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臺北都會區北部地區地表覆蓋變遷下之氣溫變化分析

Analysis of Temperature Change Under Land Cover

Change in Northern Taipei Metropolitan Area

卡吾妲

Undrakh Ganzorig

指導教授：石婉瑜 博士

Advisor: Wan-Yu Shih, Ph.D.

共同指導教授：羅敏輝 博士

Co-Advisor: Min-Hui Lo, Ph.D.

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Analysis of Temperature Change Under Land Cover Change in
Northern Taipei Metropolitan Area

The undersigned, appointed by the Department / Institute of MS Program in Disaster Risk Reduction and Resilience on July 21th 2025, have examined a Master's thesis entitled above presented by Undrakh Ganzorig R12H46001 candidate and hereby certify that it is worthy of acceptance.

口試委員 Oral examination committee:

石婉瑜
(指導教授 Advisor)

羅敏婷
(共同指導教授 Co-Advisor)

李時雨

羅資婷

系(所、學位學程)主管 Director: 

摘要



過去三十年來，臺北都會區北部的都市發展導致了大量綠地與農地轉為建成區的地表覆蓋變化。為探討此類變化如何影響夏季白天與夜間的近地表空氣溫度，本研究分析 1990 年至 2023 年間的氣溫變化趨勢。研究方法結合衛星影像進行的土地覆蓋分類、臺灣氣象觀測站資料，以及臺灣歷史氣候重建資料 (TReAD)，並依據不同土地覆蓋類型進行分類分析。

研究結果顯示，新興都市化區域，特別是林口與龜山，出現最顯著的升溫，夜間氣溫上升超過 2°C 。相較之下，綠地比例較高或海拔較高的區域則呈現較小的氣溫增幅，凸顯綠地與地形在緩和氣溫上升方面的作用。1990 年代至 2000 年代初期的資料顯示，夜間升溫相對較強，而 2010 年代以後則顯示白天升溫趨勢明顯上升，在都市核心區中更與夜間升溫持平甚至超越，可能與不透水鋪面增加、綠地減少以及通風不良導致的日間熱累積效應有關。

整體而言，研究結果顯示地表覆蓋組成與在地環境條件共同影響都市熱環境的時空變化。雖然 TReAD 為基於觀測資料建構的模擬資料，其格網化的特性有助於掌握區域性氣候趨勢，但氣象觀測站則能補足模型對微氣候變異的限制。整合兩種資料來源有助於更全面理解都市氣溫變化機制，為未來都市發展、綠地配置與熱風險緩解策略提供實證參考。

關鍵字：都市熱島效應、都市化、綠地縮減、氣溫、土地覆蓋變遷、臺北都會區、衛星影像

Abstract



Urban development in the northern Taipei Metropolitan Area has resulted in extensive conversion of vegetated and agricultural land to built-up surfaces over the past three decades. This study investigates how such land cover changes have influenced summer daytime and nighttime air temperatures from 1990 to 2023. Using satellite-derived land cover classifications, Taiwan's weather station observations, and the Taiwan Re-Analysis Downscaling dataset (TReAD), temperature trends were assessed across clustered land cover types.

The findings show that newly urbanized areas—especially Linkou and Guishan—experienced the highest warming, with nighttime temperatures rising by over 2 °C. In contrast, vegetated and higher elevation areas showed less warming, suggesting that green space and topography help moderate temperature increases. While the 1990s to early 2000s were marked by stronger nighttime warming, recent years (2010s onward) show a shift toward intensified daytime warming, particularly in long-urbanized city centers where built-up surfaces and reduced airflow may amplify heat buildup.

These findings suggest that both land cover and local environmental conditions shape temperature changes over time. This study shows the value of combining gridded model outputs with station data to better understand urban heat warming trends. Insights from the findings may help inform decision makers regarding development consequences and potential land use interventions.

Keywords: Urban Heat Island (UHI), Urbanization, Greenspace Reduction, Air Temperature, Land Cover Change, Taipei Metropolitan Area, Satellite Imagery

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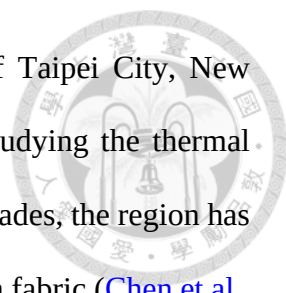
Chapter 1 Introduction



1.1. Background

In recent decades, rapid urbanization has emerged as one of the most significant anthropogenic drivers of local climate change, particularly through its transformation of land cover and the resulting intensification of urban heat. The replacement of vegetated areas with impervious surfaces reduces evapotranspiration, alters surface energy balances, and increases heat storage—all of which contribute to elevated air temperatures in urban regions ([Oke, 1982](#); [Oke, 1988](#); [Kalnay & Cai, 2003](#)). These processes, especially when sustained over time, reinforce the phenomenon of urban warming, with wide-ranging consequences for energy use ([Santamouris et. al., 2015](#)), public health ([Gasparrini et. al., 2015](#)), social equity ([Saeed et. al., 2022](#), [Santamouris & Kolokotsa, 2015](#)), air quality ([Lai & Cheng, 2009](#)), urban livability ([Alijani et. al., 2020](#)) and environmental sustainability ([Urban et. al., 2024](#)).

The urban heat island (UHI) effect has been widely studied across global cities, often using land surface temperature (LST) from remote sensing, although these studies vary in the duration and scope of their analyses ([Abdulmana et al., 2021](#); [Chang et al., 2021](#); [Chen et al., 2017](#); [Connors et al., 2013](#); [Kong et al., 2014](#)). While many past studies worldwide have examined decadal air temperature trends in relation to land cover and land use changes ([Fenner et al., 2014](#); [Huang et al., 2021](#); [Song & Park, 2021](#)), differences in methods, spatial scales, and regional climate conditions leave room for further research. Capturing the long-term impacts of land cover change is crucial not only for expanding the scientific understanding of land–atmosphere interactions but also for informing how the aftermath of urbanization shapes present and future thermal environments.



The northern Taipei Metropolitan Area—including parts of Taipei City, New Taipei City, and Taoyuan City—provides a compelling case for studying the thermal consequences of long-term land cover change. Over the past four decades, the region has undergone substantial conversion of vegetated lands into dense urban fabric ([Chen et al., 2017](#); [Chen et al., 2019](#); [Huang et al., 2009](#)). This study investigates how these shifts have affected summer daytime and nighttime air temperatures, drawing on classified land cover data and multi-decadal records from the Taiwan Re-Analysis Downscaling dataset (TReAD) and weather station observations to provide insights into how urbanization has altered local thermal environments.

1.2. Research Questions and Objectives

This study aims to quantify how land cover change has influenced summer daytime and nighttime air temperatures in the northern Taipei Metropolitan Area from 1990 to 2023.

Research Question:

How has land cover change influenced summer daytime and nighttime air temperatures across different spatial contexts in the northern Taipei Metropolitan Area between 1990 and 2023?

This question guides an integrated analysis of urbanization patterns, diurnal temperature change, and spatial variability in warming intensity.

Objectives:

1. To classify land cover change in the northern Taipei Metropolitan Area between 1990 and 2023 using Landsat imagery.
2. To assess trends in summer daytime and nighttime air temperatures using both observational station data and reanalysis datasets.

3. To examine how temperature trends differ between areas that have undergone land cover change and those with stable land cover.
4. To identify spatial patterns in the relationship between land cover characteristics and summer air temperature variations.
5. To evaluate differences between modeled and observed temperature trends.



Chapter 2 Literature Review



2.1. The Influence of Land Cover on Urban Temperature Patterns

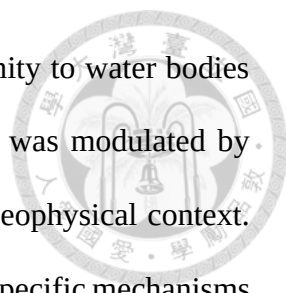
Urban thermal environments are shaped not only by climate but also by the static composition of the urban surface: the relative dominance of vegetation, water bodies, and built-up lands ([Chen et. al., 2024](#); [Fajary et. al., 2024](#); [Xi et. al., 2025](#)). Numerous studies have established that vegetated areas exhibit significantly lower temperatures compared to built-up areas due to enhanced latent heat flux and surface shading ([Crum et. al., 2017](#); [Huang et. al., 2008](#); [Yan et. al., 2014](#)). However, this cooling effect is not evenly distributed throughout the day. A recurring pattern in the literature is that urbanization amplifies nighttime warming more than daytime, a phenomenon attributed to the heat storage properties of impervious surfaces that retain water ([Oke, 1982](#); [Shiu et. al., 2009](#); [Huang et al., 2021](#); [Jabbar et. al., 2023](#)). The diurnal asymmetry is critical, as nighttime thermal stress is more strongly associated with mortality risks, health complications and reduced human comfort, especially during summer ([Murage et. al., 2017](#); [He et. al., 2022](#); [Ebi et. al., 2021](#)).

Studies examining the relationship between land cover and temperature often note that spatial configuration and urban morphology modulate these effects. For instance, landscape metrics such as patch size, connectivity, and fragmentation of greenspace influence the intensity and distribution of cooling ([Kong et. al., 2014](#); [Connors et al., 2013](#)). Although vegetation generally cools and impervious surfaces warm, this relationship varies with urban form, climate, and time of day, shaping localized heat intensity and exposure patterns ([Crum et. al., 2017](#); [Connors et al., 2013](#)).

2.1.1. The Influence of Land Cover on Air Temperature in Taiwan

Land use, land cover, and urban morphology significantly shape thermal conditions in Taiwan's major metropolitan areas, with the effects becoming especially pronounced during the summer months. In Taipei, denser urban development consistently corresponds to elevated air temperatures. Areas characterized by compact building layouts and high floor area ratios tend to exhibit higher ambient temperatures, while districts with greater vegetation coverage show measurable cooling benefits. [Lau & Lin \(2024\)](#) found that a 10% increase in fractional vegetation cover (FVC) resulted in an average air temperature reduction of approximately 0.32°C, whereas higher building and floor area ratios were associated with incremental warming. Similarly, higher building density in compact form registered the most elevated air temperatures in Taipei ([Chen et al., 2019](#)).

While Taipei remains the focal point of most urban climate research in Taiwan, studies from other cities add valuable spatial contrast to the understanding of land cover–temperature dynamics. In Taichung, thermal stress mapping based on the Physiological Equivalent Temperature (PET) index—derived from mobile and fixed-point meteorological measurements conducted over a year—revealed that densely developed city centers consistently registered the highest levels of heat stress ([Lin et al., 2017](#)). These thermal hotspots were not merely a function of elevated air temperature but reflected the combined effects of radiation fluxes, wind speed, humidity, and surface characteristics. The findings highlight how compact urban form and impervious surfaces concentrate heat load, particularly where vegetation is sparse and cooling capacity is limited. Meanwhile in Tainan, the deployment of a high-density street-level temperature network (HiSAN) provided granular insight into how development intensity and geographic features interact to shape microclimates. [Chen et al. \(2019\)](#) found that



nighttime cooling was enhanced in vegetated zones, whereas proximity to water bodies improved daytime thermal conditions. Moreover, thermal variation was modulated by distance from the coastline, underscoring the influence of broader geophysical context. These consistent results from major cities in Taiwan confirm that the specific mechanisms and intensity of heat vary depending on local urban morphology, land cover composition, and geographic context.

2.1.2. Insights and Limitations of Using Land Surface Temperature (LST)

A substantial body of Taiwan-based research employs land surface temperature (LST) as a proxy for evaluating the thermal effects of land cover, revealing consistent evidence of spatial heterogeneity shaped by both biophysical and urban design factors. Across Taipei, areas with higher fractional vegetation cover (FVC) consistently exhibit cooler LSTs, while impervious zones, especially commercial and residential, drive thermal intensification ([Chang et al., 2021](#); [Chen & Lin, 2021](#)). This thermal differentiation is not only compositional but also configurational: compact urban layouts with dense building masses tend to elevate surface temperatures, whereas open low-rise forms integrated with greenspace clusters produce localized cooling ([Shih et al., 2020](#)). The spatial correlation between vegetation and cooling holds across scales; MODIS-based analyses have found that areas with declining Normalized Difference Vegetation Index (NDVI) correspond with surface warming trends, particularly in the rapidly urbanizing zones of Taiwan's western plain ([Abdulmana et al., 2021](#)).

While most studies relied on daytime LST due to satellite overpass timing, [Chen et al. \(2017\)](#) analyzed diurnal LST variation across urban Taipei and found that it increased with urbanization, indicating larger differences between daytime and nighttime surface temperatures in more built-up areas. This result contrasts with prior findings that

diurnal air temperature variation decreased in cities due to the nocturnal heat retention effect of impervious surfaces ([Shiu et. al., 2009](#)). Reinforcing this distinction, [Shiflett et al. \(2017\)](#) observed in Los Angeles that LST is more tightly linked to land cover during the day, while air temperature responds more strongly to land cover during the night. Therefore, LST is not a direct proxy for air temperature and should be regarded with caution when assessing human thermal comfort or diurnal urban heat dynamics.

2.2. Land Cover Change and its Impact on Decadal Temperature Trends

Over multi-decadal timescales, the cumulative thermal impact of land cover change, particularly urban expansion, becomes increasingly evident. Across both modeled and observational studies, a clear pattern emerges: urbanized areas not only intensify local warming, but they also sustain elevated temperatures long after land change occurs, with pronounced effects on nighttime air temperature and cooling dynamics.

Using a mesoscale climate model, [Huang et al. \(2021\)](#) simulated the effects of projected urban expansion from 2000 to 2050 in five mega-urban regions and found persistent increases in nighttime heat stress, with nocturnal wet-bulb globe temperature (WBGT) rising by up to 3°C in hotspot areas. WBGT is a composite index that accounts for temperature, humidity, wind, and solar radiation to estimate heat stress on the human body ([Budd, 2008](#)). This diurnal asymmetry is driven by a shift in energy partitioning: as rural landscapes are replaced by urban fabric, daytime sensible and latent heat fluxes are redirected into heat storage within impervious surfaces, which is then released after sunset. This mechanism not only dampens daytime cooling capacity but also sustains elevated nighttime temperatures, reinforcing the persistent nature of urban warming. Even under

scenarios that incorporate mitigation measures such as green roofs, the thermal inertia of built environments ensures that urban heat accumulation is not easily reversed.

[Kalnay and Cai's \(2003\)](#) reanalysis-based assessment for quantifying the climatic impact of land cover change in the United States revealed that land cover change, including but not limited to urbanization, contributed approximately 0.27°C of mean surface warming per century—nearly twice the amount previously attributed to urbanization alone. By comparing observed surface temperature trends with those derived from the NCEP-NCAR reanalysis (a model that does not assimilate land-based surface temperature data), they isolated the portion of warming attributable to land surface modifications. They argued that traditional urban–rural station comparisons underestimate the full extent of anthropogenic land influence, as transformations such as agricultural expansion and irrigation also drive significant warming at the regional scale.

While the previous studies relied on modeled or hybrid data, long-term observational analyses reinforce the conclusions. In South Korea, [Song and Park \(2021\)](#) used 40 years of weather station data along with a buffer analysis at a radius of 2.5 kilometers to quantify air temperature trends in areas experiencing different rates of land cover change. Stations located in heavily urbanized zones recorded up to 2°C of mean temperature rise, while areas with stable or increasing vegetation showed significantly smaller increases.

Land cover affects the nocturnal cooling rate of an area. [Chow and Svoma \(2011\)](#), examining Phoenix, Arizona's 20-year transition from rural to urban land use, employed direct cooling-rate metrics, focusing on the speed and magnitude of temperature decline after sunset, under ideal synoptic conditions to remove regional climate noise. Their results reveal that stations that underwent rural-to-urban transitions experienced pronounced reductions in nocturnal cooling capacity, particularly within the first few

hours after sunset. These decreases were not observed at rural–rural control sites, reinforcing that localized land cover change, not broader climate variability, drove the observed trends. Furthermore, the spatial variability in cooling-rate changes—most intense in urban cores but also detectable at the urban fringe—suggests the influence of emerging urban-induced circulation systems that may extend the thermal footprint of development beyond the immediate built environment.

Land cover change modifies not only atmospheric composition but also the fundamental surface energy dynamics that regulate climate ([Feddema et al., 2005](#)). Alterations in albedo, evapotranspiration, and surface roughness shift the balance of sensible and latent heat fluxes, with regionally specific but globally consequential effects. These bio-geophysical processes, especially when driven by rapid and fragmented urban development, intensify local heat retention and reduce the system’s ability to dissipate energy efficiently.

Across reanalysis datasets, mesoscale climate simulations, and multi-decade observational studies, a consistent conclusion emerges: urbanization initiates a lasting thermal transformation. Converted landscapes, particularly those that changed from vegetated to impervious, exhibit diminished nocturnal cooling, elevated mean temperatures, and a narrowing of diurnal and seasonal variability. This warming is not a short-term impact but long-lasting and hard to reverse, embedding itself in the physical structure of the urban environment. Despite variations in method and spatial scale, the literature stresses the persistent and largely irreversible nature of anthropogenic land modification, calling for a more spatially explicit and temporally nuanced understanding of urban thermal dynamics.

Chapter 3 Research Design and Methods



3.1. Study Area

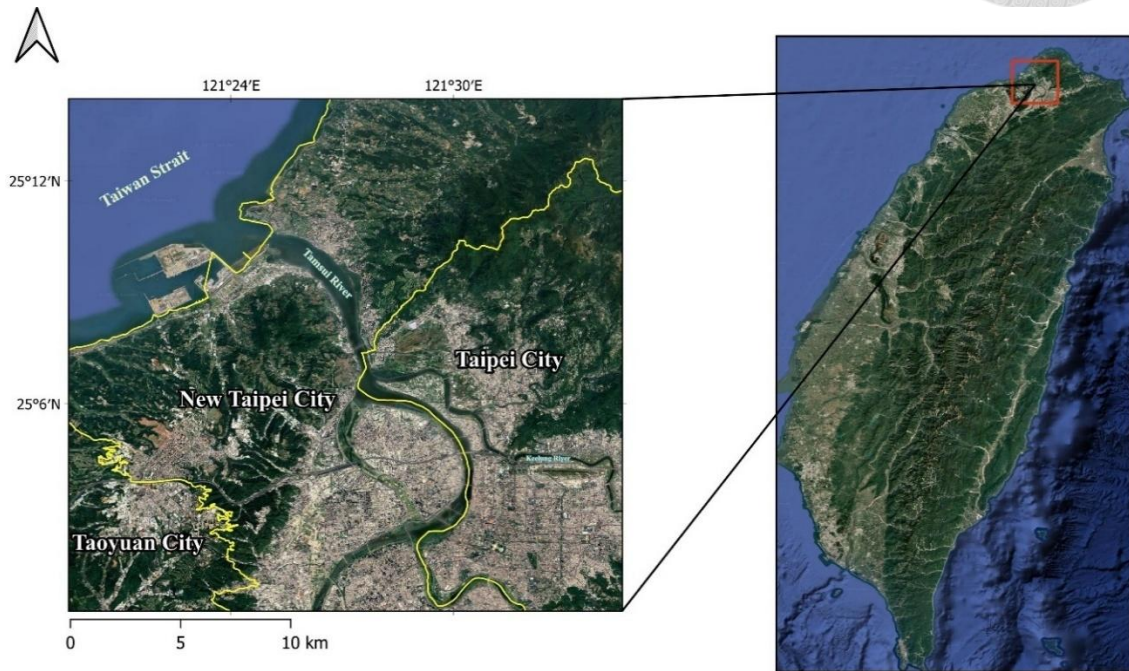


Figure 3.1 Study Area Map (Google Satellite Basemap).

The study area encompasses parts of Taipei City, New Taipei City, and Taoyuan City in northern Taiwan (Fig. 3.1). This region is shaped by complex atmospheric dynamics, including sea–land breezes from the Taiwan Strait to the west and mountain–valley winds from the north ([Shih et al., 2024](#)). It covers the highly urbanized core of downtown Taipei, the connecting metropolitan area of New Taipei, and the more recently urbanized corridors extending into Taoyuan. To the north of Taipei City, smaller suburban settlements and agricultural lands persist, though they have significantly shrunk ([Huang et al., 2009](#)).

The climate is classified as humid subtropical, with hot, humid summers typically spanning from late May through September. In 2023, the Taipei weather station recorded an average annual temperature of 23.94 °C, with a peak temperature of 37.9 °C reached

in July (CWA, n.d.). On July 5, 2024, the Shezih weather station recorded an extreme high of 40 °C at 11:03 a.m., prompting the issuance of multi-day heat alerts across the region. According to the [Central Weather Administration \(CWA\)](#), "high temperature" conditions are defined as maximum surface temperatures reaching 36 °C or above. These thermal extremes are of particular concern in Taipei City, which has the oldest population among Taiwan's major cities with 22% of residents being over the age of 65 ([Taipei City Government, 2023](#)).

3.2. Research Design

The overall research design follows a structured, data-driven approach to investigate how long-term land cover changes have influenced summer daytime and nighttime air temperatures in the northern Taipei Metropolitan Area from 1990 to 2023. The complete process from data collection to statistical analysis is illustrated in Figure 3.2.

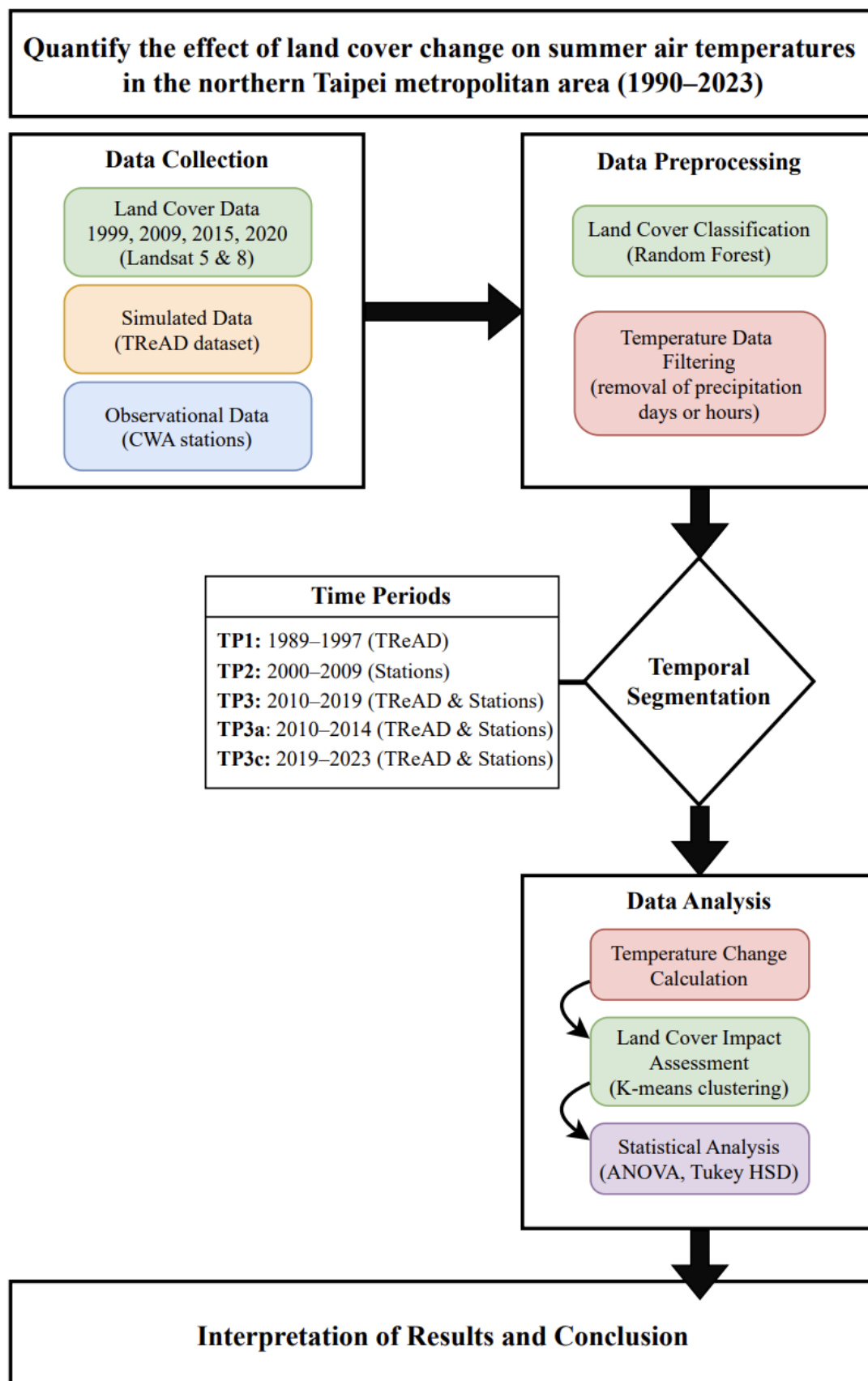


Figure 3.2 Data Processing and Analytical Workflow.

Three primary datasets were used: (1) land cover data derived from Landsat 5 and 8 imageries (1999, 2009, 2015, 2020), (2) hourly reanalysis-based air temperature from the Taiwan Re-Analysis Downscaling dataset (TReAD, 1989–2023), and (3) hourly air temperature observations from 19 Central Weather Administration (CWA) stations (1990–2024). These datasets were preprocessed through Random Forest classification of land cover and filtering of temperature records to exclude precipitation-affected hours (TReAD) and days (CWA).

The study area and dataset distribution are shown in Figure 3.3, which includes 125 TReAD grids of 2×2 km resolution and the spatial locations of the 19 meteorological stations. Station relocation during the study period is reflected by suffixes (_1, _2).

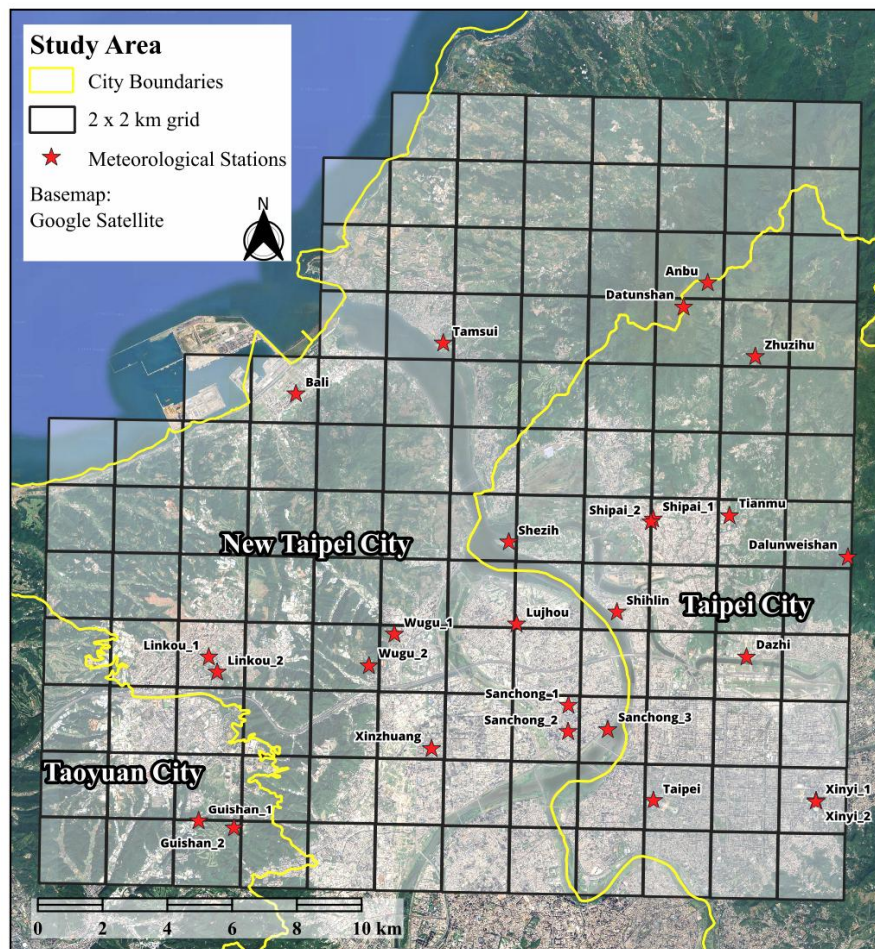


Figure 3.3 Spatial Distribution of Grids and Stations.

Temperature change was calculated for each grid cell or station across time periods, disaggregated by day and night. K-means clustering was used to group land cover conditions, and statistical significance of observed thermal differences was tested using ANOVA and Tukey HSD.



The full set of time periods and corresponding data sources is illustrated in Figure 3.4 and summarized in Table 3.1. These segments were selected to capture both decadal-scale trends and recent conditions under stable land cover. For station data, TP2 (2000–2009) and TP3 (2010–2019) were used to assess decadal change, while TP3a (2010–2014) and TP3c (2019–2023) allowed for comparison during recent periods with minimal land cover variation.

The intermediate period TP3b (2015–2018) was excluded from the main analysis due to major station-level data disruptions, including relocations and missing observations. For example, Wugu(五股) was inactive from 2015 to 2019 after operating from 2010; Linkou(林口) relocated in 2017; and Sanchong(三重) moved after 2017. In contrast, TP3a and TP3c provided more complete and stable records, allowing for analysis of relocation effects on temperature measurements and the thermal influence of stable land cover.

For the TReAD dataset, TP1 (1989–1997) and TP3 (2009–2018) were selected for decadal comparisons, while TP3a and TP3c were used to align with the stable land cover periods from the station analysis. TP2 was excluded due to concerns about the accuracy of its land cover input. This dual-period comparison framework captures both the effects of land cover change and the thermal response under relatively stable landscape conditions.

All data extraction, filtering, and statistical analysis were conducted using Python (xarray, pandas, NumPy, scikit-learn, SciPy, statsmodels) in the PyCharm Professional

development environment. Landsat image classification was performed in Google Earth Engine, while QGIS Desktop (v3.34.6) was used for spatial visualization and overlay analysis.

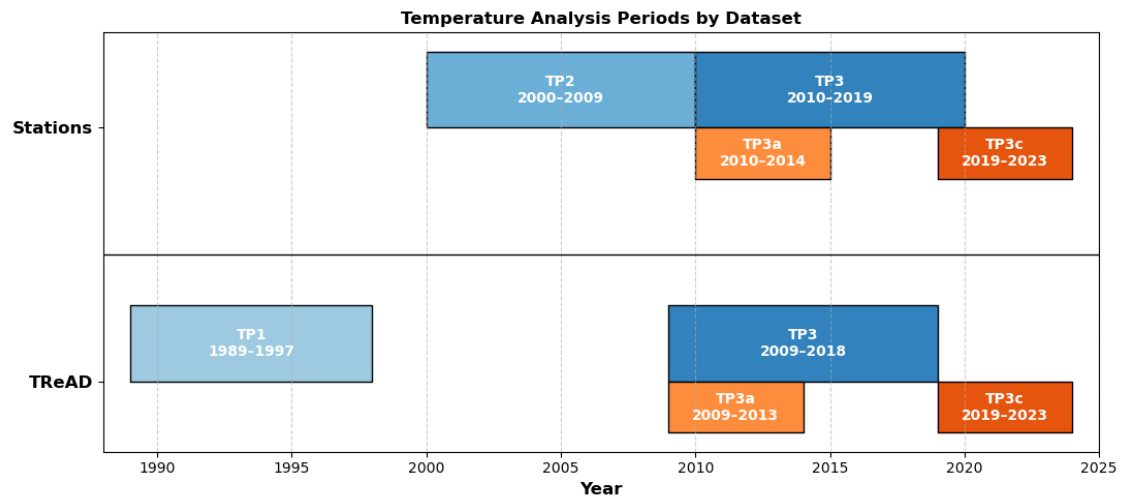


Figure 3.4 Timeline of Temperature Analysis Periods.

Table 3.1 Time Periods and Land Cover References.

Dataset Type	Period 1	Period 2	Satellite Image Year(s) / TReAD Land Use Inputs	Purpose
Meteorological Stations	TP2 (2000– 2009)	TP3 (2010– 2019)	1999 (for TP2) 2015 (for TP3)	Analyze decadal temperature change related to land cover change
Meteorological Stations	TP3a (2010– 2014)	TP3c* (2019– 2023)	2009 (for TP3a) 2020 (for TP3c)	Focus on recent changes in temperature with more stations under relatively stable land cover
TReAD Dataset	TP1 (1989– 1997)	TP3 (2009– 2018)	1995 (proxy for TP1) 2015 (proxy for TP3)	Simulated land cover and temperature change
TReAD Dataset	TP3a (2009– 2013)	TP3c (2019– 2023)	2015 (proxy for TP3)	Simulated stable land cover periods to assess temperature change

*TP3b (2015–2018) was excluded due to several stations' site relocations and data gaps during this period.

3.3. Taiwan Re-Analysis Downscaling dataset (TReAD)



To analyze decadal air temperature patterns in northern Taipei Metropolitan Area, this study used the Taiwan Reanalysis Downscaling dataset (TReAD), developed by the Taiwan Climate Change Projection and Information Platform (TCCIP) ([Lin et al., 2021](#)). TReAD is a high-resolution (2 km), dynamically downscaled climate product based on the WRF model nested within ERA5. It provides hourly climate variables—including 2 m air temperature—from 1980 to 2023 with yearly updates.

TReAD has been applied across multiple disciplines—including agriculture ([Li, 2024](#)), renewable energy and wind analysis ([Lai, 2024](#)), urban thermal comfort mapping ([Ou et al., 2023](#)), and livestock heat stress assessment ([Chueh et al., 2024](#))—highlighting its versatility for climate-related research.

TReAD incorporates land cover change through four time-specific land cover maps (1982, 1995, 2000, 2015), reconstructed from historical sources and SPOT satellite imagery ([Chen et al., 2019](#)). These maps were classified into the USGS 24-category land cover scheme and aggregated to 2 km grids for model input. Table 3.2 summarizes these land cover sources and their corresponding simulation periods.

Table 3.2 TReAD Land Cover Inputs and Simulation Periods.

Land Cover Input	Data Simulation Period	Imagery / Source Used
1982	1979–1989	Taiwan Agriculture Land Use Map (1982–1983); historical maps and aerial photos
1995	1990–1998	SPOT-2 and SPOT-3 images from 1994 (multi-band mosaics of 60 km × 60 km subsets)
2000	1999–2008	SPOT-2 and SPOT-4 images from 2000 (multi-band mosaics of 60 km × 60 km subsets)
2015	2009–2023	SPOT-5 and SPOT-6 images from 2015 (multi-band mosaics of the full island)

Each grid cell in TReAD represents the ratio of land cover types, enabling spatial analysis of land cover change. However, classification inconsistencies within the study area, particularly in the 2000 land cover map, led to overestimation of built-up and cropland ratios and underestimation of forested areas (Table 3.3). These errors affected the 1999–2008 (TP2) simulation, which was excluded from further analysis due to poor input reliability.

Table 3.3 USGS Land Cover Composition Across TReAD Input Years.

USGS Land Cover Type	1982	1995	2000	2015
Urban and Built-Up Land	27.72%	26.92%	47.69%*	43.36%
Dryland Cropland and Pasture	9.39%	12.49%	22.37%*	6.13%
Irrigated Cropland and Pasture	0.97%	7.14%	0.00%	0.40%
Cropland/Grassland Mosaic	10.79%	0.74%	0.16%	0.34%
Evergreen Broadleaf Forest	33.00%	41.39%	21.76%*	40.30%
Evergreen Needleleaf Forest	0.47%	0.55%	0.35%	0.57%
Mixed Forest	1.09%	1.28%	0.82%	1.33%
Water Bodies	7.24%	4.74%	2.63%	2.78%
Herbaceous Wetland	0.08%	0.08%	0.08%	0.08%
Barren or Sparsely Vegetated	9.26%	4.66%	4.14%	4.70%

* Forest is misclassified as either Cropland or Built-Up.

Within the study area, 10 of the 24 USGS categories were present, which were grouped into four major land cover types:

- **Built-Up:** Urban and Built-Up Land
- **Vegetated:** Includes all vegetated types, combined from Dryland Cropland and Pasture, Irrigated Cropland and Pasture, Cropland/Grassland Mosaic, Evergreen Broadleaf Forest, Evergreen Needleleaf Forest, Mixed Forest, and Herbaceous Wetland
- **Barren:** Barren or Sparsely Vegetated
- **Waterbody:** Water Bodies

To evaluate temperature trends, hourly 2 m air temperature data during the summer months (June–September) were extracted from 125 TReAD grid cells. To reduce the cooling influence of rainfall, only hours with 0 mm precipitation were included. Because TReAD tends to overestimate precipitation, filtering was applied at the hourly level rather than by full day, which preserved more valid temperature records available for statistical analyses.

TReAD's performance was compared with observed data from the Taipei CWA station for validation, the only site with complete hourly records since 1980. Mean summer daytime and nighttime temperatures from TReAD closely aligned with observations, especially for the grid cell containing Taipei (Figure 3.5), validating its use for trend analysis.

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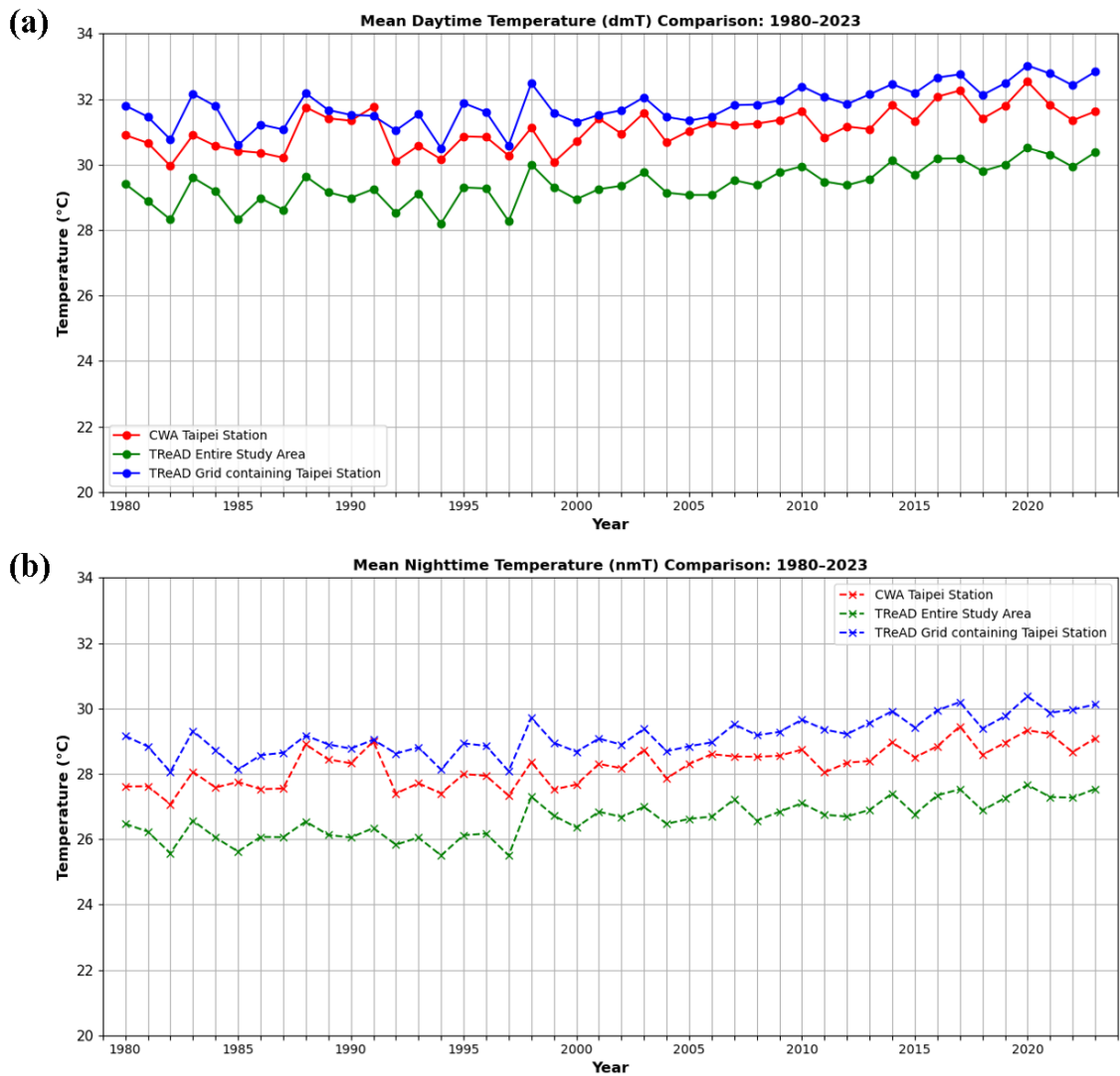


Figure 3.5 TReAD vs. Taipei station (1980–2023). **(a)** Daytime, **(b)** Nighttime.

To assess temperature responses under varying land cover conditions, four representative grids were selected based on their land cover trajectories across the input years: (1) a grid with the lowest built-up ratio in 1995 but higher built-up ratios in other periods (blue); (2) a grid with unchanging mixed land cover across all inputs (orange); (3) a grid with unchanging 100% forest cover (green); and (4) a grid with the highest built-up ratio in 2000 but lower built-up ratios in other periods (red). As shown in Figure 3.6, distinct shifts in temperature trends follow each land cover update (1982, 1995, 2000,

2015), though the model response consistently occurred about one year earlier than the official simulation periods defined in the TReAD technical documentation (Table 3.2). To reflect this observed timing more accurately, the simulation periods were redefined as **1980–1988, 1989–1997, 1998–2007, and 2008–2023** for subsequent analyses.

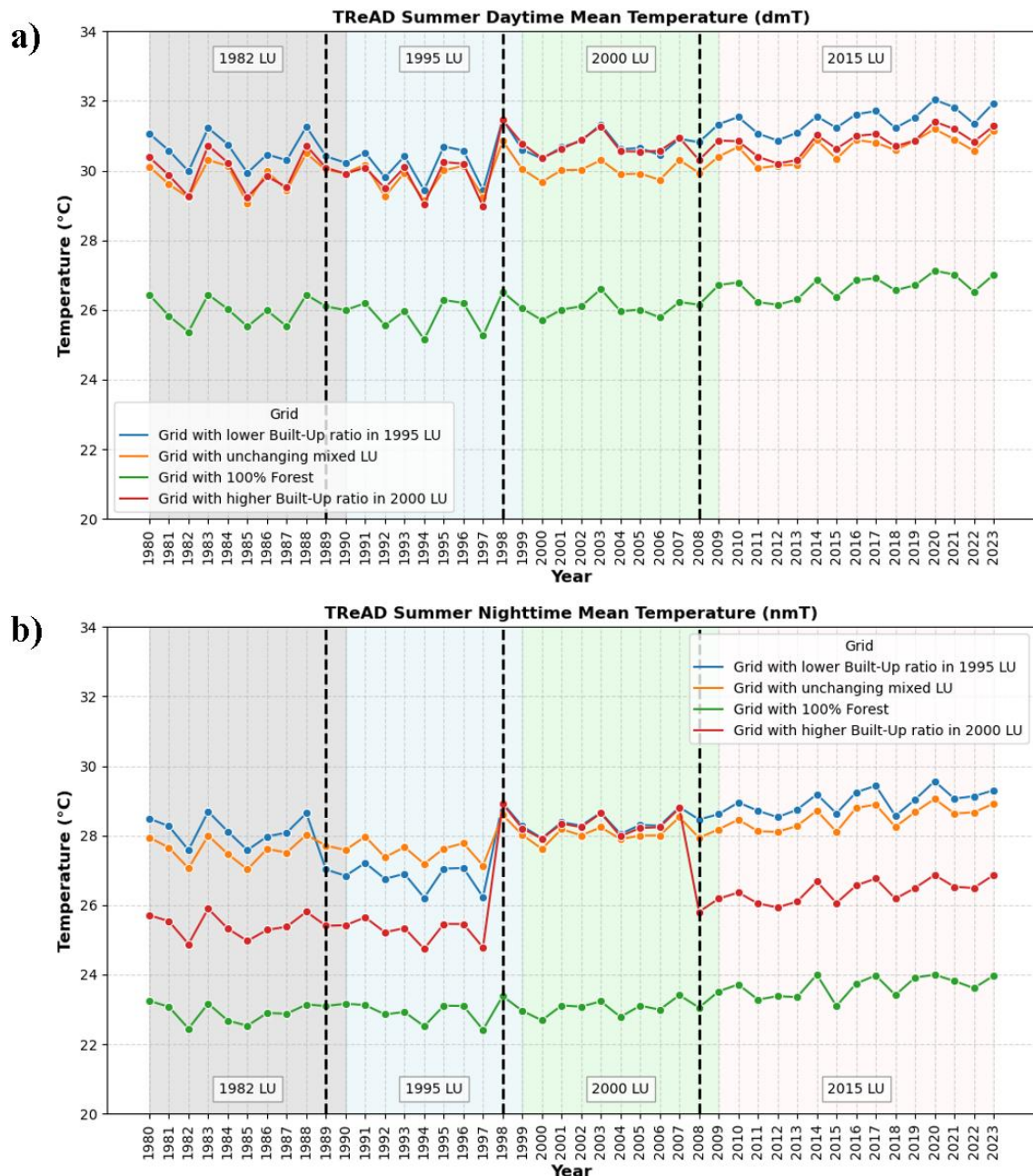
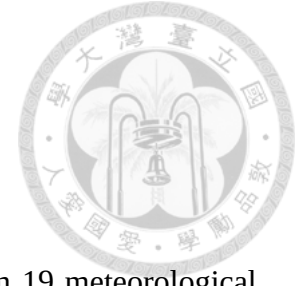


Figure 3.6 TReAD Mean Summer Temperatures in Sample Grids. **(a)** Daytime, **(b)** Nighttime. Dashed lines mark shifts in modeled temperature response.

3.4. Observational Data



3.4.1. Meteorological Station data

This study utilized hourly air temperature observations from 19 meteorological stations operated by the Central Weather Administration (CWA) within the study area (Fig. 3.1). Stations were selected based on their availability of at least five consecutive years of valid hourly data between 1990 and 2023.

Data from the summer months (June to September) were included in the analysis to focus on the season with the highest temperatures. To ensure data quality, two levels of filtering were applied: (1) days with any recorded precipitation were removed to avoid short-term cooling effects associated with rainfall events, and (2) individual hours affected by instrument malfunctions or anomalous recordings were excluded based on CWA metadata and visual inspection.

Among the 19 stations, seven sites—Shipai, Sanchong, Xinyi, Wugu, Linkou, Guishan (石牌, 三重, 信義, 五股, 林口, 龜山)—were relocated during the study period. To account for this influence, land cover conditions surrounding both the original and relocated sites were analyzed using classified satellite imagery, and temperature data were segmented accordingly. The two time periods TP3a (2010–2014) and TP3c (2019–2023) were selected to compare temperature trends before and after relocation, enabling a direct assessment of how changes in surrounding land cover influenced observed warming.

In contrast to the TReAD gridded dataset, where only hours with precipitation (>0 mm) were excluded to account for model precipitation overestimation, the meteorological station dataset applied precipitation filtering at the daily scale: any day with recorded rainfall was entirely excluded. This approach minimized the influence of rain-induced

cooling and ensured that the analyzed temperature trends primarily reflected clear-sky, surface-driven thermal conditions ([Shih et. al., 2024](#)).

Table 3.4 provides a summary of each station, including the period of available data, relocation status, and the total number of valid daytime (06:00–17:00) and nighttime (18:00–05:00) hourly records after filtering.

Table 3.4 Meteorological Stations: Periods, Relocation, and Valid Records.

Station	Station ID	Alt.	LON	LAT	Data Period	Day N	Night N
Anbu	466910	837.6	121.5297	25.1826	1990 - 2023	24003	24007
Bali	C0AD10	27	121.4039	25.1502	2010 - 2023	13501	13510
Dalunweishan	C0A990	463	121.5736	25.1063	1998 - 2015	12639	12589
Datunshan	C0AC40	1079	121.5224	25.1757	2006 - 2023	9979	9992
Dazhi	C0A9A0	24	121.5429	25.0780	1998 - 2019	17502	17516
Guishan_1	C0C640	177	121.3757	25.0303	2008 - 2016	8242	8256
Guishan_2	C0C680	228	121.3866	25.0285	2017 - 2023	5500	5500
Linkou_1	C0A710	238	121.3782	25.0764	2010 - 2016	6634	6644
Linkou_2	C0AH50	275	121.3808	25.0722	2017 - 2023	6059	6061
Lujhou	C0AD30	20	121.4723	25.0866	2010 - 2023	12353	12391
Sanchong_1	C0A9I0	18	121.4885	25.0640	1998 - 2010	10543	10546
Sanchong_2	C0A9I1	18	121.4885	25.0567	2011 - 2017	6404	6413
Sanchong_3	C0AI30	26	121.5006	25.0573	2019 - 2023	3455	3459
Shezih	C0A980	11	121.4697	25.1095	1998 - 2023	20820	20895
Shihlin	C0A9E0	26	121.5030	25.0903	1998 - 2021	18681	18724
Shipai_1	C0A9B0	7	121.5138	25.1163	1998 - 2019	18259	18220
Shipai_2	C0AI40	35	121.5131	25.1156	2020 - 2023	3179	3272
Taipei	466920	5.3	121.5149	25.0377	1961 - 2023	44870	44870
Tamsui	466900	19	121.4489	25.1649	1990 - 2023	25515	25530
Tianmu	C0A9C0	35	121.5372	25.1175	1998 - 2023	21863	21926
Wugu_1	C0A680	95	121.4350	25.0834	2010 - 2015	5971	5974
Wugu_2	C0AI00	188	121.4273	25.0745	2019 - 2023	3414	3405
Xinyi_1	C0A9H0	51	121.5646	25.0381	1998 - 2008	6948	6975
Xinyi_2	C0AC70	71	121.5646	25.0378	2010 - 2023	10503	10510
Xinzhuang	C0ACA0	25	121.4468	25.0515	2010 - 2023	12204	12211
Zhuzihu	466930	607.1	121.5445	25.1621	1990 - 2023	25106	25116

3.4.2. Satellite Imagery and Land Cover Classification

Landsat imagery was employed to map land cover at four key time points aligned with the temperature analysis periods (Table 3.5). For the TP3–TP2 comparison, Landsat 5 Thematic Mapper (TM) imagery from August 16, 1999 and a composite of two images (July 10 and September 12, 2009) were used, with cloud- and shadow-free areas from both images combined to optimize surface coverage. For the TP3c–TP3a comparison, Landsat 8 Operational Land Imager (OLI) imagery from June 9, 2015 and August 25, 2020 were selected to represent summer conditions with minimal cloud cover and temporal alignment with the temperature datasets. In addition to the four Landsat images used for land cover classification and temperature analysis, Landsat 5 TM imagery from August 22, 1984 and July 22, 1990 was also processed to create reference land cover maps. These early images were not used in quantitative analysis due to substantial cloud cover and the lack of corresponding observational temperature records. However, they were included for visual comparison only, offering useful context to identify areas of long-term or continuous land cover change.

Table 3.5 Landsat Imagery for Land Cover Classification.

Satellite / Sensor	Acquisition Date(s)	Analysis Period	Purpose	Notes
Landsat 5 TM	1984-08-22	—	Visual reference only	Excluded due to cloud cover
Landsat 5 TM	1990-07-22	—	Visual reference only	Excluded due to cloud cover
Landsat 5 TM	1999-08-16	TP2	Classification & analysis	—
Landsat 5 TM	2009-07-10 2009-09-12	TP3a	Classification & analysis	Composite to reduce cloud cover
Landsat 8 OLI	2015-06-09	TP3	Classification & analysis	—
Landsat 8 OLI	2020-08-25	TP3c	Classification & analysis	—

To ensure spatial and spectral consistency, all imagery was acquired from the Google Earth Engine (GEE) platform at Level 1 terrain-corrected (TOA) processing level. A cloud masking procedure was applied manually by delineating cloud-contaminated regions, and the imagery was clipped to the study area boundaries. Six spectral bands (blue, green, red, near-infrared, and two shortwave infrared bands) were selected for subsequent processing. In addition to the raw bands, three spectral indices were calculated to enhance classification accuracy:

- a) **Normalized Difference Vegetation Index (NDVI)** for detecting vegetation health:

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

- b) **Normalized Difference Built-up Index (NDBI)** for detecting built-up or impervious surfaces:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

- c) **Modified Normalized Difference Water Index (MNDWI)** for detecting water bodies:

$$MNDWI = \frac{GREEN - SWIR}{GREEN + SWIR}$$

Training data were manually picked for four major land cover classes: built-up land, vegetated land, barren land, and water bodies. For each Landsat image year (1999, 2009, 2015, and 2020), independent sets of training points were created by referencing historical high-resolution imagery available in Google Earth. Between 30 and 95 points per class were collected per year, ensuring broad representation across different spatial

zones and minimizing class imbalance. The Random Forest (RF) classifier, a widely used ensemble learning method known for its robustness and non-parametric nature ([Breiman, 2001](#)), was applied separately to each year. Each classifier was trained with 200 decision trees using the six spectral bands and three spectral indices (NDVI, NDBI, and MNDWI) as input features.

The classification model was trained using 70% of the labeled samples and validated on the remaining 30%. Performance was evaluated using confusion matrices, overall accuracy, user's and producer's accuracy for each class, and the Kappa coefficient (Tables 3.6 and 3.7). All years achieved overall accuracy above 89% and Kappa values between 0.84 and 0.93. While vegetation and waterbodies were consistently classified with high accuracy due to their distinct spectral signatures, built-up and barren land were more frequently misclassified. This was largely due to spectral confusion, as barren areas, which are often active construction sites, share similar reflectance with impervious surfaces like roads and rooftops. The resulting classified maps form the baseline for land cover change detection and land cover–temperature relationship analysis.

Table 3.6 Classification Accuracy: Landsat-Based Land Cover (1984–2020).

Year	1984	1994	1999	2009	2015	2020
Overall Accuracy (%)	90.00	90.11	89.19	95.4	94.05	89.74
Kappa Coefficient	0.859	0.855	0.844	0.927	0.914	0.856

Table 3.7 Producer's/User's Accuracy by Year (1999, 2009, 2015, 2020).

Year	1999		2009		2015		2020	
Accuracy (%)	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Built-Up	79.41	96.43	100	87.10	93.55	93.55	86.21	89.29
Vegetated	100	87.5	97.73	100	96.77	100	100	96.15
Barren	92.31	80	62.5	100	81.82	75	75	75
Waterbody	100	85.71	100	100	100	100	91.67	91.67

3.4.3. Meteorological Station Buffer Zone Analysis

To characterize the land cover surrounding each meteorological station, a buffer zone analysis was conducted using a 1-kilometer radius around each station location. This radius was chosen to maintain spatial consistency with the TReAD dataset, which has a grid resolution of approximately 2 kilometers (2 km × 2 km), ensuring that the land cover environment analyzed for each station is comparable in scale to the gridded reanalysis data.

The selection of a 1-kilometer radius buffer also reflects common practices in urban climate studies, where buffer radii typically range from a few hundred meters to several kilometers depending on the satellite image resolution, urban structure, and research objectives. Previous studies have adopted buffer radii between 150 meters and 2.5 kilometers to assess the microclimatic and regional land cover influence on the thermal environment ([Yan et. al., 2014](#); [Chen et. al., 2019](#); [Song and Park, 2021](#)).

Land cover within each buffer was derived from classified Landsat images corresponding to each time period analyzed. The proportions of built-up, vegetated, barren, and waterbody areas were calculated for each station and used to interpret surrounding land cover conditions over time.

For stations that underwent relocation during the study period, separate buffers were made for the original and new locations. Land cover was assessed independently for each site to maintain an accurate association with the corresponding temperature records. These stations were included in the temperature analysis, and changes in land cover conditions before and after relocation were explicitly considered when comparing temperature trends, particularly between TP3a and TP3c.

3.5. Temperature Aggregation and Change Calculation

To analyze summer diurnal temperature patterns (June–September), hourly air temperature data from both TReAD grids and CWA stations were split into daytime (06:00–17:00) and nighttime (18:00–05:00). Mean temperatures for each time period were calculated per grid cell or station i

To assess temperature change over time, the difference in mean temperature from the earlier time period to the later time period was calculated for each grid cell as follows:

$$\begin{aligned}\Delta dmT_i &= dmT_{TP2,i} - dmT_{TP1,i} \\ \Delta nmT_i &= nmT_{TP2,i} - nmT_{TP1,i}\end{aligned}\tag{eq.1}$$

Where:

ΔdmT_i : Daytime mean temperature change at grid or station i ;

ΔnmT_i : Nighttime mean temperature change at grid or station i ;

$dmT_{TP1,i}$, $dmT_{TP2,i}$: Daytime mean temperatures at station/grid i for earlier (TP1) and later (TP2) periods;

$nmT_{TP1,i}$, $nmT_{TP2,i}$: Same for nighttime.

For the TReAD dataset, temperature change was further analyzed by grouping grid cells into distinct land cover transformation categories using **k-means clustering**. This unsupervised learning method groups observations into clusters based on similarity in land cover characteristics—in this case, built-up and vegetated land ratios from 1995 and 2015, along with their changes over time.

To ensure comparability across variables with different units and scales, all input features were standardized using StandardScaler, which is a preprocessing tool that removes the mean and scales each variable to unit variance:

$$z = \frac{x - \mu}{\sigma}$$

Where x is the original value, μ is the mean, and σ is the standard deviation. This step prevents features with larger numerical ranges (e.g., built-up ratio) from dominating the clustering outcome.

To decide how many clusters to use, the elbow method was applied. This involves running the k-means algorithm for different values of k and plotting the within-cluster sum of squares (WCSS). As the number of clusters increases, the WCSS decreases, but the rate of improvement slows down. The "elbow point" on the graph indicates where adding more clusters no longer significantly improves the fit. This point was used to choose an appropriate number of distinct land cover change groups that are meaningful yet not overly complex, enabling clearer interpretation of temperature differences across land cover transitions. As shown in Figure 3.7, the WCSS decreases until $k = 5$, after which the improvement levels off. Based on this point of inflection, five clusters were selected to represent distinct land cover change types.

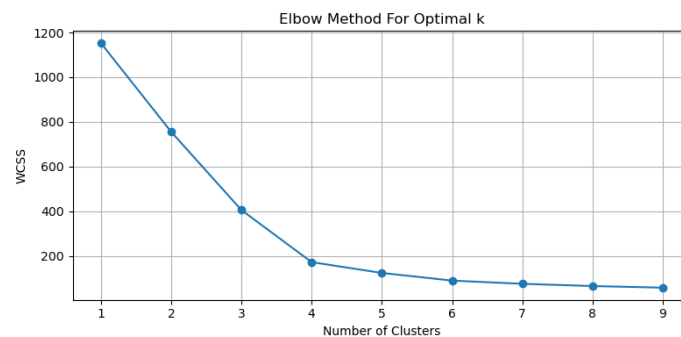


Figure 3.7 Elbow method for Land Cover Clusters.

The resulting five clusters reflected distinct land cover change patterns, ranging from high built-up growth with vegetation loss, moderate built-up growth with vegetation loss, and persistent heavily urbanized areas, to stable highly vegetated zones and stable mixed land cover conditions.

Once the optimal cluster count was determined, grid cells were grouped accordingly and average temperature changes were calculated for each cluster:

$$\begin{aligned}\Delta dmT_{LC} &= \frac{1}{n} \sum_{i=1}^n \Delta dmT_i \\ \Delta nmT_{LC} &= \frac{1}{n} \sum_{i=1}^n \Delta nmT_i\end{aligned}\tag{eq.2}$$

Where:

ΔdmT_{LC} : Mean temperature change for land cover group LC during the day;

ΔnmT_{LC} : Mean temperature change for land cover group LC during the night;

n : Number of grid cells within land cover group LC .

3.6. Statistical Analysis

To assess long-term temperature trends, ordinary least squares (OLS) linear regression was applied to yearly mean summer daytime and nighttime temperatures for Taipei, Tamsui, Zhuzihu, and Anbu stations. The regression slope ($^{\circ}\text{C}/\text{year}$) represents the estimated rate of temperature change over time. The statistical significance of each trend was evaluated by testing whether the slope differed significantly from zero using the t-statistic produced as part of the regression output. This approach tests the null hypothesis that there is no temperature trend (slope = 0) against the alternative hypothesis that a significant warming or cooling trend exists (slope $\neq$ 0). For each regression, the slope estimate, standard error, t-value, p-value, and coefficient of determination (R^2) were

recorded. A significance level of $p < 0.05$ was used to determine whether trends were statistically meaningful.

ANOVA (Analysis of Variance) was used to test whether mean temperature changes differed significantly across the land cover clusters. This method is appropriate when comparing more than two groups, as it evaluates whether at least one group mean is statistically different from the others.

The ANOVA test produces an F-statistic, which is the ratio of variance between group means to the variance within groups. A higher F-value suggests that differences between group means are more pronounced relative to within-group variability. The associated p-value indicates whether the observed F-statistic is statistically significant. A p-value below 0.05 typically suggests that at least one group mean is significantly different from the others, justifying further analysis.

When ANOVA indicated significant differences ($p < 0.05$), a **Tukey HSD (Honestly Significant Difference)** test was conducted as a post-hoc analysis to identify which specific pairs of groups differ.

All statistical analysis were conducted using Python in the PyCharm Professional IDE.

Chapter 4 Results



This chapter presents key findings structured around three main objectives: (1) identifying land cover changes in the northern Taipei Metropolitan Area (1984–2023), (2) evaluating summer air temperature trends with a focus on daytime and nighttime differences, and (3) assessing the influence of land cover change on summer air temperatures using both modeled and observational data.

4.1. Land Cover Change in the northern Taipei Metropolitan Area (1984–2023)

To evaluate long-term land cover changes in the northern Taipei Metropolitan Area, Landsat images from six summer periods (1984, 1994, 1999, 2009, 2015, and 2020) were classified into four primary categories: built-up, vegetated, barren, and waterbody using a Random Forest algorithm. Figure 4.1 displays classified land cover maps across six time points. The expansion of urban land is evident, particularly when comparing 1994 to 2015, during which conversion of croplands to built-up areas was most active across Taiwan ([Chen et. al., 2019](#)). This change was confirmed in the study area in Table 4.1, which quantifies land cover transitions and shows peak expansion occurring between 1999 and 2015. The classification results show a steady increase in built-up area, from 158.2 km² in 1994 to 174.6 km² in 2020—an overall growth of approximately 9%.

Urban expansion was most notable in the western districts, particularly Linkou (林口) and Guishan(龜山), which have evolved from semi-rural zones into urbanized areas integrated within the Taipei metropolitan footprint ([Huang et al., 2009](#)). Additional expansion was observed along the Tamsui and Bali coastlines and near the Keelung River corridor.

Vegetated areas remained largely stable over the 36-year period, with minor fluctuations influenced by seasonal greenness and moisture conditions. Barren land showed localized variability, which may partially reflect actual land disturbance from construction or transitions between vegetated and built-up surfaces. However, given the spectral similarity between barren land, impervious surfaces, and sparsely vegetated areas, this class is prone to misclassification. Therefore, some of the observed changes in barren land proportions may also result from classification uncertainty rather than true land cover changes.

Table 4.1 Land Cover Area and Proportion (1984–2020).

	1984		1994		1999	
	Area (km ²)	Ratio	Area (km ²)	Ratio	Area (km ²)	Ratio
Built-Up	130.52	28.33%	158.24	30.50%	156.77	29.89%
Vegetated	275.6	59.81%	303.99	58.59%	307.37	58.61%
Barren	14.85	3.22%	18.73	3.61%	26.78	5.11%
Waterbody	39.82	8.64%	37.85	7.30%	33.54	6.40%
Cloud-free Area (km ²)	460.79		518.81		524.46	
Cloud Area (km ²)	64.36		6.34		0.69	
	2009		2015		2020	
	Area (km ²)	Ratio	Area (km ²)	Ratio	Area (km ²)	Ratio
Built-Up	165.34	31.53%	174.16	33.21%	174.61	33.29%
Vegetated	295.98	56.44%	306.84	58.51%	293.45	55.95%
Barren	32.26	6.15%	12.67	2.42%	24.72	4.71%
Waterbody	31.22	5.95%	31.3	5.97%	30.52	5.82%
Cloud-free Area (km ²)	524.8		524.97		523.3	
Cloud Area (km ²)	0.35		0.18		1.85	

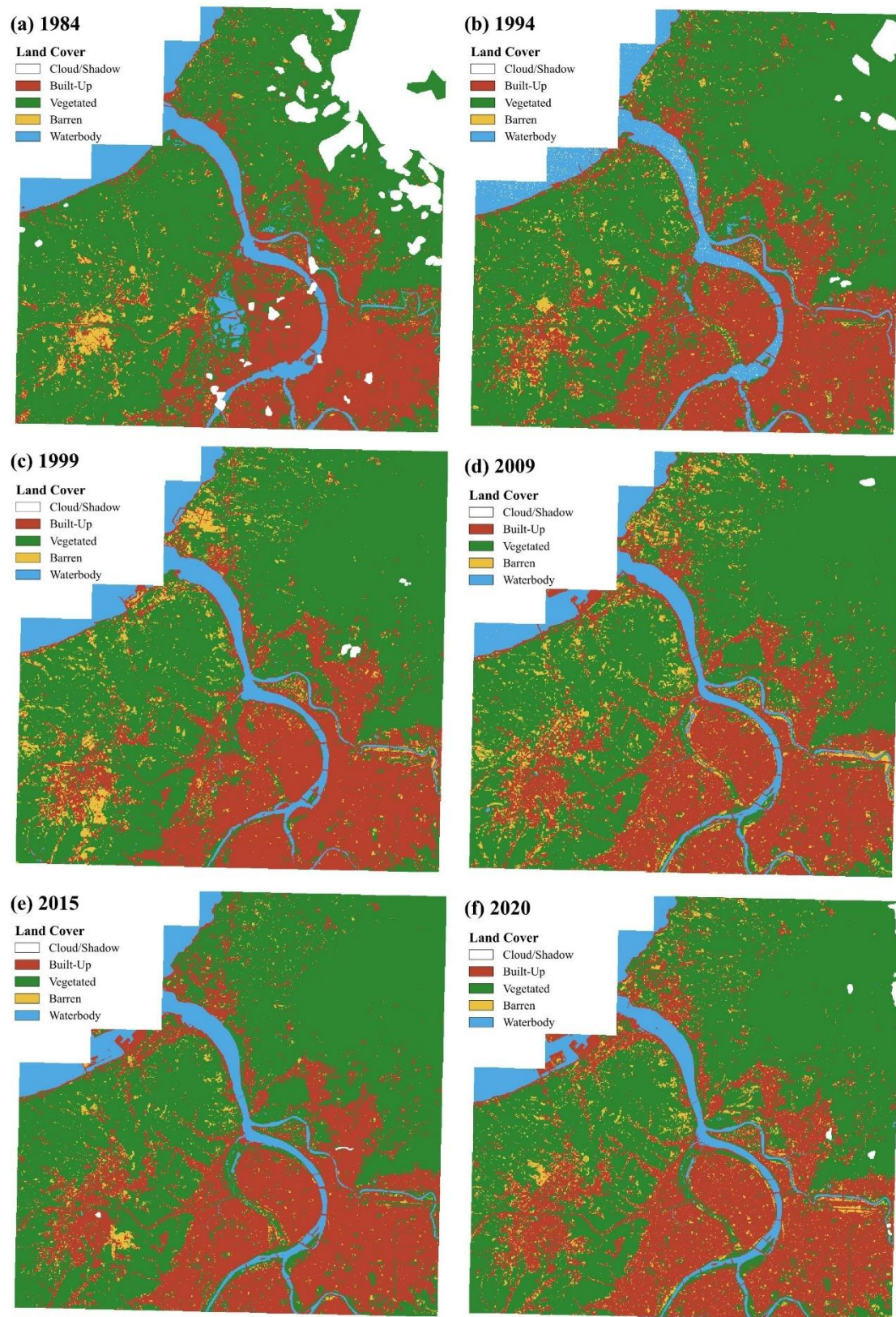


Figure 4.1 Landsat Land Cover Classifications: 1984–2020.

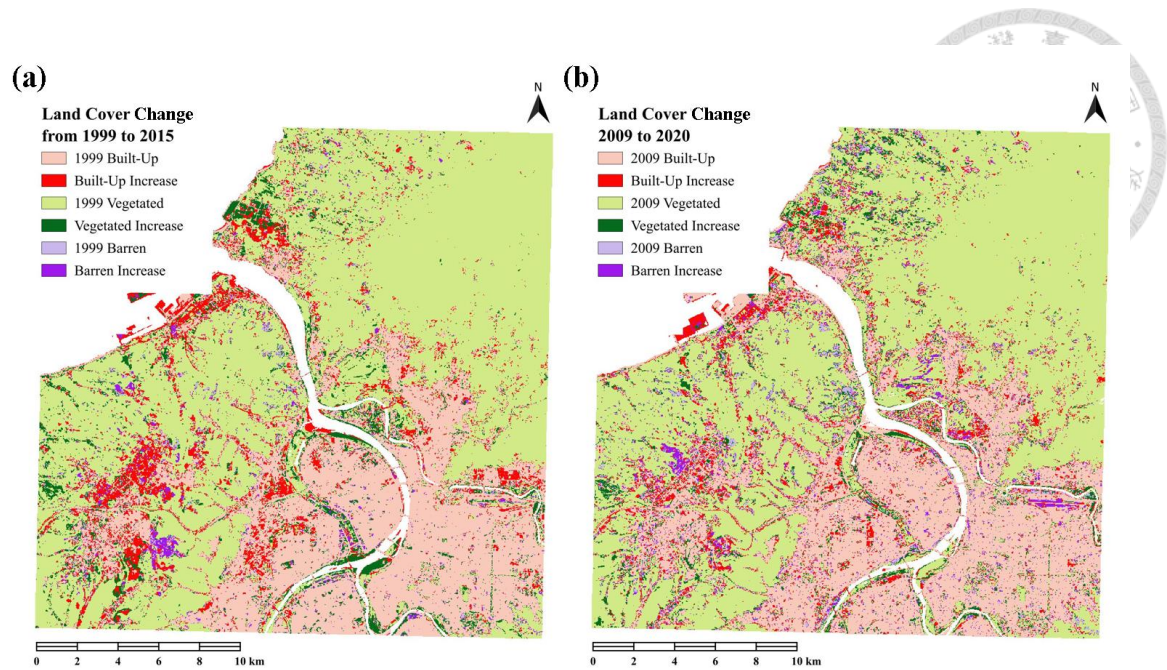


Figure 4.2 Land Cover Change: **(a)** 1999–2015, **(b)** 2009–2020.

To align with the temperature analysis periods, land cover change maps for 1999–2015 and 2009–2020 were created (Fig. 4.2). These maps reveal extensive urban expansion during the earlier period, especially at the city's edge, followed by a slowdown in the 2010s.

4.2. Summer Temperature Trends (1961 – 2023)

To evaluate long-term summer temperature trends in northern Taipei, daily mean daytime (dmT, 06:00–17:00) and nighttime (nmT, 18:00–05:00) temperatures were analyzed. The Taipei station (466920) provided the longest continuous dataset (1961–2023), allowing assessment of multi-decadal trends. Additional analysis was conducted for three other stations (Tamsui (淡水), Anbu (鞍部), Zhuzihu (竹子湖)), which have records beginning in 1990, to examine spatial differences across urban, coastal, and vegetated environments. For all stations, rainy days were excluded to minimize transient atmospheric cooling effects associated with precipitation.

As shown in Figure 4.3, both daytime (dmT) and nighttime (nmT) summer temperatures at Taipei station have increased over the study period (1961–2023). Daytime temperatures remained relatively stable from the 1960s to the 1990s (30.43 °C to 30.74 °C), but increased more rapidly in the 2000s and 2010s (Fig. 4.3c), peaking at 32.53 °C in 2020. Nighttime temperatures exhibited a sharper rise earlier, increasing from 26.76 °C in the 1960s to 27.85 °C in the 1980s, followed by a more gradual upward trend that reached 29.45 °C in 2017. This early acceleration in nighttime warming coincides with the period of rapid suburban expansion in Taipei driven by population growth ([Chen et. al., 2019](#)).

Linear regression analysis showed statistically significant warming trends for both daytime and nighttime temperatures. The slope for dmT was 0.0237 °C/year ($t = 6.94$, $p < 0.0001$, $R^2 = 0.441$), while the slope for nmT was 0.0388 °C/year ($t = 12.55$, $p < 0.0001$, $R^2 = 0.721$), confirming a persistent and substantial warming trend particularly at night.

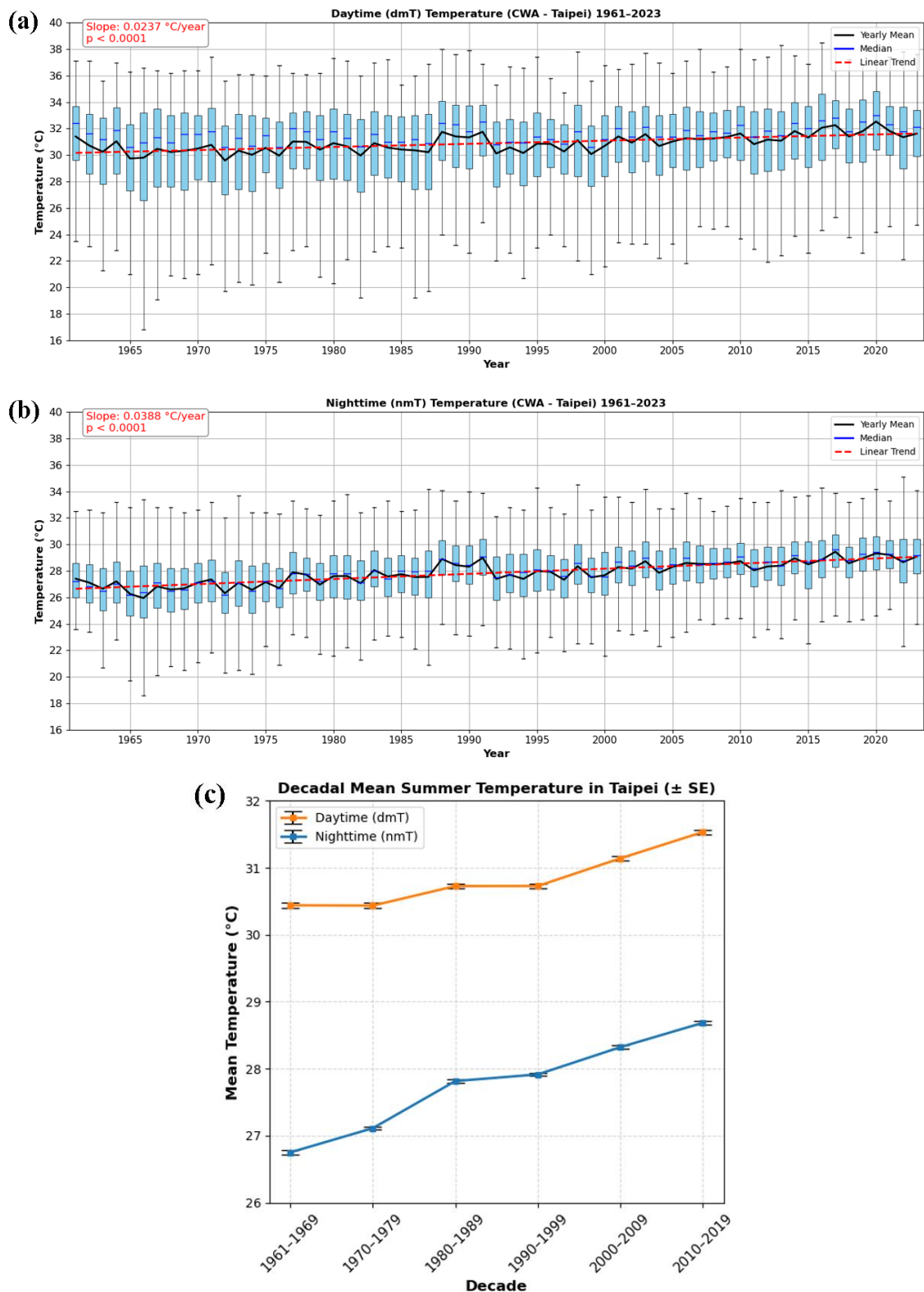


Figure 4.3 Summer Temperature Trends at Taipei Station (1961–2023). Boxplots show annual distributions and linear trends for **(a)** daytime and **(b)** nighttime mean temperatures. Panel **(c)** presents decadal means with standard error bars.

To illustrate spatial differences in temperature trends, linear regression was applied to four representative stations for the period 1990–2023 (Fig. 4.4). For each station, separate regressions were performed on daytime and nighttime summer mean temperatures, with the slope representing the warming rate ($^{\circ}\text{C}/\text{decade}$). The statistical significance of each trend was assessed based on the t-test of the slope parameter from the regression. Table 4.2 summarizes the slope estimates, t-values, p-values, and R^2 values for each station.

- Taipei(臺北) (urban core) exhibited steady warming of $0.37^{\circ}\text{C}/\text{decade}$ for both daytime and nighttime, with significant trends ($p = 0.0004$ and 0.0001) and moderate R^2 values (0.331 and 0.402), indicating consistent long-term warming with some year-to-year variability.
- Tamsui(淡水) (coastal) showed moderate daytime warming at $0.23^{\circ}\text{C}/\text{decade}$ ($p = 0.0029$, $R^2 = 0.245$) but the strongest nighttime warming at $0.57^{\circ}\text{C}/\text{decade}$ ($p < 0.0001$, $R^2 = 0.727$), likely reflecting delayed heat release in the coastal environment.
- Anbu(鞍部) and Zhuzihu(竹子湖) (vegetated, higher-elevation sites) recorded the lowest daytime warming rates (0.18 and $0.15^{\circ}\text{C}/\text{decade}$, respectively), with statistically significant but weaker trends ($p = 0.0048$ and 0.0081). Nighttime warming at both sites remained substantial (0.24 – $0.30^{\circ}\text{C}/\text{decade}$, $p < 0.001$), suggesting that nighttime heat retention has increased even in cooler, vegetated environments.

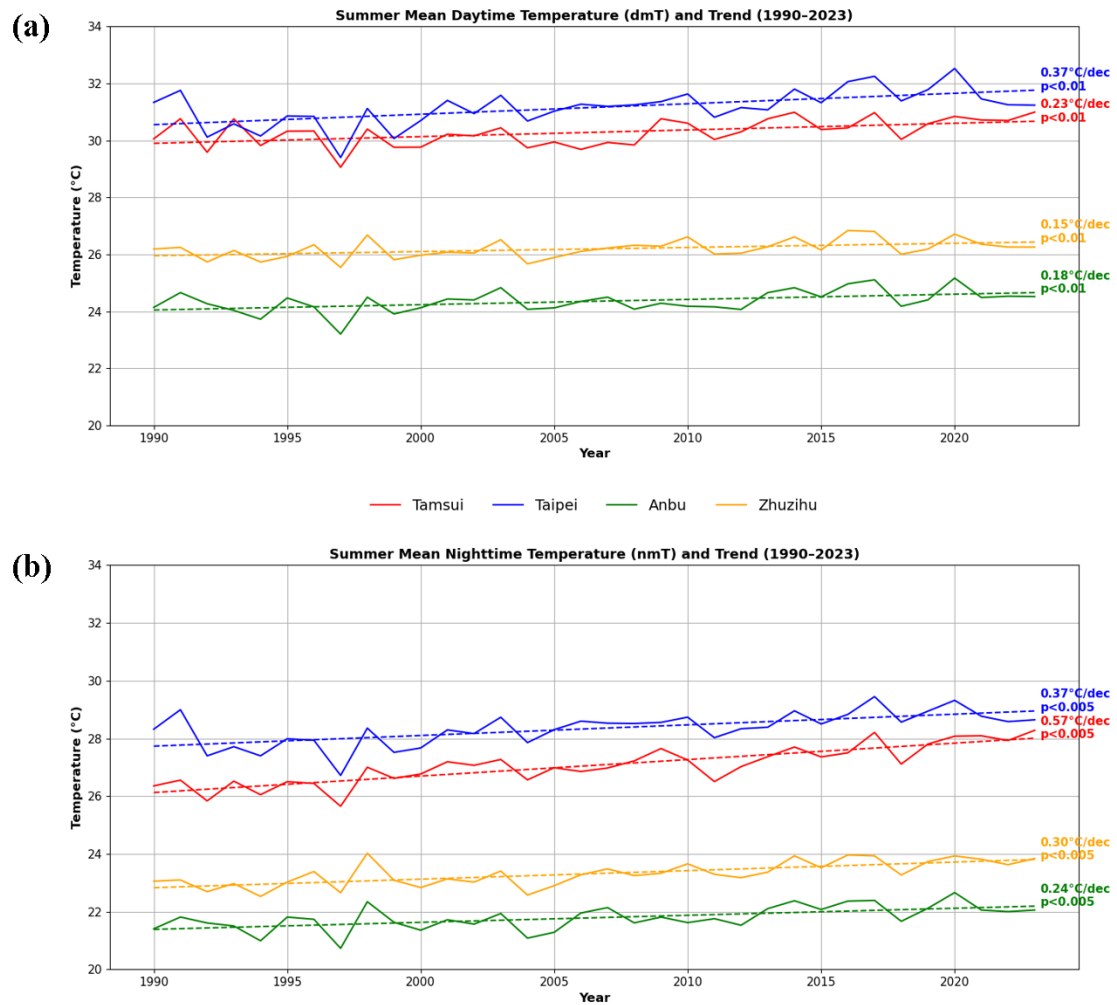
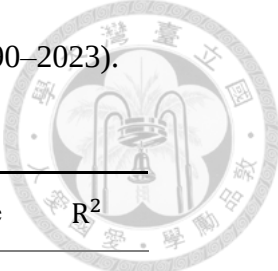


Figure 4.4 Summer Temperature Trends at Taipei(臺北), Tamsui(淡水), Anbu(鞍部), and Zhuzihu(竹子湖) (1990–2023). **(a)** Daytime (dmT), **(b)** Nighttime (nmT).

Table 4.2 Linear Regression Results for dmT and nmT (1990–2023).



(a) Daytime (dmT)						
Station		N (hours)	Slope (°C/decade)	t-value	p-value	R ²
Tamsui	淡水	25,514	0.23	3.22	0.0029	0.245
Taipei	臺北	25,583	0.37	3.98	0.0004	0.331
Anbu	鞍部	24,002	0.18	3.03	0.0048	0.223
Zhuzihu	竹子湖	25,105	0.15	2.82	0.0081	0.199

(b) Nighttime (nmT)						
Station		N (hours)	Slope (°C/decade)	t-value	p-value	R ²
Tamsui	淡水	25,529	0.57	9.24	<0.0001	0.727
Taipei	臺北	25,744	0.37	4.64	0.0001	0.402
Anbu	鞍部	24,006	0.24	3.95	0.0004	0.327
Zhuzihu	竹子湖	25,115	0.30	5.42	<0.0001	0.479

Overall, nighttime warming was stronger and more consistent across all stations, while daytime warming varied more depending on location, elevation, and land cover.

4.3. Influence of Land Cover Change on Summer Temperatures

4.3.1. Grid-Based Patterns from TReAD

The modeled summer temperatures from the TReAD dataset revealed a clear warming trend across the study area between TP1 (1989–1997) and TP3 (2009–2018), with the most intense warming observed in the western districts and urban core (Fig. 4.5). Daytime temperatures in the urban core exceeded 31 °C by TP3, while nighttime temperatures surpassed 28 °C, marking a shift from the cooler gradients of TP1.

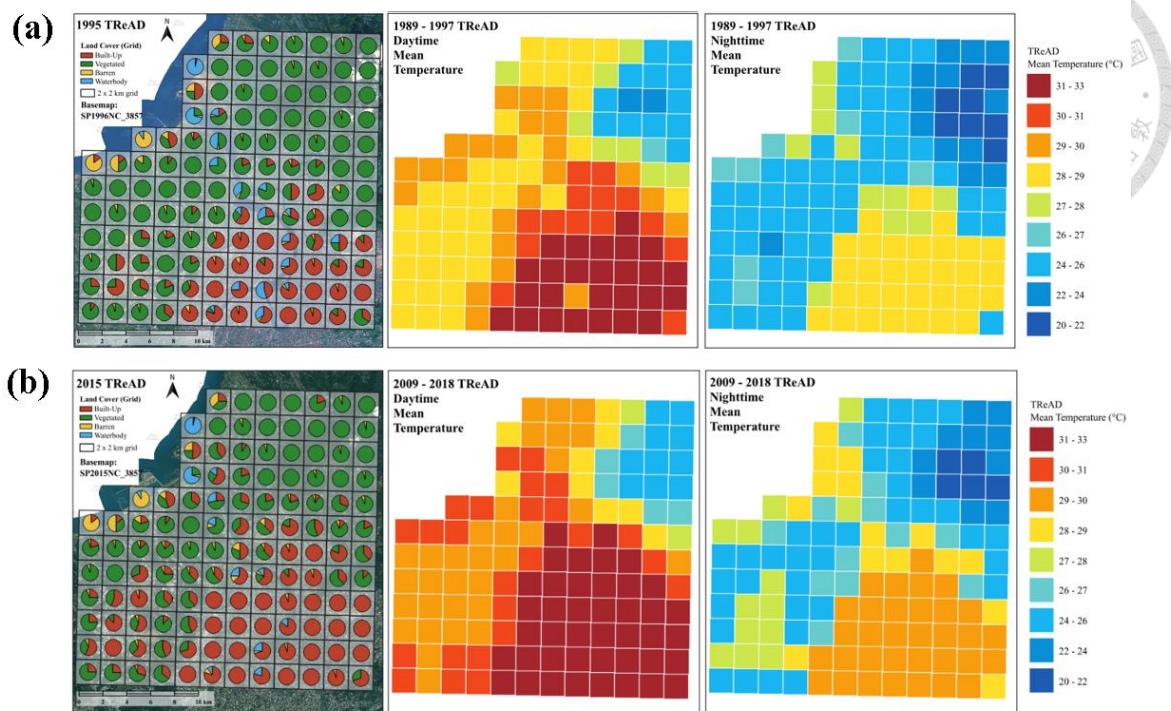


Figure 4.5 TReAD Modeled Temperatures and Land Cover: TP1 vs TP3. **(a)** TP1 (1989–1997), **(b)** TP3 (2009–2018). Pie charts represent land cover proportions per 2×2 km grid.

To explore how land cover change influenced temperature patterns, K-means clustering was applied to the built-up and vegetated land cover compositions of each grid cell, using both absolute values from 1995 and 2015 as well as their changes over time. Specifically, six land cover metrics were used for clustering: (1) built-up ratio in 1995 (1995_BUratio), (2) built-up ratio in 2015 (2015_BUratio), (3) change in built-up ratio between 1995 and 2015 (BU_change), (4) vegetated ratio in 1995 (1995_VRatio), (5) vegetated ratio in 2015 (2015_VRatio), and (6) change in vegetated ratio between 1995 and 2015 (VE_change). These combined variables allowed differentiation between areas with varying levels of urban expansion, vegetation stability, and land cover change. The

resulting five clusters, ranging from high built-up growth and vegetation loss to stable, vegetation-dominated areas, are summarized in Table 4.3 and visualized in Figure 4.6.

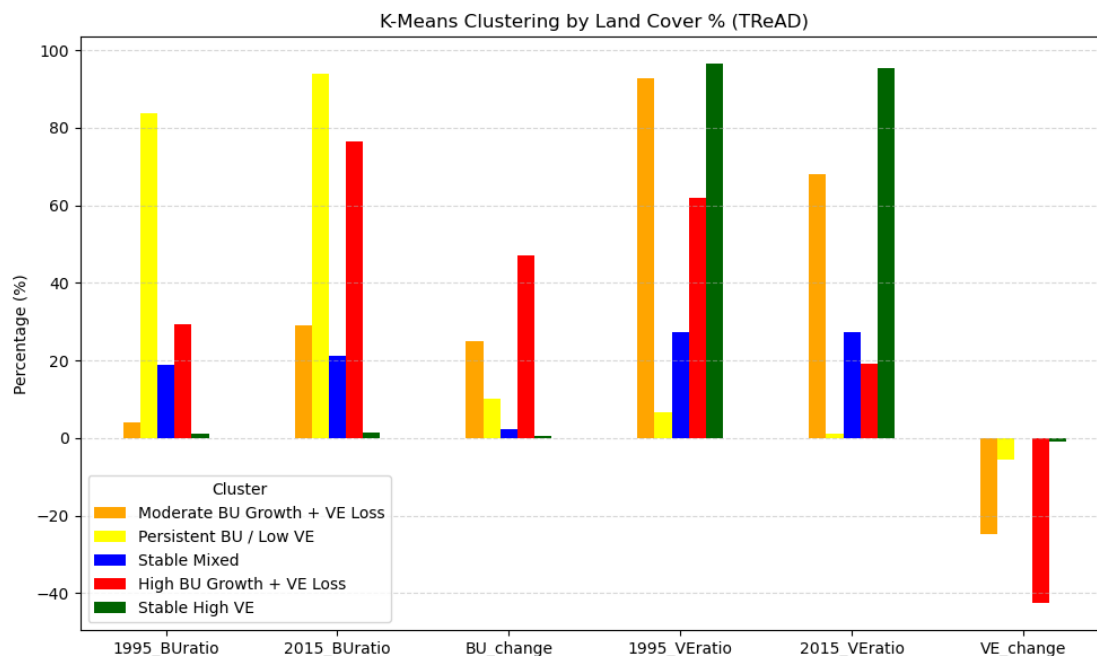


Figure 4.6 K-Means Clustering of Land Cover (1995 & 2015). Bars represent the mean values for each cluster across six land cover metrics: 1995 and 2015 built-up (BUratio) and vegetated (VEratio) percentages, as well as the absolute changes in built-up (BU_change) and vegetated area (VE_change) between 1995 and 2015.

Table 4.3 K-Means Land Cover Cluster Descriptions (TReAD 1995 & 2015).

K-Means Cluster	Land Cover Change Groups	Grids (N)	Descriptions
Cluster 1	High BU Growth and VE Loss	20	Areas with substantial built-up expansion (~47% increase) and major vegetated land loss (~43% decrease).
Cluster 2	Moderate BU Growth and VE Loss	31	Areas with moderate built-up growth (~25% increase) accompanied by notable vegetated land loss (~25% decrease).
Cluster 3	Persistent BU and Low VE	29	Already heavily urbanized areas (~84–94% BU) with minimal further land cover change.
Cluster 4	Stable High VE	35	Predominantly vegetated areas (>95%) with little land cover change.
Cluster 5	Stable Mixed	10	Areas with relatively balanced built-up (~20%) and vegetated (~27%) proportions, remaining stable.

Temperature change between TP1 and TP3 was calculated for each cluster (Table 4.3). The most urbanizing areas (Cluster 1) experienced the highest warming—1.29 °C for daytime and 2.17 °C for nighttime—followed by moderate and already-urbanized zones. Stable vegetated areas warmed the least, with increases under 0.75 °C. ANOVA results confirmed significant differences among clusters ($p < 0.00001$ for both dmT and nmT), and post-hoc tests showed Cluster 1 differed significantly from all others, especially for nighttime warming.

Table 4.4 $\Delta_{dm}T$ and $\Delta_{nm}T$ by Land Cover Change Group (TP3 vs TP1, TReAD).

Land Cover Change Groups	Grids (N)	$\Delta_{dm}T \pm SE$ (°C)	$\Delta_{nm}T \pm SE$ (°C)
1. High BU Growth + VE Loss	20	1.29 ± 0.10	2.17 ± 0.23
2. Moderate BU Growth + VE Loss	31	0.92 ± 0.03	1.05 ± 0.11
3. Persistent BU / Low VE	29	1.02 ± 0.08	1.00 ± 0.03
4. Stable High VE	35	0.75 ± 0.02	0.72 ± 0.02
5. Stable Mixed	10	0.89 ± 0.15	0.80 ± 0.07
One-Way ANOVA		F = 9.17 p < 0.00001	F = 25.95 p < 0.00001

Despite these trends by land cover change groups, Figure 4.7 highlights grid-level variability within each group. While areas with high built-up growth and vegetation loss (red triangles) generally show strong warming—especially at night—this correlation is not consistent. Some of these grids show similar temperature increases to those in the Stable High Vegetation group (green triangles), indicating that land cover change alone does not fully explain the warming intensity. Additionally, grids adjacent to those with the highest temperature increases also tend to show elevated warming compared to areas with more uniform temperature change. This likely reflects the spatial configuration and temperature interpolation process within the TReAD model, rather than representing direct observational evidence of heat transfer across neighboring grids.

These patterns suggest that local factors such as elevation, land cover composition, or wind circulation can influence land cover–temperature relationships at the grid level.

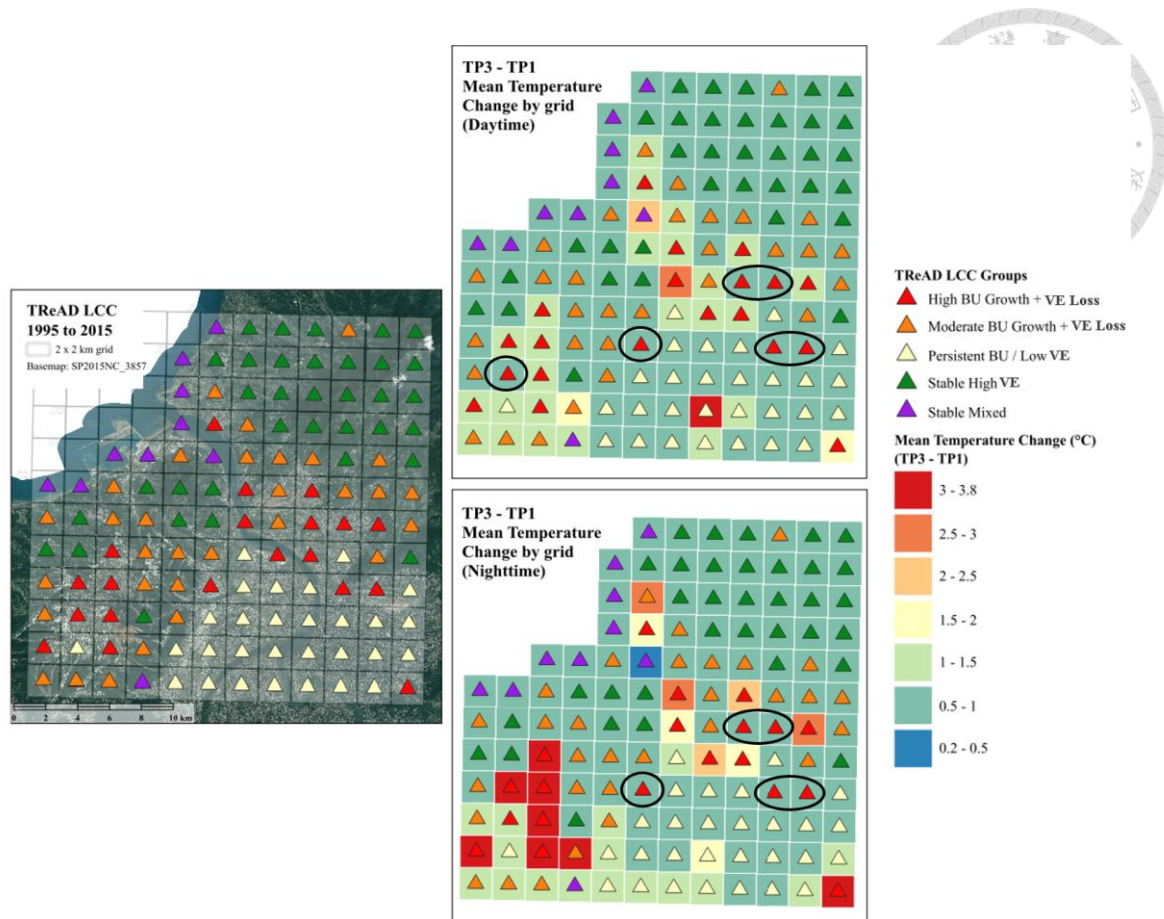


Figure 4.7 Land Cover Change Groups and Grid-Level Temperature Change. Left: cluster map over 2015 satellite imagery. Right: $\Delta_{dm}T$ and $\Delta_{nm}T$ (TP3–TP1) by grid, with color intensity showing warming magnitude and triangle symbols denoting cluster group. Black circles highlight grids where some High Built-Up Growth + Vegetation Loss areas (red triangles) show temperature increases comparable to nearby Stable High Vegetation grids (green triangles), showing variability in warming intensity within the same land cover change group.

4.3.2. Station-level Analysis

To assess localized temperature trends, observational data from Taiwan's Central Weather Administration (CWA) stations were analyzed for two time period comparisons: TP3–TP2 (2010–2019 vs. 2000–2009) and TP3c–TP3a (2019–2023 vs. 2010–2014). While the modeled TReAD dataset supports analysis beginning from 1990 (TP1), most CWA stations have data only from 1998 onward, making TP2 a more appropriate baseline for observed data. The TP3–TP2 comparison includes 11 stations (one relocated site), while the more recent TP3c–TP3a comparison includes 17 stations, five of which underwent relocation. Figure 4.8 presents the spatial distribution of temperature change ($\Delta_{dm}T$ and $\Delta_{nm}T$) across station locations with 1 km buffer zones, and Table 4.5 summarizes the corresponding mean changes with associated standard errors.

Mountain stations Anbu(鞍部) and Zhuzihu(竹子湖), characterized by high elevation and dense vegetation, recorded the lowest daytime warming (0.20 ± 0.03 °C and 0.24 ± 0.04 °C, respectively) but interestingly showed moderate nighttime increases (0.36 ± 0.02 °C and 0.46 ± 0.02 °C).

Urban-fringe stations (e.g. Shihlin(士林) and Shipai(石牌)) exhibited moderate daytime warming (~ 0.47 °C) but higher nighttime increases (0.57 – 0.64 °C), surpassing Taipei station (0.36 ± 0.03 °C). These patterns highlight how local features modulate thermal performance beyond general land cover categories.

Dazhi(大直) station exhibited the strongest observed decadal warming among all stations, with increases of 0.90 °C during the day and 0.86 °C at night. This trend aligns with the rapid urban development in the nearby Neihu district along the Keelung River. While the TReAD simulation captured the area's built-up expansion and general warming signal, it assigned Dazhi's grid to the 0.5 – 1 °C warming category for both daytime and

nighttime—similar to Stable High Vegetation areas. This discrepancy suggests that local-scale factors driving stronger warming at Dazhi, such as dense built structures or microclimatic effects, may not be fully captured in the model.

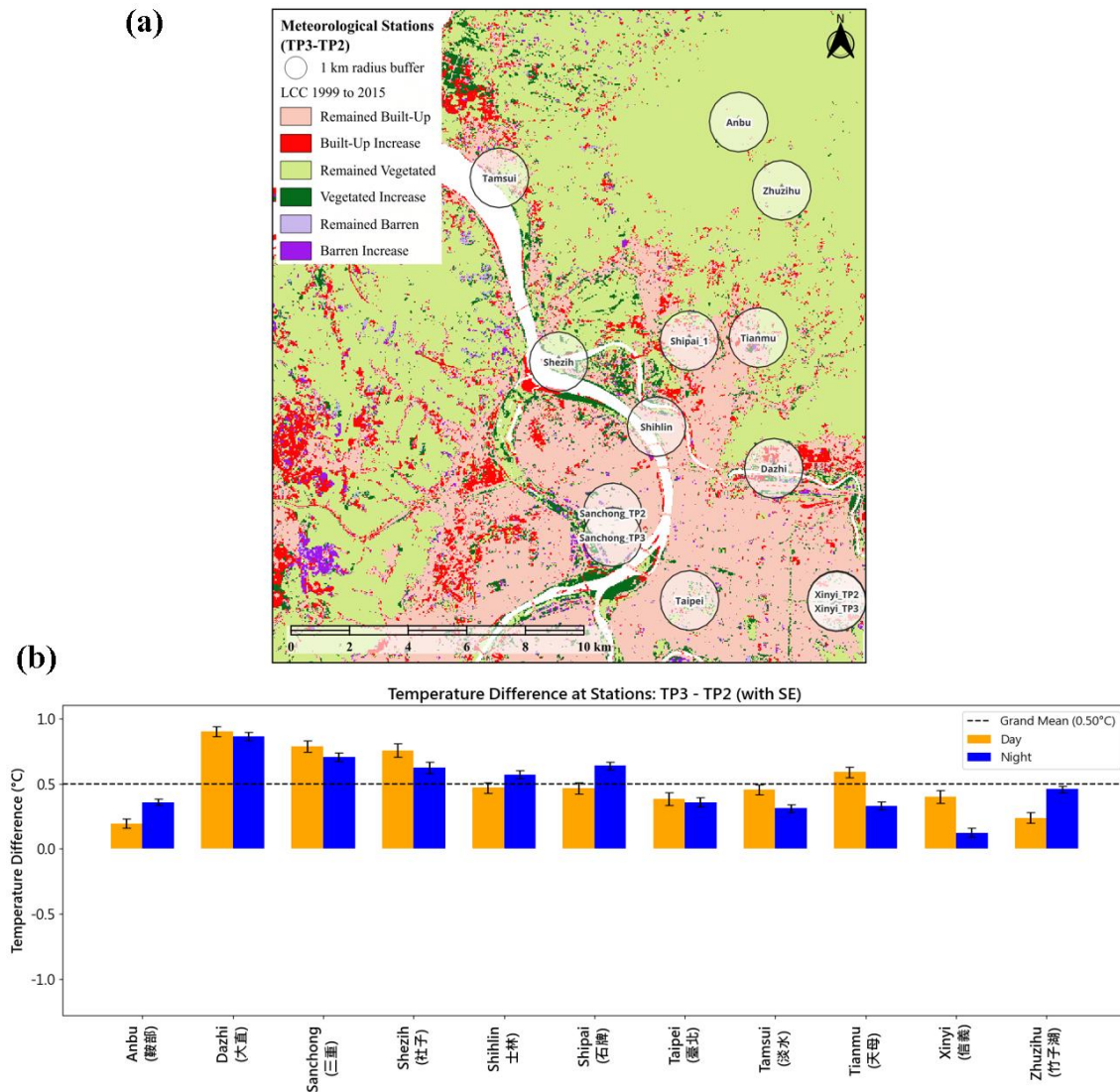


Figure 4.8 (a) Stations in TP3 – TP2 Comparison (1 km Buffers), **(b)** Mean Temperature Change at Stations. Error bars represent the standard error.

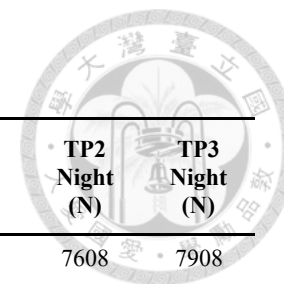
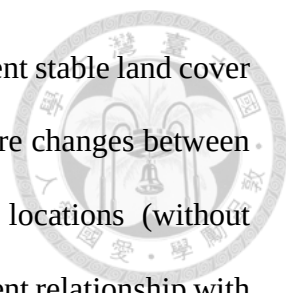


Table 4.5 ΔdmT and ΔnmT by Station Buffer (TP3 vs TP2).

Station		Remained Built-Up	Built-Up Increase (+)	Remained Vegetated	Vegetated Increase (+)	Vegetated Loss (-)	$\Delta dmT \pm SE$ (°C)	$\Delta nmT \pm SE$ (°C)	TP2 Day (N)	TP3 Day (N)	TP2 Night (N)	TP3 Night (N)
Anbu	鞍部	0.03%	0.17%	99.53%	0.23%	0.17%	0.20 ± 0.03	0.36 ± 0.02	7608	7908	7608	7908
Dazhi	大直	53.15%	12.49%	14.74%	9.14%	7.78%	0.90 ± 0.04	0.86 ± 0.03	6866	8882	6869	8892
Sanchong*	三重	82.84%	0.00%	0.64%	10.62%	0.00%	0.79 ± 0.04	0.71 ± 0.03	7963	6403	7980	6412
Shezih	社子	8.42%	4.95%	29.37%	10.26%	1.72%	0.76 ± 0.05	0.62 ± 0.05	7610	8421	7635	8455
Shihlin	士林	55.11%	6.32%	5.18%	6.23%	3.79%	0.47 ± 0.04	0.57 ± 0.03	7764	8465	7793	8471
Shipai	石牌	69.88%	8.95%	17.61%	2.54%	6.62%	0.47 ± 0.04	0.64 ± 0.03	7936	8592	7959	8609
Taipei	臺北	84.93%	2.30%	6.79%	4.46%	1.37%	0.39 ± 0.05	0.36 ± 0.03	7080	7181	7080	7206
Tamsui	淡水	24.66%	6.35%	29.32%	4.10%	5.41%	0.46 ± 0.04	0.31 ± 0.03	8940	9166	8940	9176
Tianmu	天母	45.60%	8.08%	41.37%	3.24%	4.61%	0.59 ± 0.04	0.33 ± 0.03	8620	8395	8646	8397
Xinyi	信義	75.72%	9.70%	5.23%	7.55%	7.76%	0.40 ± 0.05	0.12 ± 0.04	5566	7662	5594	7668
Zhuzihu	竹子湖	0.47%	0.44%	98.40%	0.50%	0.50%	0.24 ± 0.04	0.46 ± 0.02	7980	7884	7980	7884

*Sanchong station was relocated between time periods.



To further explore temperature dynamics during the more recent stable land cover period, Figure 4.9 and Tables 4.6 and 4.7 present summer temperature changes between TP3c and TP3a. Among the 12 stations that remained at fixed locations (without relocations), temperature changes varied considerably, but no consistent relationship with local land cover compositions was found (Fig. 4.9, Table 4.5). For instance, Tamsui(淡水) exhibited notable nighttime warming (0.88°C , $\text{SE} = 0.04$), an increase compared to the earlier TP3–TP2 period. In contrast, the high-elevation vegetated stations Anbu(鞍部) and Zhuzihu(竹子湖) showed minimal daytime warming (0.25°C and 0.06°C) but moderate nighttime increases (0.30°C and 0.31°C), consistent with their earlier trend.

Urban core stations (Taipei(臺北), Xinyi(信義)) showed moderate warming, while fringe stations (e.g. Shihlin(士林) and Tianmu(天母)) experienced stronger increases during both day and night. A contrast emerged between Lujhou(蘆洲) and Xinzhuang(新莊) stations—despite their similar urban surroundings, Lujhou warmed during both day and night, whereas Xinzhuang showed a slight cooling trend, underscoring the influence of local microclimates.

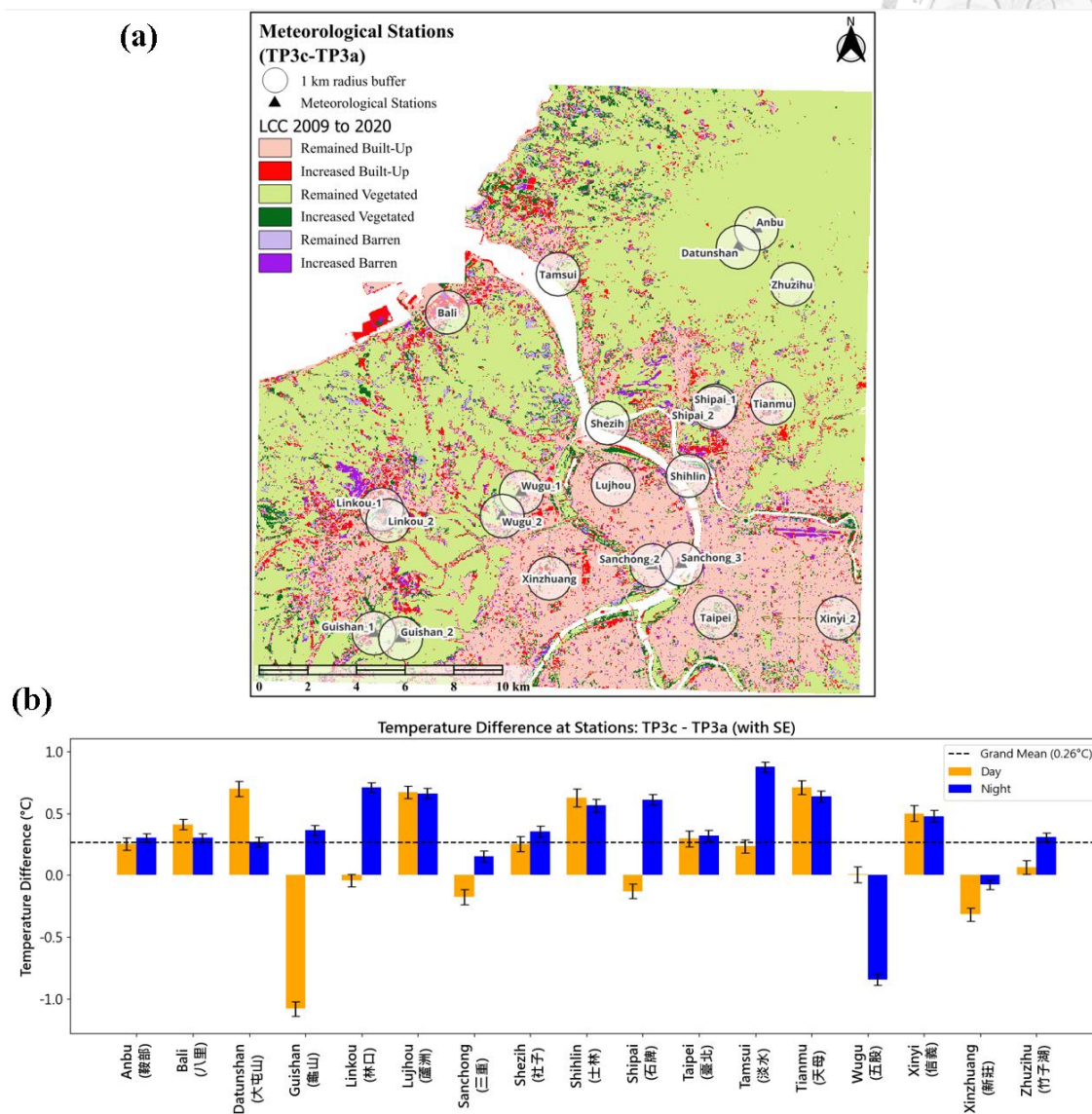


Figure 4.9 (a) Stations in TP3c – TP3a Comparison (1 km Buffers). Stations Sanchong, Wugu, Linkou, Guishan, and Shipai were relocated between time periods. **(b)** Mean Temperature Change at Stations. Error bars represent the standard error.

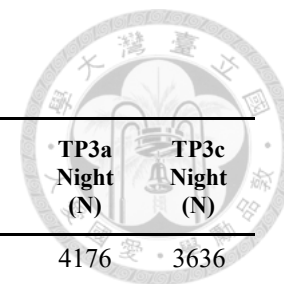


Table 4.6 $\Delta_{dm}T$ and $\Delta_{nm}T$ by Station Buffer (TP3c vs TP3a).

Station		Remained Built-Up	Built-Up Increase (+)	Remained Vegetated	Vegetated Increase (+)	Vegetated Loss (-)	$\Delta_{dm}T \pm SE$ (°C)	$\Delta_{nm}T \pm SE$ (°C)	TP3a Day (N)	TP3c Day (N)	TP3a Night (N)	TP3c Night (N)
Anbu	鞍部	0.04%	0.86%	98.68%	0.25%	0.93%	0.25 ± 0.05	0.30 ± 0.03	4176	3636	4176	3636
Bali	八里	25.88%	25.99%	32.83%	3.64%	26.88%	0.41 ± 0.04	0.30 ± 0.04	5166	4444	5171	4452
Datunshan	大屯山	0.04%	0.07%	99.79%	0.04%	0.07%	0.70 ± 0.06	0.27 ± 0.04	3595	2690	3598	2695
Lujhou	蘆洲	89.08%	4.18%	0.71%	1.78%	2.14%	0.67 ± 0.05	0.66 ± 0.04	4651	4183	4653	4219
Shezih	社子	10.19%	4.45%	30.40%	7.06%	3.81%	0.25 ± 0.06	0.36 ± 0.04	4743	3525	4759	3533
Shihlin	士林	45.18%	6.00%	6.00%	7.11%	2.89%	0.63 ± 0.07	0.56 ± 0.05	4302	1788	4308	1788
Taipei	臺北	70.66%	5.63%	9.69%	9.62%	4.59%	0.30 ± 0.06	0.32 ± 0.04	3704	4945	3711	5085
Tamsui	淡水	28.01%	5.71%	24.37%	4.96%	5.67%	0.23 ± 0.05	0.88 ± 0.04	4783	4270	4790	4273
Tianmu	天母	42.02%	7.54%	41.87%	3.64%	6.40%	0.71 ± 0.06	0.64 ± 0.04	4639	4211	4643	4226
Xinyi	信義	75.64%	6.78%	5.74%	7.06%	4.17%	0.50 ± 0.06	0.48 ± 0.05	4254	3632	4256	3633
Xinzhuang	新莊	84.36%	7.37%	2.00%	4.60%	4.31%	-0.32 ± 0.05	-0.08 ± 0.04	4648	3993	4654	3992
Zhuzihu	竹子湖	0.21%	1.04%	97.79%	0.61%	1.18%	0.06 ± 0.05	0.31 ± 0.03	4056	4146	4056	4152

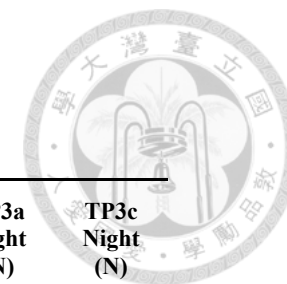


Table 4.7 ΔdmT and ΔnmT by Station Buffer (TP3c vs TP3a) – Relocated Stations.

Station		2009 Built-Up	2009 Vegetated	2020 Built-Up	2020 Vegetated	$\Delta dmT \pm SE$ (°C)	$\Delta nmT \pm SE$ (°C)	TP3a Day (N)	TP3c Day (N)	TP3a Night (N)	TP3c Night (N)
Guishan	龜山	19.82%	67.84%	15.77% (-)	79.25% (+)	-1.08 ± 0.06	0.36 ± 0.04	4599	3706	4607	3712
Linkou	林口	56.53%	26.75%	55.50% (-)	36.91% (+)	-0.04 ± 0.05	0.71 ± 0.04	4893	4018	4903	4020
Sanchong	三重	88.06%	7.95%	57.37% (-)	6.96% (-)	-0.18 ± 0.06	0.15 ± 0.05	3775	3454	3784	3458
Shipai	石牌	74.72%	21.38%	79.28% (+)	16.29% (-)	-0.13 ± 0.06	0.61 ± 0.04	4674	3178	4660	3187
Wugu	五股	50.11%	44.27%	33.23% (-)	59.53% (+)	0.01 ± 0.06	-0.84 ± 0.04	4903	2706	4907	2697

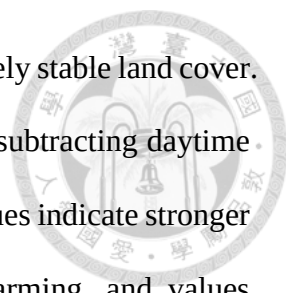
In contrast, five stations—Guishan, Linkou, Sanchong, Shipai, and Wugu (龜山, 林口, 三重, 石牌, 五股)—were relocated between TP3a and TP3c. As shown in Table 4.6, four of the five experienced reductions in daytime temperature, most notably Guishan(龜山) (-1.08°C), which moved from 177 m to 228 m elevation and into a greener, more mountainous setting. Linkou(林口) also shifted to higher ground (238 m to 275 m) with increased vegetated cover, while Shipai(石牌) relocated only a short distance to a higher local elevation (from 7 m to 35 m).

Sanchong(三重) was moved closer to the riverside, leading to a decrease in both built-up and vegetated cover. Despite this, it still showed a modest daytime cooling (-0.18°C). Wugu(五股), which moved from 95 m to 188 m elevation, was the only station to show a slight daytime warming ($+0.01^{\circ}\text{C}$) but a substantial nighttime cooling (-0.84°C) at its new hillside location.

Notably, nighttime temperatures increased at most relocated sites despite greener surroundings, suggesting that urban heat retention and broader climate effects may be influencing nocturnal warming patterns. These results underscore the importance of considering station background information—including relocation, elevation, and land use land cover changes—when interpreting temperature trends over time. Apparent warming or cooling reflect the environmental contexts of a specific location.

4.3.3. Comparison Between Modeled and Observational Temperature Variation

This section compares modeled (TReAD) and observational (CWA) temperature data to evaluate the consistency of summer temperature changes across two key periods—



one characterized by active land cover change and the other by relatively stable land cover. To assess diurnal differences, the comparison uses a simple metric: subtracting daytime warming from nighttime warming at each grid or station. Positive values indicate stronger nighttime warming, negative values indicate stronger daytime warming, and values within $\pm 0.05^{\circ}\text{C}$ are considered balanced. Figure 4.10 presents side-by-side comparisons of daytime and nighttime warming across two time periods: (a) TP3–TP1/TP3–TP2 (active land cover change) and (b) TP3c–TP3a (stable land cover).

In the TP3–TP1 period, TReAD data showed a modest but spatially varied nighttime-dominant warming trend (mean difference: $+0.15^{\circ}\text{C}$; range: -2.00°C to $+2.13^{\circ}\text{C}$). This pattern was most prominent in coastal and newly urbanized areas like Linkou(林口) and Guishan(龜山), which experienced strong nighttime heat retention.

Observational data from the corresponding TP3–TP2 period partially echoed this trend. Nighttime-dominant warming appeared at high-elevation, vegetated stations like Zhuzihu(竹子湖) ($+0.22^{\circ}\text{C}$) and Anbu(鞍部) ($+0.16^{\circ}\text{C}$), as well as urban fringe sites such as Shipai(石牌) ($+0.17^{\circ}\text{C}$) and Shihlin(士林) ($+0.10^{\circ}\text{C}$). In contrast, several core urban stations showed either balanced or daytime-dominant warming, including Taipei (-0.03°C), Dazhi(大直) (-0.04°C), Xinyi(信義) (-0.28°C), and Tianmu(天母) (-0.26°C). These cases deviate from the TReAD result, likely reflecting localized land characteristics or microclimate influences not fully captured in the model.

During the TP3c–TP3a period, TReAD grids exhibited a consistent shift toward daytime-dominant or balanced warming (mean difference: -0.06°C ; range: $+0.09^{\circ}\text{C}$ to -0.19°C), suggesting reduced diurnal contrast under stable land cover conditions.

CWA station data during this same period revealed more variability. Many stations matched the TReAD trend—such as Bali(八里) (-0.11°C), Tianmu(天母) ($-$

0.07 °C), and Shihlin(士林) (−0.07 °C)—indicating a shift toward daytime warming.

However, some stations diverged:

- Tamsui(淡水) showed strong nighttime warming (+0.65 °C), while Shezih(社子) reversed its earlier daytime-dominant trend and shifted toward nighttime warming.
- Zhuzihu(竹子湖) (+0.25 °C) and Anbu(鞍部) (+0.05 °C) remained nighttime-dominant, reinforcing the moderating role of elevation and vegetation.
- Core urban stations such as Taipei, Xinyi(信義), and Luzhou(蘆洲) showed near-balanced warming.
- Xinzhuang(新莊) uniquely recorded cooling during both day and night, a trend not reflected in TReAD.

Overall, while TReAD and CWA station data show broadly consistent spatial patterns in summer temperature change, key differences remain—especially in warming magnitude and whether daytime or nighttime temperatures increased more. These differences highlight the influence of local conditions, such as topography, vegetation, or nearby water bodies, which station data can capture more directly.

TReAD, although based on weather station inputs, uses only a few stations within the study area (e.g., Taipei, Tamsui, Anbu, and Zhuzihu). It also uses gridded land cover inputs derived from SPOT satellite images, where each 500 × 500 m pixel was assigned its dominant land cover category (Chen et al., 2019). This means mixed or changing land cover—common in urban fringe zones—were not fully represented in the model.

Because TReAD aggregates to 2 km grids, it smooths out microclimatic variations that are often captured by ground stations. Still, in fully urbanized areas where land cover and temperature conditions are more homogeneous, both datasets reflected similar

patterns, especially the trend toward nearly equal daytime and nighttime warming. This suggests that despite resolution limitations, the model performs reasonably well in stable urban contexts.

However, when land cover is more heterogeneous or undergoing change, as in urbanizing or vegetated zones, the differences between modeled and observed data become more noticeable. These findings underline the importance of using both types of data to understand temperature changes.

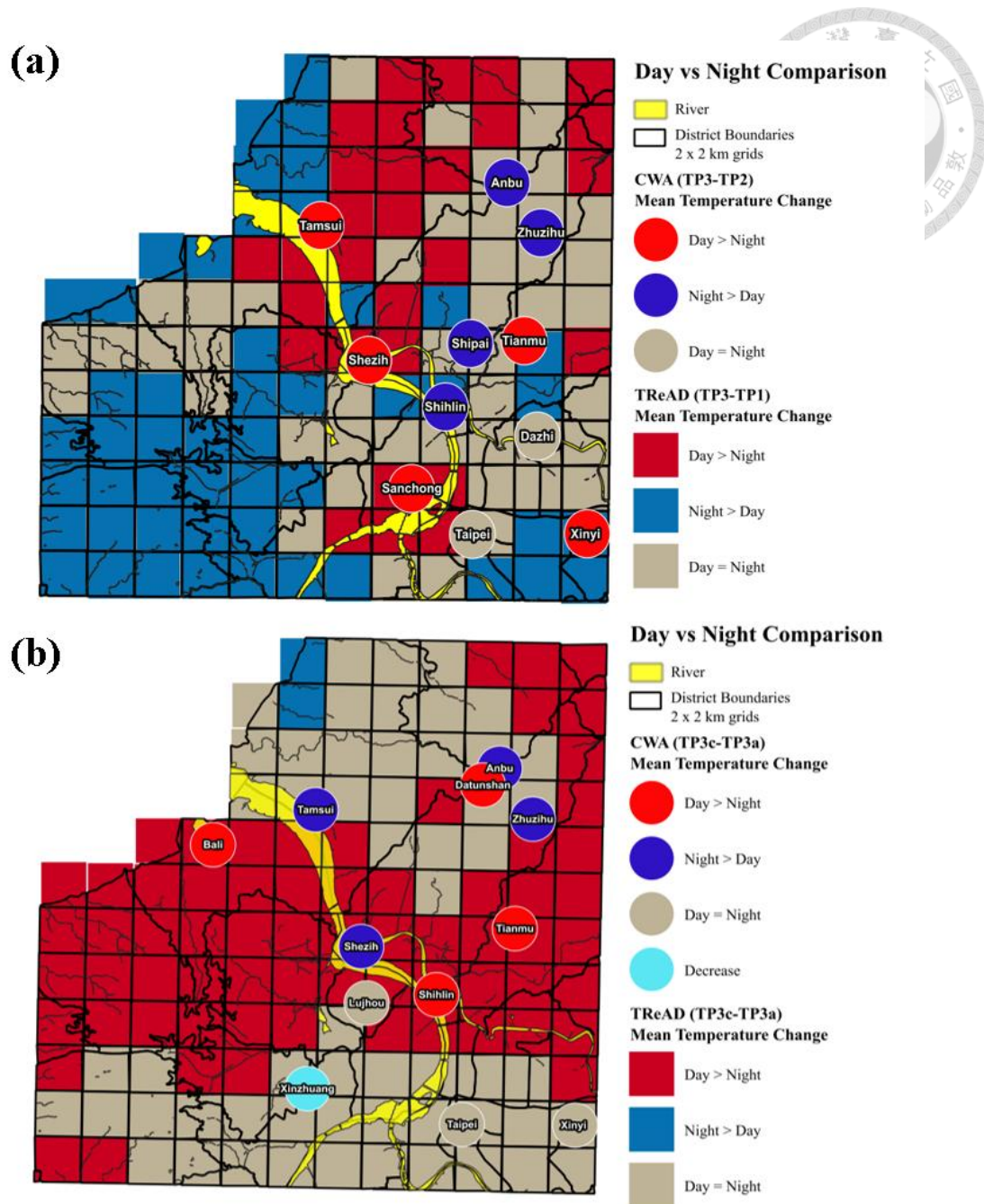
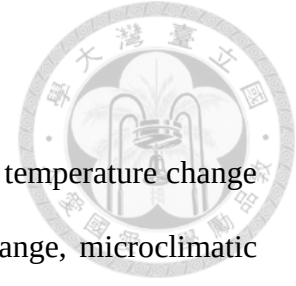


Figure 4.10 Modeled vs Observed Day and Night Temperature Change. **(a)** TReAD (TP3–TP1) and CWA (TP3–TP2) comparison. **(b)** TP3c–TP3a comparison.

Day $\approx$ Night (beige) if the absolute difference in warming is less than 0.05 °C.

Chapter 5 Discussion

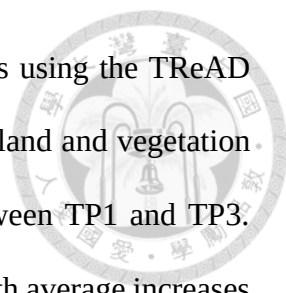


This chapter interprets the spatial and temporal dynamics of temperature change in northern Taipei Metropolitan Area in relation to land cover change, microclimatic factors, and diurnal variation. The findings reveal that areas experiencing rapid urbanization and vegetated land loss showed the strongest warming, especially at night, while high-elevation and dense vegetated zones remained relatively unchanged. However, temperature trends were not entirely consistent—some urban fringe and long-urbanized areas showed varying warming behaviors, and there are indications in some locations that daytime temperatures may be rising at a pace similar to or faster than nighttime temperatures (Fig. 4.10). These patterns suggest that land cover change alone does not determine thermal outcomes; rather, local morphology, climate interactions, and differences between daytime and nighttime heating and cooling jointly shape urban temperature patterns.

5.1. Impact of Land Cover Change on Temperature

This study used a comparative approach to assess how land cover change influenced summer air temperature, focusing on time periods that represented either significant land cover transitions or relatively stable conditions. Daytime and nighttime mean temperatures were calculated from hourly reanalysis (TReAD, 1989–2023) and weather station (CWA, 2000–2023) data, and temperature differences were linked to specific land cover patterns using cluster-based grouping. This approach enabled a more detailed understanding of where and how warming occurred, moving beyond annual trends and offering clearer spatial and diurnal contrasts.

The results of this study demonstrate a clear association between long-term land cover change and increased summer air temperatures in the northern Taipei Metropolitan



area. Analyses of individual grid cells and grouped land cover types using the TReAD dataset revealed that areas with more than 40% increase in built-up land and vegetation loss (Cluster 1) experienced the highest temperature increases between TP1 and TP3. These changes were most pronounced for nighttime temperatures, with average increases exceeding 2 °C. The strong warming trend observed in these newly urbanized zones aligns with the understanding that urbanization leads to the urban heat island effect through multiple mechanisms, including surface modification, and anthropogenic heat emissions. In contrast, areas with stable high vegetation (Cluster 4) experienced the lowest warming of 0.72 °C. This relationship aligns with [Song & Park \(2021\)](#), who reported a strong positive correlation between increased urban area ratios and temperature trend slopes across 38 weather stations in South Korea. Their finding that reductions in forest area were similarly linked to increased warming ($r = -0.495$, $p < 0.01$) supports the present study's observation that vegetated areas buffer temperature rise, while urban expansion accelerates it.

Further corroboration is found in [Ren et al. \(2008\)](#), whose analysis of over 280 meteorological stations in North China found that urbanization significantly impacted annual surface air temperature trends—rising up to 0.16 °C per decade in large cities and decreasing when the rate of urbanization is lower.

A study conducted in Taipei by [Chen et al. \(2017\)](#) used MODIS satellite images (1 km × 1 km resolution) from 2004, 2007, and 2010 to examine how urbanization influences diurnal LST variation during the summer months. They found that diurnal LST variation increased significantly with urbanization, especially in areas at earlier stages of development. Urbanization was measured using an index based on built-up area and vegetation cover within each grid cell. Their results showed that the strongest warming effects occurred when the urbanization index exceeded 0.6. This supports the findings of

this study, which also observed steeper warming trends during the rapid land cover changes of 1995–2015 compared to the slower development period of the 2010s.

In this study, several of the fastest-warming areas—such as Dazhi, Guishan, and Linkou (大直, 龜山, 林口)—are industrial and high-density residential zones, where elevated anthropogenic heat (AH) emissions are likely. These warming patterns, particularly during nighttime, suggest that AH plays a significant role in reducing cooling potential and increasing heat accumulation. [Lin et al. \(2008\)](#) similarly found that adding 100 W/m² of anthropogenic heat in Taipei could raise surface temperature by approximately 0.3 °C and weaken land–sea breezes. The alignment between their simulation and the observed warming in densely developed zones in this study supports the interpretation that AH emissions may be a key contributor to nighttime temperature increases, especially in stagnant summer conditions.

However, the spatial differences in warming observed across the study area suggest that factors beyond land cover change—such as local microclimatic and morphological characteristics—may also influence temperature patterns. While this study did not explicitly analyze variables like urban form or wind exposure, the differences in warming among similarly urbanized areas point to their potential importance. For example, [Fenner et al. \(2014\)](#), in a study of Berlin, found that densely built-up zones exhibited stronger nighttime warming, whereas shading from trees and buildings helped reduce daytime temperatures. These findings suggest that future research incorporating urban morphology and local ventilation conditions could provide deeper insights into the spatial variability of urban warming.

These findings confirm that urbanization and vegetation loss are major drivers of regional warming but emphasize that their effects are uneven. By using temporally defined land cover phases and spatial clustering, this study offers a more nuanced view

of where and how urbanization contributes to thermal change—revealing both broader trends and local variations.



5.2. Spatial Context Effects

Spatial factors such as elevation ([Crétat et. al., 2024](#)), proximity to the coast ([Guan et. al., 2016](#)), and existing urban morphology ([Li et. al., 2020](#)) modulate the thermal environment in a region. The results of this study suggest that these same factors influence the magnitude and pattern of long-term temperature change across northern Taiwan.

Elevation and Coastal Effects

High-elevation stations (e.g. Zhuzihu(竹子湖), Anbu(鞍部)) recorded the lower rates of daytime warming most probable due to the cooling effect of altitude and dense vegetation. In contrast, coastal Tamsui(淡水) station exhibited higher nighttime warming rate of 0.57 °C per decade compared to a daytime warming rate of 0.23 °C per decade (Fig. 4.4). This pattern can be explained by coastal thermal dynamics: after sunset, the land cools faster than the sea, triggering a land breeze that moves warm, urban-origin air toward the coast. These land–sea breeze transitions typically occur around noon and midnight—a phenomenon well documented in subtropical climates ([Cuxart et al., 2014](#)).

Moreover, [Shih et al. \(2024\)](#) observed that prevailing east winds in the Taipei Basin and weak sea breezes along the Tamsui River estuary contributed to strong daytime heat advection at Tamsui station, with a diurnal heat advection magnitude of 1.67 °C (SD = 2.33). While their study focused on daytime dynamics, it is possible that similar mechanisms influence nighttime conditions. These patterns suggest that Tamsui’s coastal proximity may facilitate the movement of warm air from the urban core via land breezes,

potentially enhancing nocturnal warming. However, further investigation would be needed to confirm the role of nighttime heat advection in this area.



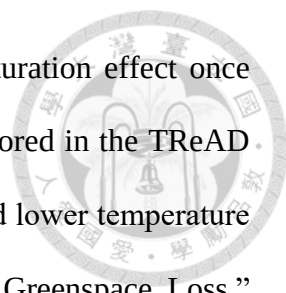
Local Warming Anomaly Beyond Urban Density

While temperature patterns across most stations aligned with their surrounding land cover characteristics, a few stations showed unexpected levels of warming that point to other determining factors. For instance, Sanchong(三重) recorded above-average warming during both day and night, consistent with its persistently dense built-up environment and low greenspace coverage. However, Shezih(社子) also exhibited high warming despite being located in a less-developed zone primarily composed of agricultural land and small factories. This contrast suggests that factors beyond surface land cover—such as wind dynamics, topographic enclosure, or heat transport from nearby urban cores—may also contribute to localized warming.

Shezih is situated at the confluence of the Tamsui and Keelung Rivers, in a basin area where airflow can become stagnant. Although [Shih et al. \(2024\)](#) found that Shezih experiences air convergence under low wind speeds, potentially drawing in urban heat from surrounding districts, this study's results highlight that even relatively green and low-density zones can exhibit elevated temperatures under certain atmospheric conditions. These anomalies emphasize the importance of considering not just land cover type but also geographic setting and air movement in interpreting urban temperature trends.

Urban Saturation and Fringe Expansion

Beyond such localized anomalies, the results also reveal broader contrasts between mature urban cores and peripheral urbanizing zones. For example, while Taipei(臺北) station recorded steep warming from the 1960s to 1980s, its temperature increases



became more moderate in later decades, suggesting a potential saturation effect once high-density urbanization was fully established. This pattern is mirrored in the TReAD dataset, where “Persistent Built-Up / Low Greenspace” areas showed lower temperature gains compared to grids classified as “High Built-Up Increase / Greenspace Loss.” Similar saturation effects have been documented globally: [Shen et al. \(2020\)](#) showed that Shanghai’s urban warming hotspots gradually shifted from the city center to its expanding suburbs, reflecting how additional urbanization contributes progressively less to air temperature rise once urban cores reaches high density ([Cui et al., 2012](#)).

In the Taipei Basin, stations like Dazhi, Shihlin, Shipai, and Tianmu (大直, 士林, 石牌, 天母) exemplify this contrast, as their stronger recent warming reflects the thermal impacts of continued urban expansion at the urban fringe.

Ventilation Design and Urban Greening

Notably, Xinyi(信義) station—despite being located in the rapidly modernized area with high-rise commercial developments like Taipei 101—did not exhibit exceptionally high warming, likely due to architectural interventions such as ventilation corridors that enhance local airflow ([Li et al., 2020](#)). Additionally, although Landsat-based classifications do not capture fine-scale changes, small-scale urban greening efforts within the city core, including pocket parks, green roofs, and urban tree plantings, likely provided localized cooling that helped moderate temperature increases ([Chang et al., 2007](#)). While such features may escape detection in moderate-resolution satellite imagery such as Landsat (30 meters), ground-based research confirms they can measurably reduce near-surface air temperatures, reinforcing the importance of local-scale design and greenery even in densely urbanized environments ([Chang et al., 2007](#); [Chen, 2009](#)).

Emerging High-Resolution Method

To capture such microclimatic differences, UAV-based studies have recently enabled high-resolution land cover mapping—often at centimeter-level precision. When combined with continuous air temperature and humidity sensors, these tools offer detailed profiling of the urban canopy layer, revealing fine-scale thermal gradients and vegetation cooling effects that stationary sensors often miss. However, their short observational durations limit their usefulness for long-term trend analysis ([Xu et al., 2022](#); [Fan et al., 2017](#); [Ornelas et al., 2023](#)).

5.3. Contrasting Diurnal Warming Patterns

The results of this thesis diverge from the widely observed pattern of urban areas experiencing stronger nighttime warming due to radiative heat retention. While this trend was present in some newly urbanized zones—such as Linkou(林口) and Guishan(龜山)—it was not consistent across the northern Taipei metropolitan region. In many areas, especially the urban core and surrounding districts, daytime warming was either equally strong or even exceeded nighttime warming.

Stations such as Taipei(臺北), in a mature urban zone, and Xinyi(信義), situated in the more recently developed Xinyi business district (urbanized since the 1980s), recorded nearly equal increases in day and night temperatures—not due to reduced nighttime warming, but rather intensified daytime warming. This suggests a shifting dynamic in urban thermal behavior: as surfaces become increasingly impervious and vegetation is reduced, daytime heat retention and solar absorption grow more influential. The narrowing of the diurnal warming gap likely reflects rising daytime heat stress rather than stabilization of nighttime trends.

Fringe areas like Shihlin(士林) and Tianmu(天母) demonstrated stronger daytime warming, which may be influenced by heat advection from the urban core during the day ([Shih et al., 2024](#)). At night, cooler air from adjacent mountain and coastal systems circulates into these fringe zones, limiting nocturnal warming. This reflects known patterns of sea–land and mountain–valley breeze circulation, which provide natural nighttime ventilation for outer districts ([Lin et al., 2008](#)).

Elevated, vegetated stations such as Zhuzihu(竹子湖) and Anbu(鞍部) remained night-dominant, likely influenced more by regional climate trends than urbanization. Their patterns are consistent with global observations of faster increases in minimum (nighttime) temperatures relative to daytime maximums ([Karl et. al., 1993](#)), particularly in cooler, less developed landscapes.

Results from the most recent period of analysis—TP3c vs. TP3a (2019–2023 vs. 2010–2014 for CWA stations; 2009–2013 for TReAD)—when land cover remained largely stable, revealed a continued shift toward daytime-dominant warming, particularly in the TReAD grids. This highlights that in the absence of new land cover change, microclimatic factors such as decreased evapotranspiration, limited shading, and reduced wind flow may increasingly drive urban thermal dynamics. In stable built environments, heat accumulation during the day may now be matching or outpacing nighttime heat retention.

Importantly, while TReAD captures broader regional patterns, station data reveal localized variations in warming behavior. This underscores the value of integrating gridded models with observational data to understand both macro and micro-scale processes shaping urban climate.

In summary, the findings suggest that daytime warming is intensifying across urban and peri-urban Taipei, narrowing the diurnal temperature gap that has traditionally

characterized urban warming patterns. This shift has important implications: while both day and night temperatures are rising under global warming, the recent acceleration of daytime heating increases population exposure during active hours. Urban adaptation efforts must therefore prioritize cooling strategies that specifically address daytime conditions, such as increasing canopy cover, enhancing ventilation corridors, and improving surface albedo in high-density areas.

These findings also highlight how model structure and data resolution shape our interpretation of thermal dynamics. TReAD's use of SPOT-derived land cover maps with 2 km resolution—where each pixel is assigned a single dominant category—limits its ability to reflect fragmented or mixed-use areas that are common in urban fringe zones. As a result, important microclimatic effects such as vegetative cooling, water body influence, or recent small-scale development may not be fully captured. Meanwhile, station data, despite their sparse coverage, reveal localized behaviors that may be masked in regional models. This underscores the need for integrated analysis, combining gridded models with dense observational networks to inform urban planning.

5.4. Limitations and Uncertainties

Several limitations should be acknowledged. First, while the TReAD dataset offered high temporal coverage and resolution, the reliability of certain simulation periods—particularly TP2—was compromised by classification errors in the 2000 land cover input, which overestimated built-up and cropland areas while underestimating forest cover. As a result, TP2 was excluded from trend analysis.

Second, spatial resolution constraints (2 km grids for TReAD, 1 km radius buffers for station analysis) may have masked sub-grid variability, particularly in mixed-use or transitional zones. The mismatch between modeled grid data and point-based

observations introduces further uncertainty, especially in areas where station relocation affected measurement consistency.

Third, the land cover classification of Landsat images, despite overall high accuracy, exhibited reduced performance in distinguishing between built-up and barren land. This was especially relevant in active construction zones, leading to possible underestimation of urban growth impacts. Additionally, while cloud-covered areas were manually removed, this process resulted in data gaps that may have excluded portions of newly developed or vegetated land from analysis, potentially leading to a slight underrepresentation of each land cover type in the final land cover maps.

Lastly, while this study uses a regional climate model (TReAD), it does not fully separate the effects of land cover change from background climate change. Comparing time periods helps reduce this issue, but future studies could improve this by using model experiments that keep land cover constant to better isolate its impact.

Chapter 6 Conclusion



6.1. Key Findings

This thesis examined how land cover change has influenced spatial and diurnal air temperature patterns across the northern Taipei Metropolitan Area between 1990 and 2023. The results demonstrate that warming trends are not uniform but instead reflect a complex interplay between the intensity of urbanization, local microclimates, and geographical factors. Areas undergoing rapid urban expansion—such as Linkou(林口) and Guishan(龜山)—experienced the most pronounced temperature increases, particularly at night. This highlights the strong thermal impact of newly developed land and declining vegetation. Conversely, stable vegetated and high-elevation areas like Anbu(鞍部) and Zhuzihu(竹子湖) showed lower daytime warming, but continued nighttime temperature rise, likely linked to broader climate trends and topographic characteristics.

At stations like Taipei (臺北) and Xinyi (信義)—representing mature and more recently developed urban areas, respectively—daytime and nighttime temperatures increased at nearly equal rates, highlighting the growing intensity of daytime warming in Taipei’ s urban environment. This shift challenges the conventional understanding that urban warming is primarily a nocturnal phenomenon. In contrast, stations in urban fringe areas like Shihlin(士林) and Tianmu(天母) exhibited stronger daytime warming. This pattern appears to be shaped by daytime heat advection from the urban core and moderated by nighttime ventilation from sea–land and mountain–valley breezes.

Collectively, these findings underscore that land cover dynamics alone do not explain urban warming. Factors such as elevation, wind flow, and urban morphology

significantly modify thermal responses at the local scale. As such, climate adaptation strategies should incorporate targeted interventions—such as preserving large vegetated zones, minimizing greenspace fragmentation, and designing ventilation corridors—to manage growing daytime heat risks across both newly developed and long-urbanized areas.

6.2.Future Research Directions

This study used Landsat satellite imagery with a 30 m resolution, which is too coarse to capture small-scale land cover features like street trees, rooftop gardens, or narrow green spaces. Future research should aim to use higher-resolution data—such as Sentinel-2, drone imagery, or aerial photos—to create more detailed land cover and land use maps. These finer maps, when combined with dense temperature measurements, could help reveal more specific patterns of how land cover affects heat in different parts of the city.

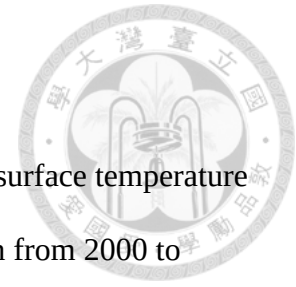
While the TReAD dataset was useful for understanding long-term temperature changes, this study found a major issue with one of its land cover inputs. Incorrect land classification led to errors in the temperature outputs. This shows how important it is to carefully check all inputs when using climate simulation models. Future research should test how sensitive model results are to errors in land cover data to improve reliability.

Another important area for future study is wind. This research found that wind patterns (direction and magnitude)—such as warm air from urban areas or cool air from mountains and the sea—likely influenced temperature patterns across Taipei. Future studies should explore how wind behavior changes with land development and how that affects local temperatures. Using wind monitoring networks or analyzing wind patterns in climate models could help explain differences in temperature trends across locations.

Finally, future studies should also consider humidity. While this thesis focused on air temperature, humidity plays a big role in how people experience heat. Including humidity or heat stress indicators such as the Wet Bulb Globe Temperature (WBGT) ([Budd, 2008](#)) would give a better picture of urban heat risks and human comfort.

In short, future research can improve our understanding of urban climate change by using more detailed land cover data, checking model accuracy more carefully, and including wind and humidity in the analysis. This will help city planners design better strategies to reduce heat and improve resilience in densely urbanizing areas like the Taipei Metropolitan Area.

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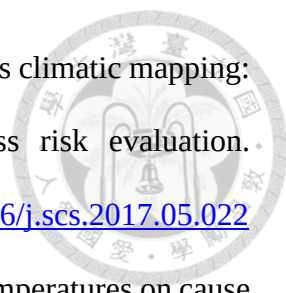
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