alpha + \beta wha_{i,t} + \sum_{j=2}^{5} \beta_j wha_{i,t} Q_i \\ & + \gamma ENyr_t + \sum_{j=2}^{5} \gamma_j ENyr_t Q_i \\ & + \delta wha_{i,t} ENyr_t + \sum_{j=2}^{5} \delta_j wha_{i,t} ENyr_t Q_i \\ & + W_i + Z_t + \epsilon_{it} \end{aligned} \tag{6.1}$$

where $\Delta \ln(Y_{i,t}^d)$ is the growth in log lights in the d km surrounding break i in year t, $wha_{i,t}$ is the mean wave height anomaly (a measure of wave height in each 24-arcminute grid relative to its average) at break i in year t, standardised to have a mean of 0 and a standard deviation of 1, $Q_i \in [1, 5]$ is the quality of break i, $ENyr_t$ is an indicator taking the value of 1 if year t was an El Niño year and 0 otherwise, W_i is break fixed effects and Z_t is year fixed effects. Standard errors are clustered at the zone level to account for spatial correlation.

The coefficients of interest are β_j and δ_j, which estimate the marginal effect of larger waves, and of larger waves during El Niño years, on breaks of different qualities. We first run the regression excluding any terms involving $ENyr_t$. This estimates the effect of wave heights on light growth, regardless of whether El Niño is responsible. We then run the full specification, to estimate the marginal impact of larger waves during El Niño events.

6.3 Results and discussion

We find that larger waves tend to have a negligible, or negative, impact on economic growth on average, but the effect becomes positive for good-quality breaks during El Niño years.

First we run the regression in equation 6.1 excluding any terms involving $ENyr_t$, to find the average effect of wave heights on light growth (columns (1) and (2) of Table 12). We find that, on average, unusually large waves had no effect on light growth for most break qualities, and a negative effect for "Normal" (2 star) breaks. This result may be attributed to a "stormy seas" effect: years with larger than average waves may also experience worse than average weather. As noted above, for large waves to be attractive to surfers, they must be accompanied by calm local conditions.

To isolate the marginal effect of waves generated by El Niño events we run the full specification in equation 6.1 at radii of 5km and 50km around each break (see columns (3) and (4) of Table 12). We find that light growth during El Niño years was 0.077 log points higher on average for the 50km surrounding all locations in our sample. This is consistent with better weather and improved agricultural yields in North America and Europe, as found by Cashin et al. (2015). However, satellite sensitivity also significantly improved in 1994, 1997 and 2010 when new satellites were launched, which also happen to be El Niño years. Therefore these improvements in sensitivity may incorrectly have been attributed to $ENyr_t$ rather than year fixed effects, overestimating the true effect. However, this is not our focus.

Our focus is the interaction of larger waves, during El Niño years, at high quality breaks. A one standard deviation increase in the wave height anomaly during El Niño years led to a marginal increase in light growth in the 50km surrounding 4- and 5-star breaks of 0.056

	Large El Niño Waves			
	(1)	(2)	(3)	(4)
VARIABLES	$D.\ln(lights^5)$	$D.\ln(lights^{50})$	$D.\ln(lights^5)$	$D.\ln(lights^{50})$
Wave Height Anomaly (cts) interacted with:				
Constant	-0.001	-0.001	-0.000	-0.001
	(0.254)	(0.306)	(0.706)	(0.533)
2 star	-0.011**	-0.007*	-0.011*	-0.008
	(0.018)	(0.095)	(0.066)	(0.120)
3 star	-0.001	-0.001	-0.001	-0.003
	(0.490)	(0.567)	(0.432)	(0.210)
4 star	0.001	0.006	-0.004	-0.014**
	(0.942)	(0.361)	(0.622)	(0.035)
5 star	0.006	-0.002	0.016	-0.014**
	(0.606)	(0.740)	(0.373)	(0.031)
El Nino Year (indicator) interacted with:				
Constant			0.177***	0.077***
			(0.000)	(0.000)
2 star			0.012*	-0.003
			(0.100)	(0.500)
3 star			0.010	0.001
			(0.140)	(0.840)
4 star			0.020	0.004
			(0.102)	(0.649)
5 star			0.024*	0.010
El Nino Year interacted with Wave Height Anomaly interacted with:				
Constant			-0.024***	-0.010
			(0.006)	(0.138)
2 star			0.021**	0.011*
			(0.027)	(0.082)
3 star			0.019***	0.014***
			(0.007)	(0.004)
4 star			0.030	0.056***
			(0.143)	(0.001)
5 star			-0.007	0.039**
			(0.835)	(0.023)
Observations	97,547	106,271	97,547	106,271
R-squared	0.473	0.758	0.473	0.758
Year FE	Yes	Yes	Yes	Yes
Break FE	Yes	Yes	Yes	Yes
Cluster	Zone	Zone	Zone	Zone

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: The effect of a 1 standard deviation increase in the wave height anomaly on lights in the surrounding 5 and 50km, during El Niño years.

and 0.039 log points per annum (5.8 and 4.0 percentage points per annum) respectively. This suggests that the average stormy seas effect is offset during El Niño years, especially for good quality surf breaks.

These results are robust to excluding the US, which is a major beneficiary of El Niño swells. They are also robust to replacing the $ENyr_t$ indicator with the continuous Southern Oscillation Index (SOI), which also includes La Niña events that produce larger waves in the western Pacific. When repeating the analysis including an additional two lags for $ENyr_t$ and $wha_{i,t}$ we find no persistence in the $Quality * ENyr * wha$ interaction. This suggests El Niño events' effect on light growth is constrained to that particular year, so picks up direct effects of surfers traveling to ride waves.[23] Any persistent effects would be picked up in the long-term growth rates in Experiment I.

7 Conclusion

This paper estimates the impact of natural amenities on the location and pace of economic growth, by exploiting exogenous variation in the quality of surf breaks. To do this we combine five high-resolution spatial datasets, on the quality and location of 5000+ surf breaks, wave heights, night-time light emissions, population and tourism, to conduct three natural experiments.

The first experiment exploits cross-sectional variation and finds that high quality rural surf breaks significantly raise economic growth in the surrounding 5km, with spillovers up to 50km away. However, the effect is reversed in urban areas in a way that is consistent with overcrowding. There is no associated impact on the permanent population, so this amounts to an increase in per-capita economic activity. Detailed data from Australia supports tourism as a mechanism, with evidence of significant spillovers to tourism activities that are not related to surfing. The second experiment exploits temporal variation and finds that discovering a high-quality break, or technology that makes cold-water breaks more accessible, increases growth in the surrounding areas. Conversely, destroying a break reduces growth, even if it is replaced by a new road or a dredged river. The third experiment uses a panel approach that exploits both cross-sectional and temporal variation, and finds that the area around good quality breaks grows particularly quickly when they have large waves during El Niño years.

Collectively these results show that natural amenities play an important role in local economic growth. As noted in the introduction, there is extensive evidence that geography

[23]Night-time lights can pick up short-term changes in activity through higher building occupancy, car headlights, etc.

is important for growth. However, most of these studies focus on natural capital that directly affects the costs of production, like access to waterways, fertile soil and mineral resources. In contrast this paper studies natural amenities, which indirectly affect production by augmenting physical capital and labour. Existing work has found inconclusive evidence that natural amenities are important for growth, due to difficulties with identifying and measuring their effect. This paper fills that gap by using three unique natural experiments and a novel dataset to estimate how one particular natural amenity affects local growth.

The paper also has implications for policy. The first is that policymakers can use natural amenities - like surf breaks - to promote local economic growth in rural areas. To do this they can encourage the public and private investment needed to enjoy these amenities, while ensuring they do not become over-exploited and do not unnecessarily hamper other industries in the area. This could include investment in hotel capacity, as Morocco's sovereign wealth fund is doing in Taghazout; shark-detection programs, as the New South Wales government is doing in Australia; or artificial inland surf breaks as in Wales, California, Australia and Dubai (see for example www.kswaveco.com). The estimates in this paper may be useful for evaluating the benefits of such projects.

The second is that policymakers must properly account for the cost of depleting natural amenities. When a coastal rock wall was built at Jardim do Mar, Portugal, and a rivermouth dredged at Mundaka, Spain, policymakers expected economic growth to increase. Our study shows that ignoring the depletion of natural amenities can have severe consequences. Policymakers should therefore be cautious in places like Doughmore, Ireland, where Trump International Golf Links seeks to build a 2.8km seawall; and Jeffreys Bay, South Africa, where a new power plant may lead to 6.3 million cubic meters of sand being pumped offshore (www.savethewaves.org). Our estimates will be useful for this, as well as assessing the amenity costs of pollution, and of rising sea levels from climate change.

The paper also suggests further avenues for research. One is to estimate the economic contribution of other natural amenities, with obvious candidates including scuba-diving, rock-climbing, and UNESCO natural heritage sites. Another extension would be to investigate whether natural amenities play a role in the location of sectoral clusters in non-tourism related industries, for example finance in Greenwich, CT and technology in Palo Alto, CA. Future work may also directly study the feedback effects of economic growth onto the quality of natural amenities, through pollution and overcrowding. Finally, amenities like surf breaks may be a useful as instruments when studying the impact of economic growth on other variables at a local level.

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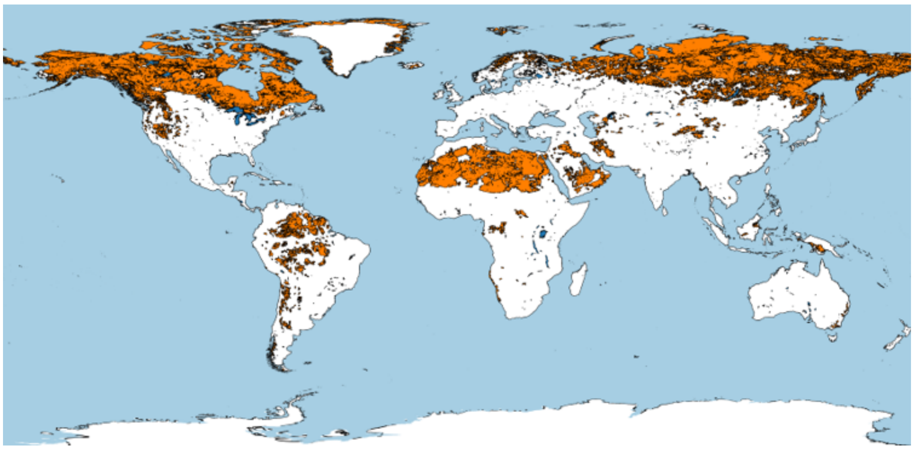

Figure 9: 1000 largest wasteland areas in the Anthropogenic Biomes v2 dataset.

Appendix

A Overglow

Overglow is when light emitted in one pixel is also recorded in surrounding pixels. It has been documented as an issue when light is used to measure the level of economic activity (Doll, 2008). Here we test how overglow changes with emitted light in two ways: comparing light either side of a wasteland boundary (following Pinkovskiy, 2013), and light emitted from isolated pixels. Both tests find that overglow varies linearly with emitted light (as do Small et al., 2005), so should not bias our study of light growth.

A.1 Test 1: Wasteland boundaries

We study overglow by comparing light either side of a wasteland border, following Pinkovskiy (2013). Wastelands are unpopulated areas classified as "wild woodlands, wild treelands and barren lands" in 2000, in the Anthropogenic Biomes Version 2 datasets (Ellis et al., 2010). Light may be emitted outside the wasteland, but any light inside should be overglow. We study lights 10km either side of the border for the 1000 largest wasteland areas (Figure 9), using the following specification,

$$\Delta Y_{j,2006}^{in} = \alpha + \beta \Delta Y_{j,2006}^{out} + \epsilon_t \tag{A.1}$$

where $\Delta Y_{j,2006}^{in}$ and $\Delta Y_{j,2006}^{out}$ is the change in light from 2005-2006, for 10km bands inside and outside the border of wasteland j respectively. The results in Table 13 estimate $\beta = 0.87$, which is not statistically different from 1 at more than the 1% level. This suggests that overglow varies proportionally with emitted light.

	$\Delta Y^{in}_{j,2006}$
$\Delta Y^{out}_{j,2006}$	0.870***
	(0.187)
Constant	0.121*
	(0.0669)
Observations	457
R-squared	0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Results of regressing light growth 10km inside wasteland borders on that 10km outside.

A.2 Test 2: Isolated light sources

We also study overglow from a small number of isolated light sources in Algeria, using gas flare data from the NOAA Earth Observation Group, and wasteland data described above. We use gas flares that i) are in wastelands with no habitation or physical economic activity within 15km, ii) come from a $< 1\text{km}^2$ site as identified on Google Earth, and iii) have the brightest light in the central pixel (Figure 10). This gives us an insight into how overglow is recorded by the DMSP-OLS satellites.

Figure 11 illustrates the change in light between 2009 and 2012 at various distances from the flare. It shows that overglow grows proportionally to light in the central pixel, for non-trivial levels of light. This may be due to differences in the intensity of emitted light or the sensitivity of the satellite. Figure 11ii. illustrates the difference in light between the original site, and another in the Algerian desert, both in 2012. Overglow differs from 15-30% but not systematically. We conclude that overglow varies proportionally to emitted light, and so will not bias our study of changes in light emissions.

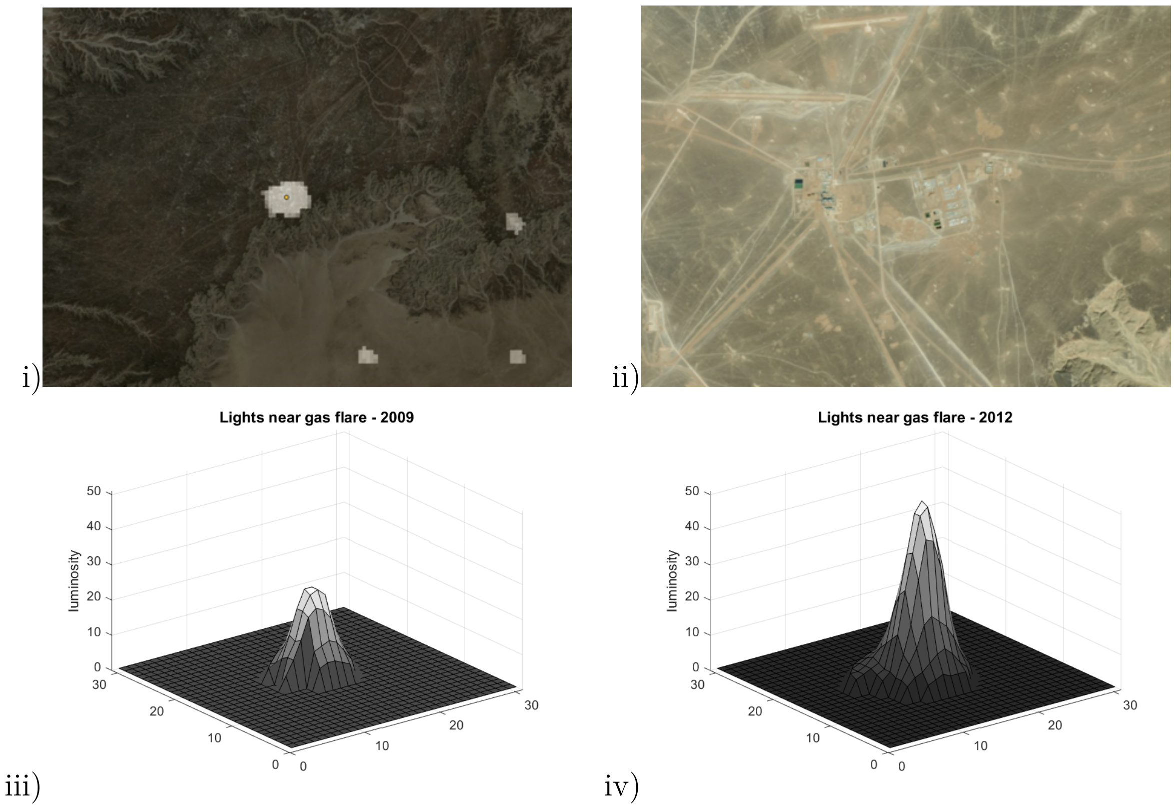

Figure 10: Example isolated gas flare site in Algerian wasteland: i) night-time lights, ii) google earth (zoomed), iii) 2009 light histogram, iv) 2012 light histogram.

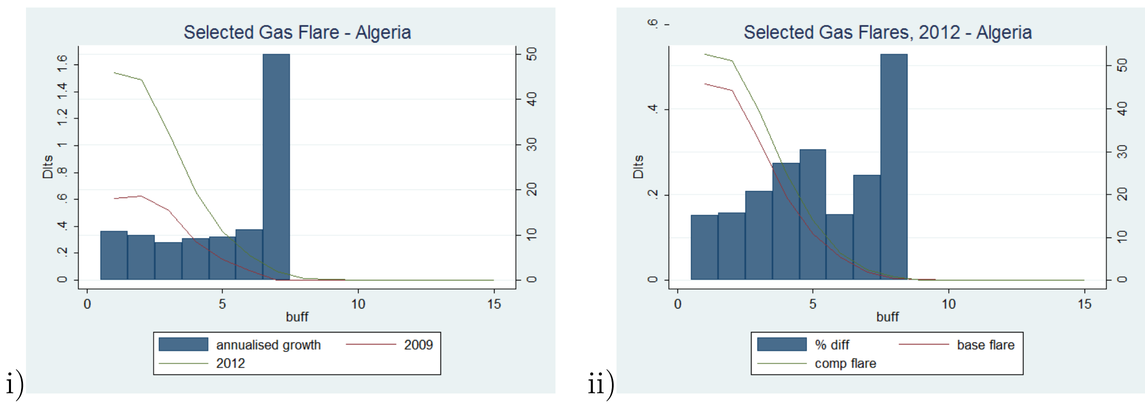

Figure 11: Overglow comparison: i) same site, 2009 vs 2012, ii) different sites, 2012.

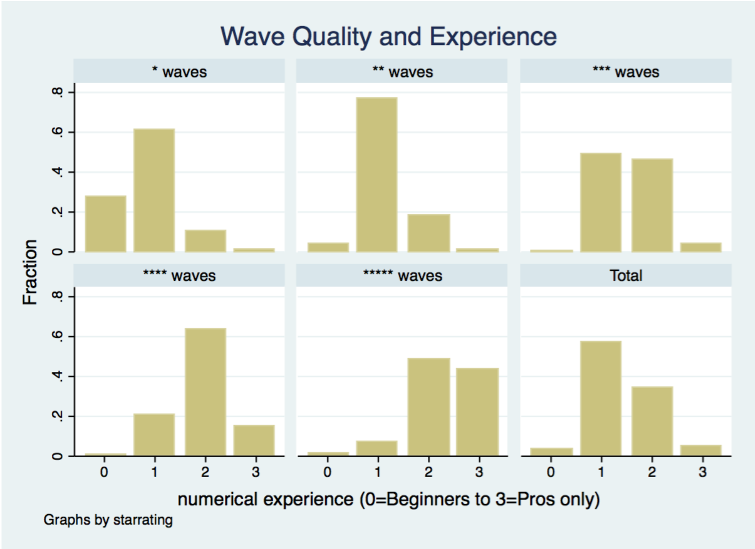

Figure 12: Distribution of surfing experience required to surf breaks of each quality. 5-star waves are disproportionately rated “3: Pros or kamikazes only”.

B Experiment I: Additional results

	Total change in $ln(lights)$ from 1992-2013			
	5 to 10km band		10 to 50km band	
	(1)	(2)	(3)	(4)
2 star	0.101	0.101**	0.0167	0.0167
	(0.116)	(0.0367)	(0.512)	(0.513)
3 star	0.102**	0.102**	0.0248	0.0248
	(0.0397)	(0.0226)	(0.395)	(0.338)
4 star	0.153**	0.153**	-0.0159	-0.0159
	(0.0409)	(0.0143)	(0.765)	(0.688)
5 star	-0.0496	-0.0496	0.00722	0.00722
	(0.667)	(0.651)	(0.885)	(0.876)
Urban	0.330***	0.330***	0.0940***	0.0940***
	(1.50e-09)	(0)	(4.63e-05)	(0.000384)
2 star*Urban	-0.124*	-0.124**	-0.0377	-0.0377
	(0.0881)	(0.0213)	(0.151)	(0.200)
3 star*Urban	-0.143**	-0.143***	-0.0651**	-0.0651**
	(0.0136)	(0.00429)	(0.0180)	(0.0208)
4 star*Urban	-0.216**	-0.216***	-0.0310	-0.0310
	(0.0106)	(0.00182)	(0.516)	(0.439)
5 star*Urban	-0.0232	-0.0232	-0.0547	-0.0547
	(0.858)	(0.845)	(0.390)	(0.338)
ln($lights_{1992}$)	-0.324***	-0.324***	-0.210***	-0.210***
	(0)	(0)	(0)	(0)
Constant	2.591***	2.591***	2.587***	2.587***
	(0)	(0)	(0)	(0)
Observations	4,480	4,480	5,004	5,004
R-squared	0.750	0.468	0.859	0.481
Sample	All breaks	All breaks	All breaks	All breaks
FE	Zone	Zone	Zone	Zone
SE	Zone	Conley	Zone	Conley

Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 14: The effect of break quality on the total change in ln(lights) from 1992-2013 within 5-10km, and 10-50km, of each break. Fixed effects are at zone level. Standard errors are clustered at the zone level, or allow for spatial correlation within 100km, and autocorrelation to 3 periods (Conley).

	Total change in $ln(population)$ from 1992-2013			
	5 to 10km band		10 to 50km band	
	(1)	(2)	(3)	(4)
2 star	-0.0287	-0.0287	0.0226	0.0226
	(0.748)	(0.727)	(0.693)	(0.707)
3 star	-0.116	-0.116	0.0377	0.0377
	(0.285)	(0.202)	(0.612)	(0.549)
4 star	-0.150	-0.150	-0.0860	-0.0860
	(0.207)	(0.177)	(0.213)	(0.247)
5 star	-0.317	-0.317	-0.153	-0.153
	(0.148)	(0.132)	(0.177)	(0.212)
Urban	0.588***	0.588***	0.141**	0.141**
	(1.40e-06)	(4.56e-09)	(0.0288)	(0.0378)
2 star*Urban	0.0244	0.0244	-0.0290	-0.0290
	(0.807)	(0.802)	(0.707)	(0.677)
3 star*Urban	0.0252	0.0252	-0.0928	-0.0928
	(0.833)	(0.807)	(0.328)	(0.194)
4 star*Urban	-0.0243	-0.0243	-0.0391	-0.0391
	(0.868)	(0.853)	(0.687)	(0.651)
5 star*Urban	0.109	0.109	0.000120	0.000120
	(0.658)	(0.637)	(0.999)	(0.999)
ln($population_{1992}$)	-0.243***	-0.243***	-0.154**	-0.154***
	(7.87e-05)	(0)	(0.0140)	(3.63e-07)
Constant	2.326***	2.326***	2.124***	2.124***
	(7.27e-06)	(0)	(0.00390)	(0)
Observations	5,083	5,083	5,155	5,155
R-squared	0.494	0.167	0.546	0.145
Sample	All	All	All	All
FE	Zone	Zone	Zone	Zone
SE	Zone	Conley	Zone	Conley

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: The effect of break quality on the total change in ln(population) from 1992-2013 within 5-10km, and 10-50km, of each break. Fixed effects are at zone level. Standard errors are clustered at the zone level, and allow for spatial correlation within 100km, and autocorrelation to 3 periods (Conley).

	$\ln(Y_{i,t})$:					
	Exp_{Total}		Exp_{Surf}		$Exp_{NonSurf}$	
	(1)	(2)	(3)	(4)	(5)	(6)
t interacted with:						
MaxQual	0.00132	0.00330***	0.0252***	0.0235***	0.00144*	0.00349***
	(0.103)	(0.00673)	(1.64e-05)	(0.00254)	(0.0762)	(0.00562)
MaxQual_{Urban}		-0.00328**		0.00194		-0.00338**
		(0.0127)		(0.679)		(0.0138)
$\ln(Y_{i,2004})$	1.044***	1.048***	0.802***	0.797***	1.046***	1.051***
	(0)	(0)	(0)	(0)	(0)	(0)
Constant	-0.511**	-0.559**	1.809***	1.856***	-0.545**	-0.594***
	(0.0151)	(0.0109)	(6.40e-06)	(2.17e-05)	(0.0108)	(0.00769)
Observations	1,218	1,218	423	423	1,218	1,218
R-squared	0.895	0.895	0.602	0.603	0.892	0.892
FE	Year	Year	Year	Year	Year	Year
SE	Robust	Robust	Robust	Robust	Robust	Robust

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: The effect of surf break quality on tourism activity in Australia. Tourism activity is measured by total expenditure at the destination of all trips (columns 1-2), trips that involved surfing (columns 3-4), and trips that did not involve surfing (columns 5-6) for each Tourism Region in Australia. Surf break quality is measured by the maximum break quality in each Tourism Region, both in aggregate, or separating out urban areas. The results control for the initial level of tourism expenditure and year fixed effects, and use heteroskedasticity-robust standard errors.

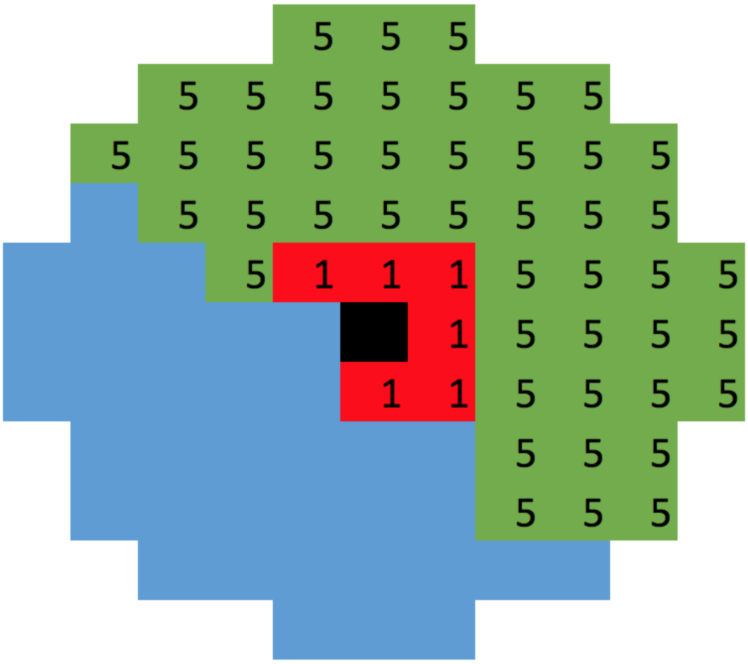

Figure 13: Pixels within 1km (red) and 5km (green) of a break (black), excluding the area over water (blue).

B.1 Pixel-level analysis

The analysis in the main text uses the area within 5km of a surf break as the unit of analysis. These areas may overlap. Here we use individual pixels as the unit of analysis, which are "treated" by surf breaks to give an estimate of the marginal contribution of each break quality to illumination. Every pixel within 5km of at least one break is included in our sample, excluding those wholly over water, which increases the sample size considerably (see Figure 13). Each pixel is treated in two ways using the specification,

$$\ln(Y_{i,2013}) - \ln(Y_{i,1992}) = \alpha + \beta Q_i + \gamma Q_i * U_i + \delta Y_{i,1992} + F_z + \epsilon_{i,t} \tag{B.1}$$

where $Y_{i.t}$ is light intensity in pixel i at time t; $Q_i \in [M_i, A_i, N_{i,k}]$ where M_i is the maximum quality of breaks within 5km of pixel i (treated as both a continuous and a categorical variable), A_i is the average quality of breaks within 5km of pixel i, and $N_{i,k}$ is the number of breaks of quality $k \in [1, 5]$ within 5km of pixel i; U_i=1 if the pixel is in an urban region and 0 otherwise; and F_z is zone fixed effects. The initial level of lights in each pixel, $Y_{i,1992}$, is included to control for possible convergence effects. Standard errors are clustered at the zone level. The results are given in Table 17.

To give a visual representation of results we use the equation,

i. Sum of breaks of quality k within 5km ii. Maximum break quality within 5km

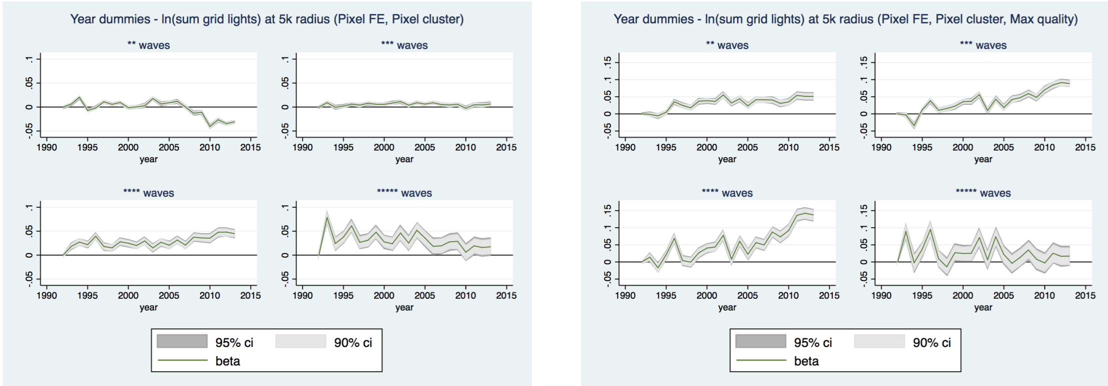

Figure 14: Results of pixel-level analysis, treating each pixel with i. the number of breaks of quality k within 5km, and ii. the maximum break quality within 5km.

$$\ln(Y_{i,t}) = \alpha + \sum_{t=1992}^{2013} \beta_t T_t Q_i + F_i + T_t + \epsilon_{i,t} \tag{B.2}$$

where $Y_{i.t}$ is light intensity in pixel i at time t, T_t is a year dummy, $Q_i \in [M_i, N_{i,k}]$ is defined above, and F_i are pixel fixed effects. Standard errors are clustered at the break and country level. The control group is 1-star breaks. The results are given in Figure 14.

	Total change in ln($PixelLights_i$) from 1992-2013				
	(1)	(2)		(3)	(4)
Max Quality *			Avg Quality *		
Non-Urban	0.0392**		Non-Urban	0.0478**	
	(0.0411)			(0.0283)	
Urban	-0.0225*		Urban	-0.0358**	
	(0.0608)			(0.0149)	
Max Quality:			Quality Count:		
1 stars		omitted	1 stars		-0.0850**
					(0.0389)
2 stars		0.103**	2 stars		-0.00792
		(0.0362)			(0.657)
3 stars		0.144***	3 stars		0.0291**
		(0.00439)			(0.0480)
4 stars		0.0937	4 stars		0.00563
		(0.262)			(0.883)
5 stars		0.212**	5 stars		0.116*
		(0.0314)			(0.0572)
Urban * Max Quality:			Urban * Quality Count:		
1 stars		omitted	1 stars		0.130***
					(0.00832)
2 stars		-0.166***	2 stars		0.0249
		(0.00491)			(0.273)
3 stars		-0.222***	3 stars		-0.0289*
		(0.000530)			(0.0693)
4 stars		-0.148	4 stars		-0.0267
		(0.150)			(0.585)
5 stars		-0.347***	5 stars		-0.182***
		(0.00601)			(0.00899)
$PixelLights_{i,1992}$	-0.0173***	-0.0173***	$PixelLights_{i,1992}$	-0.0173***	-0.0175***
	(0)	(0)		(0)	(0)
Urban	0.0308	0.114*	Urban	0.146*	-0.0643
	(0.494)	(0.0527)		(0.0629)	(0.111)
Constant	1.025***	0.973***	Constant	0.965***	1.078***
	(0)	(0)		(0)	(0)
Observations	88,539	88,539	Observations	88,539	88,539
R-squared	0.595	0.595	R-squared	0.595	0.596
Sample	All Waves	All Waves	Sample	All Waves	All Waves
FE	Zone	Zone	FE	Zone	Zone
SE	Zone	Zone	SE	Zone	Zone

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: The effect of break quality on the change in ln(lights) for each pixel within 5km of a surf break, from 1992-2013. Columns (1)-(2) treat each pixel with the maximum break quality within 5km. Columns (3)-(4) do the same using max-quality indicators. Columns (5)-(6) treat each pixel with the number of breaks of each quality within 5km.