

Article

Gauging Heat Vulnerability in Southeast Florida: A Multimodal Approach Integrating Physical Exposure, Sensitivity, and Adaptive Capacity

Kevin Cresswell ^{1,*}, Diana Mitsova ², Weibo Liu ¹ , Maria Fadiman ¹ and Tobin Hindle ¹

¹ Department of Geosciences, Florida Atlantic University, Boca Raton, FL 33431, USA; liuw@fau.edu (W.L.); mfadiman@fau.edu (M.F.); thindle@fau.edu (T.H.)

² Department of Urban and Regional Planning, Florida Atlantic University, Boca Raton, FL 33431, USA; dmitsova@fau.edu

* Correspondence: kcresswell2014@fau.edu

Abstract: Urbanization and warming climate suggest that health impacts from extreme heat will increase in cities, thus locating vulnerable populations is pivotal. However, heat vulnerability indices (HVI) overwhelmingly interpret one model that may be inaccurate or methodologically flawed without considering how results compare with other HVI. Accordingly, this analysis applied a multimodal approach incorporating underrepresented health and adaptability measures to analyze heat vulnerability more comprehensively and better identify vulnerable populations. The Southeast Florida HVI (SFHVI) blends twenty-four physical exposure, sensitivity, and adaptive capacity indicators using uncommon statistical weights removing overlap, then SFHVI scores were compared statistically and qualitatively with ten models utilizing alternative methods. Urban areas with degraded physical settings, socioeconomic conditions, health, and household resources were particularly vulnerable. Rural and agricultural areas were also vulnerable reflecting socioeconomic conditions, health, and community resources. Three alternative models produced vulnerability scores not statistically different than SFHVI. The other seven differed significantly despite geospatial consistency regarding the most at-risk areas. Since inaccurate HVI can mislead decisionmakers inhibiting mitigation, future studies should increasingly adopt multimodal approaches that enhance analysis comprehensiveness, illuminate methodological strengths and flaws, as well as reinforce conviction about susceptible populations.

Keywords: extreme heat; composite index; vulnerability; urban health; UHI; Southeast Florida



Citation: Cresswell, K.; Mitsova, D.; Liu, W.; Fadiman, M.; Hindle, T. Gauging Heat Vulnerability in Southeast Florida: A Multimodal Approach Integrating Physical Exposure, Sensitivity, and Adaptive Capacity. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 242. <https://doi.org/10.3390/ijgi12060242>

Academic Editor: Wolfgang Kainz

Received: 30 March 2023

Revised: 8 June 2023

Accepted: 15 June 2023

Published: 17 June 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Extreme heat is a growing public health concern facing cities worldwide. This is, in part, because urban heat islands (UHI) elevate temperatures compared to surrounding land posing serious and immediate consequences for people residing in urban areas [1–4]. Coupled with urbanization and warming climate, future health risks will be amplified unless vulnerable populations are accurately identified, and prudent strategies introduced. Currently, about 83% of people in the United States reside in urban areas, and with continued growth, this should surpass 89% by 2050 [5]. Average urban temperatures are projected to rise 1.9–4.4 °C by 2100 from global warming [6] and hotter background conditions will increase heatwave frequency, duration, and intensity [7,8]. This is especially problematic because studies show synergies between heatwaves and UHI [9,10]. Meanwhile, continued urbanization will also cause higher UHI strength elevating temperatures. Collectively, this suggests that extreme heat occurrence and population exposure in cities will likely increase with severe health implications.

High ambient temperatures are detrimental to human health. Extreme heat inflicts more deaths annually in the United States than other weather-related hazards (e.g., floods,

tornados, hurricanes) [11]. In addition to triggering illnesses such as heat stroke, heat exhaustion, and dehydration, extreme heat increases hospitalizations and mortalities among people with chronic illnesses [12–14]. Therefore, as the threat from extreme heat in urban areas grows, reducing heat-related health impacts is imperative. To lessen these negative effects, we must accurately assess population vulnerability across heterogeneous urban landscapes [15], then efficiently deploy community resources [3].

Gauging heat vulnerability is complex since vulnerability is influenced by an interaction of three primary dimensions: physical exposure, sensitivity and adaptive capacity [7,16,17]. Hence, it not only depends on the proximity and intensity of environmental threats but also on community demographic, socioeconomic, and health conditions [18,19] as well as social networks, resources, governance, and resident behaviors, attitudes, and perceptions [7,16,20]. As these dimensions vary over space and time, illuminating what factors heighten vulnerability within specific populations is essential. Yet, with multiple inputs, synergistic and counteractive dimensional relationships, and shifting urban landscapes, accurately measuring heat vulnerability poses a significant challenge.

Urban heat exposure encompasses UHI and microclimate variation, which are multidimensional and shaped by various factors: meteorological conditions [21–23]; land surface characteristics [22–27]; urban form [23,28,29]; land use, land cover, and development patterns [22,24,25,27,30,31]; human heat emissions [23,28,32]; geographic features [4,23]. For instance, areas with high building density and low vegetation are generally warmer during the daytime [23,29] albeit an intricate combination of interrelated variables determines urban temperatures rather than one or several predominant drivers [27]. Regarding sensitivity, research agrees some groups are comparatively vulnerable: poor and minority persons, children and elderly, as well as those with chronic illnesses or disabilities [12,19,24,33]. Attending to dimensional interrelatedness, adaptive capacity, and the ability to cope with heat, such as using air conditioning, is inextricably linked to socioeconomic conditions [2,17].

Southeast Florida (Figure 1) represents an important region to examine heat vulnerability. This tropical region features an urban agglomeration—the Miami–Fort Lauderdale–West Palm Beach Metropolitan Area—with a population over 6.1 million. It has hot, humid summers and an average heat index that could rise as much as 4 °C by 2100 [34]; projected population gains around 25% by mid-century under moderate growth [35] and geographic constraints (Atlantic Ocean, Everglades) limiting horizontal urban expansion; as well as substantial poor, elderly, and racially/ethnically diverse populations. Further conversion from natural to and densification of built settings should elevate regional temperatures resulting from innate land use land cover thermal differences [30,31,36,37].

Even though some local and regional governments formally recognize extreme heat as a public health threat, especially during summer when the regional heat index regularly surpasses dangerous thresholds, few studies have explored heat vulnerability in the region. Those that do typically focus on specific facets rather than heat vulnerability broadly. For example, refs. [25,38] examined UHI characteristics that influence heat exposure while [39] considered population sensitivity to locate at-risk elderly persons. Hence, little is presently known about which areas are most susceptible to heat.

To identify at risk populations, studies employ composite indicators known as heat vulnerability indices (HVI). Although HVI has grown considerably in number over the past two decades, these tools have notable shortcomings that must be addressed. Many HVI [40–47] prioritize physical exposure and sociodemographic variables while health and adaptive capacity are underrepresented [20,48]. Neglecting either aspect misses crucial information. Moreover, HVI performance has varied [48] which is problematic as tools designed to inform decision-making. For instance, some studies determined constructed HVI performed adequately [49] while others found inadequate performance [50].

This partly reflects modeler subjectivity because no universal framework exists creating inconsistencies across studies regarding HVI methodological aspects (e.g., data selection and weighting). Another shortcoming stems from overreliance on one HVI that may be flawed. With the exception of studies mostly evaluating different methodological ap-

proaches [45–47,51], heat vulnerability analyses overwhelmingly interpret one HVI despite exploring links to other models being an integral composite indicator component [52]. Considering multiple HVI enhances analysis comprehensiveness and provides a more realistic picture of vulnerability [47,51]. Furthermore, when validation data is unavailable like this analysis of Southeast Florida and most former heat vulnerability studies [48], it can potentially bolster conviction about highly susceptible areas.

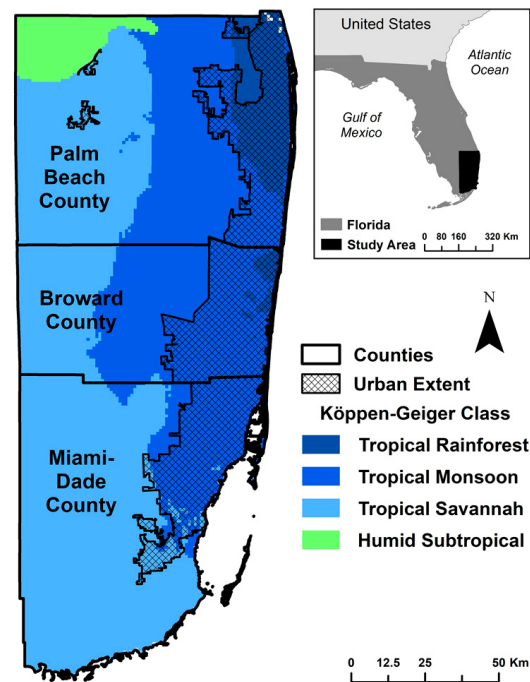


Figure 1. The study area: Southeast Florida, featuring the Miami-Fort Lauderdale-West Palm Beach Metropolitan Area.

Thus, we applied a novel multimodal approach comparing a primary HVI with ten alternative models while incorporating health and adaptability measures to provide a more thorough representation of heat vulnerability, illuminate methodological strengths and weaknesses, and better identify at-risk populations. Research objectives are (1) fuse twenty-four physical exposure, sensitivity, and adaptive capacity variables into a Southeast Florida HVI (SFHVI) using uncommon statistical weights removing overlap, (2) generate ten alternative models employing different methods at composite indicator construction stages, and (3) statistically and qualitatively compare SFHVI results with the ten alternative models. Accurately evaluating and mapping heat vulnerability can help direct mitigation strategies and resources [3,15,53,54]. As urbanization increases and temperatures climb throughout Southeast Florida, identifying vulnerable populations will enhance regional livability and potentially translate into human lives being saved.

2. Materials and Methods

2.1. SFHVI Data

Including various relevant indicators enhances HVI comprehensiveness [20]. Hence, UHI, heat vulnerability, environmental hazard, public health, and epidemiological articles were reviewed to identify germane variables for inclusion (Table 1). Data were compiled at the census tract (CT) level except for several chronic illnesses (asthma, chronic obstructive pulmonary disease (COPD), and renal disease). These were converted from the zip code to CT scale using zonal statistics in ArcMap 10.8 because of data instability issues the Florida Department of Health recognizes that can introduce biases into HVI [55]. A similar concern discouraged granular analysis at the census block group level. Several indicators were combined when fundamental and unit of measurement similarities existed.

Table 1. Twenty-four selected indicators comprising SFHVI.

Dimension	Variable	Source	Year
Physical Exposure	Anthropogenic Heat (W/m ²)	Varquez et al. (2021) Global 1 km AHE Dataset	2010s
	Building Density (%)	Microsoft Nationwide Building Footprints	2019–2020
	Crowding (%)	ACS 5-Year Estimates	2015–2019
	Imperviousness (%)	Multi-Resolution Land Characteristics Consortium	2016
	LST (°C)	USGS Earth Explorer	2014–2017
	Tree Canopy (%)	Multi-Resolution Land Characteristics Consortium	2016
	Water/Wetlands (%)	National Land Cover Database	2016
Social Sensitivity	Age Dependent (%)	ACS 5-Year Estimates	2015–2019
	Education (%)	ACS 5-Year Estimates	2015–2019
	Health Insurance (%)	ACS 5-Year Estimates	2015–2019
	Race/Ethnicity (%)	ACS 5-Year Estimates	2015–2019
	Poverty (%)	ACS 5-Year Estimates	2015–2019
Health Sensitivity	Asthma (Rate/100 k)	FL Health Tracking Network	2015–2019
	Cardiovascular (Rate/100 k)	FL Health CHARTS	2015–2019
	COPD (Rate/100 k)	FL Health Tracking Network	2015–2019
	Diabetes (Rate/100 k)	FL Health CHARTS	2015–2019
	Disabilities (%)	ACS 5-Year Estimates	2015–2019
	Renal (Rate/100 k)	FL Health CHARTS	2015–2019
Adaptive Capacity	Internet (%)	ACS 5-Year Estimates	2015–2019
	Libraries/Malls (km)	Florida Geographic Data Library/Google Earth	2015/2021
	Medical Facilities (km)	Homeland Infrastructure Foundation-Level Data	2018–2020
	Parks (%)	FL Health Tracking Network	2016–2017
	Phone (%)	ACS 5-Year Estimates	2015–2019
	Swimming Pools (#)	Florida Geographic Data Library	2018

2.1.1. Physical Exposure Indicators

Multiple variables represent physical exposure. Land surface temperature (LST) was used for thermal data consistent with prior HVI [40,42,43,46], so LST was calculated from six nearly cloud free Landsat 8 image pairs—Supplementary file (Row 015/Path 041; Row 015/Path 042) acquired on 17 October 2014; 24 January 2016; 25 February 2016; 22 October 2016; 26 November 2017; 12 December 2017, with a formula proposed by [56]. Landsat was chosen for its high spatial resolution (30 m) making it adept capturing thermal heterogeneity coupled with the presence of small (<0.5 km²) CTs. Integrating data from two Landsat images was necessary due to the large study area size. Fmask [57] identified cloudy LST pixels for removal.

However, LST alone is insufficient to depict UHI exposure [58] and physical neighborhood attributes also influence heat vulnerability [24]. Thus, additional variables were included: imperviousness, tree canopy cover, building footprint ratio, anthropogenic heat emissions, household overcrowding, and water/wetlands. While household overcrowding (when a dwelling exceeds one occupant per room) compounds heat health risks [59], the latter was included due to regional waterbody and wetland prevalence.

2.1.2. Sensitivity Indicators

Common indicators representing social sensitivity—poverty, age (above 65 and below 5 years), race/ethnicity (racial minorities and Hispanics), and education (high school degree)—as well as a not often applied indicator, health insurance, were utilized. Non-

white and Hispanic persons [24,33,41] as well as those with less education [24,41] are particularly vulnerable to heat. As Southeast Florida has large Black and Hispanic populations and lower high school completion than state and national rates, indicators for these aspects were included. Meanwhile, not having insurance and high healthcare costs discourages people from seeking medical help [60]. Personal health also influences sensitivity. Epidemiological research found extreme heat increased asthma [61], cardiovascular disease [62], and renal disease [63] hospitalizations. Similarly, studies determined people with diabetes [14], chronic obstructive pulmonary disease (COPD) [13], and disabilities [33,64] were at heightened risk for heat-related mortality.

2.1.3. Adaptive Capacity Indicators

Although commonly overlooked in urban heat vulnerability research, adaptive capacity is an integral aspect since it entails how people respond to dangerous heat. Higher household and community resource access generally reduces heat vulnerability including phone, Internet, medical facilities, swimming pools, libraries/malls, and parks (percent of population within a 0.8 km/10 min walk). The Internet is useful for accessing information about weather (e.g., daily temperature, heat advisories) and cool facility location [65] while phones facilitate automated heat warnings [66]. People seek reprieve from extreme heat in community cool spaces such as shopping malls, libraries, swimming pools, and public parks [67]. Hospital, urgent care, and emergency medical services access also influences vulnerability [68].

2.1.4. Data Preparation

Physical exposure and several adaptive capacity indicators (libraries/malls, medical facilities, and swimming pools) required conversion to the CT level in ArcMap 10.8. Average LST, imperviousness, tree canopy, and anthropogenic heat emissions were determined. Building footprint density along with water/wetlands ratios were calculated. Distances between CT urban centroids and the closest libraries/malls as well as medical facilities were measured; urban centroids were used to avoid biases from CT size and shape variation in addition to the existence of natural spaces. And lastly, the number of swimming pools per CT was counted. Following data compilation, the twenty-four indicators were assigned a direction of influence—increasing or decreasing vulnerability—based on a priori rationale, existing literature, and logical inferences. CT with no population or households were omitted, reducing the dataset to 1196 CT. Mean values were used for missing data since a fractional number of missing values does not require sophisticated imputation techniques [52].

2.2. Methods

2.2.1. Composite Indicator Construction

SFHVI was assembled consistent with the Handbook on Constructing Composite Indicators: Methodology and User Guide [52]. Composite indicators have notable benefits such as the ability to summarize complicated realities and guide decision making, interpretability compared to numerous individual variables, enabling input variable reduction without sacrificing underlying information, and allowing complex dimensional comparisons [52]. Accordingly, heat vulnerability assessments commonly utilize composite indicators when gauging population risk.

After univariate analysis, indicators were transformed closer to a Gaussian distribution using an inverse normal approach because skewness and outliers which were present can alter statistical tools (PCA), normalization, and index performance [52,69]. Data were then normalized (z-scores), adjusting for cardinality so that higher values denoted higher vulnerability, rendering data measured on different scales comparable. Z-scores were chosen to preserve data structure as other common methods like min-max can force indicators to fall within a relatively small interval influencing composite indicator outputs [52]. Spearman's rho affirmed high indicator correlation. Thus, statistical weights were derived

from principal component analysis (PCA) that essentially removed indicator overlap [52] since equal weighting, the most common HVI approach [48], introduces biases from double counting when variables correlate highly [52,70].

PCA was conducted in SPSS Statistics. Components were determined by Kaiser criterion, component eigenvalues exceeding one [71]; component grouping comprehensibility [72], indicators loading on the same component sharing a concept; indicator component loadings exceeding 0.500. Varimax rotation (100 rotations) and Kaiser criterion (100 iterations) were used ensuring indicators did not load highly on several components [52]. PCA weights were derived from the component loading matrix post rotation taking squared factor loadings as a ratio of component eigenvalues multiplied by the proportion of variance explained by a component with final weights scaled to 1 consistent with [52]. Assigned PCA weights eliminated multicollinearity rather than denoting relative influence determining vulnerability. Linear aggregation combined PCA components into a comprehensive SFHVI score because other aggregation techniques (e.g., geometric) are not compatible with negative values [70]. Outputs were scaled 1–100 producing final SFHVI scores, where 100 reflected the most vulnerable CT regionwide.

2.2.2. Hot Spot Analysis (Getis-Ord Gi*)

Getis-Ord Gi* statistics were produced in ArcMap 10.8 for SFHVI and its subdimensions (PCA components). This tool considers CT scores within the context of neighbors identifying areas of high/low vulnerability clusters by proportionally comparing the local sum of a CT and neighbors to the collective sum [73]. A contiguity (queen) neighborhood approach was chosen to accommodate CT shape/size variation and unbalanced distribution across the Southeast Florida landscape.

2.2.3. SFHVI Performance Assessment

Assessing HVI performance can illuminate methodological strengths and weaknesses as well as support or contradict results. Fine-scale validation data were too few and unstable (e.g., heat related mortality) or unavailable (e.g., heat-related hospitalizations) for Southeast Florida so model validation was unfeasible using these common metrics consistent with most prior urban heat vulnerability studies [48]. Alternatively, this analysis explored how SFHVI scores compared with other HVI because examining links to other indicators is a key methodological component [52] that is nearly always overlooked. Hence, this study statistically and qualitatively compared SFHVI scores with ten alternative models employing different methods (Table 2). Specifically, alternative decisions regarding data transformation, standardization, weighting, subdimension scaling, and subdimension aggregation were considered. Figure 2 overviews the methodological workflow.

Table 2. SFHVI and alternative model methodological overview.

Model	Transformed	Standardization	Weighting	Scaled	Aggregation
SFHVI	Yes	Z-score	PCA	No	Linear
Alternative 1	Yes	Z-score	Equal (none)	No	Linear
Alternative 2	Yes	Z-score	Equal (none)	Yes	Linear
Alternative 3	Yes	Z-score	PCA	Yes	Linear
Alternative 4	Yes	Min-Max	Equal (none)	No	Linear
Alternative 5	Yes	Min-Max	PCA	No	Linear
Alternative 6	Yes	Min-Max	Equal (none)	Yes	Linear
Alternative 7	Yes	Min-Max	PCA	Yes	Linear
Alternative 8	No	Z-score	Equal (none)	No	Linear
Alternative 9	No	Z-score	PCA	No	Linear
Alternative 10	Yes	Z-score	PCA	Yes	Geometric

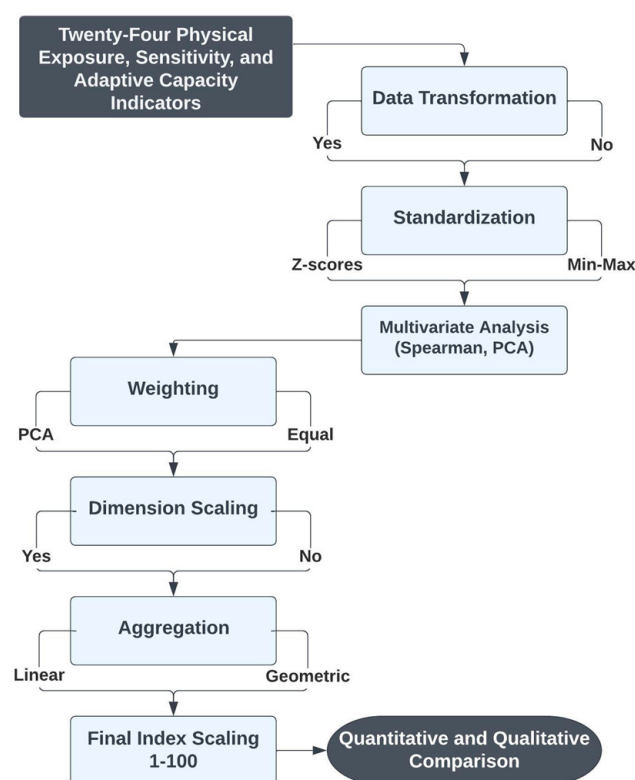


Figure 2. SFHVI and alternative model methodological workflow.

Ranked inverse normal transformation, which determines percentile ranks on which inverse normal transformation is applied, was chosen because common methods (e.g., log, square/cube root) failed to eliminate skewness/outliers. Conversely, two models utilized raw data like many prior HVI. While z-scores preserve data structure, the other most common standardization method, min-max [52], was also employed. The former measures the number of standard deviations an observation is from a variable mean whereas min-max converts data onto a consistent scale (0–1).

Equal (no) weights, where variables are theoretically assigned the same influence, are regularly used despite multicollinearity elevating the influence of highly correlating variables [52,70]. Thus, PCA-derived weights were also applied removing overlap [52]. Using raw subdimension scores preserves integrity while scaling facilitates comparison and aligns with hierarchically imposing subindex weights common amongst HVI. Scaling was also required for geometric aggregation, which is incompatible with z-scores due to negative values [52,70]. Linear aggregation assuming full compensability is primarily used for integrating HVI dimensions despite alternatives existing that assume partial (e.g., geometric) or full compensability. Therefore, geometric aggregation offering diminishing returns was likewise utilized, an uncommon HVI method.

First, alternative vulnerability scores were calculated reflecting the different methodological decisions. SFHVI and corresponding scores were then randomly sampled and processed through paired sample *t* tests determining if vulnerability score differences between paired observations were significantly different than zero. Additionally, alternative model scores were mapped for visual comparison examining whether there was geospatial agreement with SFHVI.

3. Results

3.1. PCA Assigned SFHVI Subdimensions

PCA grouped indicators into five components (C1–C5) with a 68.93% cumulative variance (Table 3), suggesting these explained 68.93% of the total data variance. PCA components denoted the following: C1, household characteristics and resources; C2, heat

exposure; C3, health variables compiled at the CT scale and age-dependent persons; C4, community resource access; C5, health variables compiled at the zip code scale.

Table 3. PCA component loading matrix and derived indicator weights.

	C1	C2	C3	C4	C5	Weight
Education	0.834	0.278	0.077	0.150	0.144	0.055
Poverty	0.802	0.138	0.096	−0.141	0.201	0.051
Health Insurance	0.779	0.204	−0.186	−0.057	0.176	0.048
Race/Ethnicity	0.760	0.360	−0.225	0.114	−0.022	0.046
Crowding	0.758	0.210	−0.223	−0.078	0.032	0.045
Internet	0.709	0.125	0.177	−0.225	0.076	0.040
Phone	0.527	−0.006	0.119	−0.289	0.043	0.022
Building Density	0.009	0.882	0.015	−0.243	−0.016	0.061
Water/Wetlands	0.192	0.771	0.044	0.046	0.214	0.047
LST	0.478	0.767	0.065	−0.066	0.132	0.046
Imperviousness	0.285	0.723	0.067	−0.411	0.117	0.041
Anthropogenic Heat	0.347	0.647	−0.058	−0.468	−0.059	0.033
Tree Canopy	0.319	0.506	0.083	−0.384	−0.200	0.020
Cardiovascular	−0.073	0.061	0.874	−0.037	0.165	0.060
Age Dependent	−0.302	−0.022	0.834	−0.044	−0.049	0.055
Disabilities	0.115	−0.024	0.825	0.013	0.178	0.054
Diabetes	0.420	0.154	0.633	0.095	0.193	0.032
Libraries/Malls	−0.099	−0.248	−0.020	0.661	0.039	0.034
Swimming Pools	0.345	0.334	−0.093	0.586	0.079	0.027
Medical Facilities	−0.089	−0.335	−0.066	0.579	−0.121	0.026
Parks	−0.196	−0.210	0.211	0.571	−0.188	0.026
COPD	0.191	0.136	0.344	−0.127	0.823	0.053
Asthma	0.451	0.036	−0.006	0.001	0.770	0.047
Renal	−0.071	0.071	0.505	−0.028	0.644	0.033
Eigenvalue Total	7.745	3.622	2.6	1.403	1.173	-
% Total Variance	32.273	15.091	10.835	5.845	4.887	-

Grey denotes designated PCA components.

As Figure 3 displays, highest C1 scores were predominantly in urban Miami Dade County (MDC), Broward County (BC), and Palm Beach County (PBC), such as greater Miami, Fort Lauderdale, and Riviera Beach. These areas are impoverished, ethnically and racially diverse, with fewer household resources. Rural and agricultural areas in MDC and PBC likewise scored high in C1. Highest C2 scores were in the same MDC, and to a lesser extent, BC urban areas where physical settings are conducive to heat—e.g., tightly packed houses; industrial, commercial, and institutional land uses; sparse natural features (e.g., vegetation, wetlands); extensive impervious surfaces.

Highest C3 scores were in urban pockets of BC, PBC, and to a lesser degree MDC, as well as coastal (Manalapan) and suburban (west Delray Beach) pockets of PBC, the latter likely resulting from a large presence of elderly retirees with high chronic illness and disability rates. C4 scores were highest in MDC and PBC rural, agricultural, as well as less developed areas along the urban agglomeration western fringe (Loxahatchee, Boynton Beach, and Weston) where the population density is lower and community resources fewer. Meanwhile, the highest C5 scores were primarily in urban as well as rural and agricultural CT in MDC and PBC (Homestead, Belle Glade) somewhat consistent with C3. Variation attests to the diverse Southeast Florida landscape comprising an urban agglomeration that is essentially engulfed by vast natural and agricultural areas.

3.2. SFHVI Spatial Variation

Figure 4 displays SFHVI results. The most vulnerable CTs regionwide were in urban MDC: Hialeah, Hialeah Gardens, and Miami neighborhoods like Little Havana, East Little Havana, and Allapattah. Although fewer and less pronounced, urban BC had highly vulnerable areas too, mostly in Fort Lauderdale and Pompano Beach, as well as several CTs

in PBC within Riviera Beach and West Palm Beach. Other urban areas with moderate-high SFHVI scores included Opa-Locka, West Miami, Miami Gardens, and North Miami in MDC; Lauderhill Lakes, Lauderhill, and West Park in BC in addition to Lake Worth Beach in PBC. High heat exposure, household characteristics and resources, health variables compiled at the CT scale and age-dependent persons, as well as health variables compiled at the zip code scale dimension scores primarily drive vulnerability in these urban areas. Conversely, the most susceptible urban CTs had relatively higher community resource access, somewhat curbing vulnerability despite a few exceptions.

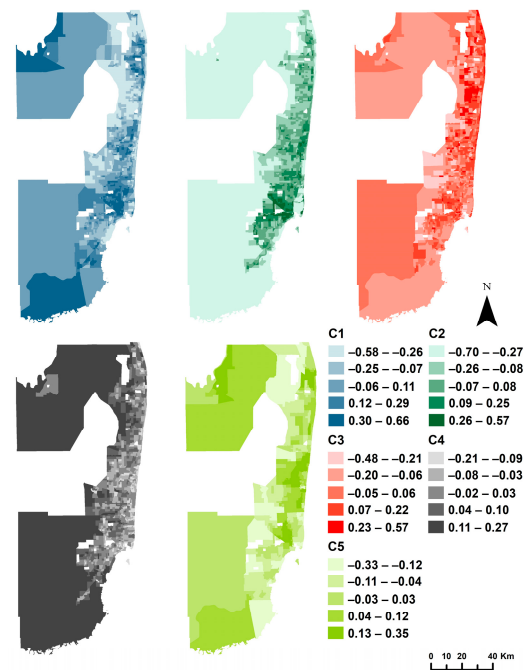


Figure 3. SFHVI subdimension spatial variation.

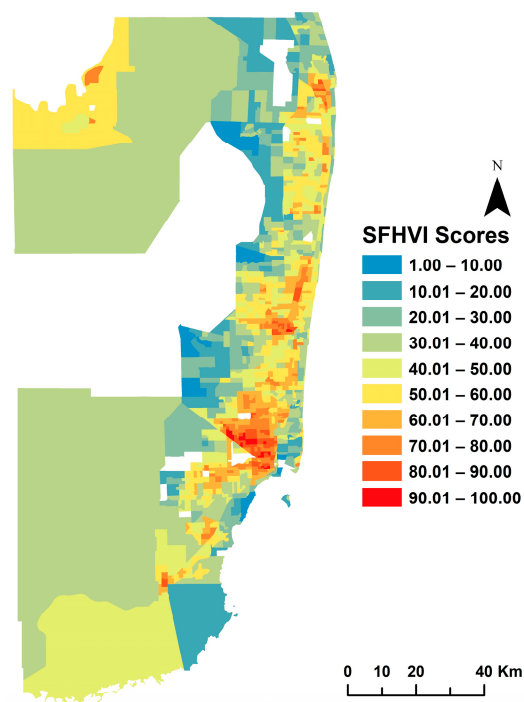


Figure 4. SFHVI spatial variation.

SFHVI identified some rural and agricultural areas as moderate-high (Belle Glade and Pahokee in PBC) to highly (Florida City in MDC) vulnerable. While counterintuitive since physical settings are not conducive to heat with fewer built surfaces, structures, or human heat emissions, vulnerability in these places is largely influenced by low household characteristics and resources, health variables compiled at the CT scale and age dependent persons, community resource access, and health variables compiled at the zip code scale dimension scores. On the other hand, the least vulnerable CTs were situated along the urban agglomeration western fringe (Royal Palm Beach, Wellington, Parkland, Weston), northern tip (Jupiter, Palm Beach Gardens, and Juno Beach), and coastal areas (Pinecrest, Palmetto Bay, Biscayne Bay, Palm Beach) that are often less developed and more affluent.

3.3. Getis-Ord G_i^* Results

Getis-Ord G_i^* results (Figure 5) mostly agreed with the urban areas exhibiting high SFHVI scores identified above with a pronounced cluster covering greater Miami, two smaller clusters in BC (Fort Lauderdale, Pompano Beach), and two even smaller clusters in PBC (Lake Worth Beach, Riviera Beach/West Palm Beach). SFHVI subdimension Getis-Ord G_i^* results (Figure 6) similarly reinforced previously discussed spatial patterns.

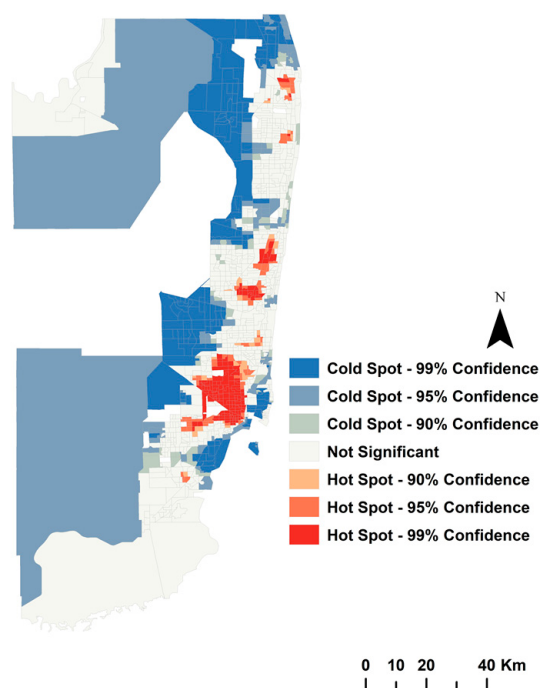


Figure 5. SFHVI Getis-Ord G_i^* hot spot results.

3.4. SFHVI Performance Assessment

SFHVI scores were statistically compared with ten alternative models (Table 4). Of the ten, three exhibited vulnerability scores not significantly different than SFHVI (95% confidence): Alternative 3 ($t = 1.665$; $p = 0.100$), Alternative 5 ($t = 1.916$; $p = 0.059$), and Alternative 7 ($t = 1.914$; $p = 0.059$). These models had mean differences of -0.95 , -0.44 , and -1.15 , respectively. Thus, SFHVI scores were typically higher than corresponding scores for the three similar models, which may be favorable to SFHVI producing lower scores because underrepresenting risk could foster false security hindering preventative efforts. While alternative model score differences with SFHVI were sometimes not pronounced (<2), certain models exhibited considerable differences such as Alternative 9 (>5) and Alternative 10 (>8) attesting to the impact of chosen HVI methodology.

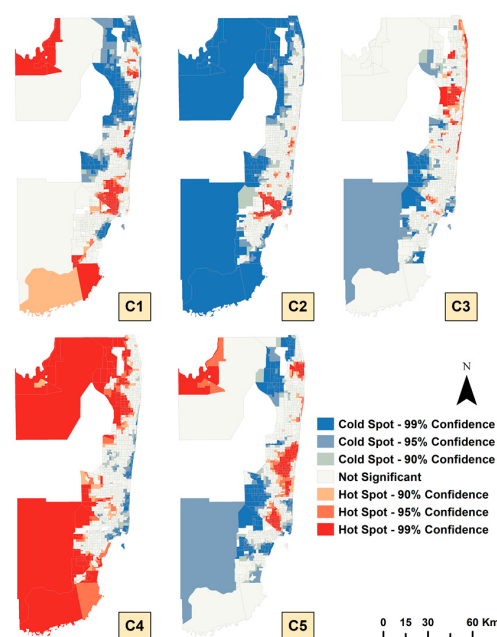


Figure 6. Getis-Ord G_i^* hot spot results for SFHVI subdimensions (C1–C5).

Table 4. Paired sample t test results comparing SFHVI scores with alternative models.

Model	Mean	t	Two-Sided p
SFHVI	50.24	-	-
Alternative 1	48.92	5.454	<0.001
Alternative 2	47.89	3.394	0.001
Alternative 3	49.29	1.665	0.100
Alternative 4	48.14	6.124	<0.001
Alternative 5	49.80	1.916	0.059
Alternative 6	47.81	3.292	0.001
Alternative 7	49.09	1.914	0.059
Alternative 8	48.29	2.631	0.010
Alternative 9	45.09	7.973	<0.001
Alternative 10	58.75	10.495	<0.001

Bold indicates statistically significant at $\alpha = 0.05$.

Seven alternative models produced vulnerability score means significantly differing from SFHVI (95% confidence). Methods using raw data (Alternative 8 and 9) or geometric aggregation (Alternative 10) yielded statistically different vulnerability scores. The former may reflect skewness or outliers of raw data impacting model outputs. The latter may reflect diminishing returns of geometric aggregation altering vulnerability scores since fully compensable linear aggregation allows high/low values to completely offset low/high values in other dimensions [52,70]. However, the similarity of Alternative 5 suggests switching between z-scores/min-max standardization may not markedly alter HVI outputs.

Removing indicator correlation with PCA-derived weights produced significantly different vulnerability scores than not addressing overlap (Alternative 1). Double counting could be present when not addressing correlation due to the large number of indicators employed and existing statistical associations. Quantitative performance assessment results emphasize the importance of data transformation consistent with statistical tool assumptions, exploring alternative aggregation techniques like geometric aggregation and addressing correlation for indices comprising many variables. Comparing SFHVI scores with alternative models demonstrates the oftentimes substantial impact that utilizing different methods has on assigned vulnerability scores.

Nevertheless, there was typically spatial agreement between SFHVI and alternative models regarding the most at-risk areas when applying a consistent vulnerability score

classification range (Figures 7 and 8). Highly urban CTs in places like Miami, Hialeah, Fort Lauderdale, Pompano Beach, and Riviera Beach were consistently the most vulnerable. Rural and agricultural CTs scored moderate-highly vulnerable across tested models also. Therefore, mitigation initiatives in these areas are likely warranted due to agreement across models. On the other hand, there was oftentimes agreement about the least vulnerable areas too: along the urban agglomeration western fringe, northern tip, and Atlantic Coast. Even so, some spatial differences were evident, particularly for CTs scoring somewhere along the middle of the vulnerability spectrum, demonstrating the impact that different methods can have on heat vulnerability maps.

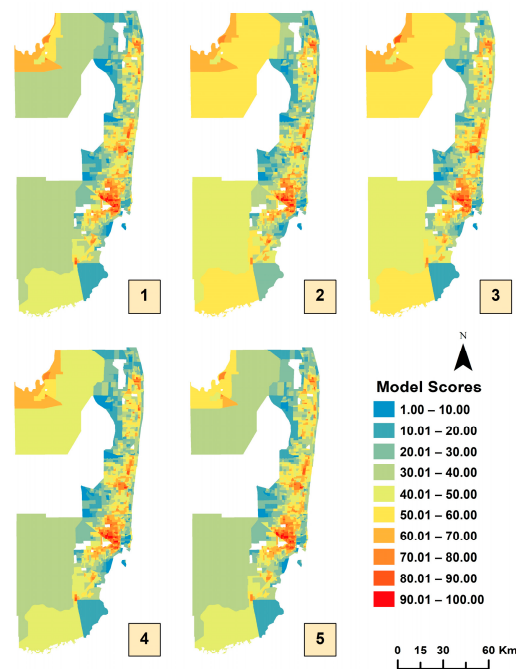


Figure 7. Alternative vulnerability model 1–5 spatial variation.

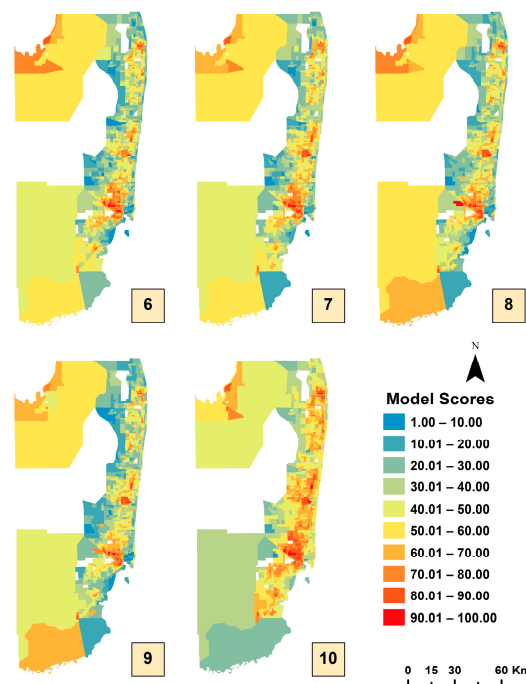


Figure 8. Alternative vulnerability model 6–10 spatial variation.

4. Discussion

SFHVI identified urban CTs with increased heat exposure (e.g., high LST and anthropogenic heat emissions, built settings conducive to heat, and sparse natural features) as the most vulnerable, which partly reflects greater population density and the presence of industrial and commercial land uses. These were situated in historically impoverished, racially, and ethnically diverse areas with fewer household resources (e.g., internet access), lower education, and insurance, where overcrowding is more common as these factors often closely associate. While previous urban heat vulnerability analyses found similar conclusions [24,33,74], integrating multiple indicators representing personal health as well as household and community resources provides additional information about what influences vulnerability within highly susceptible urban areas.

For instance, chronic illness prevalence (e.g., cardiovascular disease, diabetes, and asthma) exacerbated vulnerability within the most at-risk urban CTs. This may reflect inferior access to nutritious food, healthcare, and greenspaces as well as increased air pollution from vehicles. Poor diet and low physical activity cause morbidity for diseases that heat adversely impacts (e.g., cardiovascular and diabetes) [75], thus community gardens can lower chronic illness rates [76] while modulating nearby temperatures [77] in highly vulnerable urban areas. On the other hand, vulnerable urban CTs often had better community resource access (e.g., parks, libraries/malls, and swimming pools) due to higher population demand, which supports organizing a cool center network. However, this demands collaboration between civil society, government, and the private sector in order to ensure maximum population coverage, awareness, transportation, and user satisfaction.

As a regional analysis, this study also examined rural and agricultural locations that usually scored moderate to moderate-highly vulnerable despite having low heat exposure. Inferior health and community resource access largely drive vulnerability in rural and agricultural areas. Nonetheless, initiatives in these places may look different than urban CTs to address different conditions. For instance, targeting smoking may be advisable because tobacco use is more prevalent in rural areas [78]. Moreover, promoting awareness, issuing alerts, and conducting well-being checks for vulnerable persons may be practical short-term strategies to enhance adaptive capacity in rural and agricultural areas with low community resource access.

Neglecting health and adaptive capacity in heat vulnerability studies may produce inaccurate results. Traditional HVI prioritizing physical environment, demographic, and socioeconomic indicators like [43–45] would likely overpredict vulnerability in urban locations while underpredicting vulnerability in rural and agricultural locations. Despite heat exposure, household characteristics and resources, and health typically elevating susceptibility in urban CTs, these areas normally had better community resource access curbing risk. Meanwhile, inferior health and community resource access both exacerbated vulnerability within rural and agricultural CTs. Urban–rural community resource access disparities emphasize the importance of including adaptability indicators when examining an urban area and its surroundings. Incorporating these integral aspects potentially improved SFHVI accuracy.

Illuminating population health and adaptive capacity provides crucial insights for reducing extreme heat impacts since warming temperatures will likely increase mortality for people with chronic diseases [79] while adaptive capacity offers cost-effective, modifiable alternatives to physical solutions [3]. Further, analyses can expand the pool of health and adaptability indicators employed. Factors like obesity, smoking, and physical activity; cooling behaviors, threat perceptions, and attitudes/beliefs; community, familial, and neighbor support systems; as well as governance, existing and abstract mitigation plans should be considered. Incorporating these overlooked variables and an array of relevant others will enhance HVI comprehensiveness [20,48]. Analyses must also account for homeless persons—a group almost always overlooked in HVI—because homeless people have increased risk exposure to environmental threats [80].

As conventional performance assessment was unavailable due to data constraints for Southeast Florida, SFHVI was compared with ten models constructed using alternative methods. Limited public health data availability has impeded urban heat vulnerability research with only about 26% of studies validating results largely for this reason [48]. Comparing SFHVI with alternative vulnerability models demonstrates that subjective choices at various methodological stages can substantially influence assigned vulnerability scores and associated spatial distribution consistent with prior studies [45,46]. Using raw/transformed data and linear/geometric aggregation produced significant vulnerability score differences while other methodological choices like z-scores/min-max produced relatively small, insignificant differences.

Results show weights derived from PCA removing indicator correlation, an uncommon technique in HVI, produced vulnerability scores differing significantly from equal weights not addressing correlation. Similarly, ref. [46] compared equal weights and standard PCA weights, the most common methods [48], finding vulnerability scores and associated spatial patterns varied. This underscores a need to explore methodological approach effectiveness more thoroughly at different HVI construction phases since most used traditional methods when many alternatives exist. Ref. [54] articulated a similar need specific to weighting. Moreover, HVI performance has varied [48], further supporting the need to evaluate alternative methods.

Uncommon weighting techniques like subject expert opinions [53] or statistical weights derived using health outcome data (e.g., heat-related mortality) may produce superior performance compared with traditional methods. Additionally, multiplicative aggregation should be rigorously explored since prior studies primarily use the additive principle when combining index dimensions. Multiplicative aggregation better captures inter-dimensional complexity [81] and has been applied in urban vulnerability studies focusing on other environmental threats like flooding [82]. Understanding how methodological decisions impact outputs and performance is crucial for enhancing HVI.

Despite sometimes notable vulnerability score differences between SFHVI and alternative models, there was oftentimes geospatial agreement about the most susceptible locations. However, there were geospatial inconsistencies as well. Although prior studies constructed several indices mostly when evaluating methodological approaches [45–47,51], analyses overwhelmingly interpret one HVI despite exploring how results compare with other models being a fundamental composite indicator aspect [52]. This is especially problematic because subjective methodological decisions at various HVI construction stages can substantially impact assigned vulnerability scores and associated spatial distribution like this analysis of Southeast Florida demonstrates.

The essence of HVI is identifying areas where strategies are needed to reduce health risks from extreme heat. As tools intended to direct policy and decision-making, future studies should refrain from only considering one HVI unless validation with heat-related health outcome data reveals sufficient performance because inaccurate findings may inadvertently mislead decisionmakers hindering mitigative efforts. Even then, comparing multiple HVI is advisable to gain a more comprehensive understanding of heat vulnerability [47,51] and bolster conviction about susceptible populations. Condensing information should facilitate interpretability for policymakers since interpreting multiple HVI featuring similar/contrasting information may be challenging [51].

It is strongly recommended that future HVI adopt a multimodal approach like this study of Southeast Florida—particularly if the goal is to inform mitigation and/or validation data is unavailable. When data permits, HVI must not only be compared with models comprising the same variables constructed using varied methods but should expand to HVI from prior analyses featuring a different blend of indicators. Ideally, these would include high-performing HVI further generating conviction about results when there is agreement between models. Exploring links to other HVI can likewise illuminate methodological weaknesses enabling improvement. In that same vein, HVI should be regularly updated with the newest data to capture changing community conditions. Collectively, this should

enhance HVI performance and paint a more accurate picture for decisionmakers that better informs mitigation.

5. Conclusions

Nearly all heat vulnerability analyses interpret one HVI without considering how results compare to other models, making this study novel through its utilization of multiple HVI for purposes other than primarily evaluating methods. Highly urban areas with relatively degraded physical environments, socioeconomic conditions, health, and household resources were exceedingly vulnerable despite having better community resource access. Some rural and agricultural areas were also vulnerable despite lower heat exposure reflecting socioeconomic conditions, health, and community resources. Incorporating health and adaptability increased SFHVI complexity, yet future studies must broaden the pool of included variables.

Despite general spatial agreement regarding the most at-risk areas, only three alternative models produced statistically similar vulnerability scores to SFHVI while seven differed significantly. Subjective methodological decisions can substantially impact assigned vulnerability scores and resulting spatial patterns. For instance, vulnerability scores sometimes shifted upwards of 8, on average, on a 1–100 scale when applying different methods. Other times, average vulnerability score differences were not pronounced (less than 2). There was also noteworthy spatial variation across models, mostly for CTs falling within the middle of the vulnerability spectrum.

Overall, results underscore the practicality of multimodal HVI. Future research should employ multimodal approaches enhancing analysis comprehensiveness, especially if results are intended to direct heat mitigation initiatives or validation data is unavailable. Since inaccurate HVI can misinform decisionmakers, comparing multiple models increases confidence identifying vulnerable populations. Multimodal approaches offer a tentative mechanism for performance assessment and comparing several HVI can highlight methodological flaws. Hence, multimodal HVI advance heat vulnerability assessment and should be increasingly applied going forward.

In addition to those mentioned, this analysis had other limitations. Pertinent variables were excluded like air conditioning, sea breeze, and humidity. Air conditioning decreases heat mortality [83], coastal advection can cool urban temperatures [4], and humidity elevates heat index. Studies in warm, humid coastal areas must incorporate these facets. Moreover, LST was used over air temperatures excluding hot season data when heat-related health outcomes peak due to extensive cloud cover. PCA-derived weights did not reflect importance but removed multicollinearity, which differs from reality where some factors are more influential determining vulnerability. The need for more precise weights is evident. Most HVI in this study used transformed data removing skewness/outliers, albeit transforming data can drastically alter values and statistical tool results influencing vulnerability scores. Addressing noted shortcomings should improve HVI.

Increasingly accurate heat vulnerability assessment is vital to foster healthier, more equitable cities. The vast majority of studies were conducted on census units, administrative areas, or grids [48], so granular analyses (e.g., neighborhood and city block) are needed to enhance precision. This may require interviewing or surveying residents as most relevant datasets reflect coarser scales (e.g., sociodemographic and health), which would enable researchers to obtain overlooked information (e.g., cooling behaviors and threat perceptions) also improving comprehensiveness. Granular studies could naturally integrate fine-scale urban heat stress models like [29].

Additionally, research is needed to examine heat vulnerability spatiotemporal characteristics—particularly, diurnal and nocturnal differences. While analyses almost exclusively gauge daytime heat risk, a recent study found the ratio of susceptible urban areas is higher at night [84]. Moreover, diurnal/nocturnal heat exposure patterns vary, and some studies found stronger UHI during nighttime [30,85,86]. Therefore, understanding

spatiotemporal variation may provide crucial insights for decisionmakers. These analyses should include factors that change temporally (e.g., heat flux and air conditioning use).

Southeast Florida faces formidable environmental threats including extreme heat. Alleviating health impacts for the more than 6.1 million people there is pivotal, which involves granularly identifying vulnerable populations and key determinants to effectively allocate resources. This will prove challenging in a region where urbanization and climate change will continue altering the thermal landscape and shift neighborhood characteristics. Thus, accurately locating at-risk populations will reduce health impacts and possibly save lives as temperatures climb throughout Southeast Florida.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi12060242/s1>, Landsat 8 image pair details.

Author Contributions: Conceptualization, Kevin Cresswell, Diana Mitsova, Weibo Liu, Maria Fadiman, and Tobin Hindle; methodology, Kevin Cresswell; software, Kevin Cresswell; validation, Kevin Cresswell; formal analysis, Kevin Cresswell; investigation, Kevin Cresswell; resources, Kevin Cresswell; data curation, Kevin Cresswell; writing—original draft preparation, Kevin Cresswell; writing—review & editing, Kevin Cresswell, Diana Mitsova, Weibo Liu, Maria Fadiman and Tobin Hindle; supervision, Diana Mitsova, Weibo Liu, Maria Fadiman, and Tobin Hindle; project administration, Diana Mitsova, Weibo Liu, Maria Fadiman, and Tobin Hindle. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: We would like to thank the three anonymous reviewers and editors for providing valuable comments and suggestions which helped improve the manuscript greatly.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. United States Environmental Protection Agency. Available online: <https://www.epa.gov/heatislands/heat-island-impacts#> (accessed on 2 November 2022).
2. Heaviside, C.; Macintyre, H.; Vardoulakis, S. The urban heat island: Implications for health in a changing environment. *Curr. Environ. Health Rep.* **2017**, *4*, 296–305. [CrossRef] [PubMed]
3. Filho, W.; Echevarria, L.; Neht, A.; Klavins, M.; Morgan, E. Coping with the impacts of urban heat islands: A literature-based study on understanding urban heat vulnerability and the need for resilience in cities in a global climate change context. *J. Clean. Prod.* **2018**, *171*, 1140–1149. [CrossRef]
4. Kotharkar, R.; Ramesh, A.; Bagade, A. Urban heat island studies in Southeast Asia: A critical review. *Urban Clim.* **2018**, *24*, 1111–1126. [CrossRef]
5. United Nations. *World Urbanization Prospects: The 2018 Revision*; United Nations: New York, NY, USA, 2019. Available online: <https://population.un.org/wup/publications/Files/WUP2018-Report.pdf> (accessed on 2 November 2022).
6. Zhao, L.; Oleson, K.; Bou-Zeid, E.; Krayenhoff, E.S.; Bray, A.; Zhu, Q.; Zheng, Z.; Chen, C.; Oppenheimer, M. Global multi-model projections of local urban climates. *Nat. Clim. Chang.* **2021**, *11*, 152–157. [CrossRef]
7. IPCC. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; IPCC: Geneva, Switzerland, 2014. Available online: <https://www.ipcc.ch/report/ar5/wg2/> (accessed on 3 January 2022).
8. Perkins-Kirkpatrick, S.E.; Lewis, S.C. Increasing trends in regional heatwaves. *Nat. Commun.* **2020**, *11*, 3357. [CrossRef] [PubMed]
9. Li, D.; Bou-Zeid, E. Synergistic interactions between urban heat islands and heat waves: The impact in cities is larger than the sum of its parts. *J. Appl. Meteorol. Climatol.* **2013**, *52*, 2051–2064. [CrossRef]
10. Li, D.; Sun, T.; Liu, M.; Yang, L.; Wang, L.; Gao, Z. Contrasting responses of urban and rural surface energy budgets to heat waves explain synergies between urban heat islands and heat waves. *Environ. Res. Lett.* **2015**, *10*, 054009. [CrossRef]
11. National Weather Service. Weather Related Fatality and Injury Statistics. Available online: <https://www.weather.gov/hazstat/> (accessed on 20 January 2023).
12. Morano, L.H.; Watkins, S.; Kintziger, K. A comprehensive evaluation of the burden of heat-related illness and death within the Florida population. *Int. J. Environ. Res. Public Health* **2016**, *13*, 551. [CrossRef] [PubMed]
13. Ma, Y.; Zhou, L.; Chen, K. Burden of cause-specific mortality attributable to heat and cold: A multicity timeseries study in Jiangsu Province, China. *Environ. Int.* **2020**, *144*, 105994. [CrossRef]

14. Moon, J. The effect of the heatwave on the morbidity and mortality of diabetes patients; a meta-analysis for the era of the climate crisis. *Environ. Res.* **2021**, *195*, 110762. [CrossRef] [PubMed]
15. Santamouris, M. Recent progress on urban overheating and heat island research. Integrated assessment of the energy, environmental, vulnerability and health impact. Synergies with the global climate change. *Energy Build.* **2020**, *207*, 109482. [CrossRef]
16. Wilhelmi, O.V.; Hayden, M.H. Connecting people and place: A new framework for reducing urban vulnerability to extreme heat. *Environ. Res. Lett.* **2010**, *5*, 014021. [CrossRef]
17. Wilson, B.; Chakraborty, A. Mapping vulnerability to extreme heat events: Lessons from metropolitan Chicago. *J. Environ. Plan. Manag.* **2019**, *62*, 1065–1088. [CrossRef]
18. Cutter, S.L.; Mitchell, J.T.; Scott, M.S. Revealing the vulnerability of people and places: A case study of Georgetown, South Carolina. *Ann. Assoc. Am. Geogr.* **2000**, *90*, 712–737. [CrossRef]
19. Levy, B.S.; Patz, J.A. Climate change, human rights, and social justice. *Ann. Glob. Health* **2015**, *81*, 310–322. [CrossRef] [PubMed]
20. Niu, Y.; Li, Z.; Gao, Y.; Liu, X.; Xu, L.; Vardoulakis, S.; Yue, Y.; Wang, J.; Liu, Q. A Systematic Review of the Development and Validation of the Heat Vulnerability Index: Major Factors, Methods, and Spatial Units. *Curr. Clim. Chang. Rep.* **2021**, *7*, 87–97. [CrossRef] [PubMed]
21. Du, H.; Wang, D.; Wang, Y.; Zhao, X.; Qin, F.; Jiang, H.; Cali, Y. Influences of land cover types, meteorological conditions, anthropogenic heat, and urban area on surface urban heat island in the Yangtze River Delta urban agglomeration. *Sci. Total Environ.* **2016**, *571*, 461–470. [CrossRef]
22. Zhou, D.; Xiao, J.; Bonafoni, S.; Berger, C.; Deilami, K. Satellite remote sensing of the surface urban heat island: Progress, challenges, and perspectives. *Remote Sens.* **2019**, *11*, 48. [CrossRef]
23. Rajagopal, P.; Priya, R.S.; Senthil, R. A review of recent developments in the impact of environmental measures on urban heat island. *Sustain. Cities Soc.* **2023**, *88*, 104279. [CrossRef]
24. Harlan, S.L.; Brazel, A.J.; Prashad, L.; Stefanov, W.L.; Larsen, L. Neighborhood microclimates and vulnerability to heat stress. *Soc. Sci. Med.* **2006**, *63*, 2847–2863. [CrossRef]
25. Alhawiti, R.H.; Mitsova, D. Using Landsat-8 data to explore the correlation between urban heat islands and urban land uses. *Int. Res. J. Eng. Technol.* **2016**, *5*, 457–466.
26. Liu, W.; Feddema, J.; Hu, L.; Zung, A.; Brunsell, N. Seasonal and diurnal characteristics of land surface temperature and major explanatory factors in Harris County, Texas. *Sustainability* **2017**, *9*, 2324. [CrossRef]
27. Mathew, A.; Sarwesh, P.; Khandelwal, S. Investigating the contrast diurnal relationship of land surface temperatures with various surface parameters represent vegetation, soil, water, and urbanization over Ahmedabad city in India. *Energy Nexus* **2022**, *5*, 100044. [CrossRef]
28. Jamei, E.; Ossen, D.R.; Seyedmahmoudian, M.; Sandanayake, M.; Stojcevski, A.; Horan, B. Urban design parameters for heat mitigation in tropics. *Renew. Sustain. Energy Rev.* **2020**, *134*, 110362. [CrossRef]
29. Souverijns, N.; De Ridder, K.; Veldeman, N.; Lefebvre, F.; Kusambiza-Kiingi, F.; Memela, W.; Jones, N.K. Urban heat in Johannesburg and Ekurhuleni, South Africa: A meter-scale assessment and vulnerability analysis. *Urban Clim.* **2022**, *46*, 101331. [CrossRef] [PubMed]
30. Mishra, M.K.; Mathew, A. Investigating the spatio-temporal correlation between urban heat island and atmospheric pollution island interaction over Delhi, India using geospatial techniques. *Arab. J. Geosci.* **2022**, *15*, 1591. [CrossRef]
31. Naikoo, M.W.; Islam, A.R.M.T.; Mallick, J.; Rahman, A. Land use/land cover change and its impact on surface urban heat island and urban thermal comfort in a metropolitan city. *Urban Clim.* **2022**, *41*, 101052. [CrossRef]
32. Doan, V.Q.; Kusaka, H.; Nguyen, T.M. Roles of past, present, and future land use and anthropogenic heat release changes on urban heat island effects in Hanoi, Vietnam: Numerical experiments with a regional climate model. *Sustain. Cities Soc.* **2019**, *47*, 101479. [CrossRef]
33. Chow, W.T.; Chuang, W.C.; Gober, P. Vulnerability to extreme heat in metropolitan Phoenix: Spatial, temporal, and demographic dimensions. *Prof. Geogr.* **2012**, *64*, 286–302. [CrossRef]
34. Runkle, J.; Kunkel, K.; Champion, S.; Frankson, R.; Stewart, B.; Sweet, W. *Florida State Climate Summary, NOAA Technical Report NESDIS 149-FL*; NOAA/NESDIS: Silver Spring, MD, USA, 2017.
35. Rayer, S.; Wang, Y. Projections of Florida Population by County, 2020–2045, with Estimates for 2016. BEBR 2017, 50. Available online: https://www.bebbr.ufl.edu/sites/default/files/Research%20Reports/projections_2020.pdf (accessed on 3 November 2022).
36. Gupta, N.; Mathew, A.; Khandelwal, S. Spatio-temporal impact assessment of land use/land cover (LU-LC) change on land surface temperatures over Jaipur city in India. *Int. J. Urban Sustain. Dev.* **2020**, *12*, 283–299. [CrossRef]
37. Sam, S.C.; Balasubramanian, G. Spatiotemporal detection of land use/land cover changes and land surface temperature using Landsat and MODIS data across the coastal Kanyakumari district, India. *Geod. Geodyn.* **2023**, *14*, 172–181. [CrossRef]
38. Kandel, H.; Melesse, A.; Whitman, D. An analysis of the urban heat island effect using radiosonde profiles and Landsat imagery with ground meteorological data in South Florida. *Int. J. Remote Sens.* **2016**, *37*, 2313–2337. [CrossRef]
39. Hames, E.; Stoler, J.; Emrich, C.T.; Tewaru, S.; Pandya, N. A GIS approach to identifying socially and medically vulnerable older adult populations in South Florida. *Gerontologist* **2017**, *57*, 1133–1141. [CrossRef] [PubMed]

40. Johnson, D.P.; Stanforth, A.; Lulla, V.; Lubet, G. Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. *Appl. Geogr.* **2012**, *35*, 23–31. [\[CrossRef\]](#)
41. Harlan, S.L.; Declet-Barreto, J.H.; Stefanov, W.L.; Petitti, D.B. Neighborhood effects on heat deaths: Social and environmental predictors of vulnerability in Maricopa County, Arizona. *Environ. Health Perspect.* **2013**, *121*, 197–204. [\[CrossRef\]](#)
42. Mushore, T.D.; Mutanga, O.; Odindi, J.; Dube, T. Determining extreme heat vulnerability of Harare Metropolitan City using multispectral remote sensing and socio-economic data. *J. Spat. Sci.* **2017**, *63*, 173–191. [\[CrossRef\]](#)
43. Méndez-Lázaro, P.; Muller-Karger, F.E.; Otis, D.; McCarthy, M.J.; Rodriguez, E. A heat vulnerability index to improve urban public health management in San Juan, Puerto Rico. *Int. J. Biometeorol.* **2018**, *62*, 709–722. [\[CrossRef\]](#)
44. Nayak, S.G.; Shrestha, S.; Kinney, P.L.; Ross, Z.; Sheridan, S.C.; Pantea, C.I.; Hsu, W.H.; Muscatello, N.; Hwang, S.A. Development of a heat vulnerability index for New York State. *Public Health* **2018**, *161*, 127–137. [\[CrossRef\]](#)
45. Conlon, K.C.; Mallen, E.; Gronlund, C.J.; Berrocal, V.J.; Larsen, L.; O'Neill, M.S. Mapping human vulnerability to extreme heat: A critical assessment of heat vulnerability indices created using principal components analysis. *Environ. Health Perspect.* **2020**, *128*, 097001. [\[CrossRef\]](#) [\[PubMed\]](#)
46. Liu, X.; Yu, W.; Yang, X.; Hu, K.; Zhang, W.; Huang, M. Mapping urban heat vulnerability of extreme heat in Hangzhou via comparing two approaches. *Complexity* **2020**, *2020*, 9717658. [\[CrossRef\]](#)
47. Karanja, J.; Wanyama, D.; Kiage, L. Weighting mechanics and the spatial pattern of composite metrics of heat vulnerability in Atlanta, Georgia, USA. *Sci. Total Environ.* **2022**, *812*, 151432. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Li, F.; Yigitcanlar, T.; Nepal, M.; Thanh, K.; Dur, F. Understanding Urban Heat Vulnerability Assessment Methods: A PRISMA Review. *Energies* **2022**, *15*, 6998. [\[CrossRef\]](#)
49. Zhang, W.; Zheng, C.; Chen, F. Mapping heat-related health risks of elderly citizens in mountainous area: A case study of Chongqing, China. *Sci. Total Environ.* **2019**, *663*, 852–866. [\[CrossRef\]](#)
50. Mallen, F.; Stone, B.; Lanza, K. A methodological assessment of extreme heat mortality modeling and heat vulnerability mapping in Dallas, Texas. *Urban Clim.* **2019**, *30*, 100528. [\[CrossRef\]](#)
51. Räsänen, A.; Heikkinen, K.; Piila, N.; Juhola, S. Zoning and weighting in urban heat island vulnerability and risk mapping in Helsinki, Finland. *Reg. Environ. Chang.* **2019**, *19*, 1481–1493. [\[CrossRef\]](#)
52. Joint Research Centre-European Commission. *Handbook on Constructing Composite Indicators: Methodology and User Guide*; OECD Publishing: Berlin, Germany, 2008.
53. Bao, J.; Li, X.; Yu, C. The construction and validation of the heat vulnerability index, a review. *Int. J. Environ. Res. Public Health* **2015**, *12*, 7220–7234. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Karanja, J.; Kiage, L. Perspectives on spatial representation of urban heat vulnerability. *Sci. Total Environ.* **2021**, *774*, 145634. [\[CrossRef\]](#)
55. Jung, P.H.; Thill, J.C.; Issel, M. Spatial autocorrelation and data uncertainty in the American Community Survey: A critique. *Int. J. Geogr. Inf. Sci.* **2019**, *33*, 1155–1175. [\[CrossRef\]](#)
56. Artis, D.A.; Carnahan, W.H. Survey of emissivity variability in thermography of urban areas. *Remote Sens. Environ.* **1982**, *12*, 313–329. [\[CrossRef\]](#)
57. Zhu, Z.; Wang, S.; Woodcock, C.E. Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. *Remote Sens. Environ.* **2015**, *159*, 269–277. [\[CrossRef\]](#)
58. Santamouris, M.; Kolokotsa, D. *Urban Climate Mitigation Techniques*, 1st ed.; Routledge: London, England, 2016.
59. Cornell, C.; Gurrán, N.; Lea, T. *Climate Change, Housing, and Health: A Scoping Study on Intersections Between Vulnerability, Housing Tenure, and Potential Adaptation Responses*; The University of Sydney, NSW Health, and the NSW Department of Planning, Industry and Environment: Sydney, NSW, Australia, 2020.
60. Taber, J.M.; Leyva, B.; Persoskie, A. Why do people avoid medical care? A qualitative study using national data. *J. Gen. Intern. Med.* **2015**, *30*, 290–297. [\[CrossRef\]](#) [\[PubMed\]](#)
61. Soneja, S.; Jiang, C.; Fisher, J.; Upperman, C.R.; Mitchell, C.; Sapkota, A. Exposure to extreme heat and precipitation events associated with increased risk of hospitalization for asthma in Maryland, U.S.A. *Environ. Health* **2016**, *15*, 57. [\[CrossRef\]](#) [\[PubMed\]](#)
62. Lin, S.; Luo, M.; Walker, R.J.; Liu, X.; Hwang, S.A.; Chinery, R. Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. *Epidemiology* **2009**, *20*, 738–746. [\[CrossRef\]](#)
63. Fletcher, B.A.; Lin, S.; Fitzgerald, E.F.; Hwang, S.A. Association of summer temperatures with hospital admissions for renal diseases in New York state: A case-crossover study. *Am. J. Epidemiol.* **2012**, *175*, 907–916. [\[CrossRef\]](#) [\[PubMed\]](#)
64. Buscail, C.; Upegui, E.; Viel, J.F. Mapping heatwave health risk at the community level for public health action. *Int. J. Health Geogr.* **2012**, *11*, 38. [\[CrossRef\]](#) [\[PubMed\]](#)
65. Nayak, S.G.; Lin, S.E.; Sheridan, S.C.; Lu, Y.; Graber, N.; Primeau, M.; Rafferty, C.J.; Hwang, S.A. Surveying local health departments and county emergency management offices on cooling centers as a heat adaptation resource in New York State. *J. Community Health Res.* **2017**, *42*, 43–50. [\[CrossRef\]](#) [\[PubMed\]](#)
66. Mehiriz, K.; Gosselin, P.; Tardif, I.; Lemieux, M.A. The Effect of an automated phone warning and health advisory system on adaptation to high heat episodes and health services use in vulnerable groups-evidence from a randomized controlled study. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1581. [\[CrossRef\]](#)

67. Sampson, N.R.; Gronlund, C.J.; Buxton, M.A.; Catalano, L.; White-Newsome, J.L.; Conlon, K.C.; O'Neill, M.S.; McCormick, S.; Parker, E.A. Staying cool in a changing climate: Reaching vulnerable populations during heat events. *Global Environ. Chang.* **2013**, *23*, 475–484. [\[CrossRef\]](#)
68. Mirzaei, S.; Eftekhari, A.; Sadeghian, M.; Kazemi, S.; Nadjarzadeh, A. The effect of disaster management training program on knowledge, attitude, and practice of hospital staffs in natural disasters. *J. Disaster Emerg. Res.* **2020**, *2*, 9–16. [\[CrossRef\]](#)
69. Nardo, M.; Saisana, M.; Saltelli, A.; Tarantola, S. *Tools for Composite Indicators Building*; European Commission, Institute for the Protection and Security of the Citizen, JRC: Ispra, Italy, 2005.
70. Greco, S.; Ishizaka, A.; Tasiou, M.; Torrisi, G. On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Soc. Indic. Res.* **2019**, *141*, 61–94. [\[CrossRef\]](#)
71. Kaiser, H.F. A second generation Little-Jiffy. *Psychometrika* **1960**, *35*, 401–415. [\[CrossRef\]](#)
72. O'Rourke, N.; Hatcher, L. *A Step-by-Step Approach to Using SAS for Factor Analysis and Structural Equation Modeling*, 2nd ed.; SAS Institute Inc: Cary, NC, USA, 2013.
73. Mitchell, A. *The ESRI Guide to GIS Analysis*, 2nd ed.; ESRI Press: Redlands, CA, USA, 2005.
74. Barron, L.; Ruggieri, D.; Branas, C. Assessing vulnerability to heat: A geospatial analysis for the City of Philadelphia. *Urban Sci.* **2018**, *2*, 38. [\[CrossRef\]](#)
75. Powell, H.S.; Greenberg, D.L. Screening for unhealthy diet and exercise habits: The electronic health record and a healthier population. *Prev. Med. Rep.* **2019**, *14*, 100816. [\[CrossRef\]](#) [\[PubMed\]](#)
76. Al-Delaimy, W.K.; Webb, M. Community Gardens as Environmental Health Interventions: Benefits Versus Potential Risks. *Curr. Environ. Health. Rep.* **2018**, *4*, 252–265. [\[CrossRef\]](#) [\[PubMed\]](#)
77. Zhang, Y.; Smith, J.P.; Tong, D.; Turner, B.L. Optimizing the co-benefits of food desert and urban heat mitigation through community garden planning. *Landsca. Urban Plan.* **2022**, *226*, 104488. [\[CrossRef\]](#)
78. Buettner-Schmidt, K.; Miller, D.R.; Maack, B. Disparities in Rural Tobacco Use, Smoke-Free Policies, and Tobacco Taxes. *West. J. Nurs. Res.* **2019**, *41*, 1184–1202. [\[CrossRef\]](#)
79. Chen, K.; Horton, R.M.; Bader, D.A.; Lesk, C.; Jiang, L.; Jones, B.; Zhou, L.; Chen, X.; Bi, J.; Kinney, P.L. Impact of climate change on heat-related mortality in Jiangsu Province, China. *Environ. Pollut.* **2017**, *224*, 317–325. [\[CrossRef\]](#) [\[PubMed\]](#)
80. Bezgrebelna, M.; McKenzie, K.; Wells, S.; Ravindran, A.; Kral, M.; Christensen, J.; Stergiopoulos, V.; Gaetz, S.; Kidd, S.A. Climate change, weather, housing precarity, and homelessness: A systematic review of reviews. *Int. J. Environ. Res. Public Health* **2021**, *18*, 5812. [\[CrossRef\]](#)
81. Estoque, R.C.; Ooba, M.; Seposo, X.T.; Togawa, T.; Hijioka, Y.; Takahashi, K.; Nakamura, S. Heat health risk assessment in Philippine cities using remotely sensed data and social-ecological indicators. *Nat. Commun.* **2020**, *11*, 1581. [\[CrossRef\]](#)
82. Lee, J.S.; Choi, H.I. Comparison of flood vulnerability assessments to climate change by construction frameworks for a composite indicator. *Sustainability* **2018**, *10*, 768. [\[CrossRef\]](#)
83. Sera, F.; Hashizume, M.; Honda, Y.; Lavigne, E.; Schwartz, J.; Zanobetti, A.; Tobias, A.; Iñiguez, C.; Vicedo-Cabrera, A.M.; Blangiardo, M.; et al. Air conditioning and heat-related mortality: A multi-country longitudinal study. *Epidemiology* **2020**, *31*, 779–787. [\[CrossRef\]](#) [\[PubMed\]](#)
84. Jiang, S. Compound heat vulnerability in the record-breaking hot summer of 2022 over the Yangtze River Delta Region. *Int. J. Environ. Res. Public Health* **2023**, *20*, 5539. [\[CrossRef\]](#) [\[PubMed\]](#)
85. Charabi, Y.; Bakhit, A. Assessment of the canopy urban heat island of a coastal arid tropical city: The case of Muscat, Oman. *Atmos. Res.* **2011**, *101*, 215–227. [\[CrossRef\]](#)
86. Peng, J.; Ma, J.; Liu, Q.; Liu, Y.; Hu, Y.N.; Li, Y.; Yue, Y. Spatial-temporal change of land surface temperature across 285 cities in China: An urban-rural contrast perspective. *Sci. Total Environ.* **2018**, *635*, 487–497. [\[CrossRef\]](#) [\[PubMed\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.