

Article

New ECOSTRESS and MODIS Land Surface Temperature Data Reveal Fine-Scale Heat Vulnerability in Cities: A Case Study for Los Angeles County, California

Glynn Hulley ^{1,*} , Sarah Shivers ², Erin Wetherley ²  and Robert Cudd ³ ¹ Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, 91109, USA² Department of Geography, University of California Santa Barbara, Santa Barbara, CA 93106, USA³ Institute of the Environment & Sustainability, University of California, Los Angeles, CA 90095, USA

* Correspondence: Correspondence: glynn.hulley@jpl.nasa.gov; Tel.: +1-818-354-2979

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Abstract: Rapid 21st century urbanization combined with anthropogenic climate warming are significantly increasing heat-related health threats in cities worldwide. In Los Angeles (LA), increasing trends in extreme heat are expected to intensify and exacerbate the urban heat island effect, leading to greater health risks for vulnerable populations. Partnerships between city policymakers and scientists are becoming more important as the need to provide data-driven recommendations for sustainability and mitigation efforts becomes critical. Here we present a model to produce heat vulnerability index (HVI) maps driven by surface temperature data from National Aeronautics and Space Administration's (NASA) new Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) thermal infrared sensor. ECOSTRESS was launched in June 2018 with the capability to image fine-scale urban temperatures at a 70 m resolution throughout different times of the day and night. The HVI model further includes information on socio-demographic data, green vegetation abundance, and historical heatwave temperatures from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard the Aqua spacecraft since 2002. During a period of high heat in July 2018, we identified the five most vulnerable communities at a sub-city block scale in the LA region. The persistence of high HVI throughout the day and night in these areas indicates a clear and urgent need for implementing cooling technologies and green infrastructure to curb future warming.

Keywords: urban; LST; temperature; ECOSTRESS; heat; vulnerability; urbanization; MODIS

1. Introduction

With a warming climate and an increasing concentration of the global population living in cities, the negative impacts of urban heat islands (UHIs) and heatwaves are intensifying [1–3]. Currently, 55% of the world's population live in urban areas, and that number is expected to increase to 68% by 2050 [4]. Accompanying this rural-to-urban demographic shift is a warming climate that is projected to increase the average global temperature by ≈ 0.2 °C per decade [5]. The UHI effect, common to city landscapes due to the thermal energy characteristics of urban surface materials, has been shown to reduce air quality, increase levels of energy and water use, and cause heat-related illness and death [2,6–8]. Mitigation of urban heat has been estimated to save over \$10 billion per year in energy use and improved air quality [6]. In terms of mortality, heatwaves are the most common cause of weather-related deaths in the United States, contributing to or directly causing over 8000 deaths from 1999 to 2010 [9]. Research has shown that heatwaves on a global scale are becoming more frequent,

longer, and deadlier [1,3], while in southern California, night-time heatwaves in the 21st century are becoming hotter and more humid, a trend linked to anthropogenic sea surface warming and a persistent moisture anomaly source off the coast of Baja California [10,11]. This makes it increasingly important for scientists to better understand the spatially disproportionate effect that heat has on cities and better communicate this data to local city planners in order to identify high-risk areas and mitigate future effects through better planning and proper design.

Past studies have attempted to quantify urban areas over the globe presenting a high risk using a heat vulnerability index (HVI) model [12] derived from either socio-demographic variables [13–17], or more commonly, a combination of both socio-demographic and temperature variables to account for the influence of a UHI. Temperature (exposure) variables are usually derived from either satellite-derived land surface temperature (LST) retrieved from thermal infrared (TIR) sensors, such as Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) [18–23] or MODIS [24–27], ground station air temperature observations [28–32], modeled air temperatures [33,34], or a combination of both satellite and ground temperatures [35]. Including temperature information is critical since we need to understand how high social vulnerability coincides with areas of high heat exposure. For example, an area of high social vulnerability may or may not correspond with an area of high temperature and vice versa. This is especially important in a city like Los Angeles (LA) that includes a mix of diverse cultural and socio-economic sectors in addition to microclimates driven by local topography and oceanic influences that are impacted disproportionately by heat [10,36].

Our best tool for studying fine-scale urban temperatures is through remote sensing because it can quantify the magnitude of the UHI effect across all permutations of urban surface temperature gradients and complexity [37]. Relying on air temperatures from ground stations alone is inadequate for representing fine scale temperature gradients due to their sparsity, and will usually lead to an underestimation of temperature effects [27]. The availability of TIR data at spatial resolutions of 100 m or less is generally required for distinguishing temperatures of urban materials that can be made useful for urban planning [38]. In this study we utilize retrieved the LST from remotely sensed TIR data to represent the surface UHI (SUHI) effect, and as the main driver for heat exposure. Ideally, the air temperature (T_{air}) should also be included to fully describe the effects of urban heat since health impacts are tied to both T_{air} (through convective processes) and the LST (through radiative emission), which means LST alone is not adequate to fully describe the socio-economic impacts of excessive heat. For example, during the daytime and especially in urban environments, the surface and air temperatures can be markedly different due to various complex factors including solar insolation intensity, wind, clouds, shading, sky-view factor, and sensor view angle [39–41]. Using the LST alone can also be a limiting factor when taking into account the effects of shading from trees and buildings since the TIR measurement is only sensitive to the “skin” layer of the surface, or for trees, this would represent the “top of canopy” temperature, and would not reflect the temperature of the shaded understory or the vertical surfaces from buildings. These shortcomings have been demonstrated using in situ radiative thermometry to highlight the true anisotropy of temperatures in the urban environment [42–44]. However at night, the LST and T_{air} will display similar spatial and temporal patterns due to reduced advection, solar shading, and greater atmospheric boundary layer stability [39,40,45]. Numerous studies have derived regression functions for estimating T_{air} from the LST [40,46–49] or T_{air} from air temperature profiles [50] on continental to global scales at coarse kilometer-scale resolution, but far fewer have developed robust relationships in urban environments due to the increased complexity of surface–air relationships in the built up urban environment [51–53]. Complicating the problem further are the sparsity of station air temperature measurements and the kilometer-scale spatial resolution of typical model derived urban air temperatures, e.g., the Weather Research and Forecasting (WRF)-urban canopy model [54], that do not correspond to the LST data at finer scales. Due to these issues and until more robust LST– T_{air} statistical models are developed, we have chosen to use the LST (primarily at night) as the driver for heat exposure over the LA study region.

LST products derived from TIR imager data are currently available from National Aeronautics and Space Administration (NASA) sensors, for example, the Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra/Aqua platforms (since 1999/2002 respectively) [55,56], and the Visible Infrared Imager Radiometer Suite (VIIRS) on Suomi National Polar-orbiting Partnership (Suomi NPP) (since 2011) [57] are both in Sun-synchronous orbits and provide data at a ≈ 1 km spatial resolution on daily time-steps. Higher spatial resolution LST data from the Advanced Spaceborne Thermal Emission and Reflection radiometer (ASTER) at 90 m [58] and Landsat 5–8 at 60–120 m [59] are also available but are not as frequent and have overpass frequencies only every 16 days. New LST products released by NASA in 2018 for MODIS in Collection 6/6.1 (MOD21/MYD21) and for VIIRS Version 1 (VNP21) use a consistent approach to physically retrieve both the LST and spectral emissivity in three thermal bands using the temperature emissivity separation (TES) algorithm [57,60,61]. This algorithm results in a more stable accuracy in LST retrieval over all land surfaces, particularly over urban areas [62]. While MODIS and VIIRS provide daily data at the same time every day (e.g., 1:30 am/pm) at city block scales, imaging of urban areas down to the roof or building level typically requires 50–100 m spatial resolution data in order to discriminate fine-scale urban features, such as green spaces, large roofs, and playgrounds [63,64], especially during summertime heatwaves [65]. To address the spatial scale issue in urban environments, a number of downscaling or “thermal sharpening” methods have been proposed to produce LST data at similar spatial scales as visible shortwave infrared (VSWIR) data (≈ 30 m), with most models assuming that robust relationships exist between the LST and VSWIR derived products such as the Normalized Difference Vegetation Index (NDVI) and albedo [66–71]. While a number of these methods have been quantitatively assessed and compared with each other [72], it is difficult to generalize an approach that is valid for representative conditions over different seasons, climates, times of day, and for intrinsic urban material characteristics of different cities around the world. For this reason, and depending on the training data used, a model that may work for a particular city during a certain time of year and particular time of day, may not be suitable elsewhere for different conditions.

The remote sensing of urban temperatures at high spatiotemporal scales took a big leap forward with the launch of the Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) to the International Space Station (ISS) on 29 June 2018. ECOSTRESS has a native spatial scale of $38\text{ m} \times 68\text{ m}$ with a large swath width of 402 km (53°) and a temporal repeat of ≈ 3 –5 days at different times of day depending on the latitude. The instrument consists of a multispectral whiskbroom scanner with five spectral bands in the TIR between 8 and $12.5\text{ }\mu\text{m}$ and an average Noise Equivalent Differential Temperature (NEDT) of $\approx 0.1\text{ K}$ at 300 K. The LST data and other higher level products are aggregated to $70\text{ m} \times 70\text{ m}$ pixels. The primary science objective of ECOSTRESS is to answer critical science questions pertaining to plant water use and stress, with applications to agricultural water consumptive use, but the data are applicable to a wide range of applications from urban heat to volcanology studies [41]. For example, a number of key imaging characteristics makes ECOSTRESS uniquely suited for observing the urban environment: (1) a high spatial resolution of $70\text{ m} \times 70\text{ m}$ (≈ 1.2 acres, or the size of a football field); (2) the inclined, precessing ISS orbit enables ECOSTRESS to sample the diurnal cycle of temperatures and heat stress at different times of day; and (3) the five thermal bands on ECOSTRESS allow for implementation of multispectral temperature/emissivity separation approaches, such as the TES algorithm [60,73], for retrieving the most accurate LST over urban areas [62].

The impacts of heat events are shaped by more than meteorological characteristics alone (e.g., wind speed, cloud cover, atmospheric stability), but are also a factor of the socio-demographics of populations living within the city itself. Certain populations are more susceptible to heat than others, due to factors, such as age and health, that can make people physically more vulnerable to heat, or due to social or economic factors, such as wealth and social capacity, that make adapting to heat events less challenging, for example, by being able to afford homes in cooler parts of a city. Persons above the age of 65 who live alone and younger children are both especially vulnerable to heat given their physical

inability to regulate heat as well as healthy adults [74]. Moreover, marginalized populations, including the poor, elderly, and minorities, are particularly at risk of heat-related impacts and experience the highest rates of heat-related mortality and morbidity due to social isolation and the lack of access to relieving factors such as air conditioning or pertinent information through media access [29,74]. Other factors, such as the cooling effects of vegetation, vegetation health, and the composition and structure of the built urban environment, also have significant effects on heat exposure and vulnerability [8,75]. Non-stressed vegetation can act as “nature’s air-conditioners” by cooling the air and surrounding environment through latent heat exchange (transpiration), in addition to providing shading, which can dramatically lower surface temperatures by several degrees. For example, Wetherley et al. [37] found that trees and turf grass in LA had significantly cooler temperatures than non-vegetated materials, with the greatest difference between mean LST observed between turf grass (41.4 °C) and commercial roofs (56.9 °C). However, the cooling effect of vegetation is subject to additional considerations, such as irrigation frequency, droughts, and green space type and size, which can all vary greatly throughout a city [76]. In some cases, the effects are contradictory, for example, asphalt and buildings have been shown to both increase and decrease the evapotranspiration of local vegetation depending on whether their dominant effect is channeling wind, advection of dry air, or shading [75,77]. Understanding these differences at the city scale is necessary to optimize the use of vegetation as a cooling mechanism and is of specific interest in arid or drought-stricken cities where water resources necessary for maintaining vegetation can be limited.

The built urban environment, including materials and structure, also affects the way in which radiation is captured and released by the surface. Urban materials, such as asphalt, absorb radiation in the day and release it into the atmosphere at night, increasing urban night-time temperatures. These effects can be mitigated through initiatives, such as cool roofs and cool roads, that replace the standard low albedo materials with a surface coating of higher albedo, such as different types of paint, that reflect more energy away from the surface, thereby lowering temperatures [78,79]. For example, the City of LA implemented an ordinance in October 2014 requiring that all new residential houses use cool roof technologies, and the LA Bureau of Street Services is similarly in the process of converting portions of pavement to cool roads using a water-based asphalt emulsion sealcoat, a change that is estimated to result in a temperature difference of as much as 10 °F on hot days. Additionally, the vertical structure of a city, such as building height, orientation, and placement, will control shading and the ability of heat to escape an urban area. For example, the geometry of buildings or “urban canyons” have a strong influence on the amount of longwave radiation that is lost to the sky, a cooling effect that is determined by the sky view factor, which is a measure of the proportion of a point to the area of the overlying hemisphere open to the sky [80,81]. All of these structural and material influences on heat will affect the vulnerability of different neighborhoods to extreme heat events.

In this study, we combined socio-economic and environmental variables overlaid with LST data as a proxy for heat exposure to generate easily interpretable HVI maps for regions of LA county, California. The HVI incorporates spatially explicit measures of sensitivity, adaptability, and exposure for a robust and realistic analysis of vulnerability patterns in the city. The HVI is based on the assumption that the effects of heat are not only a factor of the heat event itself, but of the population demographics and urban structure that make some areas more susceptible to heat than others. By identifying these most vulnerable areas, HVIs can act as powerful tools for informing policy, mitigation efforts, and targeting resources.

2. Materials and Methods

2.1. Study Region

The study area we selected includes the urbanized LA basin in California, covering portions of Los Angeles County, Orange County, Ventura County, Riverside County, and San Bernardino County, as shown in Figure 1. The LA metropolitan area, referred to as the Los Angeles-Long

Beach-Anaheim Metropolitan Statistical Area, is the second largest metropolitan area in the United States with a population of over 13 million people (U.S. Census Bureau [82]). The LA metropolitan area is characterized by a high degree of urbanization and low-density population due to the prevalence of single-family detached houses, and is served by decentralized retail areas that rely on complex road networks. The LA basin consists of an area with complex topography, and combined with the coastal influence of a net diurnal onshore flow, results in distinctive microclimates and ecological zones, in which the effects of heat propagate in different ways and result in disproportionate effects. For example, stalled high pressure systems can be exacerbated by a weak offshore flow that adiabatically draws in warm, dry air from the desert region into the coastal basin (e.g., Santa Ana events), resulting in coastal heatwaves, while the marine layer and cooler ocean breezes may moderate coastal temperatures during more intense inland heatwaves [83,84].



Figure 1. Los Angeles county study area in California with boundaries of 16 local regions delineated by blue boundaries and used in statistical analyses of heat vulnerability.

2.2. Heat Vulnerability Index (HVI) Framework

In order to quantify heat vulnerability, we use a normalized heat vulnerability index (HVI) model derived from a principal component (PC) analysis of exposure (E), sensitivity (S), and adaptive capacity (A) variables [85]. A number of past studies have estimated HVI using a combination of E , S , and A variables in either multiplicative or summative models to estimate societal heat vulnerability [85–88], but all are based on a similar and more generalized human–environmental framework of vulnerability [89]. Using this framework, vulnerability can be defined as a function of three independent components as described in Wilhelmi and Hayden [85]: exposure (e.g., from heat, humidity, and other climate and synoptic weather conditions), sensitivity (i.e., the extent to which a system or population can absorb impacts without suffering long-term harm), and adaptive capacity (the potential of a system or population to modify its features and behavior so as to better cope with existing and anticipated stresses and natural hazards, e.g., in cities by planting more trees and using cool roof technologies, air conditioning, etc.). After Wilhelmi and Hayden [85], we adopt a summative model where E , S , and A are defined for each pixel, i , within the city represented by the input data:

$$HVI_i = E_i + S_i - A_i \quad (1)$$

In terms of adaptive capacity, research has shown that including adaptive capacity in societal vulnerability models to better characterize society's short term responses to extreme heat (e.g., cooling centers), and long term adaptation strategies (e.g., planting more trees), is critical to a more complete understanding of vulnerability, since both are closely related to social inequalities [90–93]. Outcomes from this research [92] suggest the need to go beyond examining demographic data exclusively to

assess vulnerability to extreme heat, but to incorporate additional adaptation factors relating to social and behavioral factors at the household level into vulnerability research. The HVI model defined in Equation (1) combines socio-demographic data, remotely sensed environmental variables produced from Landsat and Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) imagery, and the LST from ECOSTRESS and MODIS thermal infrared data.

Since the demographic variables may not necessarily be independent, correlation tests in addition to a PC analysis using principal components is necessary to statistically compare different variables for the region of interest. This is an important step since a PC analysis using demographic variables for one urban region may yield very different results from another region due to differences in regional climate, urban structures, and local climate zones. The input data into the HVI are first collocated and interpolated onto a common geographic equal angle grid of $\approx 100 \text{ m} \times 100 \text{ m}$ pixels over the LA county region, as shown in Figure 1, and the final HVI is normalized between [0, 1], where higher values are indicative of a higher heat vulnerability. The following subsections describe the derivation of the HVI and variables used for the *E*, *S*, and *A* variable inputs.

2.2.1. Heat Exposure (*E*) Variables

For heat exposure (*E*) variables, we used three different types based on remotely sensed LST data: (1) present day exposure from high spatial resolution ECOSTRESS LST data throughout the diurnal cycle, (2) historical exposure from a climatology of MODIS LST heatwave data from 2002–2018, and (3) exposure from MODIS trends in extreme temperatures using LST data from 2002–2018. All three exposure variables will produce a different vulnerability map depending on the desired application. For example, ECOSTRESS exposure will provide information on present day vulnerability at different times of the day at fine spatial scales the size of a football field or a large industrial roof, while MODIS LST climatology data will tell us more about what neighborhoods have been historically affected by extreme heat events, such as heatwaves, and potentially where future communities will be at most risk from the derived trends in extreme heat [94]. As discussed in the Introduction, both *T*_{air} and the LST are required to fully represent the effects of heat vulnerability in urban environments. However, until more robust statistical models can be developed to estimate *T*_{air} from remotely sensed LST data at fine spatial scales ($<100 \text{ m}$), we continue to use the LST as the main driver for heat exposure in this study. Furthermore, three of the four ECOSTRESS scenes chosen in this study were during the night when LST and *T*_{air} temperatures were much more closely related due to reduced insolation and advection [39].

ECOSTRESS Land Surface Temperature

ECOSTRESS LST data are available in the Level-2 product (ECO2LSTE Version 1), which can be downloaded from the NASA Land Processes Distributed Active Archive Center (NASA-LPDAAC [95]). The ECO2LSTE product provides the LST and emissivity in five thermal bands between $8\text{--}12 \text{ }\mu\text{m}$ at a $70 \text{ m} \times 70 \text{ m}$ resolution, including estimated uncertainties for each retrieved quantity in addition to a quality control (QC) bit field. The ECO2LSTE product data are not cloud-screened, but a cloud bit mask is available in the ECO2CLD product. Users should note that since ECOSTRESS started acquiring data in August 2018, issues with the onboard data recorders resulted in no data being acquired in two windows from 29 October 2018–10 January 2019, and 15 March–15 May 2019. However, since 15 March 2019, this issue was fixed using a direct file streaming option, and data acquisitions have been proceeding as normal since then. The combined high spatiotemporal resolution of ECOSTRESS provides unprecedented information on the UHI effect and heatwaves over urban environments since temperatures can be monitored at different times of the day over the diurnal cycle. Currently only geostationary sensors, such as the Geostationary Operational Environmental Satellite (GOES) series, are able to provide temperatures over the diurnal cycle, but are not effective over urban areas due to coarse resolution pixel sizes of $2.5\text{--}4 \text{ km}$, depending on the sensor. During an extended period of high heat over LA from mid-July to the first week of August 2018, ECOSTRESS acquired images over LA

at five different times during the day: 04:07 am, 02:10 pm, 05:01 pm, 09:26 pm, and 11:43 pm Pacific Standard Time (PST). By comparison, Landsat 8 only had two acquisitions over the same area during the same time period (14 July and 30 July at 11:27 am PST).

Figure 2 shows ECOSTRESS-retrieved LST images over the LA study area for four of the selected times geolocated onto the fixed study grid. The LST's during the daytime image in Figure 2a are hottest in the San Fernando and San Gabriel Valley areas ($>55^{\circ}\text{C}$), and coolest along the coastal regions of Westside, South Bay, and beach cities due to cooling effect of the ocean ($<25^{\circ}\text{C}$). The coolest temperatures along coastal areas in the southeast beach cities is due to the marine layer moving in over land at that time. As temperatures decrease throughout the night-time and early morning hours (Figure 2b–d), materials with high heat capacity (e.g., concrete, asphalt, waterbodies) remain warm and continue to radiate heat stored during the daytime hours. By 11:43 pm PST, areas of downtown LA have cooled off, while areas in San Gabriel Valley (e.g., Chatsworth), San Gabriel Valley (e.g., El Monte), North County (e.g., Anaheim), Long Beach, and airports (e.g., Bob Hope, Ontario) remain warm at $>25^{\circ}\text{C}$. The road networks and freeways start to become clearly visible in Figure 2c,d during the night, with some roads being warmer than others, likely due to their orientation, asphalt depth, shading, and weathering [96]. The hottest surfaces during the early morning hours were identified as large asphalt parking lots and airport runways/tarmac, for example, the Santa Anita race-track in the San Gabriel Valley, Angels baseball stadium parking lot in Santa Ana, and Bob Hope airport were still as warm as $\approx 23^{\circ}\text{C}$ at 4:07 am PST.

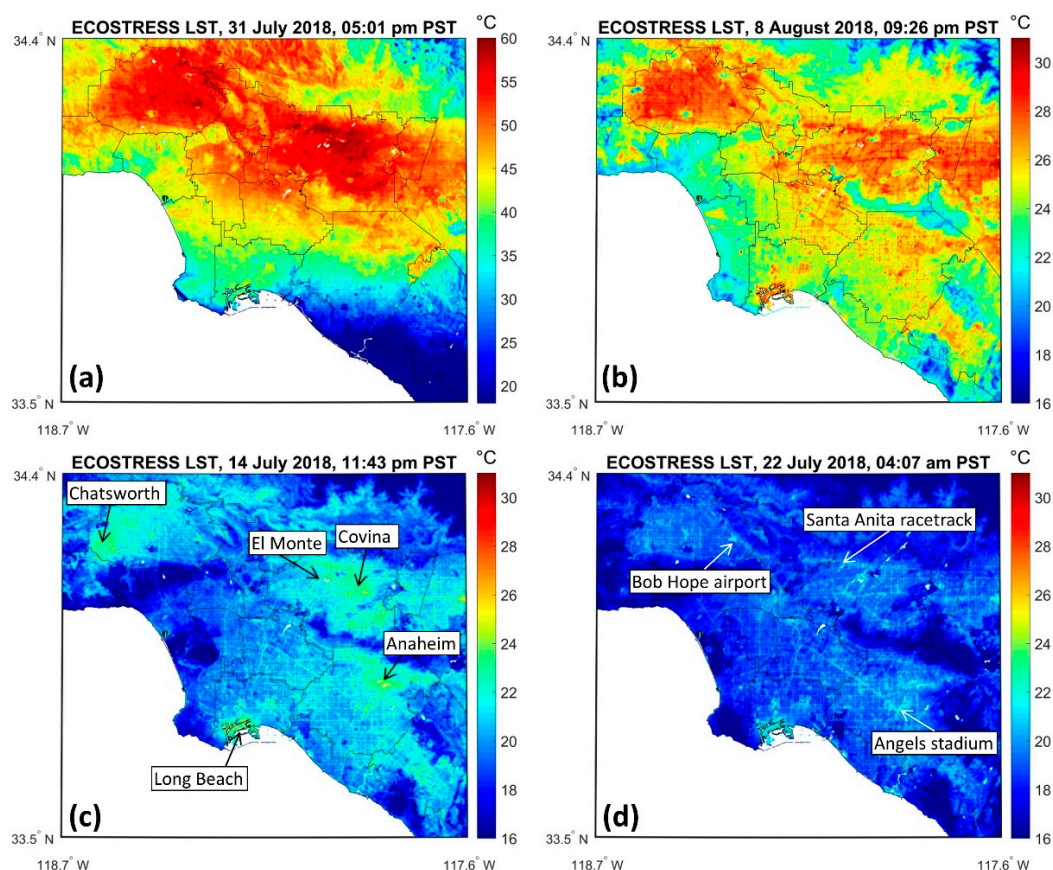


Figure 2. ECOSTRESS land surface temperature (LST) retrieved over the LA county study region on: (a) 31 July 2018, 05:01 pm; (b) 8 August 2018, 09:26 pm; (c) 14 July 2018, 11:43 pm, and; (d) 22 July 2018, 04:07 am. All times are Pacific Standard Time (PST). Ocean and inland waterbody pixels have been screened and appear as white pixels.

MODIS Land Surface Temperature

We included additional exposure variables based on historical heatwave climatologies over the LA basin from 2002–2018 using a new MODIS LST product (MYD21) [94]. The MODIS sensors are polar-orbiting multispectral instruments on NASA's Terra (since 1999) and Aqua (since 2002) satellites that provide global coverage at ≈ 1 km resolution at nadir [97]. The LST climatologies were derived from the new MYD21 LST product available in Collection 6 (overpass at $\approx 2:15$ am/pm PST over LA). The MYD21 LST's are retrieved using the TES algorithm and provide more consistent accuracy regarding the LST [60,61], particularly over urban surfaces, since the LST and emissivity are dynamically retrieved as opposed to using split-window approaches (e.g., MOD11/MYD11) that assumed a fixed and constant emissivity of 0.97 over all urban surfaces [98].

From MODIS MYD21 LST data we calculated two climatological exposure variables over the LA study area from 2002–2018: (1) heatwave average daily temperature, and (2) trend in number of days per year with daily average temperature $>35^{\circ}\text{C}$ (95th percentile). Based on recommendations from a summary paper on the measurement of heatwaves by Perkins and Alexander [99], we used the excess heat factor (EHF) [100] as the definition of a heatwave in our study. The EHF compares average minimum and maximum daytime temperatures to climatological reference temperatures from ground station data (97.5th percentile) over a 3-day period, combined with an acclimatization index that represents the anomaly of the present-day temperatures with respect to the previous 30 days. A detailed methodology of the approach used for detecting heatwaves over LA using the EHF is available in Hulley et al. [11], while an example of this methodology applied to MYD21 LST data to investigate trends in extreme temperatures over LA is detailed in Hulley and Dousset [94]. The heatwave day/night climatologies provide information on historical values of extreme heat throughout the LA region during the 21st century, while the trends provide information on regions potentially vulnerable to future extreme heat.

2.2.2. Sensitivity Variables

To assess the sensitivity of regions/individuals to total vulnerability, we used seven variables: (1) elderly population, (2) population density, (3) poverty level, (4) disabled population, (5) unemployment, and (6) building height. The population density and elderly population data were acquired from NASA's Socioeconomic Data and Applications Center (SEDAC [101]) Metropolitan Statistical Areas (MSA) v1 [102]. MSA v1 data are provided for 50 metropolitan statistical areas with at least one million in population with a grid resolution of 7.5 arc-seconds (0.002075 decimal degrees), or approximately 250 square meters. The gridded variables are based on census block geography from Census 2000 Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line Files and census variables (population, households, and housing variables). Education level, income, disability status, poverty level, and employment status data were acquired from the American Community Survey (ACS) using 5-year estimates from data collected from 2011 through 2015. ACS variables for education, disability, poverty and unemployment were calculated as population percentages, as opposed to actual population numbers from SEDAC. Percentages were used because the ACS survey does not include as many participants as the census, and therefore a percentage of surveyed participants was thought to be a more accurate representation of the data than raw numbers. See Table A1 for more information on data sources and data characteristics. A brief justification for picking each sensitivity variable follows.

Elderly Population

Elderly population data were calculated as the percentage of the population aged 65 years and older. The elderly are particularly vulnerable to heat given their physical inability and are unable to regulate heat as well as healthy adults [74]. The elderly can also be considered a marginalized population group, which puts them at risk of heat-related impacts due to social isolation and lack of access to relieving factors such as air conditioning or pertinent information through media access [29,74].

In fact many studies have shown that the elderly have both higher mortality rates [103–105] and hospital admission rates [106,107] during heatwaves, exacerbated by underlying health conditions such as cardiovascular diseases, diabetes, and pulmonary disease [108].

Population Density

The UHI effect has been found to be correlated with high population and building density (“urbanicity”) [29,109], which is a major contributing factor to heat vulnerability, particularly for populations with lower socioeconomic status [110,111]. Inner city housing usually consists of a mix of multi-unit buildings and apartment complexes associated with greater population density, both of which are thought to increase the risk of heat-related mortality during hot weather, particularly for occupants on upper levels of multi-unit buildings [111–114]. Koreatown, just west of downtown LA, is the most-densely populated district in LA County with 120,000 residents in 7.0 km².

Poverty Level

Poverty levels in the ACS include the number of people who answered that they were living in poverty divided by the total population for whom poverty status is determined. Several studies have shown that residents living in poverty may be more vulnerable to the effects of excessive heat [114–116], largely because of their inability to afford transportation, air conditioning, hospital trips, information resources, or other preventive measures to diminish heat-related mortality and morbidity [29,74,117,118]. Poverty also contributes to a growing number of individuals living in isolation, which has been recognized by several studies as a major risk factor in heat-related mortality [90,108,114,119].

Disabled Population

The disabled population was computed as the percentage of people who responded that they had a hearing difficulty, vision difficulty, cognitive difficulty, ambulatory difficulty, self-care difficulty, and/or independent living difficulty divided by the total civilian noninstitutionalized population. Similar to the elderly population, disabled members of the community and those with other chronic conditions are at a high risk of heat-related impacts due to social isolation and lack of access to relieving factors [29,74]. They are also often overlooked in the design of response plans to heatwaves [120], and in addition, have limited access to assistance and transpiration from cooling centers during excessive heat events [120].

Unemployment

Unemployment was calculated as the number of unemployed persons divided by the total population in the civilian labor force. Similar to the poverty level and population density variables, unemployment is a socioeconomic status indicator that is linked to a higher risk of heat vulnerability [110,111]. Unemployment also heightens the risk of poverty and social isolation [121], further increasing risk factors of heat-related mortality [90,108,114,119].

Building Height

Building height can be associated with higher building density, greater population density, and higher levels of the UHI effect, all of which are considered contributing factors to heat vulnerability [110,111]. Building height also provides a proxy for the sky-view factor, i.e., the portion of sky viewable from ground level that is correlated with the formation of the UHI effect [75,122]. Street canyons surrounded by higher buildings, while providing shading depending on time of day, will predominately experience more heating effects, particularly at night, since longwave radiation is not able to escape efficiently to the atmosphere and gets trapped in urban canyons [75,80].

An average building height map for the LA study scene was provided by the University of Maryland (UMD) at a 30 m resolution using two Landsat 8 images from 2018. The new method uses an object-based machine learning approach by fusing Landsat and elevation data to estimate building height and volume at a 30 m resolution [123].

2.2.3. Adaptive Capacity Variables

Four variables were used to quantify adaptive capacity to heat: (1) education, (2) income, (3) green vegetation fraction, and (4) distance to cooling centers. These variables aim to capture information that is correlated to both individual and city-based strategies for heat resilience: education and awareness, access to air conditioning, increased vegetation fraction and vegetation greenness, and access to cool roof and solar technologies.

Education

Education level was computed in ACS by dividing the number of people with higher education degrees (summation of those who had received a Bachelor's Degree, Master's Degree, Professional Degree, or PhD) by the total population over the age of 25. Member of the community with higher education can be considered to have higher adaptive capacity because it helps with critical thinking and problem solving, both of which are important when identifying and reacting to extreme heat circumstances [15]. For example, a number of studies have shown that those with lower levels of education (high school and less) were at a greater risk of heat-related mortality than those with higher levels of education, which seemed to provide a preserving effect [112,113,115,124].

Income

Similar to education, households with higher incomes are more likely to have newer homes with better insulation, access to air-conditioning, larger properties with more trees, and live in cooler neighborhoods. These factors decrease their vulnerability and increase their adaptive capacity to excessive heat [125,126]. Income can also be considered a type of socioeconomic status that has been found to have an inverse relationship with the risk of heat-related mortality [112,114,115].

Green Vegetation Fraction

Variations in the distribution and density of vegetation in cities can create microclimates that have a significant effect on reducing heat-related vulnerability [6,29]. Conversely a lack of green space is also associated with an increase in heat stress and the resulting morbidity [20,127]. Vegetation shifts the energy partitioning in cities from higher latent heat release (cooling) to lower sensible heat (warming the air), thereby reducing the UHI effect and associated heat vulnerability. However, the effectiveness of cooling through vegetation is dependent on a number of factors, including irrigation frequency, type and size, and placement (vegetation along west-facing walls will have a greater cooling effect), which can all vary greatly throughout a city [76].

Green vegetation fraction was computed using the multiple endmember spectral mixture model (MESMA) [128] on AVIRIS imagery during 2014 to estimate fractional green vegetation (GV) cover throughout the study site at a 36 m resolution [37]. Since the AVIRIS GV data are static and only available from 2014 flights, we also had the option to include normalized difference vegetation index (NDVI) data from Landsat 8 data within 16 days of the exposure variable acquisitions from ECOSTRESS. NDVI was derived from Landsat 8 surface reflectance analysis ready data (ARD) [129] for a clear-sky Landsat scene over LA on 15 August 2018. NDVI uses a ratio between light reflectance in the near infrared (NIR) and red bands [130]. ARD data are currently available from the United States Geological Survey (USGS) over the conterminous United States (CONUS), and are tiled, georegistered, and atmospherically corrected on a common equal area projection for ease of use. The NDVI data is indicative of plant greenness and photosynthetic efficiency and is used extensively to monitor seasonal and annual land cover changes in green biomass [130–133]. Higher NDVI values are associated with

greener, healthier vegetation, while lower values are indicative of more senesced, drier vegetation and bare soils. In general, we expect plants and trees with a higher NDVI to be cooler since they will transpire more and release latent heat, resulting in cooling.

Distance to Cooling Centers

A number of large cities (e.g., New York City, Boston, Chicago, Los Angeles, Toronto) have begun using air-conditioned public buildings, such as schools, senior centers, and libraries, as cooling centers where nearby residents can seek relief from extreme heat, especially during heatwaves. While cooling centers provide shade, water, restrooms, and other social services to help the public escape the heat, their strategic placement is often not optimal. For example, keeping facilities open for extended hours in areas where they are not fully needed will end up unnecessarily costing the city and taxpayer. Their location requires information and an understanding of the spatial variability of temperature and related vulnerability in any given city, which is what the HVI maps aim to provide. Therefore, while cooling centers can serve as effective adaptation strategies, studies have found that they will have limited use if outreach and transportation assistance to vulnerable individuals is not practiced [120,134]. We extracted cooling center locations from the LA location management system [135]. In order to represent cooling centers as an adaptive capacity variable we computed a distance map from the cooling center location points to every pixel in the raster-gridded map of LA. That is, any given pixel was assigned the minimum radial distance from any of the cooling centers. Values were then normalized between zero and one. Figure A1 shows the distance to a cooling center map with the darkest red spots representing the cooling centers and values start decreasing in space as the pixels get further from the respective cooling center, representing a lower adaptive capacity.

2.2.4. Principal Component Analysis

A principal component analysis (PCA) extracts the most important information from a dataset and removes assumptions as to the relative importance of the variables considered while retaining as much of the variance of the original data as possible [136]. The resultant principal components (PCs) are new orthogonal variables ordered by the amount of variance they represent in the data. Variables within the *E*, *S*, and *A* categories described above may not necessarily be independent; for example, there may be strong correlations between different demographic variables (e.g., low income and education levels), but at the same time, a priori assumptions regarding the relative importance of different variables may result in biases. Therefore, correlations tests in addition to a PCA approach is necessary to statistically compare different variables for the region of interest and reduce the original set of variables to a small number of PCs that account for the most variance. All variables were normalized to have a mean of zero and a standard deviation of one (z-score). In accordance with Kaisers rule [137], only those PCs that had an eigenvalue greater than one were retained for analysis. The PCs that had eigenvalues greater than one were then rotated using a varimax rotation to improve their interpretation and maximize the dispersion of loadings across PCs. These rotated PC scores were weighted by variance and then used to reconstruct the original observations. From the reconstructed data, the variables within each category shown in Table A1 were averaged and used to compute the exposure, sensitivity, and adaptability scores used in the final HVI (Equation (1)). All partial results for sensitivity, exposure, and adaptive capacity were normalized from zero to one, in addition to the final HVI.

3. Results and Discussion

3.1. Statistical Analyses of Sensitivity and Adaptive Capacity Variables

The results of the PCA for sensitivity and adaptive capacity variables yielded four PCs based on the Kaiser rule (eigenvalues greater than 1). The first four components accounted for a total of 70% of the variance in the data. The loadings of the components signify the correlation between the respective

variable and the associated PC. Table 1 shows the results of the PCA with loadings (after varimax rotation) for the first four PCs with eigenvalues greater than one.

The variables in PC1 with the highest loadings were green vegetation fraction (0.42), income (0.50), and education (0.47), and can be interpreted as a measure of adaptability through socioeconomic status (wealth, education, green space availability). The resultant adaptive capacity image in Figure 3 shows the highest loadings along cooler coastal areas (e.g., Westside, beach cities), but also inland in wealthy neighborhoods with a higher percentage of green spaces such as in San Marino, Silverlake, Thousands Oaks, La Crescenta, and Calabasas.

The dominant components in PC2 were elderly (0.62), population density (0.57), and building height (0.42), which reflects sensitivity primarily through urban congestion. The highest loadings in PC3 were poverty (0.21), disabled (0.67), and unemployment (0.48), which can be interpreted as sensitivity through social isolation. The resultant sensitivity map in Figure 3 shows the highest loadings in and around downtown LA, Koreatown, and other densely populated areas of Glendale, and Century City on the Westside. Small pockets of distinctively high sensitivity values occurred in census blocks with a primarily disabled population data, but in general, had higher loadings in the poorer neighborhoods in LA county (e.g., south and southeast LA in the cities of Inglewood and Torrance), and other areas within the San Fernando valley. In PC4, the only dominant component was cooling center proximity (0.82), which is independent of all other variables. This indicates that the locations of cooling centers in LA were most likely not in optimal areas that correlated with the sensitivity variables in PC2 and PC3.

Table 1. Principal component (PC) coefficients (loadings) after varimax rotation for four principal components.

		PC1	PC2	PC3	PC4
Adaptability 1 "Socioeconomic status"	Green vegetation fraction	0.42	−0.05	0.13	−0.02
	Income	0.50	−0.06	−0.05	−0.01
	Education	0.47	0.09	−0.11	−0.07
Sensitivity 1 "Congestion"	Elderly	0.11	0.62	0.03	−0.15
	Population density	−0.11	0.57	−0.08	−0.03
	Building height	−0.12	0.42	−0.04	0.24
Sensitivity 2 "Isolation"	Poverty	−0.36	0.12	0.21	−0.04
	Disabled	0.01	−0.08	0.67	−0.07
	Unemployment	−0.23	−0.07	0.48	−0.05
Adaptability 2	Cooling center proximity	−0.11	−0.11	−0.16	0.82

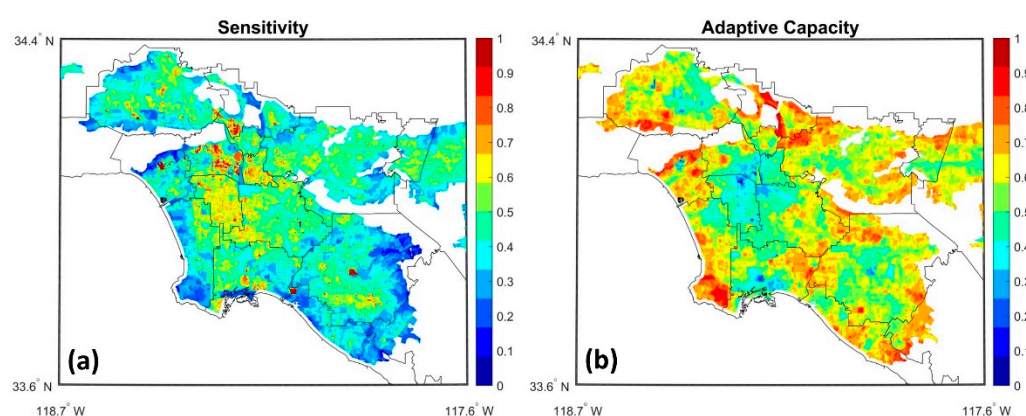


Figure 3. (a) Sensitivity and (b) adaptive capacity images derived from socio-demographic and environmental variables and their principal component coefficients from Table 2.

3.2. HVI from ECOSTRESS over the Diurnal Cycle

Figure 4 shows the resultant HVI displayed from [0, 1] with the exposure index derived from four ECOSTRESS LST acquisitions in Figure 2 at different times of day over a 3-week period from July–August 2018 (17:01, 21:26, 00:43, and 04:06 PST). From the four images, we calculated the average HVI by region, and the resulting statistics and vulnerability rankings are shown in Table 2 and histograms are plotted in Figure 5. The late afternoon acquisition at 17:01 had the highest HVIs with an average (standard deviation) of 0.63 (0.2) when LSTs were still high and exceeded 50 °C over large portions of the urban environment (reds, dark red colors in Figure 2a). While the hottest areas at this time of day occurred in the San Gabriel and Pomona Valley areas (Figure 2), these two regions only ranked 5 and 8 respectively in terms of mean HVI (Table 2). This was most likely due to other compensating socio-demographic factors represented in the sensitivity and adaptive capacity variables. The highest HVIs greater than 0.8 occurred in areas around downtown LA and also in the Pomona and San Fernando Valley. These are both regions with large proportions of impervious surfaces, few green spaces, combined with densely populated and poorer communities. The top four most vulnerable regions in terms of average HVI with values >0.6 all occurred in neighborhoods surrounding downtown LA (east, south, central, and southeast in Figure 1). The most vulnerable region was eastside LA with an average HVI value of 0.74. Eastside LA includes the wholesale district with a high proportion of industrial and warehouse facilities that enhanced the UHI effect, in combination with a historically low-income community and low percentage of education. Table 2 also shows that eastside LA had no cooling centers, and also the lowest percentage of green space in LA. These factors combined with having the second highest average daily temperature (29 °C) over the ECOSTRESS acquisition period to result in high vulnerability scores.

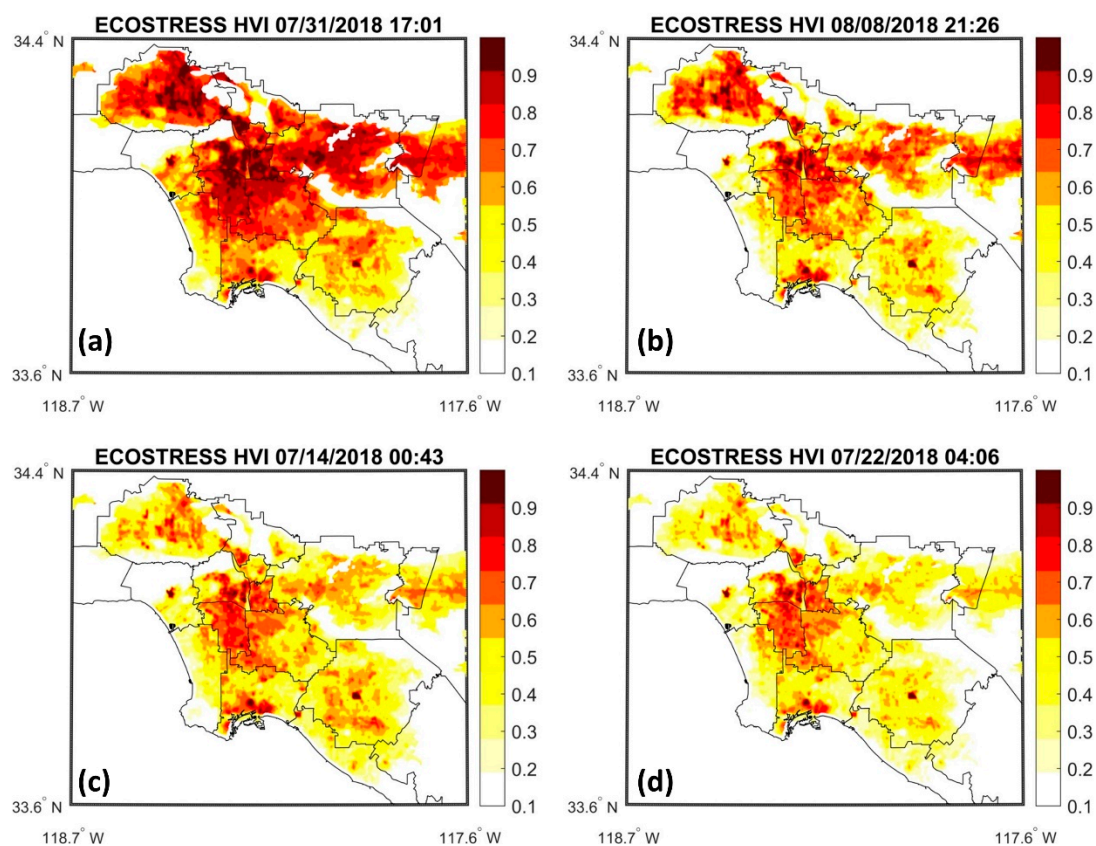


Figure 4. Heat vulnerability index (HVI) maps derived from ECOSTRESS acquisitions for: (a) 31 July 2018 at 17:01, (b) 8 August 2018 at 21:26, (c) 14 July 2018 at 00:43, and (d) 22 July 2018 at 04:06. All times are in Pacific Standard Time (PST).

Correlation results in Table A2 for selected variables show that HVI had the highest correlation with poverty level (0.83) and income (−0.85), followed by LST (0.69) and impervious fraction (0.55), and was negatively correlated with vegetation fraction (−0.49), as expected. LST and vegetation fraction both played a strong role in determining the HVI; however, their correlation was relatively low over the urban environment (−0.23). LST-NDVI relationships usually have a strong negative correlation over natural landscapes with the exception being over waterbodies and soil moisture [138]; however, over urban areas, the relationship is more complex and depends on a number of factors including subpixel contamination from impervious surfaces [37], plant species type and green vegetation fraction [68], shading, and proximity to asphalt and buildings that increase/decrease evapotranspiration depending on whether their dominant effect is channeling wind, advection of dry air, or shading [75,77].

The coastal regions had the lowest HVIs on average with values <0.4 in the South Bay, Westside, beach cities, and South County. This was due to a combination of ocean cooling effects and areas with high adaptive capacity in affluent communities with a high income that live in highly sought after areas such as Venice, Brentwood, Santa Monica, Newport, and Laguna Beach. All four coastal regions ranked in the bottom four spots on the most vulnerable list (Table 2 and Figure 5), and all had unsurprisingly low average temperatures (<25 °C) and high green space fractions (25–39%). These areas had few cooling center locations, as expected, since they likely would have lower demand for them. The HVI decreased during the night-time with values of 0.50 at 21:26, 0.48 at 00:43, and 0.42 for the early morning acquisition at 04:06 (in Figure 4b–d, respectively). However, small pockets of high vulnerability (HVI between 0.6–0.9) were still present at night and were concentrated mostly in areas around downtown LA that ranked the highest in vulnerability. Parts of San Fernando valley and North County also remained vulnerable during the night, primarily due to higher sensitivity values from elderly and disabled census blocks (e.g., red areas in Figure 3a). We should expect heat vulnerability to remain high at night for the most vulnerable populations to heat since studies have shown that high night-time temperatures are strongly correlated with the highest morbidity and mortality rates [2,139]. In Southern California, this is compounded by the fact that humid night-time heatwave events are becoming more common due to anthropogenic warming feedbacks [10,11]. The increase in night-time heatwave temperatures and corresponding HVI is a serious concern for the elderly and disabled populations because they need more time to recover from daytime heat stress and cannot sustain consecutive warm nights, all exacerbated by sleep deprivation [2]. Sustained night-time air temperatures over 20 °C can lead to a higher risk of heat related illness and death [139–141].

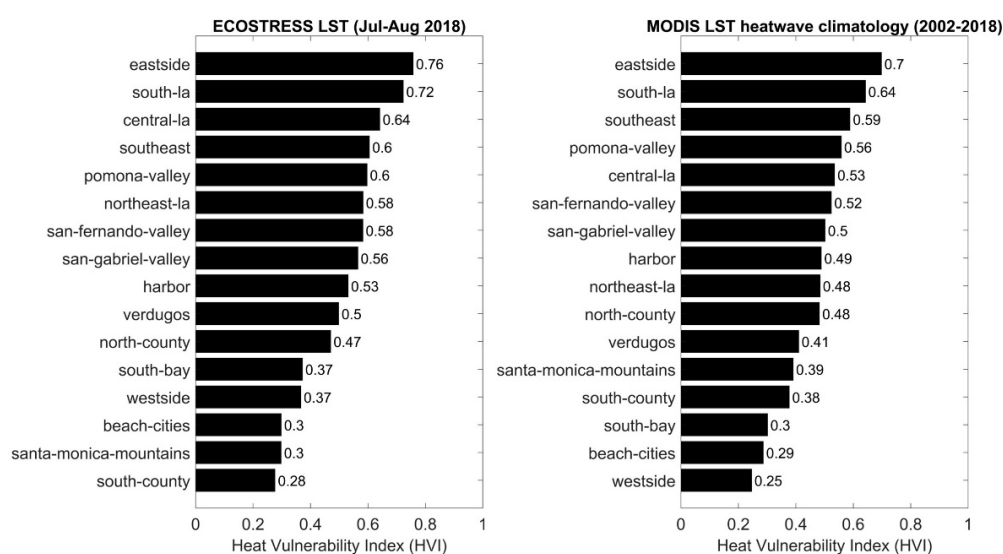


Figure 5. Histograms showing ranking of regions with highest average HVI derived from exposure variable driven by ECOSTRESS LST images from July–Aug 2018 (left), and from MODIS LST heatwave climatology from 2002–2018 (right).

Table 2. The most vulnerable regions in Los Angeles county ranked by mean HVI for the four ECOSTRESS acquisitions from July–August 2018. Also shown are the number of cooling centers, percentage of green space, and average surface temperatures from ECOSTRESS.

Vulnerability Ranking	HVI (%) (mean $\pm$ SD)	Number of Cooling Centers	Green Space (%)	Temperature (°C) (mean $\pm$ SD)
1. East LA	76 $\pm$ 8	0	14	29.0 $\pm$ 0.8
2. South LA	72 $\pm$ 10	3	15	26.8 $\pm$ 1.0
3. Central LA	64 $\pm$ 19	1	18	27.4 $\pm$ 1.5
4. Southeast LA	61 $\pm$ 10	13	18	27.5 $\pm$ 1.2
5. Pomona Valley	59 $\pm$ 14	9	24	28.8 $\pm$ 1.7
6. Northeast LA	58 $\pm$ 10	3	25	28.6 $\pm$ 1.1
7. San Fernando	58 $\pm$ 15	5	26	29.6 $\pm$ 1.5
8. San Gabriel	56 $\pm$ 12	13	26	29.4 $\pm$ 2.0
9. Harbor	53 $\pm$ 14	11	18	25.2 $\pm$ 1.5
10. Verdugos	50 $\pm$ 19	4	32	29.0 $\pm$ 1.4
11. North County	47 $\pm$ 12	1	25	25.5 $\pm$ 2.1
12. South Bay	37 $\pm$ 18	3	23	23.9 $\pm$ 1.5
13. Westside	36 $\pm$ 17	2	30	24.6 $\pm$ 1.3
14. Beach cities	30 $\pm$ 12	0	25	17.6 $\pm$ 3.5
15. Santa Monica	30 $\pm$ 6	0	39	25.1 $\pm$ 1.6
16. South County	27 $\pm$ 9	0	27	20.5 $\pm$ 2.9

3.3. Historical HVI from MODIS Heatwave Climatology

While ECOSTRESS data provides temperature information at a fine scale in urban areas over the diurnal cycle, knowledge of the spatiotemporal variability of historical temperatures and trends over urban areas is also important for better understanding long-term change and to develop future sustainability plans. NASA’s MODIS imager on the Aqua spacecraft has been providing twice-daily LST data since 2002 that can be used to accurately quantify the spatiotemporal variability of temperature changes over the LA region [60,94]. A recent study looked at all heatwaves between 2002–2018 detected from ground measurements [11], and used that data to find all corresponding clear-sky MODIS LSTs from a new product (MYD21) that is able to more accurately account for changes in temperature and emissivity over the urban environment [94]. The resultant MYD21 LSTs were extracted during the heatwave events to build up a clear-sky climatology of extreme temperatures over LA from 2002–2018 at a $\approx$ 1 km spatial resolution.

The spatial variability of heatwaves over the LA area will vary depending on the intensity of the heatwave and other factors, such as the influence of ocean breezes and the inversion layer, but we do expect to see persistent hotspots. In fact, when looking at the average daily heatwave LST from the MYD21 product (Figure 6a), we see just that, i.e., persistent hotspots of high average daily heatwave temperatures (>35 °C) over similar areas as the ECOSTRESS LST data in Figure 2. For example, distinct hotspot areas can be seen in areas of southeast LA and North County, including the cities of Norwalk, Whittier, Anaheim, and Irvine, while Chino, Ontario, and La Puente were the hottest regions in the San Gabriel and Pomona Valleys. In the San Fernando valley, cities of Chatsworth, Van Nuys, and Sun Valley were the hottest areas. A significant temperature gradient and cooling from inland to coastal regions is also evident; for example, downtown LA was on average almost 10 °C warmer than the westside coastal areas of Venice and Santa Monica during heatwave events.

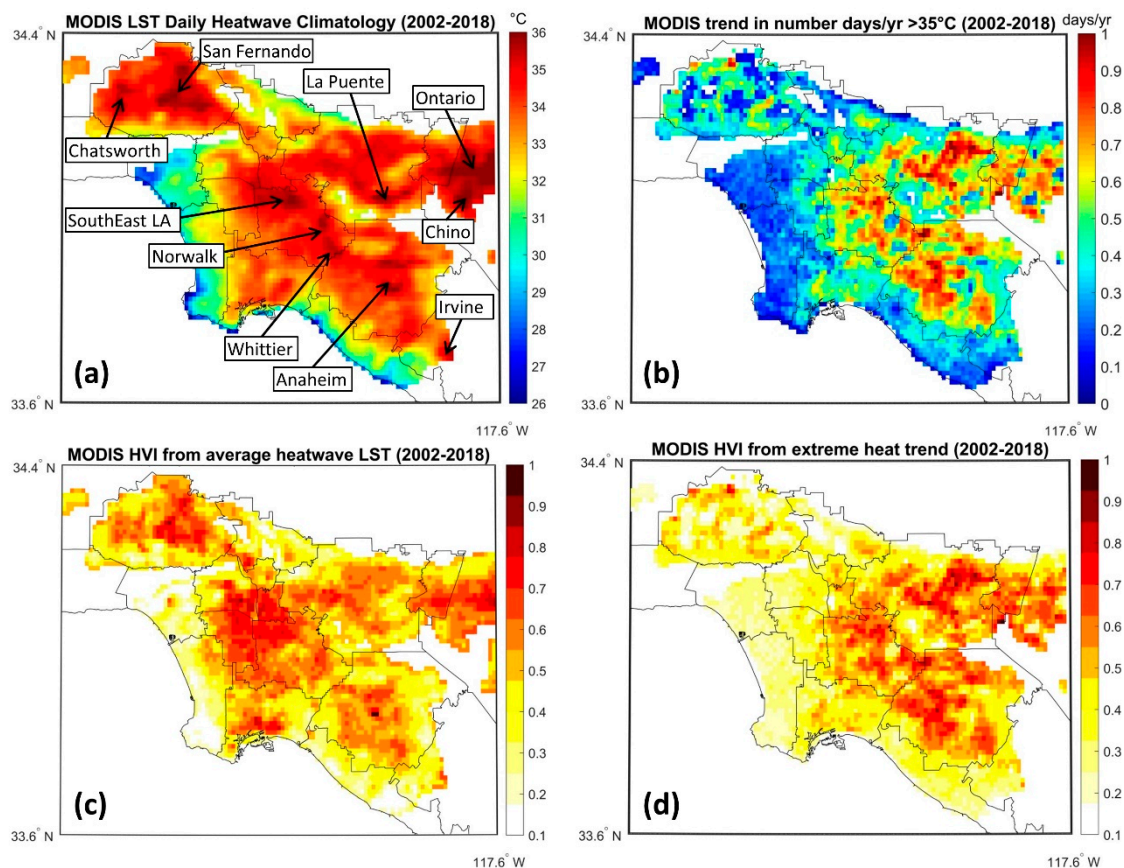


Figure 6. (a) MODIS daily heatwave climatology derived from the MYD21 land surface temperature (LST) product from 2002–2018 at ~1 km resolution; (b) trends (in days/yr) of number of days per year exceeding an average daily LST of 35 °C (only data with significance at < 5% level shown); (c) corresponding HVI map using data from (a), and; (d) corresponding HVI map using data from trends in (b).

The corresponding HVI from the MODIS daily heatwave LSTs is shown in Figure 6c using the same sensitivity and adaptive capacity data used to derive the ECOSTRESS HVI maps. The MODIS HVI map reveals communities that were historically the most vulnerable to the effects of extreme heat and are concentrated in areas in and around downtown LA, Long beach, Anaheim, San Fernando, and Ontario. The histogram ranking of LA regions by HVI for MODIS data in Figure 5 are very similar to that from the ECOSTRESS data, with both agreeing on the top five most vulnerable regions (Eastside, South LA, Southeast LA, Pomona Valley, and Central LA). The persistence of high HVI over these regions using both current daily ECOSTRESS and historical MODIS data indicate that surface temperature variability during hot conditions was remarkably similar from a regional perspective, and likely tied to the unique “local climate zone (LCZ)” comprising a combination of surface structure, land cover, and human activity within each region [142]. These results also indicate a clear and urgent need for implementing cooling innovations and green infrastructure initiatives in these persistently hot regions.

In terms of trends, Figure 6b shows the MODIS trend in the number of days per year with average daily LST exceeding an extreme temperature threshold of 35 °C (95th percentile of historical temperatures) [94]. The image shows that regions of high temperature do not necessarily correspond with high trends in temperature extremes, and that inland and valley areas had the highest trends. For example, while the San Fernando valley experiences some of the hottest temperatures historically (and a resulting high HVI), the trends over this area (<0.5 days/year) were on average lower than other hotspots zones including southeast LA, North County (e.g., Anaheim), and the San Gabriel Valley, where trends in number of days per year in extreme temperatures are close to 1 days/year. These results largely agree with a modeling study by Sun et al. [36] who showed that by mid-century

(2041–2060), air temperatures would increase more in inland and valley locations in LA by on average 2.4°C, in addition to experiencing 60–90 extremely hot days (>35 °C) per year. The corresponding HVI for the MODIS trend map in Figure 6d have areas of high vulnerability that are different to the heatwave climatology map in Figure 6c. For example, San Fernando has lower HVIs, while San Gabriel Valley and North County regions have higher HVIs on average in terms of trends in extreme heat. While causes for the disproportionate increasing trends in extreme heat over the LA region is not fully understood and warrants more research, accurately monitoring these trends over time is important for building future sustainability plans in those vulnerable areas.

4. Future Outlook and Validation Plans

An inherent shortcoming in models that estimate vulnerability is their lack of testing and validation with actual observation statistics [12]. Validation of the HVI for the LA region is essential prior to the adoption of the index by public sector institutions such as departments of public health, sustainability, and various planning agencies. Measurement of a particular HVI's ability to predict heat-related injury and death requires thorough and careful treatment of health outcome data and of other environmental hazards associated with high heat [14,24,143,144].

Validation of an HVI is complicated most especially by the relationship between high heat and various pathologies that result from sustained exposure. In addition to being the proximal cause of death and injury, heat also exacerbates a wide variety of chronic health conditions, such as cardiovascular disease or impaired renal function. The multifarious effects of heat on human health complicate the task of establishing relationships between high heat events and elevated rates of hospitalization and death [145]. Thus, it is essential to obtain the most detailed record of injury and mortality possible in order to evaluate an HVI's ability to predict the occurrence of specific heat-related injuries. In order to validate the LA region's HVI, patient-level hospitalization and emergency room visit data will need to be obtained from California's Office of Statewide Health Planning and Development (OSHPD), along with vital statistics from the California Department of Public Health. OSHPD patient-level data contain diagnoses codes and demographic information, affording the opportunity to learn how well the HVI predicts specific heat-related hospital visits in addition to total visits [146,147]. Validation of a fine-scale heat vulnerability index also necessitates that health outcome data be spatially disaggregated. OSHPD data is disaggregated to the zip code level and include the patient's zip code of origin and the zip code of the hospital where they received treatment. This will allow for comparison of mortality and hospitalization rates in high- and low-vulnerability zip codes in the LA region.

Ideally, the validation of LA's HVI should also control for the effects of air pollution [148]. Many of the same pathologies exacerbated by high heat are also worsened by exposure to air pollution. Given the significant impacts of air pollution on public health in the LA region [6,149], validation efforts should, to the extent possible, control for spatiotemporal trends in ozone and particulate matter pollution, or potentially include them as part of the HVI. Joint effects of air pollution and high heat have been documented both in the LA region and other cities with Mediterranean, semi-arid climates, such as Perth, Australia [150,151].

5. Summary and Conclusions

With an overall increase in urbanization worldwide combined with a warming planet, climate-related health threats in cities are becoming increasingly more significant and will disproportionately affect the most vulnerable communities, including the poor, younger children, the elderly and disabled, and those with chronic diseases. With increasing trends toward heatwave night-time intensification in Southern California linked to feedbacks of anthropogenic climate change and mean warming, the urban heat island (UHI) effect is expected to intensify and lead to a greater risk of heat-related mortality and morbidity, particularly for communities most vulnerable to the ill effects of extreme heat and humidity. Partnerships between policy makers and scientists in cities are

becoming more important as the need to provide evidence-based and data-driven recommendations for planning and future mitigation efforts becomes more critical.

In this study we developed a remote sensing driven heat vulnerability index (HVI) model driven primarily by high spatial resolution land surface temperature (LST) data from NASA's new ECOSTRESS thermal infrared sensor that was launched to the International Space Station (ISS) in June 2018. ECOSTRESS is able to image fine scale temperatures in cities at a $70\text{ m} \times 70\text{ m}$ resolution throughout different times of the day an every 3–5 days on average over most parts of the globe. The HVI model also depends on socio-demographic data (e.g., age, income, poverty levels) and other factors influencing heat vulnerability such as distance to cooling centers, green vegetation fraction, and building height. The final HVI is produced at $100\text{ m} \times 100\text{ m}$ resolution and ranges from values of $[0, 1]$ with values close to 1 indicative of highest vulnerability. The model can be applied to any city with similar types of socio-demographic information used in this study, but for cities with limited data, a single variable out of each of the PC groups in Table 1 could be selected to represent information within that group. However, correlations between variables are also likely unique to each city, so users would have to experiment with the socio-demographic variables at their disposal. In this study we focus on the densely population region of Los Angeles (LA) county in California (≈ 13 million people), a culturally and ethnically diverse region with distinct microclimates and ecological zones that are impacted differently during extreme heat events.

ECOSTRESS imaged the city of Los Angeles at different times of day over a 3-week period of extended heat from mid-July to the first week of August 2018 (17:01, 21:26, 00:43, and 04:06 PST). Results showed that the late afternoon acquisition at 17:01 resulted in the highest temperatures in the San Gabriel and Pomona Valley areas ($>55^\circ\text{C}$), while the highest HVIs greater than 0.8 occurred in areas around downtown LA (Eastside, South, Central, and Southeast LA) and also in the Pomona and San Fernando Valley. These areas have a number of common factors including high average temperatures: they are densely populated areas with large proportions of industrial and warehouse complexes and few green spaces, and consisted mostly of low income and elderly communities. The most vulnerable region was Eastside LA with an average HVI value of 0.74. Eastside LA includes the wholesale district consisting of mostly industrial facilities that enhanced the UHI effect in combination with a historically low-income community with a low percentage of education. Although the HVI decreased over large portions of the city at night, small pockets of high vulnerability persisted and were concentrated mostly in areas around downtown LA that ranked highest in the daytime vulnerability rating. Increasing trends in more humid night-time heatwave temperatures and corresponding HVI is a serious concern for the elderly and disabled populations because they need more time to recover from daytime heat stress and cannot sustain consecutive warm nights in combination with sleep deprivation.

In addition to ECOSTRESS, we used historical LST data from a new MODIS product (MYD21) optimized for urban environments to map out a climatology of heatwave temperatures across the LA region from 2002–2018. The corresponding MODIS HVI maps using the heatwave temperatures as the exposure variable revealed persistent hotspots corresponding to communities that were historically the most vulnerable to the effects of long-term extreme heat. These areas included regions around downtown LA, and cities of Long Beach, Anaheim, San Fernando, and Ontario. In terms of regions defined in this study, the MODIS results matched very closely with those from ECOSTRESS data for 2018, with HVI results from both data agreeing on the top five most vulnerable regions (Eastside, South LA, Southeast LA, Central LA, and Pomona Valley). The persistence of high HVI over these areas from both current ECOSTRESS and historical MODIS data show a clear and urgent need to focus cooling efforts in these regions in order to increase resiliency during extreme heat events. In terms of future trends in extreme temperatures (number of days per year with a daily average LST $> 35^\circ\text{C}$), MODIS data revealed the highest trends primarily in inland areas of Southeast LA, North County (e.g., Anaheim), and the San Gabriel Valley where trends in number of days per year in extreme temperatures are close to 1 day/year. The hottest regions, for example in San Fernando valley, did not correspond

necessarily with highest trends in extreme temperatures, which is why future trends are also critical for addressing and planning for future vulnerability in cities.

With thermal infrared spaceborne measurements, such as ECOSTRESS, providing a pathway forward for the future sustainability of high spatial resolution thermal measurements, such as the Surface Biology and Geology (SBG) designated observable in the second Decadal Survey: Earth science and applications from space (ESAS 2017), the TIRS-2 thermal instrument on Landsat 9 (launch Dec. 2020), and the European Space Agency (ESA) Land Surface Temperature Monitoring (LSTM) mission as part of the Copernicus program, the future of remote sensing of urban temperatures and heat vulnerability at <100 m scales on 3–5-day timescales will continue and ensure that city planners and health department officials around the globe have the critical information necessary to monitor spatiotemporal variations in extreme heat from space. Future plans include developing a robust statistical regression model to estimate air temperatures from LST data over LA using a combination of ECOSTRESS diurnal LST and air temperatures derived from a WRF-urban canopy model optimized for the LA region [54]. Further work will involve integrating air-conditioning use information into the HVI model derived from electricity consumption data for LA county, continue to update the HVI model with the most recent socio-economic data, and to produce HVI maps from ECOSTRESS and other thermal sensors in a consistent fashion and available for public use in easily readable formats.

Author Contributions: conceptualization, G.H. and S.S.; methodology, G.H. and S.S.; software, G.H. and S.S.; formal analysis, G.H. and S.S.; investigation, G.H. and S.S.; data curation, G.H., S.S., and E.W.; writing—original draft preparation, G.H. and S.S.; writing—review and editing, G.H. and R.C.; funding acquisition, G.H.; validation, R.C.

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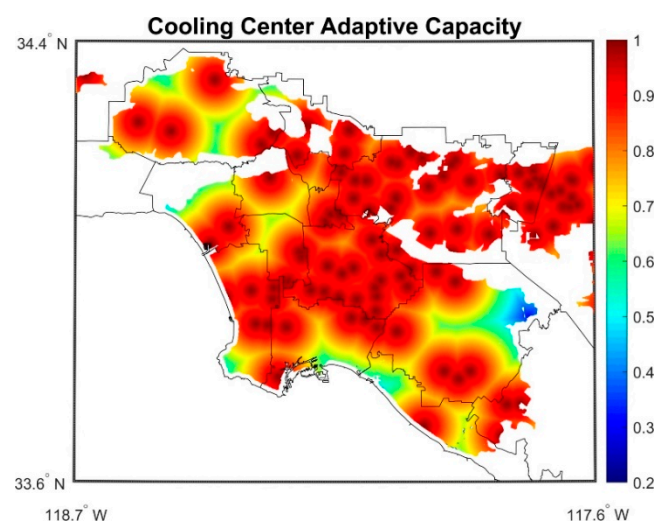
Appendix A

Table A1. Variables used as inputs to compute the HVI with information showing the source of data, time and spatial scales, and the assigned HVI index variable (exposure, sensitivity, adaptive capacity).

Variable	Source	Temporal Scale	Spatial Scale	Index
Land Surface Temperature	ECOSTRESS	Diurnal cycle	70 m	Exposure
Extreme Heat Trends	MODIS	2002–2019	1 km	Exposure
Heatwave Average Daily Climatology	MODIS	2002–2019	1 km	Exposure
Age of Housing	ACS	2010	200 m	Sensitivity
Elderly Population	SEDAC	2010	200 m	Sensitivity
Total Population	SEDAC	2010	200 m	Sensitivity
Poverty	ACS	2010	200 m	Sensitivity
Disabled Population	ACS	2010	200 m	Sensitivity
Unemployment	ACS	2010	200 m	Sensitivity
Building Height	University of Maryland	Static	30 m	Sensitivity
Education	ACS	2010	200 m	Adaptive Capacity
Income	ACS	2010	200 m	Adaptive Capacity
Green Vegetation Fraction	AVIRIS	2014	36 m	Adaptive Capacity
Normalized Difference Vegetation Index (NDVI)	Landsat	16 days	30 m	Adaptive Capacity

Table A2. Correlation coefficients of selected variables used in the HVI analysis.

Variables	HVI	LST	Veg Fraction	Impervious Fraction	Building Height	Population Density	Poverty
HVI	1						
LST	0.69	1					
Vegetation Fraction	−0.49	−0.23	1				
Impervious Fraction	0.55	0.51	−0.80	1			
Building Height	0.51	0.17	−0.64	0.74	1		
Population Density	0.45	0.08	−0.05	0.28	0.66	1	
Poverty	0.83	0.23	−0.51	0.52	0.49	0.49	1
Income	−0.85	−0.30	0.61	−0.61	−0.56	−0.45	−0.96

**Figure A1.** Cooling center locations represented as an adaptive capacity variable by calculating radial distances from each pixel on the LA study region grid to the nearest cooling center. Higher values represent areas nearest to a cooling center, corresponding to a higher adaptive capacity, i.e., a lower vulnerability.

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