



國立臺灣大學理學院氣候變遷與永續發展國際學位學程

碩士論文

International Degree Program in Climate Change and Sustainable Development

College of Science

National Taiwan University

Master's Thesis

利用觀測為主之網格化資料分析台灣熱壓力

與人口暴露之時空變化

Spatiotemporal Analysis of WBGT-Based Heat Stress

and Population Exposure in Taiwan

Using Observation-Based Gridded Data

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中華民國 115 年 1 月

January, 2026

誌謝



能夠完成本篇論文，首先要誠摯感謝我的指導教授羅敏輝老師與徐辛老師。謝老師們沒有因為我的經濟學背景而設限，反而給予我充分的空間探索研究方向，並在關鍵時刻提供明確而務實的指引。感謝老師們的循循善誘，讓我得以跨越領域的門檻，順利完成這項研究。同時，也要感謝口試委員們的細心審閱與建議，使本論文在論述與結構上更加嚴謹與完整。

身為一名跨領域的在職研究生，這條路走來並不容易。從以社會科學為主的思維方式，轉換至氣象資料處理與分析程式撰寫，其間經歷了大量的試錯與反覆修正。特別感謝工作上許多經驗豐富的前輩，以及研究室的同學們，在我遇到瓶頸時願意停下來分享經驗、一起 debug，讓我能在工作的同時持續累積研究能力，一步步將龐雜的數據轉化為有意義的科學圖表。這個過程雖然辛苦，但也充滿挑戰與樂趣，讓我逐漸體會研究所帶來的成就感。

此外，感謝中央氣象署在資料上的開放與協助，提供本研究所需的氣象網格資料，使本研究能建立在穩固且可靠的數據基礎之上。

回首這段碩士生活，日子過得極其充實。在工作與研究並行的狀態下，我學著在專業成長、家庭責任與生活間取得平衡。感謝 IPCS 的老師與同學們，讓我在奔波於公司與學校之間時，仍能感受到快樂與歸屬感，這份情誼已成為這段旅途中不可或缺的一部分。最後，感謝我的家人與朋友，謝謝你們包容我在這幾年因投入研究而減少了相處時光，你們的理解與陪伴，是我能順利完成論文的重要支持。

謹以此文，獻給所有在這段研究歷程中，曾給予我支持與溫暖的人。

摘要



在全球氣候變遷影響下，熱壓力已成為威脅健康與生產力的重要風險。台灣位處高溫高濕的副熱帶氣候區，地形複雜、都市密集與人口高齡化，對熱環境變化尤為敏感。然而，過往研究多受限於觀測資料解析度或聚焦於特定區域，難以在全台尺度下量化熱脆弱性的空間分布，可能低估實際風險。

本研究首次整合中央氣象署的五項氣象網格變數（氣溫、相對濕度、10 米風速、地表氣壓與向下短波輻射），透過物理機制模型（Liljegren 模型）建構全台逐時、1 公里高解析度的濕球黑球溫度（WBGT）網格資料。該資料作為分析 2015–2023 年台灣暖季（含過渡季節，4 月至 10 月）白天時段（08:00-17:00 LST）熱壓力時空變化特徵及人口暴露風險的核心依據。

研究結果顯示，台灣熱壓力分布具有顯著的地形依賴性，高 WBGT 值主要集中於西部平原與花東縱谷等區域。趨勢分析指出，2015–2023 年間全台平均 WBGT 呈顯著上升趨勢，極端熱危害（ $WBGT \geq 32^{\circ}\text{C}$ ）的發生頻率與影響範圍亦同步擴大。除西南平原等傳統高風險區外，熱壓力增幅最快的區域已逐漸延伸至山麓地帶及花東縱谷。其中，花東縱谷在後期（2020–2023 年）的每月極端熱日數，較前期（2015–2018 年）增加約 6–8 天。此趨勢主要受整體氣溫上升、過渡季節（4 月與 9 月）短波輻射增強，以及近地表風速普遍減弱等因子共同驅動。

在人口暴露評估方面，本研究整合 1 公里解析度之分齡人口資料，發現高暴露風險高度集中於西部都會走廊。其中，65 歲以上老年族群落於極端熱區之空間比例為各年齡層最高，顯示脆弱族群之空間分布與高熱危害區域具有高度重疊性。

本研究建立全台首個高解析度 WBGT 人口暴露評估框架。研究結果顯示，WBGT 指標能有效補足傳統乾球溫度預警閾值（ $\text{Temp} \geq 36^{\circ}\text{C}$ ）之限制，更全面地反映濕熱環境下之人體所承受的熱壓力與潛在健康風險。本研究結果可作為未來發展在地化熱預警制度、公共衛生介入措施，以及氣候調適策略的重要科學依據。

關鍵字：濕球黑球溫度、熱壓力、人口暴露、高解析度網格資料

ABSTRACT



Under ongoing global climate change, heat stress has emerged as a major threat to human health and labor productivity. Taiwan, located in a hot and humid subtropical climate zone, is particularly sensitive to thermal stress due to its complex topography, dense urbanization, and rapidly aging population. However, previous studies have often been constrained by limited observational resolution or a focus on specific regions, making it difficult to quantify the spatial distribution of heat exposure and its intersection with demographic structure across Taiwan at the national scale. This limitation may lead to an underestimation of actual heat-related risks. This study examines the spatiotemporal variability of humid heat stress and associated population exposure across Taiwan during the warm-season daytime period (April–October, 08:00-17:00 LST) from 2015 to 2023, using observation-based meteorological data at 1-km spatial resolution. Five key gridded meteorological variables (air temperature, relative humidity, 10-m wind speed, surface pressure, and downward shortwave radiation) from the Central Weather Administration (CWA) were integrated to construct, for the first time, an hourly Wet-Bulb Globe Temperature (WBGT) gridded dataset covering Taiwan’s main island.

The results indicate a pronounced topographic dependence of heat stress in Taiwan, with high WBGT values primarily concentrated in the western plains and the Hualien-Taitung Rift Valley. Trend analyses reveal a significant increase in mean WBGT across Taiwan during 2015–2023, accompanied by a concurrent expansion in the frequency and spatial extent of extreme heat hazards ($WBGT \geq 32\text{ }^{\circ}\text{C}$). While the southwestern plains remain the dominant heat hotspot throughout the study period, the most rapid intensification has extended toward foothill regions and the Hualien-Taitung Rift Valley in recent years. In particular, the Hualien-Taitung Rift Valley experienced an increase of approximately 6–8

extreme heat days per month during the late period (2020–2023) compared with the early period (2015–2018). These changes are jointly driven by global warming, enhanced downward shortwave radiation in April and September, and a widespread weakening of near-surface wind speed.

Population exposure was assessed by integrating extreme WBGT hazard frequency with 1-km gridded population data stratified by age groups. Areas of high exposure are primarily concentrated along the western urban corridor. Among all age groups, older adults (≥ 65 years) exhibit the highest spatial proportion within extreme heat exposure hotspots, indicating a strong spatial overlap between climatic heat hazards and population aging.

In conclusion, this research presents the first high-resolution WBGT-population exposure assessment framework for Taiwan. The findings demonstrate that WBGT complements existing dry-bulb air temperature thresholds ($\text{Temp} \geq 36\text{ }^{\circ}\text{C}$) by capturing additional physiological heat risks across broader spatial extents and higher seasonal frequencies. These results provide a high-resolution scientific basis for refining heat-health warning systems and supporting targeted climate adaptation strategies in Taiwan.

Keywords: Wet-Bulb Globe Temperature (WBGT); heat stress; population exposure; high-resolution gridded data

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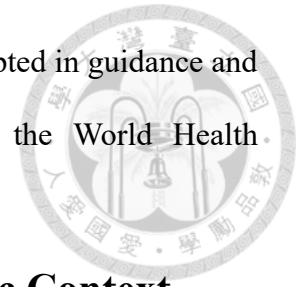
Chapter 1 Introduction

1.1 Global Context and the Significance of Heat Stress

Extreme heat has emerged as a growing climate-related risk over recent decades. Assessments in the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report indicate that heatwaves have become more frequent, longer in duration, and more intense, with documented consequences for human health, including increases in heat-related illness, cardiovascular stress, renal disorders, and excess mortality (IPCC, 2022). Heat exposure also affects economic activity by reducing labor capacity, particularly among outdoor and physically demanding occupations, and by disrupting productivity in sectors such as agriculture and construction (ILO, 2019; Alahmad et al., 2025).

While air temperature is a primary driver of thermal discomfort, the human body's ability to dissipate heat is fundamentally governed by the interplay of evaporation, convection, and radiation (Parsons, 2014). Accurately characterizing heat stress therefore requires consideration of multiple environmental factors rather than air temperature alone. The Wet-Bulb Globe Temperature (WBGT) accounts for air temperature, humidity, solar radiation, and wind speed, providing an integrated measure of the thermal load experienced by the human body (Liljegren et al., 2008). Because these components do not peak simultaneously, WBGT can exhibit diurnal patterns that differ substantially from those of air temperature, particularly in humid or highly irradiated environments. Observational studies have shown, for example, that WBGT may reach its daily maximum during the late morning under conditions of high humidity and strong solar radiation, even when air temperature peaks later in the day (Clark & Konrad, 2024). As a result, WBGT is widely used in occupational and public health contexts as a

physiologically relevant indicator of heat stress, and it has been adopted in guidance and assessment frameworks by international organizations such as the World Health Organization (WHO) and International Labour Organization (ILO).



1.2 Taiwan's Climatic and Socio-Demographic Context

Taiwan's hot and humid subtropical climate, combined with complex topography, makes the island particularly sensitive to heat stress. Observational and projection studies indicate that Taiwan has warmed at nearly twice the global average rate (Chen, 2008), with the hot season beginning earlier in the year and extending later into autumn (TCCIP, 2024). Intense and persistent heat hotspots frequently develop in urban basins such as Taipei and Taichung, as well as across densely built coastal plains and western lowlands. Mountain regions remain comparatively cooler, but recent climatic assessments (TCCIP, 2024) suggest that warming signals are also emerging at higher elevations. In parallel, humid heat has been increasingly recognized as a key determinant of heat-related mortality, with global analyses showing that humidity-sensitive indices capture health risks more effectively than air temperature alone, particularly in subtropical and coastal settings such as Taiwan (Guo et al., 2024).

The escalating health impacts of heat are empirically supported by data from the Taiwan Centers for Disease Control (CDC) Real-Time Outbreak and Disease Surveillance System. These records show that the number of reported heat-related emergency visits has increased markedly over the past decade, rising from 1,487 cases in 2011 to 3,942 cases in 2024 (HPA, 2025). Although this surveillance system does not cover all medical institutions and therefore does not represent the complete national burden of heat-related illness, it provides a consistent indicator of temporal trends. The observed increase underscores the growing public health relevance of heat stress in Taiwan and reinforces

the need for systematic heat-risk assessment.

Taiwan is also experiencing rapid demographic change. As of late 2025, the proportion of adults aged 65 years and older in Taiwan has reached 19.9% (MOI, 2025), closely approaching the 20% threshold defining a “super-aged society” as previously projected by the National Development Council (NDC, 2022). This demographic shift places Taiwan among the rapidly aging societies globally and substantially increases population vulnerability to thermal stress, as aging is associated with diminished thermoregulatory capacity (WHO, 2024). Other population groups face distinct exposure pathways: children and adolescents, for example, often experience substantial heat exposure due to prolonged outdoor activities in school and recreational environments (Lung et al., 2024). Spatial patterns of heat exposure are further shaped by urbanization and land-use change. In northern Taiwan, neighborhoods with declining green infrastructure or limited open space have exhibited increasing heat exposure, while in rapidly developing districts, recent warming trends have, in some cases, outpaced the cooling benefits provided by existing green spaces (Shih & Ouyang, 2025).

Taken together, these climatic, demographic, and urban development factors point to the need for heat stress assessments that resolve fine spatial variability and explicitly account for population exposure across Taiwan.

1.3 Progress and Limitations of Heat-health Policies in Taiwan

In recent years, Taiwan has increasingly incorporated scientific evidence into its heat-health policy framework in response to rising heat-related risks. Early nationwide studies, such as Cheng et al. (2019), established strong associations between WBGT and health outcomes, demonstrating that WBGT values around 32 °C were associated with

significant increases in both emergency department visits and mortality. These findings prompted the Central Weather Administration (CWA) to adopt WBGT as the foundation for Taiwan's national heat-warning system. In 2020, the CWA launched a four-level WBGT-based framework, ranging from "Caution" (32 °C) to "Extreme Danger" (38 °C), implemented through the "Health Weather" platform in collaboration with the Ministry of Health and Welfare. This multi-factor approach distinguishes Taiwan as one of the few countries to move beyond air-temperature-only warnings at a national scale.

Subsequent research has further validated this framework while expanding its scope. For instance, days exceeding WBGT 32.5 °C were associated with nearly twice the number of emergency visits (Lung et al., 2021), and WBGT above 36 °C in the Taipei Basin led to even sharper increases, especially among males and young children (Lung et al., 2023). More recent investigations have shifted focus from these immediate acute effects of heat exposure, such as heatstroke and exhaustion, toward chronic health impacts, including kidney outcomes and gastrointestinal disorders (Su et al., 2024; Chen et al., 2025; Gau et al., 2025).

Despite this progress, significant limitations remain in the current assessment infrastructure. While recent studies have utilized modeling and machine-learning techniques to map spatial heat variations (Hsu et al., 2024), most efforts rely on coarse-resolution inputs or focus on short-term extreme events. Nevertheless, as national-level frameworks, Taiwan still lacks the fine-scale microclimatic resolution necessary to support neighborhood-scale interventions. An observation-based, long-term, and high-resolution WBGT dataset with nationwide coverage is needed to evaluate spatial heat patterns and population vulnerability.

1.4 Research Gaps and Motivation

Despite advances in Taiwan's heat-health policies, important limitations remain in translating scientific knowledge into effective, localized adaptation strategies.

One key constraint arises from the lack of high-resolution, observation-based thermal indices. Existing assessments largely depend on sparse meteorological stations or coarse-resolution model outputs, which are insufficient for capturing the pronounced kilometer-scale heterogeneity associated with Taiwan's complex terrain. As a result, heat stress in urban basins, foothill regions, and other localized environments is often inadequately represented, leading to distorted perceptions of exposure risk at fine spatial scales.

Current research is also limited by spatiotemporal fragmentation. Many studies focus on individual extreme events or specific metropolitan areas, leaving a gap in continuous, island-wide assessments conducted over multiple years. In the absence of a long-duration, high-resolution dataset, it remains challenging to examine how regional heat stress patterns evolve and interact across Taiwan's diverse landscapes.

Additional limitations stem from the way population exposure is commonly quantified. The frequent use of city-level averages or spatially uniform population representations obscures the spatial coincidence between thermal hotspots and vulnerable groups. This form of spatial smoothing masks the true intensity of exposure in areas experiencing the most severe heat stress and constrains the ability to identify locations where targeted interventions are most urgently needed.

These methodological and analytical constraints are particularly consequential in the context of Taiwan's rapidly aging society. High-resolution analyses that explicitly link WBGT hazard intensity with age-specific population distributions remain scarce, despite their importance for identifying communities facing disproportionate heat exposure.

Motivated by these gaps, this study develops a multi-year WBGT dataset at 1-km spatial resolution for Taiwan and integrates it with age-stratified population data. By explicitly coupling fine-scale heat hazards with demographic vulnerability, the research seeks to clarify the spatial intersection of heat stress and population exposure, providing a stronger scientific basis for public health planning and equitable climate adaptation.

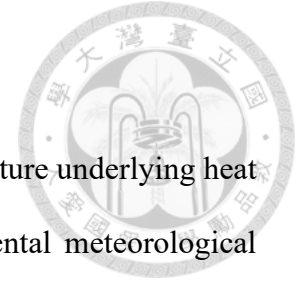
1.5 Research Objectives and Policy Relevance

The overarching objective of this study is to investigate the spatial intersection of humid heat stress and population exposure across Taiwan from 2015 to 2023. Grounded in the IPCC risk framework ($\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}$), this research focuses on the quantification of WBGT-based heat hazards and their interaction with population distribution, while representing vulnerability through age-structure proxies.

To address this objective, the study examines the spatial and temporal characteristics of humid heat stress during the warm season (April–October, 08:00–17:00 LST) and evaluates how population distribution shapes heat exposure patterns across different age groups. Heat hazard intensity is assessed using nationally adopted WBGT thresholds ($\text{WBGT} \geq 32^\circ\text{C}$, as defined by the CWA), and population-weighted exposure is analyzed to identify areas where persistent heat hazards overlap with vulnerable demographic groups. A bivariate perspective is employed to distinguish exposure regimes driven primarily by climatic intensification and those driven by population concentration.

This study provides 1 km resolution, exposure-oriented evidence on the spatial and demographic distribution of humid heat stress in Taiwan. Rather than modeling health outcomes or behavioral responses, we characterize potential heat risk based on observed hazard–exposure relationships, providing a scientific basis for interpreting and refining existing heat–health warning frameworks.

Chapter 2 Literature Review



This chapter provides a comprehensive review of the scientific literature underlying heat stress and population vulnerability. We first examine the fundamental meteorological mechanisms governing WBGT, with particular attention to the combined roles of air temperature, humidity, radiation, and wind in shaping heat stress conditions in Taiwan. The discussion then evaluates the evolution of WBGT modeling approaches, highlighting the necessity of high-resolution gridded assessments over coarse reanalysis products. Beyond the physical environment, we synthesize the documented acute and chronic health impacts of thermal stress and discuss how demographic shifts, particularly population aging, amplify population exposure risks. Furthermore, this chapter explores the emerging literature on environmental justice and heat-risk inequality. Finally, we review the current status and limitations of Heat Early Warning Systems (EWS) in Taiwan, thereby establishing the scientific motivation for the high-resolution WBGT-based assessment framework developed in this study.

2.1 Meteorological Drivers of Heat Stress and WBGT

Heat stress is a multifaceted phenomenon governed by the interaction between atmospheric conditions and human thermoregulation. The Wet Bulb Globe Temperature (WBGT) provides a more holistic assessment than temperature-only metrics by integrating air temperature (T_a), humidity, wind speed, and solar radiation.

Physiologically, these factors determine the body's heat dissipation capacity (Bernard, 2012). High humidity suppresses sweat evaporation, while solar radiation increases the radiant heat load absorbed by the body. Wind speed further modulates both convective and evaporative heat loss; consequently, stagnant air can drastically amplify thermal strain. Due to its physiological relevance, WBGT has been adopted as the international

standard for heat stress assessment by agencies such as the International Organization for Standardization (ISO 7243, 2017) and OSHA.

However, direct WBGT measurement is often limited by the availability of specialized instrumentation. To address this, this study employs the model developed by Liljegren et al. (2008) to derive WBGT from standard meteorological data. The Liljegren model is widely regarded as the most physically robust estimation method because it explicitly solves the energy and radiative balances of the thermometers, accounting for convective fluxes governed by wind speed and pressure. Given that WBGT can vary by several degrees Celsius across short distances due to microclimatic factors such as surface type and shading (Clark & Konrad, 2024), applying a physically based WBGT model at high spatial resolution is critical for accurately characterizing population exposure across Taiwan's complex terrain. Furthermore, these meteorological drivers directly impact public health. In Taiwan, Huang (2013) observed that heat exposure significantly reduces heart rate variability among older adults, signaling elevated cardiovascular strain.

2.1.1 Meteorological Characteristics of Heat Stress in Taiwan

Taiwan's heat stress patterns differ from those observed in many tropical regions, shaped by its complex topography, basin-like terrain, and strong land-sea interactions. Previous studies supporting Taiwan's heat early warning system, including the National Science and Technology Council (NSTC) Heat Early Warning Project (2017–2019, MOST 107-2621-M-001-003) and Lung et al. (2023), indicate that heat stress in Taiwan is governed by the combined influence of radiative and thermal factors, rather than by humidity alone. Across northern, central, and southern Taiwan, peak WBGT events are primarily associated with the concurrence of high ambient temperatures and intense shortwave radiation, often occurring under conditions of relatively moderate humidity. This finding challenges the conventional assumption that humidity is the dominant driver of heat stress

in subtropical climates. In eastern Taiwan, the contribution of solar radiation is even more pronounced, frequently acting as the dominant factor during extreme heat stress events.

A notable temporal characteristic of heat stress in Taiwan is the early diurnal peak in WBGT. Maximum WBGT values commonly occur between 10:00 and 12:00, substantially earlier than the daily maximum air temperature (Lung et al., 2024). This pattern reflects the rapid intensification of solar radiation during the morning hours, preceding the development of afternoon convective cloud cover or the onset of cooling sea-breeze circulation.

In addition, Taiwan's rugged terrain produces sharp topographic gradients in WBGT intensity. Abrupt transitions between coastal plains, urban basins, and mountain foothills generate localized thermal environments that are poorly captured by coarse-resolution datasets. These features underscore the limitations of coarse-resolution products and the importance of fine-scale assessments for characterizing spatial heterogeneity in heat stress.

2.1.2 Global Context and Regional Specificity

The shift toward multi-variable heat metrics is supported by broader global evidence. Guo et al. (2024) demonstrated that the independent contribution of humidity to heat-related mortality varies significantly by region and is often less dominant than previously assumed, as temperature and other factors frequently capture the bulk of the risk. These findings challenge the humidity-centric interpretations often applied to subtropical regions and align with the observed importance of the radiative-thermal components in Taiwan.

By situating Taiwan's unique radiative-thermal regime within this global context, the necessity for a physically-based, high-resolution approach becomes clear. Relying on simplified temperature-humidity indices would overlook the critical role of radiant heat,

leading to a fundamental miscalculation of heat-related health risks in Taiwan's specific climatic and geographic setting.

2.2 WBGT Modeling: From Station Observations to Gridded Assessment

While the gold standard for WBGT remains direct measurement using specialized instrumentation, large-scale spatial assessments necessitate the use of numerical modeling to estimate thermal stress across unmonitored areas. Among these, the Liljegren et al. (2008) model is widely adopted due to its ability to physically simulate radiative and convective heat exchange using standard meteorological inputs. In Taiwan, most existing heat stress studies utilize the Liljegren model or similar physical formulations, but these remain primarily station-based. While accurate at the specific sensor locations, point-based estimates fail to resolve the continuous spatial gradients of heat stress across Taiwan's heterogeneous landscapes.

To address these spatial gaps, recent research has explored hybrid approaches; for instance, Hsu et al. (2024) integrated the Liljegren physical model with land-use-based machine learning to map WBGT variations across Taiwan. However, while such data-driven approaches effectively utilize station-based physical estimates to train predictive models, their spatial fidelity remains contingent on the density of the underlying station network. Consequently, empirical models may still struggle to capture complex fine-scale interactions in regions with extreme topographical relief where stations are sparse.

Furthermore, although global reanalysis products such as ERA5 (Hersbach et al., 2020) provide readily available gridded WBGT fields, their relatively coarse spatial resolution (~25-31 km) is inadequate for Taiwan's complex geography (Tuholske et al., 2021). At this scale, such products tend to smooth out critical localized phenomena, including basin-

scale heat accumulation in the Taipei metropolitan area and sharp altitudinal gradients along the Central Mountain Range (Lung et al., 2023). As a result, recent studies increasingly recognize the limitations of applying coarse-resolution reanalysis products and station-based WBGT estimates in regions characterized by pronounced microclimatic heterogeneity (Clark & Konrad, 2024; Hsu et al., 2024). Even products advertised as high-resolution, whether temperature-based or WBGT-derived, may still lack the local meteorological fidelity required to accurately represent complex terrain such as Taiwan.

2.3 Health Impacts of Heat Stress

Heat stress is associated with substantial acute morbidity. A nationwide analysis utilizing the National Health Insurance Research Database (NHIRD) identified 34,973 heat-related emergency department (ED) visits across Taiwan between 2004 and 2020 (Lin et al., 2025), with an observed odds ratio of 1.414 for heat-related illness per 1.0°C increase in WBGT. Furthermore, multiple studies consistently report a sharp increase in ED visits when WBGT reaches approximately 32-33 °C, a range that aligns with the thresholds adopted by Taiwan's national heat-warning system (Cheng et al., 2019; Lung et al., 2023). Sensitivity to acute heat exposure is not uniform; children and male adults exhibit disproportionately higher risks, particularly in the highly urbanized environments of northern Taiwan.

Beyond acute outcomes, emerging evidence indicates that prolonged heat exposure is associated with diverse chronic health effects. Recent Taiwanese cohort studies have linked sustained heat stress to renal function decline, elevated risks of chronic kidney disease, mental health burdens, and gastrointestinal disorders (Su et al., 2024; Chen et al., 2025; Gau et al., 2025). These findings suggest that heat stress contributes not only to immediate health crises but also to broader, long-term health inequality as cumulative

exposure impacts vulnerable populations over time.

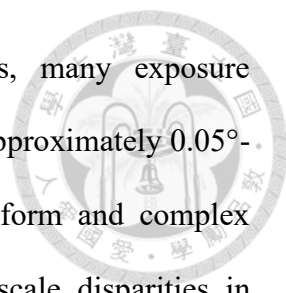
Physiological evidence further elucidates the specific vulnerability of older adults. Using Taiwan-based observations, Huang (2013) demonstrated that increasing temperatures significantly reduce heart rate variability (HRV) among healthy elderly individuals, reflecting elevated cardiovascular strain and impaired autonomic regulation. As reduced HRV is a well-established indicator of cardiovascular vulnerability under thermal stress, this physiological response provides mechanistic insight into the disproportionate susceptibility of older adults to heat-related morbidity and mortality.

2.4 Population Exposure and Demographic Vulnerability

Heat exposure is commonly conceptualized as the spatial and temporal intersection between thermal hazards and population distribution. Global assessments have shown that heat exposure has increased substantially over recent decades, driven by the combined effects of rising temperatures and changes in population density and settlement patterns (Tuholske et al., 2021; Li et al., 2022).

In Taiwan, this interaction is further shaped by rapid demographic transition. The proportion of adults aged 65 years and older is projected to exceed 20% by 2025, amplifying population vulnerability to heat stress. Older adults are physiologically more susceptible due to reduced thermoregulatory capacity, while children and adolescents may experience elevated exposure associated with behavioral patterns such as prolonged outdoor activities in school and recreational environments (Lung et al., 2024).

Taiwan-specific evidence also indicates that demographic vulnerability interacts with ongoing urban warming. Studies have reported that warming rates in major metropolitan areas approach nearly twice the global average, accompanied by a marked increase in heatstroke-related emergency department visits over the past decade (Lung et al., 2023).



Despite growing recognition of these demographic dimensions, many exposure assessments continue to rely on relatively coarse population grids (approximately 0.05°-0.1°), which are poorly suited to Taiwan's heterogeneous urban form and complex topography. Such spatial aggregation can obscure neighborhood-scale disparities in exposure and limit the ability to resolve where thermal hazards and vulnerable populations most strongly overlap. Recent studies have highlighted these limitations, particularly in regions where fine-scale population structure and microclimatic variability play a critical role in shaping heat risk.

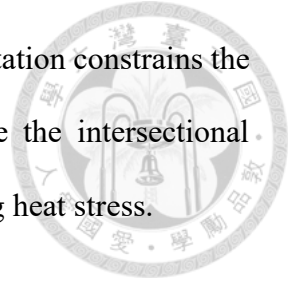
2.5 Heat Risk Inequality and Environmental Justice

Heat exposure is fundamentally intertwined with socioeconomic inequality. In Taiwan, recent studies indicate that older and lower-income neighborhoods disproportionately bear the brunt of rising heat risk (Shih & Ouyang, 2025). This disparity is exacerbated by the unequal distribution of cooling-effective green spaces, a phenomenon that global environmental justice literature warns can lead to "green gentrification" if adaptation strategies are not spatially explicit (Anguelovski et al., 2018). Consequently, there is an urgent need to move beyond aggregate city-level data to identify localized "heat-risk inequality" at the neighborhood scale.

Beyond residential vulnerability, heat stress poses a severe threat to occupational health and labor productivity. Global analyses suggest that intensified urban heat stress substantially reduces safe working hours, with construction and outdoor workers in rapidly warming Asian cities facing the highest risks (Lee et al., 2022; Alahmad et al., 2025). In Taiwan, field monitoring has confirmed that elevated WBGT correlates with increased thermal burden and diminished labor efficiency (Lung et al., 2019).

However, many existing socio-occupational assessments continue to rely on sparse

station observations or coarse-resolution WBGT estimates. This limitation constrains the ability to resolve fine-scale risk patterns and to fully characterize the intersectional vulnerabilities of aging populations and outdoor workers under rising heat stress.



2.6 Heat Early Warning Systems (EWS)

Taiwan's national heat-warning system uses WBGT thresholds, Caution (32°C), Alert (34°C), Danger (36°C), Extreme Danger (38°C), supported by empirical health relationships. The NSTC Heat Early Warning Project (2017–2019) provided foundational scientific evidence for adopting these thresholds, yet the system still lacks spatially continuous WBGT fields. Despite its policy relevance, the effectiveness of this system remains constrained by the lack of spatially continuous, high-resolution WBGT fields capable of resolving local heat variability.

Chapter 3 Datasets and Methodology



This chapter details the datasets and analytical procedures used to evaluate heat stress and population exposure in Taiwan. The overall methodological workflow, integrating meteorological data processing, WBGT estimation, and spatial hotspot analysis, is illustrated in Figure 3.1.

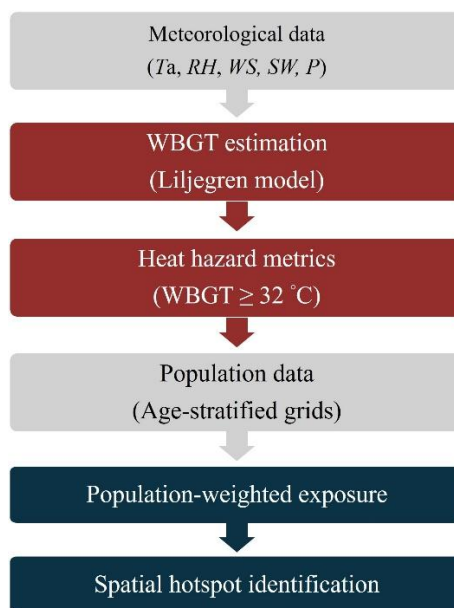


Figure 3.1 *Methodological Workflow of the Study.*

The workflow illustrates the analytical steps used to assess physiological heat stress and population exposure in Taiwan. Hourly gridded meteorological variables, including air temperature (Ta), relative humidity (RH), wind speed (WS), shortwave radiation (SW), and surface pressure (P), were first processed as inputs to estimate WBGT using the Liljegren model. Based on the WBGT estimates, heat hazard metrics were derived using a threshold of $WBGT \geq 32$ °C. These hazard metrics were then integrated with age-stratified gridded population data to calculate population-weighted heat exposure. Finally, spatial hotspot identification was conducted to identify areas with elevated heat hazard and population exposure.

3.1 Study Area and Period

This study focuses on Taiwan's main island, a subtropical region characterized by complex topography where the majority of the population and heat-related risks are concentrated. The analysis spans from 2015 to 2023, a period marked by intensified warming trends. The temporal scope is restricted to the warm season (April-October) and daytime hours (08:00-17:00 LST) to capture peak thermal loading. All analyses were conducted on a harmonized 1-km spatial resolution grid.

3.2 Data Sources

To evaluate potential heat risk, this study integrates high-resolution meteorological datasets, gridded population layers, and official administrative boundaries. All spatial datasets were processed in a consistent geographic coordinate system (WGS84; EPSG:4326), resampled to a common 1-km grid, and clipped to the extent of Taiwan's main island.

3.2.1 Meteorological Gridded Data

WBGT estimation requires five primary meteorological variables obtained from the CWA:

- (1) Near-surface temperature, relative humidity, and pressure were taken from the CWA's TaiSA gridded climate products, which are based on long-term station observations and kriging interpolation (CWA, 2023a; CWA, 2023b; CWA, 2023c).
- (2) Shortwave radiation was retrieved from Himawari-8/9 AHI using a radiative-transfer inversion algorithm (CWA, 2023d).
- (3) Wind speed at 10 m was obtained from the Mesoscale Dynamic Analysis System (MDAS), which applies dynamical downscaling and multiscale variational data assimilation using ERA5 reanalysis and local observations (CWA, 2023e).

Most meteorological variables were provided on a consistent 1-km geographic grid (650 × 650). Wind speed and shortwave radiation data, which had slightly different spatial grids, were aligned to a common 1-km grid using nearest-neighbor resampling (WGS84; EPSG:4326). All meteorological datasets were converted to Taiwan local time (UTC+8) and filtered to April–October, 08:00–17:00 LST.

3.2.2 Population Data

To ensure demographic accuracy, annual 1-km gridded population datasets from WorldPop (Bondarenko et al., 2025) were adjusted to match the official national registered population totals reported by the Ministry of the Interior (MOI). An annual scaling factor was applied as follows:

$$\text{AdjustedPop}_y = \text{WorldPop}_y \times \frac{\text{MOI TotalPop}_y}{\text{WorldPop TotalPop}_y} \quad (3-1)$$

Age-specific population layers (0–14, 15–64, and ≥ 65 years) were generated by applying MOI age-composition ratios to the adjusted grids. To mitigate short-term demographic fluctuations, these layers were averaged across the 2015–2023 period to produce a stable, multi-year mean population surface for exposure assessment.

3.2.3 Administrative District Boundaries

County and township boundaries were obtained from the National Land Surveying and Mapping Center (NLSC, 2025) and aligned to the 1-km analysis grid.

3.3 WBGT Estimation

WBGT estimation was conducted using the physically based model developed by Liljegren et al. (2008), which is widely recommended for outdoor environments

characterized by variable solar radiation, wind speed, and humidity conditions. The Liljegren model explicitly computes the natural wet-bulb temperature (T_{nwb}) and black-globe temperature (T_g) by iteratively solving the coupled heat and mass balance equations at the sensor surface.

The calculation of T_g accounts for the equilibrium between radiative heat gain from incoming shortwave radiation, longwave thermal emission, and convective heat loss driven by ambient wind speed. Meanwhile, T_{nwb} is derived by simulating the evaporative cooling process, balancing latent heat loss due to evaporation against convective heat gain and radiative exchange under ambient atmospheric conditions. The governing equations and definitions of the physical parameters are provided in the Appendix.

Based on the derived T_{nwb} and T_g , WBGT was calculated by combining these components with the dry-bulb air temperature (T_a) following the ISO 7243, 2017 standard for outdoor environments:

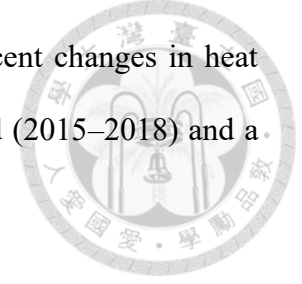
$$WBGT_{\text{outdoor}} = 0.7T_{nwb} + 0.2T_g + 0.1T_a \quad (3-2)$$

3.4 Heat Hazard Indicators

Heat hazard was defined using a threshold of $WBGT \geq 32\text{ }^{\circ}\text{C}$, corresponding to the “Caution” level of Taiwan’s national heat-warning system. Two indicators were derived: (1) hazard days, defined as the annual number of days when daily maximum WBGT reached or exceeded $32\text{ }^{\circ}\text{C}$, and (2) hazard frequency, defined as the cumulative number of hazard days over the 2015–2023 study period.

Trend magnitudes were estimated using Sen’s slope estimator (Sen, P. K., 1968) estimator, and statistical significance was assessed using the Mann–Kendall test (Mann, 1945;

Kendall, 1970) at a significance level of $\alpha = 0.05$. To examine recent changes in heat hazard, results were additionally compared between an early period (2015–2018) and a later period (2020–2023).



3.5 Exposure and Hotspot Framework

3.5.1 Population-Weighted Exposure (PWE)

In climate risk studies, population exposure refers to the presence of people in locations where hazardous conditions occur. Grounded in the IPCC risk framework, heat hazard in this study is first independently defined by WBGT exceedance threshold ($WBGT \geq 32$ °C), hereafter referred to as extreme heat events. Population-weighted exposure is then operationalized by conditioning gridded population counts on the temporal occurrence of these heat hazards. In this formulation, population is weighted by the number of days on which hazardous heat conditions occur, such that populations residing in areas experiencing more frequent heat hazards contribute more strongly to the overall exposure metric. Exposure at each grid cell is quantified as the product of gridded population counts and the cumulative number of hazard days:

$$\text{Exposure}_{(x,y)} = \text{Population}_{(x,y)} \times \text{HazardDays}_{(x,y)} \quad (3-3)$$

where $\text{HazardDays}_{(x,y)}$ denotes the number of days during which WBGT exceeds the hazard threshold at grid cell (x,y) .

The resulting metric is expressed in person-days, enabling quantitative comparison of exposure magnitude across regions and age cohorts. Consistent with the IPCC framework, vulnerability is not incorporated as a multiplicative term in Equation (3-3); instead, demographic sensitivity is examined through analytical stratification (i.e., age-stratified

exposure patterns) as a proxy for social vulnerability (Figure 3.2), rather than a direct quantification of vulnerability. Accordingly, this metric characterizes potential heat risk conditional on hazard occurrence and provides a spatially explicit basis for interpreting heat-related risk patterns, without extending to realized clinical health outcomes. The conceptual relationships among hazard, exposure, and vulnerability within the IPCC framework are further illustrated in Figure 3.2, which builds upon the methodological workflow presented in Figure 3.1.

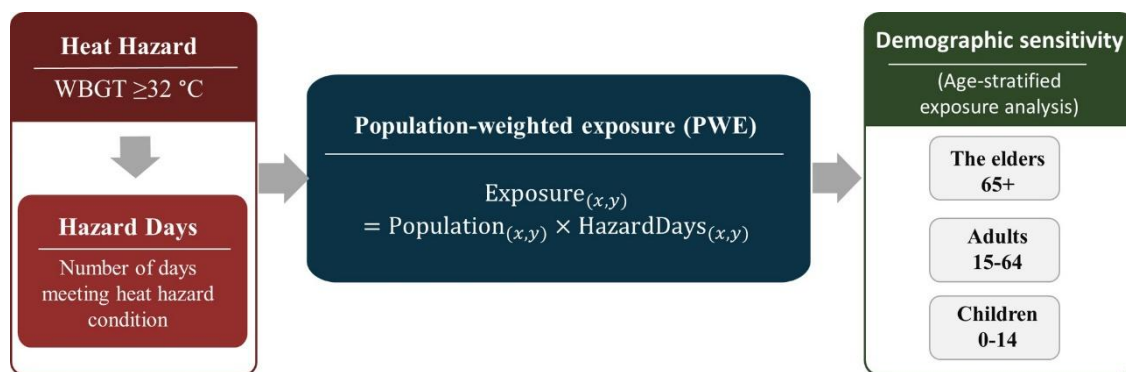
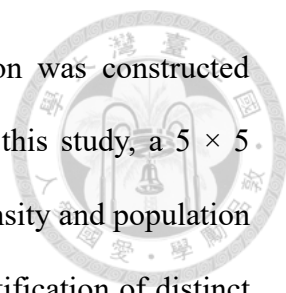


Figure 3.2 Conceptual schematic illustrating the operationalization of population-weighted exposure (PWE) within the IPCC risk framework.

(1) Heat hazard is independently defined by WBGT exceedance ($WBGT \geq 32\text{ °C}$), from which the temporal metric of hazard days is derived. (2) Population-weighted exposure is quantified by conditioning gridded population counts on the temporal occurrence of heat hazards (Equation 3-3). (3) Age-stratified exposure patterns (0–14, 15–64, and ≥ 65 years) are used to examine demographic differences in exposure, without explicitly quantifying vulnerability.

3.5.2 Bivariate Hotspot Classification

To explicitly distinguish whether spatial patterns of heat exposure are primarily driven by



population distribution or climatic hazard, a bivariate classification was constructed drawing on the exposure framework of Tuholske et al. (2021). In this study, a 5×5 bivariate scheme was adopted, categorizing both WBGT hazard intensity and population density into quintiles (Q_1 - Q_5). This classification facilitates the identification of distinct exposure regimes, ranging from population-driven to hazard-driven risk conditions. Pixels classified as Q_5 in both dimensions (High-High) represent the most critical socio-climatic hotspots, where extreme heat stress coincides with the highest population concentration.

3.5.3 “Extreme $\times$ Extreme” Upper-Tail Analysis

An upper-tail analysis was conducted using the 80th percentile (P80) as the threshold for both hazard and population. Pixels satisfying both conditions were identified as “Extreme $\times$ Extreme” areas and aggregated at the township level to highlight priority regions for targeted climate adaptation. The P80 threshold was selected to ensure a robust statistical baseline that identifies persistent thermal stress while maintaining sufficient sample representation. This threshold was specifically chosen to avoid the data sparsity often associated with the joint occurrence of higher percentiles (e.g., P90) across two fields, thereby ensuring that the identified hotspots possess enough spatial contiguity to inform meaningful municipal-level adaptation planning.

Chapter 4 Spatiotemporal Distribution and Trends of Heat Stress



To better capture emerging spatial patterns in short time series and high-resolution gridded data, a slightly relaxed significance level ($p < 0.1$) was adopted for spatial trend visualization, while stricter criteria ($p < 0.05$) were retained for extreme event analyses.

4.1 WBGT climatic background

This chapter evaluates recent WBGT variability and extreme heat characteristics in Taiwan over the period from 2015 to 2023. The analysis focuses on the nine-year trends, the changes in meteorological drivers contributing to WBGT variability, and the frequency and trend of extreme heat events ($\text{WBGT} \geq 32^\circ\text{C}$). All results are based on data collected between April and October, from 08:00 to 17:00 Local Standard Time (LST).

4.1.1 Multi-year Mean WBGT (2015–2023)

Figure 4.1 shows that the multi-year mean monthly WBGT distribution over the analysis period (2015–2023) exhibits pronounced topographical and seasonal patterns. WBGT values demonstrated a strong negative correlation with elevation. Low WBGT values are consistently observed over the Central Mountain Range and other high-altitude areas. Conversely, the Western Plains of Taiwan, the Eastern Coastal regions, and the Rift Valley show higher levels of heat stress. The Southwestern Plains, including the Chianan Plain and the Pingtung Plain, emerge as the most prominent annual WBGT hotspot area, with multi-year mean values exceeding 27°C .

Seasonally, WBGT increases gradually starting in April, reaching its annual maximum in July and August. During these peak months, the mean WBGT in the Southwestern Plains

commonly surpasses 28.5 °C, with localized maxima exceeding 30 °C. The WBGT subsequently decreases from September to October.

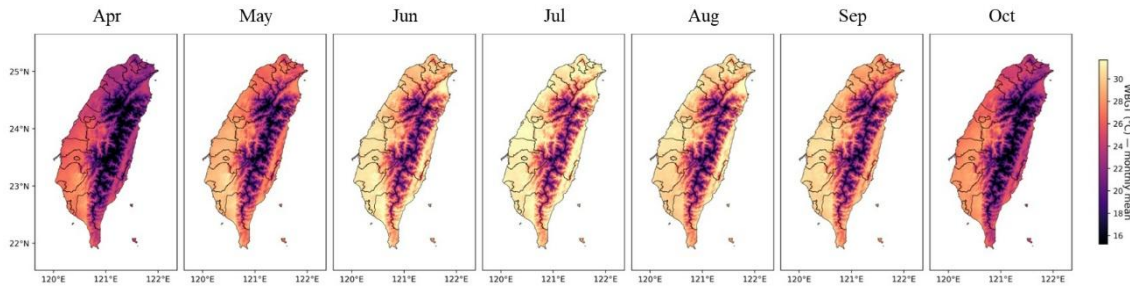


Figure 4.1 Multi-year mean WBGT during the warm season (Apr–Oct, 08:00–17:00 LST) for 2015–2023.

Panels in this and subsequent figures follow the same monthly chronological arrangement.

4.1.2 Trends in Monthly WBGT

The analysis employed the Sen’s slope method combined with the Mann–Kendall (MK) test for statistical significance. To better resolve emerging spatiotemporal patterns and account for the high microclimatic variability inherent in the 1-km gridded data, a significance level of $p < 0.1$ was adopted for spatial trend mapping. The monthly WBGT revealed a statistically significant and widespread increasing trend during the nine-year period (Figure 4.2). The warming trend exhibited strong seasonal concentration, primarily occurring in the core summer months (July, August) and the transitional months (April, September). The spatial distribution of the WBGT trend revealed distinct regional patterns in acceleration.

The WBGT trends in the Western Plains were mainly concentrated in July. This region, which already held the highest WBGT absolute values, showed strong intensity, with the Sen’s slope in many areas exceeding 0.2 °C per year. Significantly strong WBGT

increasing trends were also observed in the Eastern Hualien-Taitung Rift Valley, and surrounding hillsides. These trends were particularly pronounced during July, August, and September. The acceleration of heat stress in these non-core regions suggests that high-temperature hazards are expanding beyond traditional hotspots, intensifying risks in previously less-impacted areas.

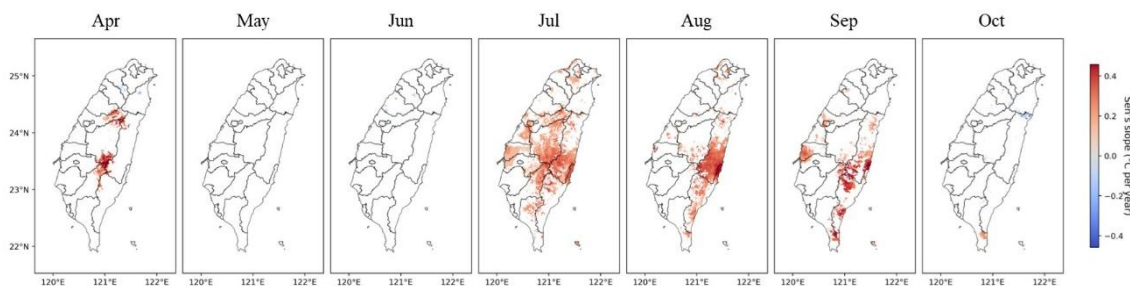


Figure 4.2 Monthly trends in WBGT estimated using Sen's slope for 2015–2023.

Sen's slope values are displayed only for grid cells with statistically significant trends based on the Mann–Kendall test ($\alpha = 0.1$). Non-significant trends are masked and shown in white. The same masking convention is applied to all subsequent figures involving statistical significance.

4.2 Trends in Meteorological Drivers

The trends in the primary meteorological drivers influencing WBGT (air temperature, relative humidity, wind speed, shortwave radiation, and surface pressure) were analyzed as follows:

- (1) **Air Temperature** : The spatial pattern and seasonal timing of air temperature trends closely mirrored those of the WBGT. The most significant increases are observed in July and August over the Western Plains, with slopes generally exceeding 0.2 °C per year. (Figure 4.3).

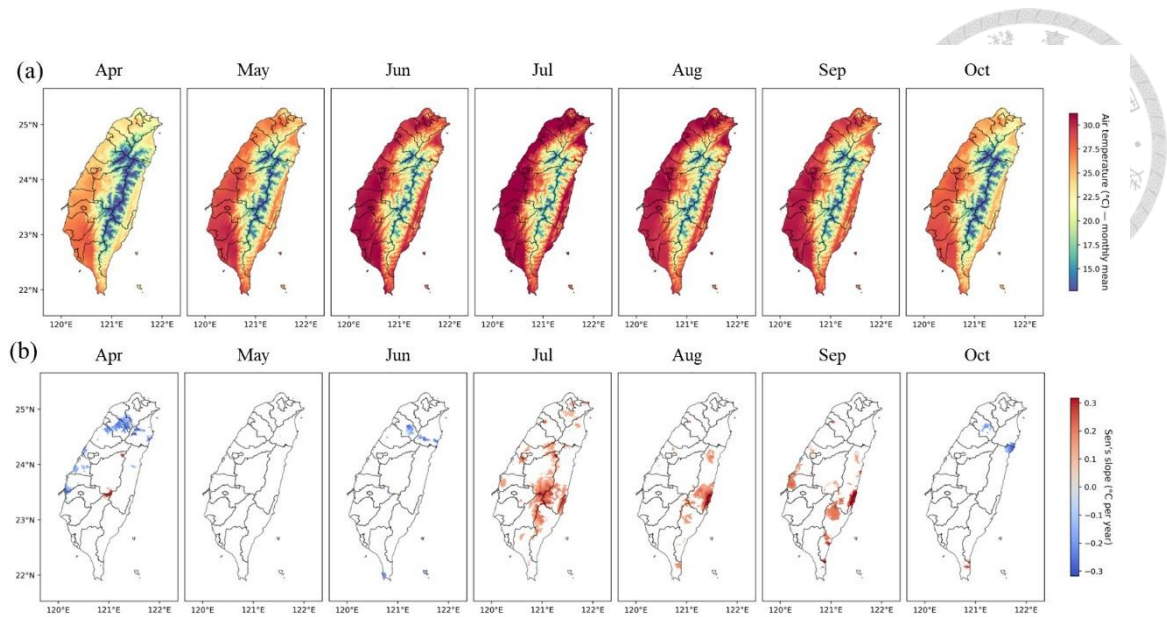


Figure 4.3 Mean air temperature during the warm season (Apr–Oct): (a) multi-year mean for 2015–2023 and (b) monthly trends estimated using Sen's slope.

- (2) **Shortwave Radiation** : Shortwave radiation exhibits a clear seasonal cycle, reaching its annual maximum during June-August. Trend analysis indicates significant increases primarily in April and September, concentrated over the western plains, south-central regions, and the Hualien-Taitung area. Because shortwave radiation elevates the globe temperature (T_g) component in WBGT, these transitional-season increases are likely a key thermodynamic driver of the observed WBGT rise in April and September (Figure 4.4).

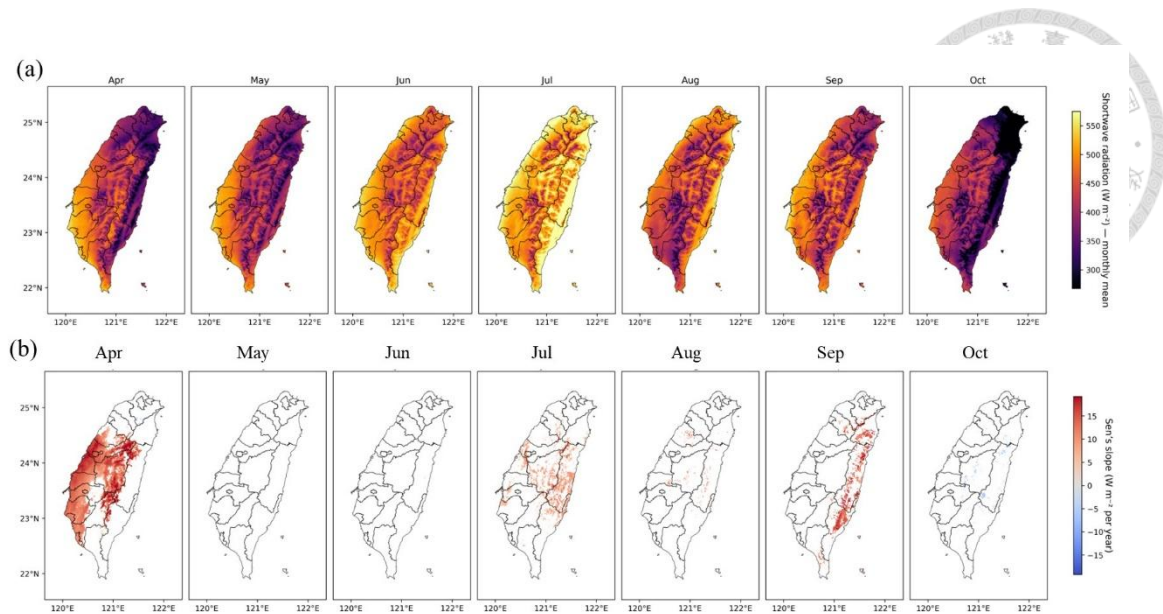


Figure 4.4 Mean downward shortwave radiation during the warm season (Apr–Oct):
 (a) multi-year mean for 2015–2023 and (b) monthly trends estimated using Sen's slope.

- (3) **Wind Speed** : Wind speed is climatologically weakest during June–August, especially over the south-central plains and the foothill regions. Trend analysis reveals predominantly negative (decreasing) wind speed trends across most of Taiwan. The most extensive and pronounced declines occur during June–September, particularly over the western and southern plains and hilly areas, where negative Sen's slopes typically range from -0.02 to $-0.04 \text{ m s}^{-1} \text{ yr}^{-1}$. This widespread decrease in wind speed potentially serves as an auxiliary factor inhibiting heat dissipation and contributes to the increased regional heat stress (Figure 4.5).

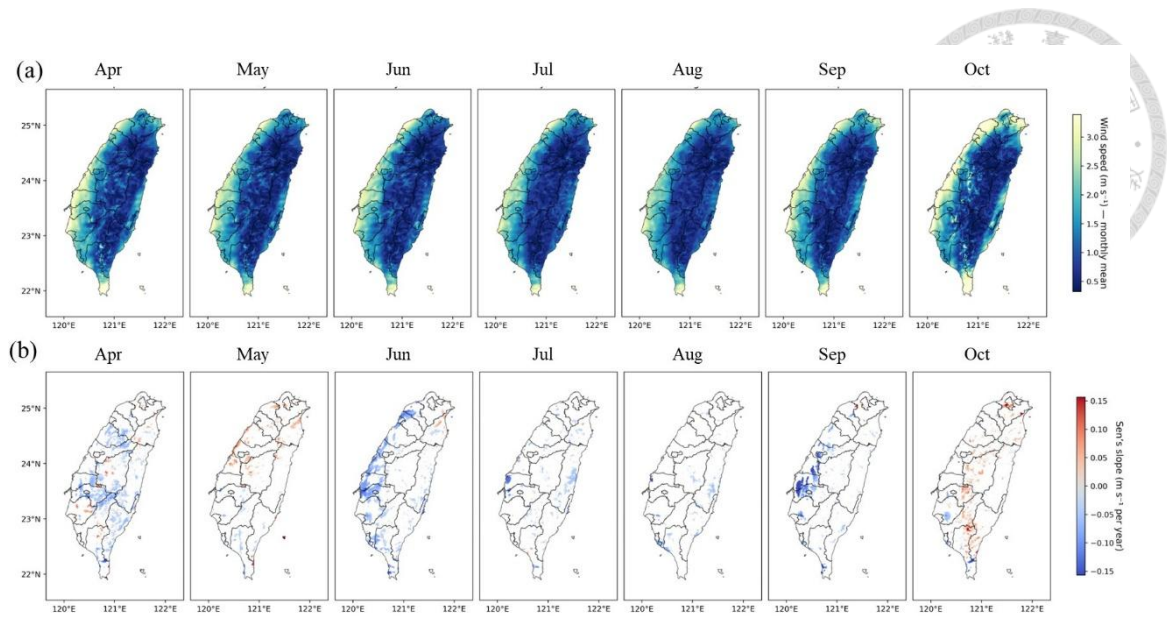


Figure 4.5 Mean wind speed during the warm season (Apr–Oct): (a) multi-year mean for 2015–2023 and (b) monthly trends estimated using Sen's slope.

- (4) **Relative Humidity** : Mean monthly relative humidity remains generally high across Taiwan, with most areas exceeding 60% throughout April–October. Spatial variations show relatively drier conditions over the central and southern lowlands during June–August, whereas higher humidity is more prominent in eastern Taiwan, particularly in early and late warm-season months. Significant increases in relative humidity were observed in April and June along the Central areas. Trends during the peak summer months (July, August) were less consistent, exhibiting lower statistical significance compared to air temperature (Figure 4.6).

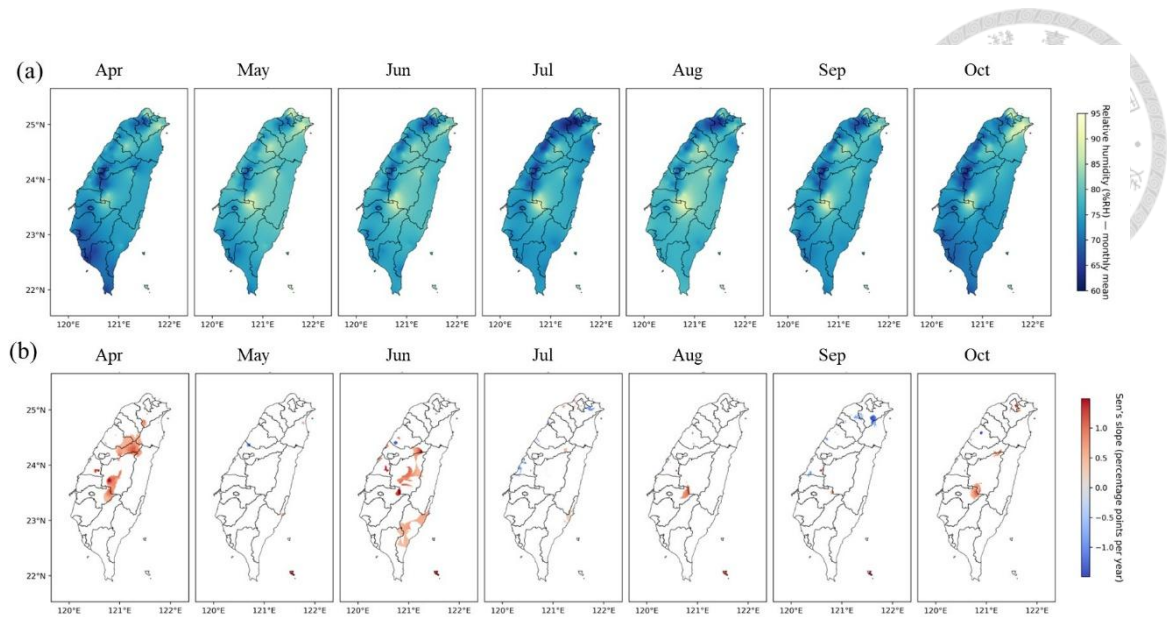


Figure 4.6 Mean relative humidity during the warm season (Apr–Oct): (a) multi-year mean for 2015–2023 and (b) monthly trends estimated using Sen's slope.

(5) **Pressure** : Trends in surface pressure are statistically non-significant across most regions (Figure 4.7).

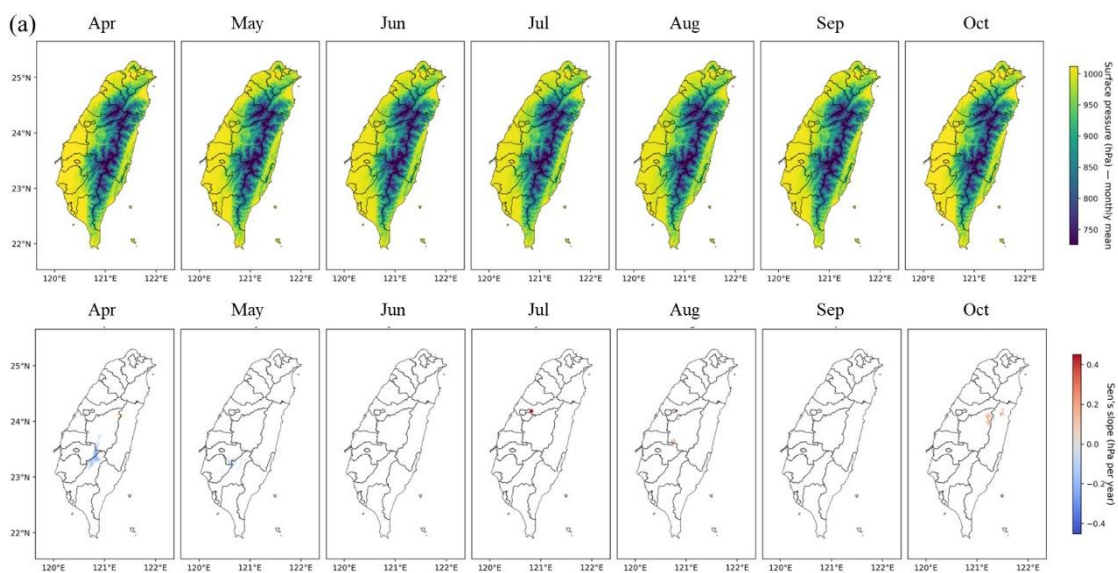


Figure 4.7 Mean surface pressure during the warm season (Apr–Oct): (a) multi-year mean for 2015–2023 and (b) monthly trends estimated using Sen's slope.

4.3 Frequency and Trends of Extreme Heat ($WBGT \geq 32^{\circ}\text{C}$)

This section presents the frequency and trend of extreme heat events, defined by the threshold $WBGT \geq 32^{\circ}\text{C}$.

4.3.1 Spatial Distribution of Extreme Heat Days

The seasonal pattern of extreme heat days ($WBGT \geq 32^{\circ}\text{C}$) reveals two distinct regional heat-stress regimes. *Figure 4.8* shows that southwestern Taiwan experiences very early onset of extreme heat, with extreme heat days already reaching 10-20 days in April and more than 20 days in May. This indicates an unusually long and persistent extreme heat season that extends through October.

In contrast, northern Taiwan and the Hualien-Taitung region exhibit a highly concentrated mid-summer peak. In July, these regions record some of the highest extreme heat day totals nationwide, with the Taipei Basin and the Hualien Valley exhibiting higher exceedance-day counts than the southwestern plains. Although these areas do not experience early-season heat, their peak-season exceedance frequency is notably higher. Overall, southwestern Taiwan is characterized by a long-duration extreme heat season, whereas northern and eastern Taiwan, including southeastern coastal areas, experience a shorter but more intense mid-summer peak in $WBGT \geq 32^{\circ}\text{C}$ exceedance days.

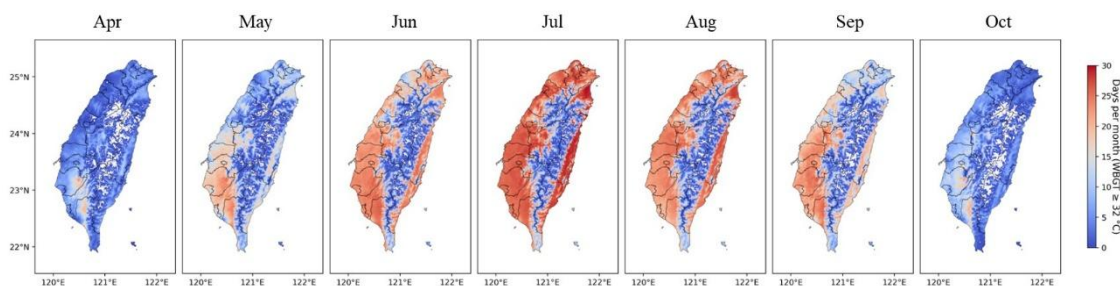


Figure 4.8 Monthly mean number of days with $WBGT \geq 32^{\circ}\text{C}$ during the warm season (Apr–Oct) for 2015–2023.

4.3.2 Trend of Extreme Heat Frequency

The Sen's slope analysis of $WBGT \geq 32^\circ\text{C}$ exceedance days reveals a statistically robust and spatially coherent increase in extreme heat frequency across Taiwan. Significant positive trends ($p < 0.05$) occur primarily in July, August, and September, corresponding to the core of the warm season. In July and August, many locations in western Taiwan exhibit an increase of approximately 1-2 extreme-heat days per year, equivalent to a cumulative rise of 9-18 days over the 2015–2023 period.

Importantly, the spatial pattern of significant trends diverges from the areas with the highest climatological frequency. Rather than being concentrated over the major western plains, statistically significant increases are more pronounced in the central foothills, the eastern edge of the Taichung Basin, and the Hualien-Taitung Valley—regions situated along low-elevation mountain slopes. These areas exhibit consistent warming signals in both mid-summer and transitional-season months, with Sen's slopes commonly reaching 1-2 days per year during July-August.

Figure 4.9 shows that regions with statistically significant trends in extreme heat frequency ($p < 0.05$, Mann–Kendall test) are clustered along the same foothill and valley zones, while most lowland plains and northern coastal regions show non-significant trends. Accordingly, the detected increases in extreme heat days over foothill and valley zones are unlikely to be driven by short-term variability alone. Seasonal aggregation across April-October reinforces this spatial pattern. Among all significant grid cells, 98.9% exhibit positive trends and only 0.6% show declines, indicating that the direction of change is overwhelmingly toward more frequent extreme heat events.

Overall, the results demonstrate that extreme heat has intensified over the past decade, particularly in low-elevation foothills and valley systems where the rate of increase has been statistically significant and spatially coherent. These patterns align closely with, but

are not identical to, those of mean WBGT, suggesting that both summer and transitional-season extreme potential heat risks are steadily increasing in Taiwan.

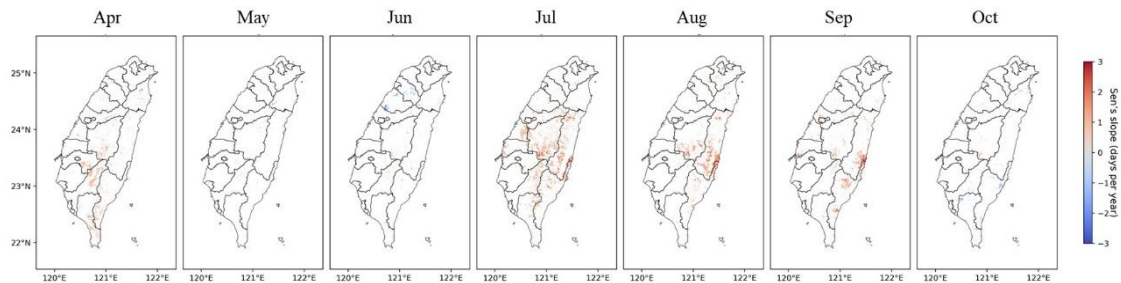


Figure 4.9 Monthly trends in the number of days with $WBGT \geq 32\text{ }^{\circ}\text{C}$ during the warm season (2015–2023), estimated using Sen's slope.

Sen's slope values are displayed only for grid cells with statistically significant trends based on the Mann–Kendall test ($\alpha = 0.05$).

4.4 Quantification of Extreme Heat Acceleration

The acceleration of extreme heat frequency was further quantified by comparing the mean monthly $WBGT \geq 32\text{ }^{\circ}\text{C}$ exceedance days between 2015–2018 and 2020–2023. The difference maps reveal a marked increase in extreme heat occurrence across Taiwan, consistent with the Sen's slope results but providing an absolute measure of the magnitude of change.

Figure 4.10 shows that the strongest acceleration of $WBGT \geq 32\text{ }^{\circ}\text{C}$ exceedance occurs during July–September. In these core summer months, the Hualien-Taitung Valley exhibits an increase of approximately +6 to +8 days per month, representing the largest rise nationwide. The southern tip of Pingtung shows similarly strong increases. Across the Western Plains, increases are more moderate but still substantial, generally ranging from +3 to +5 days per month.

In contrast, April, May, and October display widespread negative or weak changes, indicating that the acceleration signal is seasonally concentrated rather than uniform across the warm season. These patterns highlight that extreme heat has intensified most sharply during the midsummer peak and has expanded particularly along the eastern lowlands and foothill regions.

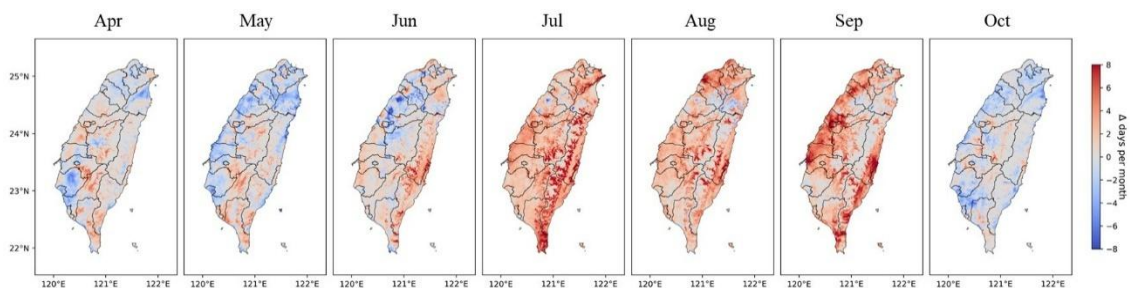
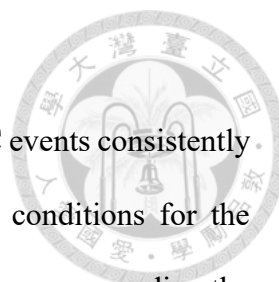


Figure 4.10 *Monthly difference in the number of days with $WBGT \geq 32\text{ }^{\circ}\text{C}$ between the late period (2020–2023) and the early period (2015–2018).*

4.5 Comparison with Dry-Bulb Air Temperature Warning Threshold ($\geq 36\text{ }^{\circ}\text{C}$)

The spatial coverage and event frequency of the physiological heat stress metric $WBGT \geq 32\text{ }^{\circ}\text{C}$ were compared with the conventional dry-bulb air temperature threshold of $\text{Temp} \geq 36\text{ }^{\circ}\text{C}$. This temperature threshold corresponds to the Yellow Signal (High Temperature Information) issued by CWA, which warns the public when the daily maximum air temperature reaches $36\text{ }^{\circ}\text{C}$.

Figure 4.11 shows that areas exceeding the $WBGT \geq 32\text{ }^{\circ}\text{C}$ threshold are geographically extensive, covering most of Taiwan's plains and basin regions. In contrast, high-frequency areas identified using the $\text{Temp} \geq 36\text{ }^{\circ}\text{C}$ threshold are highly localized and spatially scattered. These temperature-based hotspots are primarily confined to specific



inland basins and localized urban heat island regions.

In regions identified as heat hotspots, the frequency of $WBGT \geq 32\text{ }^{\circ}\text{C}$ events consistently exceeded 14 days per month, with some areas experiencing such conditions for the majority of the month during the peak warm season. By comparison, areas exceeding the $Temp \geq 36\text{ }^{\circ}\text{C}$ threshold recorded a maximum frequency of approximately 3 days per month.

In terms of seasonal distribution, $Temp \geq 36\text{ }^{\circ}\text{C}$ events are largely concentrated in July and August, whereas $WBGT \geq 32\text{ }^{\circ}\text{C}$ events exhibited high frequencies across a broader period from May to September. In addition, several regions show contrasting responses between the two metrics. For example, parts of the eastern coastal region experienced frequent $WBGT \geq 32\text{ }^{\circ}\text{C}$ conditions but did not register any $Temp \geq 36\text{ }^{\circ}\text{C}$ events.

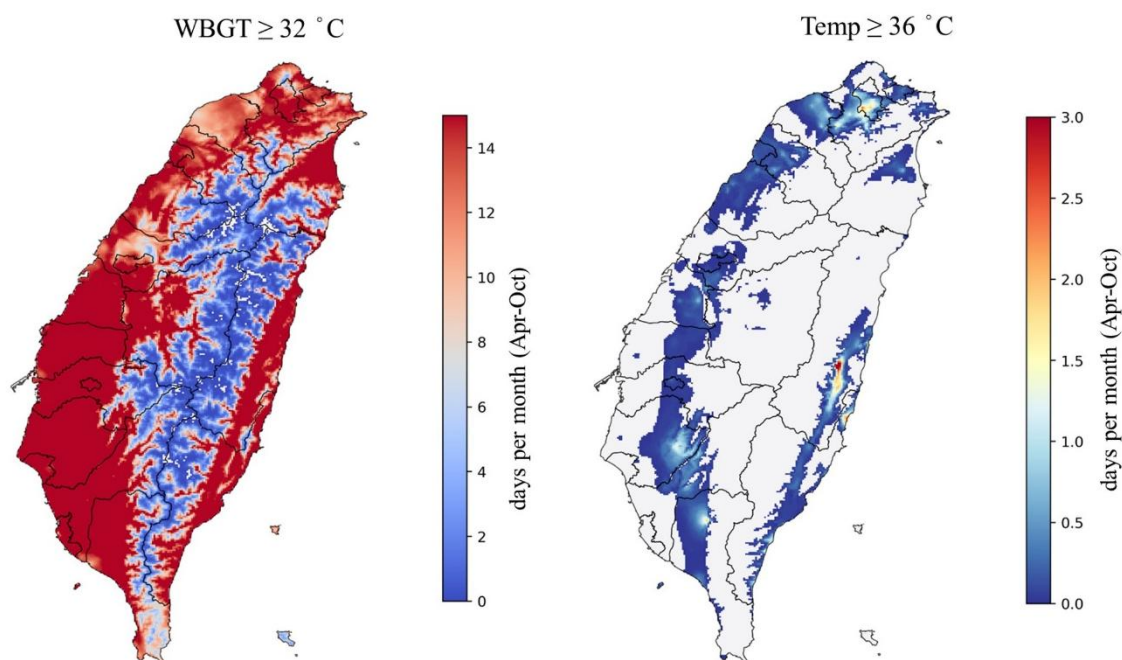


Figure 4.11 Comparison of the mean number of days per month during the warm season (Apr–Oct) with $WBGT \geq 32\text{ }^{\circ}\text{C}$ and air temperature $\geq 36\text{ }^{\circ}\text{C}$ for 2015–2023.

4.6 Synthesis of Key Findings

The analysis of WBGT from 2015 to 2023 shows that heat stress in Taiwan is strongly influenced by topography, with the Southwestern Plains and the Eastern Rift Valley consistently exhibiting the highest and most persistent WBGT levels. Mean monthly WBGT increased significantly during the study period, particularly in July-August, where warming rates exceeded 0.2 °C per year across major lowland areas. These increases correspond to concurrent rises in air temperature and shortwave radiation, along with declining wind speeds that may limit heat dissipation. Extreme heat events (WBGT ≥ 32 °C) have intensified and accelerated, most notably in the Hualien-Taitung Valley, where late-period exceedance days are 6-8 days per month higher than in the early period. The spatial distribution of emerging hotspots indicates that potential heat risk is expanding from traditional western plains toward foothill and valley regions. Comparison with dry-bulb air temperature thresholds further shows that dry-bulb air temperature warning underestimates the true extent and frequency of physiological heat stress.

Chapter 5 Population Exposure to Heat Stress

This chapter combines the extreme heat hazards (days with WBGT $\geq 32^{\circ}\text{C}$) analyzed in Chapter 4 with population distribution data to analyze the spatial heterogeneity of heat exposure and identify population groups with higher exposure levels.

5.1 Exposure Patterns for All Ages

This section examines the spatial distribution of heat hazard, population density, and exposure patterns for the overall population, establishing a baseline exposure context for subsequent age-specific analysis.

5.1.1 Spatial Characteristics of Heat Hazard and Population Distribution

The spatial distributions of extreme heat hazard and population density reveal clear geographic contrasts across Taiwan (Figure 5.1). Heat hazard exhibits a strong dependence on topography, with the southwestern plains, the Taichung Basin, the Kaohsiung-Pingtung region, and parts of the Taipei Basin showing more than 121 hazard days per year. In contrast, the Central Mountain Range and other high-elevation areas consistently experience very low hazard frequencies.

Population distribution also displays pronounced spatial concentration, with dense clusters in Taipei, Taichung, Kaohsiung, and along the western urban corridor. Eastern Taiwan and mountainous areas remain sparsely populated. Together, these patterns establish a foundational context for understanding population exposure: Taiwan's most intense heat hazard occurs predominantly where its population is also most concentrated.

5.1.2 Spatial Hotspots of Population Exposure

Population exposure is defined as the product of extreme heat hazard frequency and population density, thereby jointly reflecting the intensity of heat stress and the degree of population concentration (Figure 5.1). This metric highlights locations where human

potential heat risk is most severe.

Taiwan's population distribution exhibits a pronounced metropolitan core-periphery structure, and the highest population exposure levels ($>500,000$ person-days km^{-2} yr^{-1}) are primarily concentrated in densely populated lowland regions of western Taiwan, including the Chianan Plain, the Kaohsiung-Pingtung region, and the Taipei metropolitan area. In these regions, areas of frequent extreme heat strongly overlap with high population density, resulting in the most severe exposure hotspots nationwide.

By contrast, although relatively high heat hazard frequencies are also observed in parts of the central and southern foothills, the Yilan Plain, and the Hualien-Taitung Valley, the overall population exposure in these regions remains comparatively low due to limited population density. This contrast highlights that the spatial distribution of heat hazard does not necessarily translate into high population exposure; rather, population concentration plays a decisive role in shaping exposure intensity.

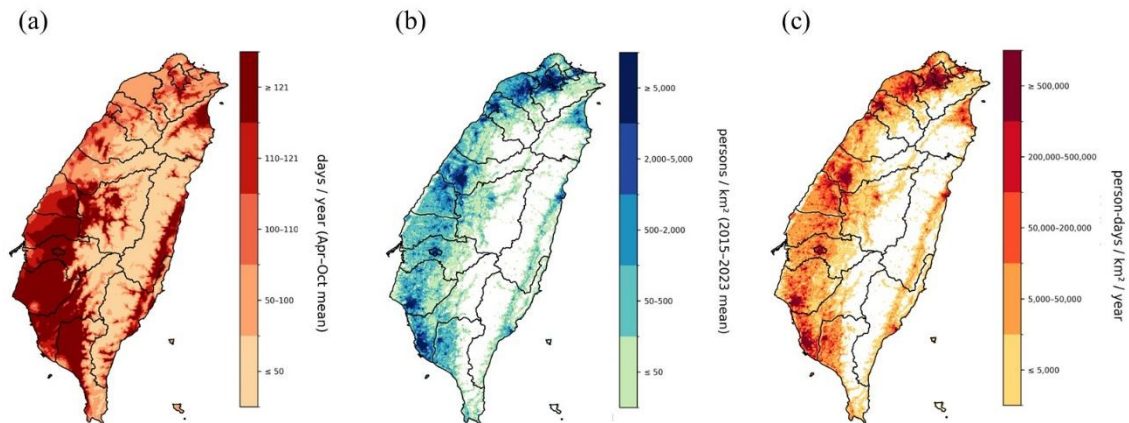


Figure 5.1 Spatial distribution of (a) heat hazard, (b) mean population density (all-age), and (c) population-weighted heat exposure associated with $\text{WBGT} \geq 32$ °C during the warm season (Apr–Oct; 2015–2023 mean).

(a) mean number of days with $\text{WBGT} \geq 32$ °C; (b) mean population density (persons km^{-2});

(c) population-weighted heat exposure (person-days km^{-2} yr^{-1}).

5.2 Bivariate Analysis of Heat Hazard and Population

This bivariate analysis explicitly distinguishes whether high population exposure is primarily driven by climatic hazard intensity or by population concentration. To characterize the combined spatial patterns of heat hazard and population density, a 5×5 bivariate quantile classification was applied using the 20th, 40th, 60th, and 80th percentiles as class boundaries (Figure 5.2). This approach enables the identification of distinct exposure types based on the joint distribution of climatic stress and population concentration.

Areas classified as high hazard and high population density (dark red to purple tones in the upper-right quadrant of the bivariate legend) are predominantly concentrated in southwestern Taiwan, including the Chianan Plain, the urban corridors of Tainan and Kaohsiung, the Pingtung Plain, and parts of the Taichung Basin. These regions represent the most critical heat-exposure environments, where intense heat stress coincides with dense human settlement.

High-hazard but lower-population areas (orange tones) are observed along the western coastal plains, the southern foothill regions, and the Hualien-Taitung Valley. In eastern Taiwan, particularly across the Hualien Plain and the longitudinal valley, elevated heat hazard is evident despite relatively moderate population densities, resulting in distinct hazard-dominated exposure patterns.

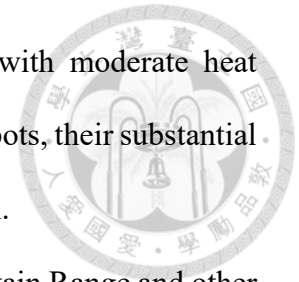
In contrast, low-hazard but high-population areas (light blue tones) are primarily located in northern Taiwan, most notably in Taoyuan and the outer metropolitan fringe of Taipei. These areas host large populations but experience comparatively fewer extreme heat days, reflecting a population-dominated exposure regime rather than a hazard-driven one.

The Taipei metropolitan core and the Yilan Plain exhibit intermediate bivariate

characteristics, combining moderate-to-high population densities with moderate heat hazard. While these regions are not classified as extreme hazard hotspots, their substantial population concentrations indicate non-negligible exposure potential.

Low-hazard and low-population regions dominate the Central Mountain Range and other high-elevation areas, corresponding to the lowest overall exposure levels across Taiwan.

Overall, the bivariate analysis highlights pronounced spatial heterogeneity in heat exposure mechanisms: hazard-driven exposure in southwestern and eastern lowlands, population-driven exposure in northern metropolitan regions, and minimal exposure in mountainous interiors. This classification provides a clear spatial framework for distinguishing region-specific heat-risk typologies across Taiwan.



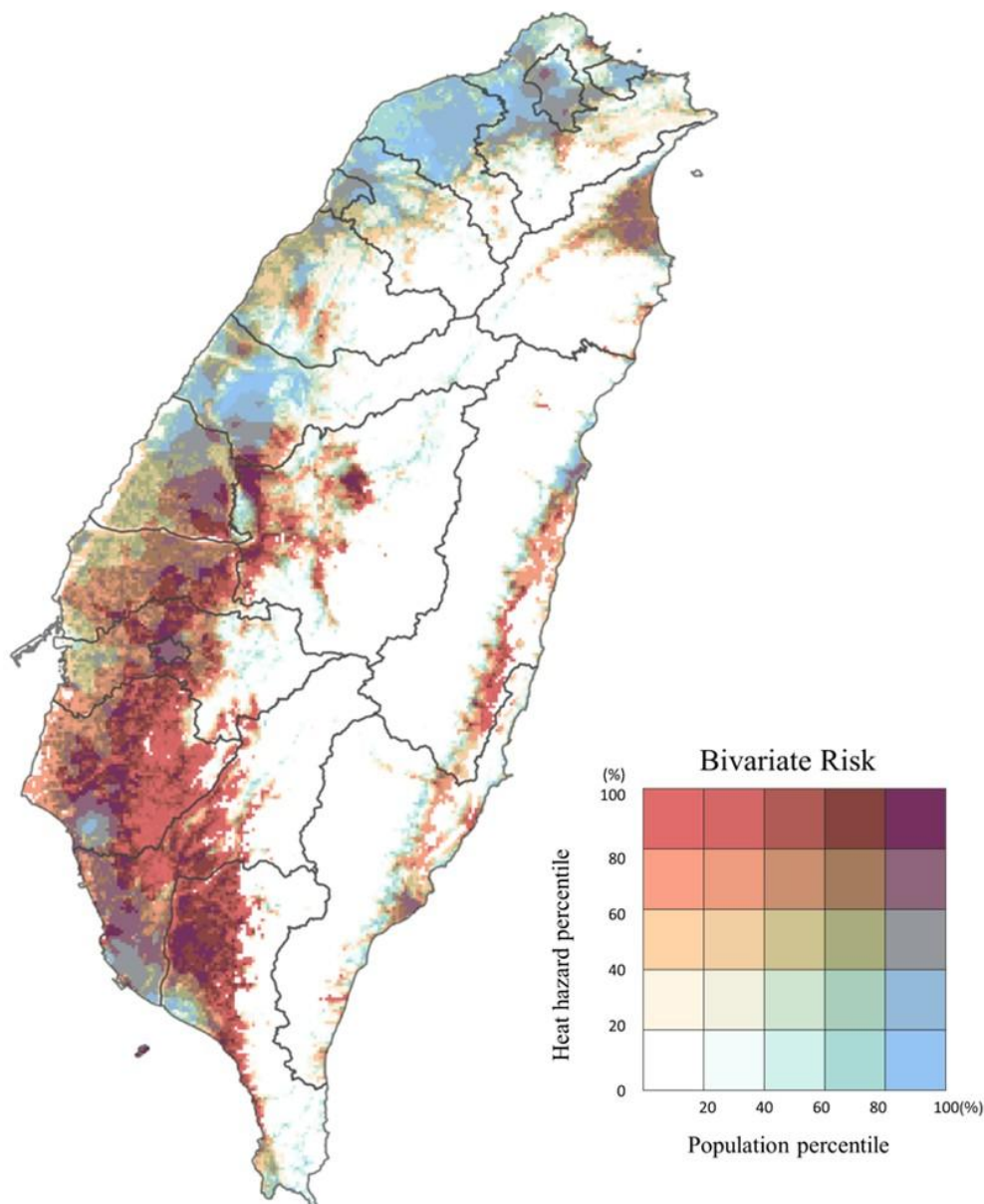


Figure 5.2 Bivariate distribution of heat hazard percentile ($WBGT \geq 32^{\circ}\text{C}$ exceedance days) and population percentile (all-age population) during the warm season (2015–2023 mean). Darker colors indicate areas with both high heat hazard and high population percentiles.

5.3 Identification of Extreme Hotspots ($P80 \times P80$)

Building upon the bivariate heat hazard-population classification, extreme exposure hotspots were further identified using dual 80th-percentile ($P80 \times P80$) thresholds applied to both heat hazard frequency and population density. Pixels exceeding both thresholds represent locations where severe climatic stress coincides with exceptionally high population concentration, delineating the most critical clusters of heat exposure. The selection of the P80 threshold, corresponding to approximately 130 hazard days per year, was made to preserve spatial contiguity. Although higher thresholds such as the 90th percentile (P90) would isolate more extreme conditions, they tend to produce fragmented and spatially discontinuous pixels, reducing interpretability. Such fragmentation would obscure coherent hotspot patterns and limit their usefulness for municipal-scale climate adaptation planning and targeted public health interventions. The resulting extreme-hotspot areas are therefore highly concentrated rather than widespread (Figure 5.3), with major clusters located in the southwestern plains of Taiwan, including parts of Chiayi County, Tainan City, Kaohsiung City, and Pingtung County. Smaller but distinct hotspot groups also emerge in central Taiwan, particularly along the foothills of Nantou County and the margins of the Taichung Basin. This spatial concentration indicates that Taiwan's most severe population heat exposure is confined to specific geographic corridors where climatic hazard and population density strongly overlap. Focusing on the upper 20% of both distributions allows persistent and intense thermal stress regions to be identified while remaining sufficiently robust to inform place-based policy decisions.

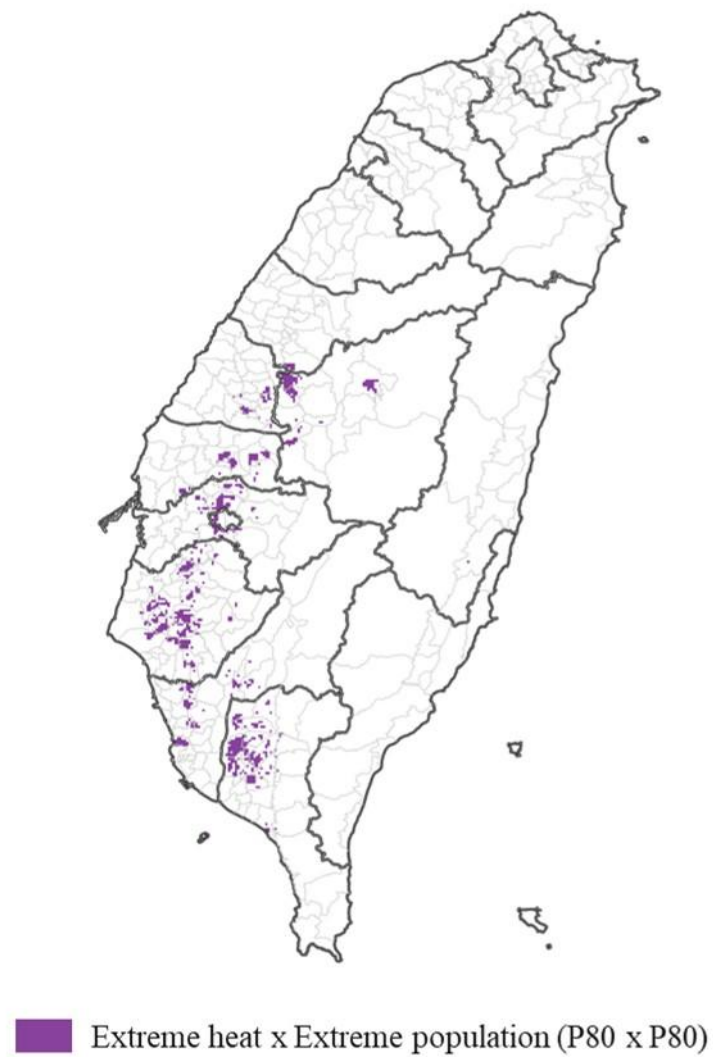


Figure 5.3 *Extreme–extreme hotspots ($P80 \times P80$) derived from the joint distribution of heat hazard and population density (all-age population), based on $WBGT \geq 32\text{ }^{\circ}\text{C}$ exceedance days during the warm season (2015–2023 mean).*

5.4 Extreme Exposure Across Age Cohorts (0–14, 15–64, 65+)

Age-specific analyses reveal broadly consistent spatial patterns of extreme heat exposure across population groups, with differences primarily reflected in magnitude rather than spatial configuration. The proportion of grid cells classified within the extreme–extreme category is 2.92% for children aged 0–14, 3.06% for adults aged 15–64, and 3.39% for the elderly population (≥ 65 years), with the all-age population showing a comparable proportion of 3.07%. While the spatial hotspots are largely concentrated in the western plains across all cohorts, the elderly group exhibits the highest concentration of extreme exposure. Because both hazard and population are independently thresholded at the 80th percentile, the expected proportion of joint classification under statistical independence is 4% of grid cells (0.2×0.2). The observed proportion for the ≥ 65 age group (3.39%) approaches this expected value, suggesting a non-random spatial overlap between persistent heat hazard and areas with higher concentrations of the elderly population. Township-level rankings further indicate strong spatial consistency of extreme hotspots across age cohorts (Figure 5.4;

Table 5.2). Pingtung City ranks first across all population groups, while Caotun Township (Nantou County), Minxiong Township (Chiayi County), and Neipu Township (Pingtung County) consistently appear among the top-ranked locations. Minor variations in subsequent rankings, such as Wantan Township (Pingtung County) and Douliu City (Yunlin County), suggest that demographic composition can modulate exposure intensity within otherwise similar climatic settings.

(a) Ages 0–14

(b) Ages 15–64

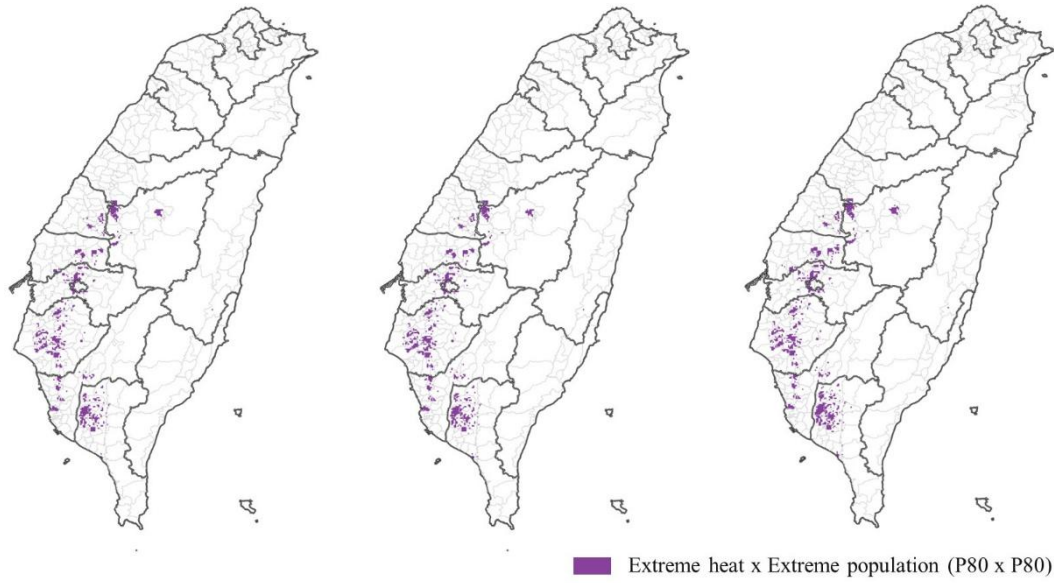
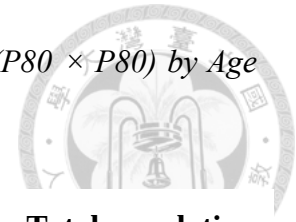
(c) Ages ≥ 65 

Figure 5.4 *Extreme-extreme population hotspots by age group: (a) ages 0–14, (b) ages 15–64, and (c) ages ≥ 65 . Hotspots are defined as areas where both heat hazard (WBGT ≥ 32 °C exceedance days) and age-specific population exceed the 80th percentile (P80), based on the 2015–2023 warm-season mean.*

Table 5.1 *Population P80 $\times$ Hazard P80 (Age group), Extreme $\times$ Extreme pixels refer to grid cells classified in the highest (P80) quantiles of both population and hazard.*

Age group	Population P80 threshold (persons km ⁻²)	Hazard P80 threshold (days, Apr–Oct)	Extreme $\times$ Extreme pixels (count)	Valid pixels (count)	Extreme $\times$ Extreme (%)
Ages 0–14	82.23	130.32	819	28,028	2.922
Ages 15–64	442.85	130.32	857	28,028	3.058
Ages 65+	99.33	130.32	951	28,025	3.393
Overall population	626.25	130.32	860	28,028	3.068

Table 5.2 *Top 10 Municipalities with Extreme Exposure Hotspots ($P80 \times P80$) by Age Group.*



Rank	Ages 0–14	Ages 15–64	Ages ≥65	Total population
1	Pingtung City (Pingtung County)	Pingtung City (Pingtung County)	Pingtung City (Pingtung County)	Pingtung City (Pingtung County)
2	Caotun Township (Nantou County)	Minxiong Township (Chiayi County)	Caotun Township (Nantou County)	Caotun Township (Nantou County)
3	Minxiong Township (Chiayi County)	Caotun Township (Nantou County)	Minxiong Township (Chiayi County)	Minxiong Township (Chiayi County)
4	Neipu Township (Pingtung County)	Shanhua District (Tainan City)	Neipu Township (Pingtung County)	Neipu Township (Pingtung County)
5	Shanhua District (Tainan City)	Neipu Township (Pingtung County)	Shanhua District (Tainan City)	Shanhua District (Tainan City)
6	Douliu City (Yunlin County)	Wandan Township (Pingtung County)	Puli Township (Nantou County)	Douliu City (Yunlin County)
7	Wandan Township (Pingtung County)	Douliu City (Yunlin County)	Wandan Township (Pingtung County)	Wandan Township (Pingtung County)
8	Puli Township (Nantou County)	Puli Township (Nantou County)	Douliu City (Yunlin County)	Puli Township (Nantou County)
9	Xinhua District (Tainan City)	Xinshi District (Tainan City)	Xinshi District (Tainan City)	Xinshi District (Tainan City)
10	Xinying District (Tainan City)	Xinhua District (Tainan City)	Xinhua District (Tainan City)	Xinhua District (Tainan City)

5.5 Synthesis of Key Findings

The population exposure analysis reveals that extreme heat exposure in Taiwan is highly spatially heterogeneous and primarily governed by the spatial overlap between extreme heat hazard and population concentration. While high frequencies of WBGT ≥ 32 °C occur across multiple lowland regions, the highest exposure levels are concentrated in densely populated areas of western Taiwan, particularly the Chianan Plain, the Kaohsiung-Pingtung region, and the Taipei metropolitan area. Bivariate classification further distinguishes hazard-dominated exposure patterns in southwestern and eastern lowlands from population-dominated exposure in northern metropolitan regions, with mountainous areas consistently exhibiting low exposure. Extreme exposure hotspots identified using dual P80 thresholds are spatially concentrated rather than widespread, forming coherent clusters mainly in southwestern Taiwan and, to a lesser extent, in central basin and foothill regions. Across age cohorts, extreme hotspots exhibit highly consistent spatial patterns, although the elderly population shows the highest concentration within extreme-extreme areas, indicating greater exposure intensity among older adults.

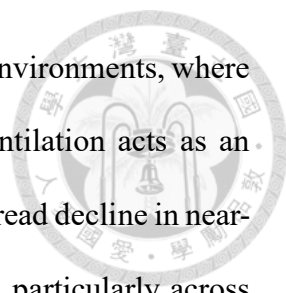
Chapter 6 Discussion



6.1 Spatiotemporal Intensification of Physiological Heat Stress

6.1.1 Meteorological Drivers and the Radiative-Thermal Regime

WBGT integrates air temperature, relative humidity, solar radiation, and wind speed, and thus provides a physiologically meaningful measure of heat stress that reflects the combined thermal load experienced by the human body. Consequently, variations in WBGT capture not only background air temperature changes, but also changes in radiative loading and ventilation conditions. Based on the analysis for 2015–2023, the results indicate that the recent intensification of physiological heat stress in Taiwan arises from the combined effects of radiative heating operating under a warming thermal background, rather than from a single dominant meteorological factor. At the national scale, the spatial and seasonal patterns of WBGT trends (Figure 4.2) closely resemble those of air temperature (Figure 4.3), suggesting that thermodynamic warming provides an important background control on increasing heat stress. The most pronounced WBGT increases occur during the core summer months, consistent with widespread warming across Taiwan's lowland regions. However, air temperature alone does not fully account for the observed magnitude or seasonal structure of WBGT changes. In particular, the enhanced WBGT observed during the transitional months of April and September is closely associated with increases in downward shortwave radiation (Figure 4.4). Increased radiative heating elevates the globe temperature (T_g) component of WBGT, contributing to an earlier onset of physiologically stressful conditions, even before peak-summer air temperatures are reached. This highlights the importance of radiative



processes in shaping early- and late-season heat stress in subtropical environments, where solar radiation remains strong outside the core summer period. Ventilation acts as an additional modulating factor in Taiwan's heat stress regime. A widespread decline in near-surface wind speed (Figure 4.5) is observed during June-September, particularly across lowland and coastal regions. This surface wind weakening is consistent with broader observations of increasing atmospheric stagnation, which has been associated with the intensification of regional heat stress. Mechanistically, reduced wind speed affects WBGT primarily by limiting convective heat loss from the globe temperature (T_g) component. Under lower ventilation conditions, heat accumulated from solar radiation on surfaces and on the human body cannot be efficiently dissipated. This amplifies experienced heat stress even under otherwise similar thermal conditions and contributes to the increased frequency of extreme WBGT exceedance. In the context of Taiwan's complex topography, such stagnation likely enhances heat retention within basins and leeward plains, creating localized thermal environments that are particularly hazardous. Relative humidity, by contrast, remains persistently high throughout the warm season across Taiwan, typically exceeding 60% in most regions (Figure 4.6). While this high humidity substantially elevates baseline WBGT values, its long-term trends exhibit weaker magnitude and lower spatial coherence than those of air temperature and shortwave radiation. This suggests that relative humidity primarily acts as a background condition that elevates overall heat stress levels island-wide, whereas recent regional intensification is more strongly associated with thermodynamic warming, radiative heating, and changes in ventilation (Figure 6.1). This interpretation is consistent with previous station-based analyses in Taiwan, which show that high-WBGT events are typically associated with elevated air temperature and strong solar radiation under persistently humid conditions (Lung et al., 2019). Taken together, these results indicate that humid heat stress in Taiwan is governed

by radiative heating operating under a warming thermal background, with ventilation acting as an important secondary control. Under such conditions, WBGT provides a practical framework for synthesizing the combined influences of temperature, radiation, humidity, and wind when examining spatial and temporal variations in human heat stress.

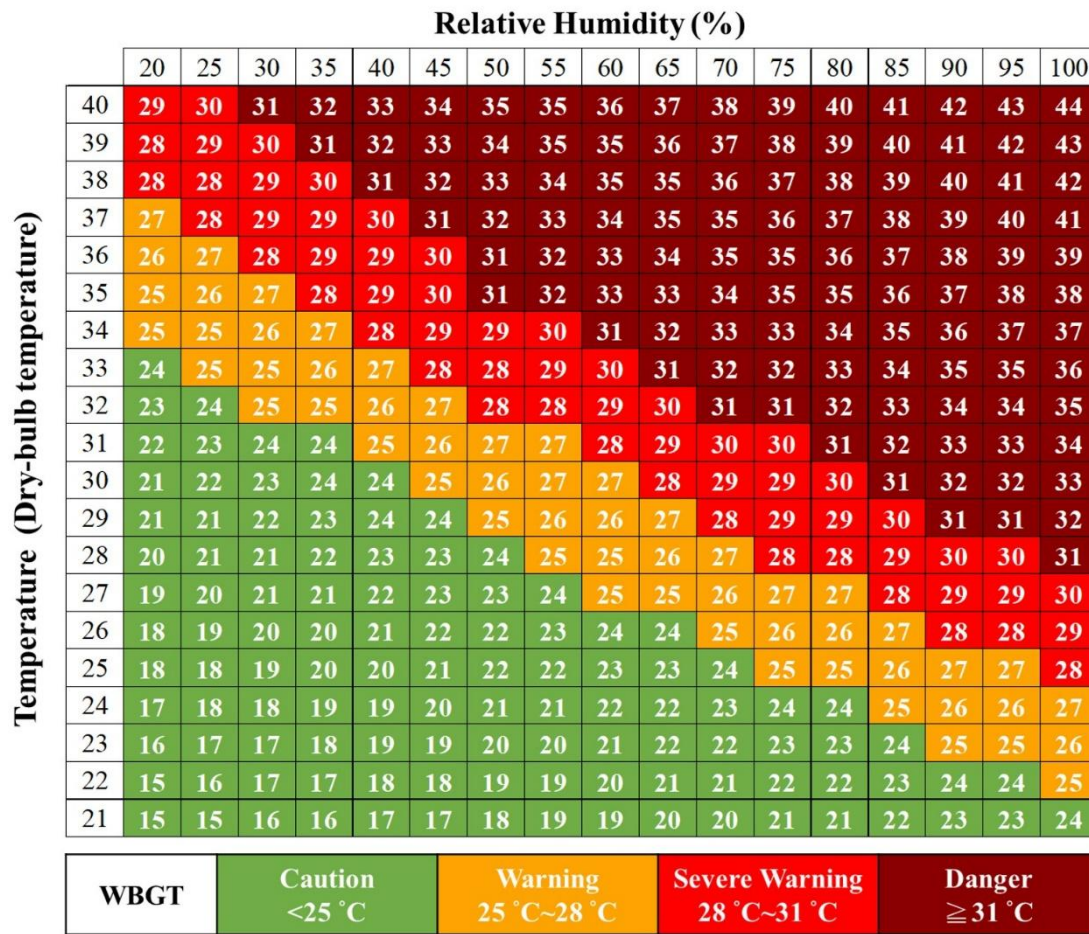
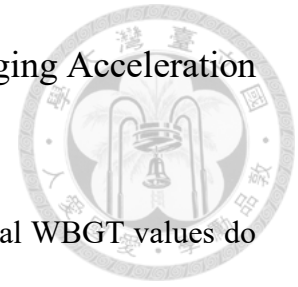


Figure 6.1 Estimated WBGT values. Redrawn by author based on Guideline for Prevention of Heat Strokes in Daily Life (Ver. 1) by Ministry of the Environment, Government of Japan (2008).

6.1.2 Spatial Divergence, Seasonal Contrasts, and Emerging Acceleration Zones



A central finding is that areas experiencing the highest climatological WBGT values do not necessarily coincide with those undergoing the most rapid intensification. The southwestern plains remain the long-term core hotspots, characterized by high absolute WBGT and an unusually long duration of extreme heat. However, the strongest and most spatially coherent increases in extreme heat frequency ($\text{WBGT} \geq 32\text{ }^{\circ}\text{C}$) emerge along low-elevation foothills, and valley systems, particularly the Hualien-Taitung Valley, indicating that potential heat risk is expanding beyond traditional lowland cores toward topographic transition zones.

These emerging acceleration zones are important from a risk management perspective because they may be overlooked by conventional assessments focusing on long-term mean temperature or historically hottest areas. The observed divergence between “where it is hottest” and “where intensification is fastest” suggests that monitoring and adaptation priorities should consider both climatological baselines and trend signals, especially in foothill-valley environments where populations and ecosystems may face rapidly changing thermal stress conditions.

The results further indicate that the expression of extreme heat differs regionally not only in magnitude but also in seasonal structure. Exceedance frequency exhibits pronounced month-to-month contrasts across Taiwan, implying that effective risk management may require temporal targeting rather than a uniform warm-season strategy. Moreover, differences between intensity and frequency are salient: northern Taiwan may experience higher peak WBGT values during mid-summer but with less persistent occurrence, whereas southern regions often exhibit more frequent exceedance and a longer season of

high heat stress without necessarily reaching the highest absolute extremes. These contrasts highlight that annual or seasonal means alone can mask meaningful differences in heat-risk regimes and that frequency-based indicators are essential for characterizing exposure-relevant heat burdens.

Finally, intensification in transition zones may have broader implications beyond human heat exposure, including potential impacts on ecological and biological systems. The expansion of high heat stress into foothill and valley regions may alter local habitat suitability and stress responses, suggesting a direction for future environmental and ecological research.

6.2 Toward a More Comprehensive Heat Warning System in Taiwan

6.2.1 Constraints of Temperature-Only Indicators under Humid Subtropical Conditions

Taiwan's current heat-warning framework relies primarily on a dry-bulb air temperature threshold, which provides a clear and administratively efficient basis for public communication. However, under Taiwan's humid subtropical climate, this single-metric approach does not fully represent the physiological heat burden experienced by the population. Human heat dissipation depends on the combined effects of evaporative, convective, and radiative processes, which are more comprehensively captured by WBGT than by air temperature alone (Parsons, 2014; ISO 7243, 2017).

Our results indicate that temperature-based warnings primarily emphasize peak summer extremes, whereas hazardous wet-hot conditions occurring in coastal regions, and transitional seasons are more likely to be overlooked. In particular, enhanced shortwave radiation during April and September elevates the globe temperature component of

WBGT, intensifying physiological heat stress before peak-summer air temperatures are reached. Under continued background warming and increasing radiative loading, these structural limitations of temperature-only metrics are likely to become more pronounced, underscoring the need for indicators that better reflect total environmental heat load.

6.2.2 Integrating Physiological Heat Stress and Population Exposure

An important implication emerging from this study is that climatic hazard alone does not directly translate into societal heat risk. While WBGT provides a physiologically meaningful representation of environmental heat stress, the spatial distribution of risk depends critically on where populations are exposed (Tuholske et al., 2021). Our analysis demonstrates that regions experiencing rapid intensification of heat hazard do not necessarily coincide with areas containing the largest exposed populations, revealing a spatial divergence between hazard dynamics and present-day exposure patterns.

By integrating WBGT-based hazard metrics with 1-km gridded population data, this study illustrates how exposure considerations fundamentally reshape the prioritization of heat risk. This exposure-oriented perspective shifts attention away from locations where extreme conditions occur in isolation toward places where physiological stress intersects with dense or vulnerable populations. From an operational standpoint, the high-resolution WBGT dataset developed here provides a spatial bridge between station-based meteorological observations and population-relevant exposure assessments. Used as a supplementary diagnostic layer, WBGT-informed exposure metrics can enhance the targeting of warnings while preserving the communicative simplicity of existing administrative thresholds.

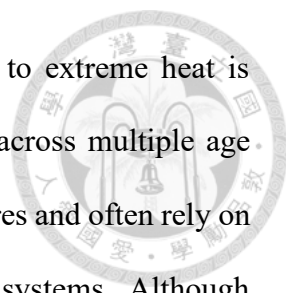
6.2.3 From Exposure Magnitude to Vulnerability Prioritization in an Aging Society



Beyond aggregate exposure, a critical distinction emerges between total exposure magnitude and the concentration of risk within vulnerable demographic groups. While larger population cohorts naturally account for greater absolute exposure, older adults tend to be disproportionately represented in environments characterized by frequent extreme heat exposure. This pattern likely reflects long-term settlement dynamics, including the persistence of aging populations in neighborhoods with older housing stock and limited access to cooling-effective green infrastructure (Shih & Ouyang, 2025). Because aging is associated with reduced thermoregulatory capacity, the spatial coupling of persistent heat hazards and older populations implies heightened cardiovascular strain and diminished physiological resilience (Huang, 2013).

This layered vulnerability highlights that heat risk is shaped not only by physiological sensitivity but also by broader socio-spatial conditions. Strategies focused solely on reducing aggregate exposure may therefore fail to capture localized heat-risk inequality at the neighborhood scale (Anguelovski et al., 2018).

Importantly, regions with higher proportions of older adults in Taiwan tend to coincide with areas of relatively limited healthcare availability, particularly outside major metropolitan centers. This spatial mismatch suggests that aging populations in non-urban regions may face disproportionate health risks under intensifying heat stress. Healthcare availability thus acts as a critical moderator between physiological heat exposure and realized health outcomes, especially for older adults. While this study does not explicitly model healthcare capacity or health outcomes, the observed spatial concurrence highlights a structural vulnerability that warrants attention in heat-risk prioritization.



The township-level rankings reveal that high population exposure to extreme heat is repeatedly concentrated in a limited set of non-metropolitan areas across multiple age groups. These locations are not primary medical or administrative cores and often rely on regional healthcare networks rather than dense urban medical systems. Although healthcare capacity is not explicitly assessed in this study, the spatial coincidence of persistent heat exposure, aging populations, and non-core urban status suggests a potential mismatch between heat-related health risks and the accessibility of medical services during extreme events. This finding highlights the importance of incorporating healthcare accessibility considerations into future heat-health risk assessments and adaptation planning.

The systematic overlap between elderly populations, persistent heat hazards, and constrained healthcare resources suggests that heat risk in these regions is a product of both climatic and structural vulnerabilities. In peri-urban and rural hotspots, climatic stressors and institutional constraints reinforce one another, amplifying population-level susceptibility. Within this context, the observed decline in near-surface wind speeds further underscores the importance of urban ventilation and healthcare accessibility as key adaptive buffers. Future place-based adaptation strategies should therefore prioritize healthcare capacity strengthening and the preservation of ventilation corridors in high-risk areas to address the compounded burden of atmospheric stagnation and limited medical response capability.

6.2.4 Policy Implications for a Tiered and Place-Based Heat Warning Framework

Taken together, these findings support the development of a tiered heat-warning framework for Taiwan. Such a system would retain the clarity and public familiarity of

existing temperature-based thresholds while incorporating WBGT-based indicators and population exposure metrics as supplementary decision layers. This approach enables spatially and demographically refined warnings without imposing excessive complexity on public communication.

At the policy level, exposure-informed heat warnings provide a foundation for more place-based adaptation strategies. This includes the targeted deployment of cooling centers in elderly-dense hotspots, the integration of urban ventilation planning into local zoning regulations to counteract atmospheric stagnation, and strengthened coordination between meteorological agencies and social welfare services to monitor high-risk households (Lung et al., 2023).

From a spatial planning perspective, the concentration of extreme heat exposure in aging, non-core urban areas highlights the need to move beyond broad, administrative-level alerts toward more localized, neighborhood-scale interventions. The high-resolution (1-km) exposure maps developed in this study provide spatially explicit information that can support such a shift by identifying areas where physiological heat stress and demographic vulnerability most strongly overlap. In this context, the findings point to the potential value of strengthening healthcare accessibility and preserving urban ventilation corridors in elderly-dense hotspots, where the potential for heat-related health burdens is greatest. By explicitly accounting for both physiological heat stress and demographic vulnerability, an integrated warning framework offers a pathway toward addressing emerging concerns of heat-related environmental justice. Ensuring that residents in resource-constrained areas have access to both timely information and physical cooling infrastructure is essential. Under continued warming, advancing toward such a comprehensive and equitable system will become increasingly critical for effective public-health protection in Taiwan's aging society.

To synthesize the above findings and their policy implications, Figure 6.2 presents a conceptual framework illustrating how temperature-based public alerts and WBGT-based physiological risk assessment can function together as a dual-track heat warning strategy.

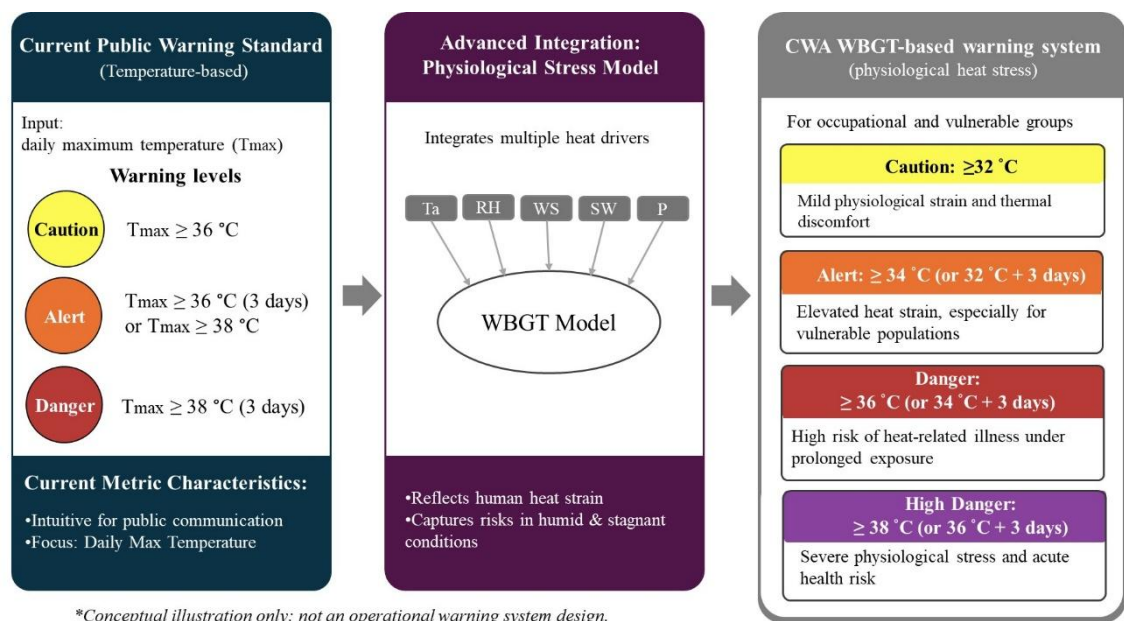


Figure 6.2 Conceptual framework for a dual-track heat warning strategy that complements primary public alerts with specialized physiological risk assessment.

6.3 Uncertainties and Limitations

Several limitations should be considered when interpreting the results of this study.

(1) The analysis period spans nine years from 2015 to 2023. While this period captures the recent intensification of heat stress, it remains sensitive to interannual variability. In particular, the quantification of extreme heat acceleration in Section 4.4 relies on comparisons between two relatively short sub-periods, namely 2015 to 2018 and 2020 to 2023. Exceptional years within these windows may exert a disproportionate influence on the estimated changes. Longer observational records would therefore be necessary to

strengthen inference regarding long-term trends.

(2) The use of a fixed threshold of $WBGT \geq 32\text{ }^{\circ}\text{C}$ provides a clear and interpretable benchmark for identifying hazardous heat conditions. However, alternative thresholds may represent different physiological or operational risk regimes. Future sensitivity analyses using multiple WBGT thresholds would help to assess the robustness of the identified spatial and temporal patterns.

(3) Population exposure in this study is derived from registered population data rather than actual residential or activity-based population distributions. The gridded population layers therefore reflect household registration records, which may differ from real residence patterns and do not account for daytime mobility, commuting, tourism, or occupational exposure. Consequently, the exposure estimates primarily characterize the spatial coupling between heat hazards and registered population distributions, rather than true activity-based heat exposure. This limitation is particularly relevant as Taiwan approaches super-aged society status in late 2025, since the daily activity patterns and healthcare needs of older adults may generate localized exposure characteristics that are not fully captured by administrative registration data.

(4) Vulnerability in this study is approximated through age structure as a proxy. While this approach captures broad demographic sensitivity to heat stress, it does not account for other dimensions of vulnerability, such as socioeconomic status, pre-existing health conditions, housing quality, or access to cooling resources. These unmodeled factors may further modulate heat-related risk at the local scale.

In addition, the study period overlaps with the COVID-19 pandemic between 2020 and 2023, during which Taiwan experienced atypical demographic dynamics. Accelerated natural decrease and social out-migration during this period produced population patterns that deviate from longer-term demographic trends. These pandemic-related anomalies

may have influenced exposure estimates, particularly in urban and peri-urban areas where population change was most pronounced.

(5) Although the 1 km spatial resolution is relatively high for a national-scale WBGT product, it does not explicitly resolve intra-urban microclimatic modifiers such as urban morphology, shading, ventilation corridors, or fine-scale green infrastructure. As a result, local heat stress variability within dense urban environments may be underestimated.

(6) Uncertainties in the gridded meteorological fields are likely larger in mountainous regions due to sparse station coverage and complex terrain. These factors may introduce additional uncertainty into local hazard estimates at higher elevations, although the overall exposure implications are limited by lower population densities in these areas.

(7) The analysis is restricted to daytime heat exposure between 08:00 and 17:00 LST.

Although this period captures the most critical WBGT peaks identified in the results, physiological heat stress is cumulative by nature. Prolonged daytime heat, when combined with insufficient nocturnal cooling under urban heat island conditions, may hinder effective dissipation of accumulated body heat. This limitation is particularly relevant for older adults, whose thermoregulatory capacity is reduced. Consequently, the exposure estimates may underrepresent compounded thermal stress associated with consecutive daytime and nighttime heat conditions.

(8) While this study provides spatially explicit information relevant to heat-risk interpretation, it does not evaluate operational aspects of early warning systems, such as warning lead time, issuance thresholds, or response effectiveness. These considerations require integration with institutional, legal, and public health frameworks and are beyond the scope of the present analysis.

6.4 Future Research Directions

Future research can strengthen and extend this framework in several directions. Expanded hazard characterization incorporating multiple WBGT thresholds and event-based metrics, such as consecutive exceedance days and compound humidity-radiation extremes, would better capture the full severity spectrum of heat stress. Dynamic exposure assessment integrating diurnal mobility proxies and occupational exposure information would enable a transition from static residential exposure toward activity-based exposure estimates.

Coupling WBGT hazards with land cover, urban form, and green infrastructure indicators would facilitate attribution of within-region variability and identification of actionable heat-mitigation pathways. Linking high-resolution WBGT exposure fields with health outcome data would allow quantification of exposure-response relationships and support evidence-based public health policy. Finally, combining observed WBGT patterns with climate-model outputs would enable evaluation of future exposure under climate change scenarios and support long-term adaptation planning.

Chapter 7 Conclusion

7.1 Research Summary

This study demonstrates that recent heat stress in Taiwan has intensified not only in magnitude but also in spatial complexity, particularly under humid subtropical conditions. The analysis shows that physiological heat stress, as represented by WBGT, exhibits strong topographic dependence and pronounced regional contrasts, with persistent hotspots in the western plains and the Hualien-Taitung Rift Valley.

Beyond long-established lowland hotspots, the results further indicate that the most rapid increases in extreme heat frequency have emerged in foothill and valley regions. This spatial divergence between areas of high climatological heat burden and areas of rapid intensification highlights the importance of considering both baseline conditions and temporal trends when assessing heat risk.

From an exposure perspective, the study finds that heat-related risk is shaped by the spatial coincidence of thermal hazards and population distribution. High exposure levels are concentrated in densely populated urban corridors, while demographic structure strongly modulates exposure intensity. In particular, older adults are disproportionately represented in extreme heat exposure hotspots, underscoring the critical interaction between climatic intensification and population aging.

7.2 Major Contributions

The findings of this study contribute to climate risk assessment and applied heat-stress research in Taiwan by explicitly linking physical heat dynamics with demographic vulnerability.

First, by establishing a long-term WBGT gridded dataset at 1-km spatial resolution, this research provides a detailed representation of physiological heat stress that complements



existing meteorological monitoring frameworks. The results indicate that potential extreme heat hazards are not only intensifying in long-established lowland hotspots but are also expanding into topographic transition zones, particularly the Hualien–Taitung Rift Valley and surrounding hillside regions. This provides new insights into the spatial expansion of heat stress that is not fully resolved by conventional dry-bulb temperature-based assessments.

Second, by integrating WBGT-based heat hazards with population distribution, this study strengthens the translation of physical climate information into societal exposure analysis. The analysis demonstrates that population concentration plays a critical role in shaping exposure intensity, and that areas experiencing increases in extreme heat frequency do not always coincide with major population centers. This distinction highlights the necessity of incorporating demographic data when identifying priority areas for heat-risk management and adaptation planning.

Third, the results reveal a pronounced concentration of potential extreme heat exposure among the elderly population. High-risk exposure areas cluster in specific municipalities, including Pingtung City and Caotun Township, where persistent heat hazards coincide with high proportions of older residents. Although health outcomes are not explicitly modeled, this spatially explicit evidence provides a practical basis for prioritizing age-sensitive heat-adaptation strategies and public health interventions.

7.3 Concluding Remarks

The findings of this study highlight the value of incorporating multi-variable, physiologically relevant indicators when characterizing heat stress in humid subtropical environments. While existing dry-bulb air temperature thresholds provide a stable and communicable baseline for public heat warnings, the inclusion of WBGT offers

complementary information that helps resolve additional dimensions of human thermal stress under conditions characterized by high humidity, strong solar radiation, and reduced ventilation.

In the context of Taiwan's rapidly aging demographic structure, spatially detailed assessments of physiological heat stress provide added value for identifying vulnerable populations and supporting targeted heat-health planning. By resolving fine-scale variability in both heat hazards and population exposure, the framework developed in this study offers a scientific basis for future localized heat-risk communication, targeted adaptation strategies, and more equitable public health planning.

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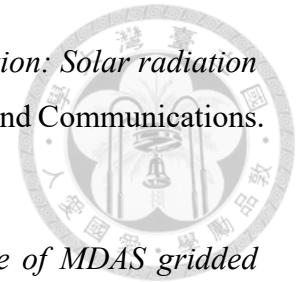
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APPENDIX



Physical Formulation of the WBGT Model

This appendix documents the physical formulations used to estimate the natural wet-bulb temperature (T_{nwb}) and globe temperature (T_g) following the physically based model of Liljegren et al. (2008). These formulations are provided for reproducibility; detailed derivations are available in the original publication.

A1. Natural Wet-Bulb Temperature Model

The natural wet-bulb temperature is calculated based on the heat and mass balance at the surface of a wetted wick. The formulation is expressed as:

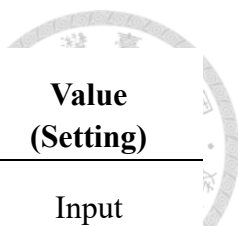
$$T_{nwb} = T_a - \frac{kx\Delta HM_{H_2O}}{h} \left(\frac{e_w - e_a}{P - e_w} \right) + \frac{\Delta F_{net}}{Ah} \quad (A1)$$

where the actual vapor pressure (e_a) is calculated as:

$$e_a = RH \times e_{sat}(T_a) \quad (A2)$$

where:

Symbol	Description	Unit	Value (Setting)
T_{nwb}	Natural wet-bulb temperature	°C	-
T_a	Air temperature	°C	Input
A	Surface area of the wick	m ²	-
ΔH	Heat of vaporization	J·kg ⁻¹	-
M_{H_2O}	Molecular weight of water vapor	kg·mol ⁻¹	0.018015
h	Convective heat transfer coefficient	W·m ⁻² ·K ⁻¹	-
v	Wind speed	m·s ⁻¹	Input



Symbol	Description	Unit	Value (Setting)
P	Barometric pressure	kPa	Input
e_w	Saturated vapor pressure at T_{nwb}	kPa	-
e_a	Actual vapor pressure	kPa	-
e_{sat}	Saturation vapor pressure at T_a	kPa	-
RH	Relative humidity	%	Input
kx	Convective mass transfer coefficient	$\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$	-
ΔF_{net}	Net radiant heat flux	$\text{W} \cdot \text{m}^{-2}$	-
α_w	Wick albedo	-	0.4
ε_w	Wick emissivity	-	0.95

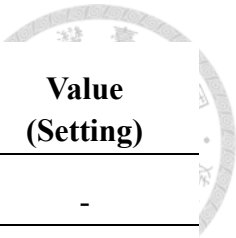
A2. Globe Temperature Model

The globe temperature is obtained by solving the energy balance of a black globe exposed to radiative and convective heat exchange. The energy balance equation is written as:

$$\begin{aligned}
 A\varepsilon_g\sigma T_g^4 + Ah(T_g - T_a) \\
 = \frac{A}{2}\varepsilon_g\sigma(\varepsilon_a T_a^4 + \varepsilon_{sfc} T_{sfc}^4) + \frac{A}{2}(1 - \alpha_g)(1 - f_{dir})S \quad (A3) \\
 + \frac{\frac{A}{4}(1 - \alpha_g)f_{dir}S}{\cos(\theta)} + \frac{A}{2}(1 - \alpha_g)\alpha_{sfc}S
 \end{aligned}$$

where:

Symbol	Description	Unit	Value (Setting)
T_g	Globe temperature	$^{\circ}\text{C}$	-
A	Surface area of the globe	m^2	-
T_{sfc}	Surface temperature	K	T_a



Symbol	Description	Unit	Value (Setting)
ε_a	Atmospheric emissivity	-	-
ε_g	Globe emissivity	-	0.95
ε_{sfc}	Surface emissivity	-	0.999
S	Solar radiation	$\text{W}\cdot\text{m}^{-2}$	Input
σ	Stefan-Boltzmann constant	$\text{W}\cdot\text{m}^{-2}\cdot\text{K}^{-4}$	5.67×10^{-8}
α_g	Globe albedo	-	0.05
α_{sfc}	Effective surface albedo	-	0.25
f_{dir}	Fraction of total horizontal solar irradiance due to direct beam	-	-
θ	Solar zenith angle	Degrees ($^{\circ}$)	-

A3. WBGT Calculation

For outdoor environments under solar radiation:

$$WBGT_{\text{outdoor}} = 0.7T_{\text{nwb}} + 0.2T_g + 0.1T_a \quad (\text{A4})$$

following ISO 7243, 2017.