

## Spatiotemporal Analysis of Land Surface Temperature in Response to Land Use and Land Cover Changes: A Remote Sensing Approach

Gulam Mohiuddin<sup>1</sup> and Jan-Peter Mund<sup>1</sup>

<sup>1</sup> Eberswalde University for Sustainable Development, Germany

### Introduction

Understanding Land Surface Temperature (LST) dynamics and its input to the Urban Heat Island (UHI) effect is pivotal for urban planning and environmental management. LST measures the temperature of the surface's skin, and its rapid ascent due to urbanization leads to the UHI effect [1, 2]. The repercussions of UHI encompass health hazards, ecological disruptions, increased energy consumption, and alterations to local microclimates [3, 4, 5, 6, 7]. Despite the understanding of UHI effects, there's a pressing need to explore deeper into the spatiotemporal variations of urban LST. Time series analysis of LST helps to discern these patterns, identify hotspots, and detect land use land cover (LULC) changes [8, 9].

The present study investigates the LST dynamics and their urban planning implications. It deciphers urban LST spatiotemporal patterns and evaluates the correlation between LULC and LST. The research hypothesizes that significant LULC shifts, especially the growth of built environments and decline in vegetation, cause noticeable LST variability, creating thermal hotspots and influencing local climates.

### Study area

The study focused on the Chbar Ampov District in the Southeast part of Phnom Penh, Cambodia (Figure 1), a rapidly developing urban area characterized by a tropical wet and dry climate and susceptible to seasonal flooding from the neighbouring rivers Tonle Mekong and Tonle Bassac [10].

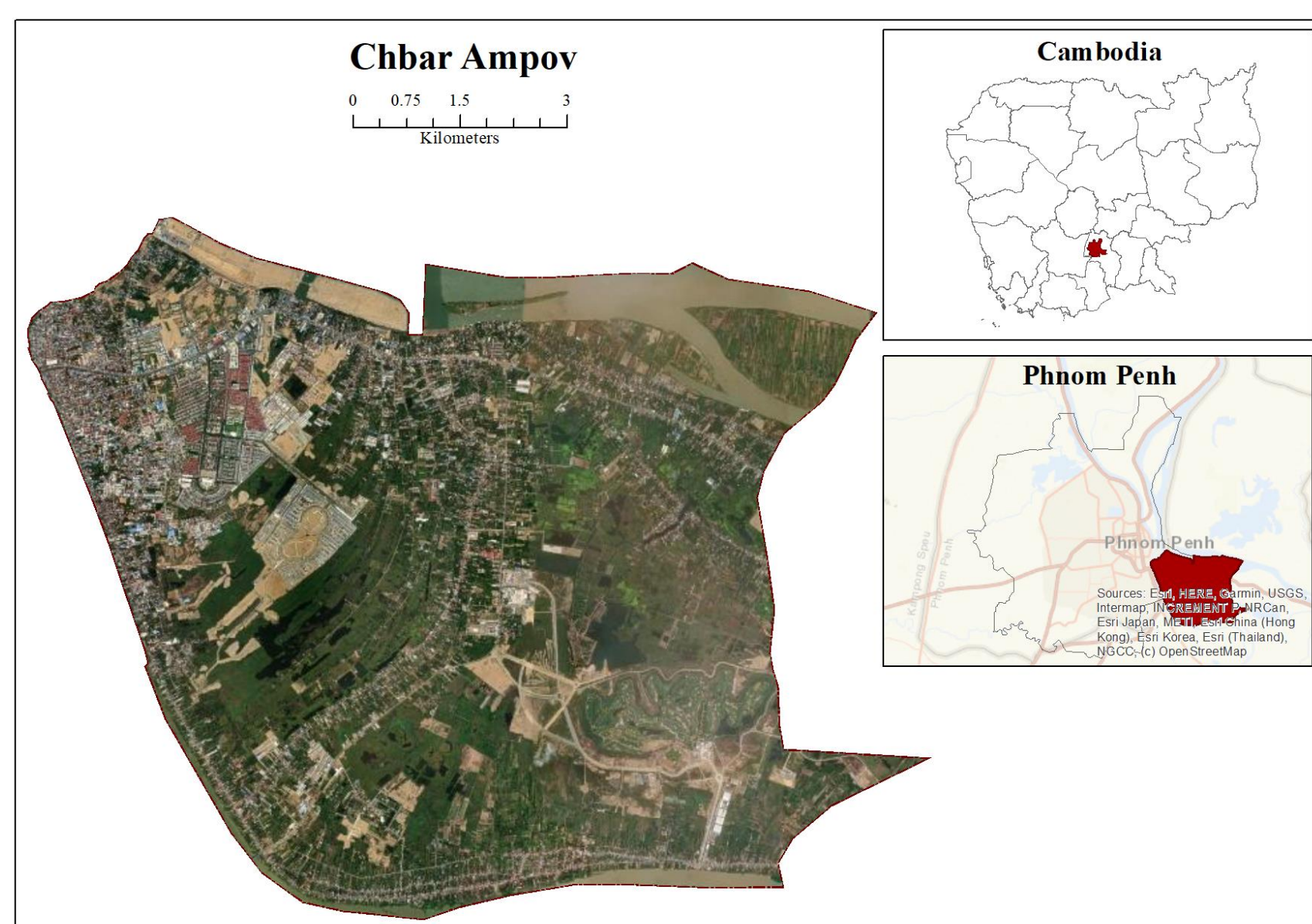


Figure 1: Location of the study area

### Results and outlook

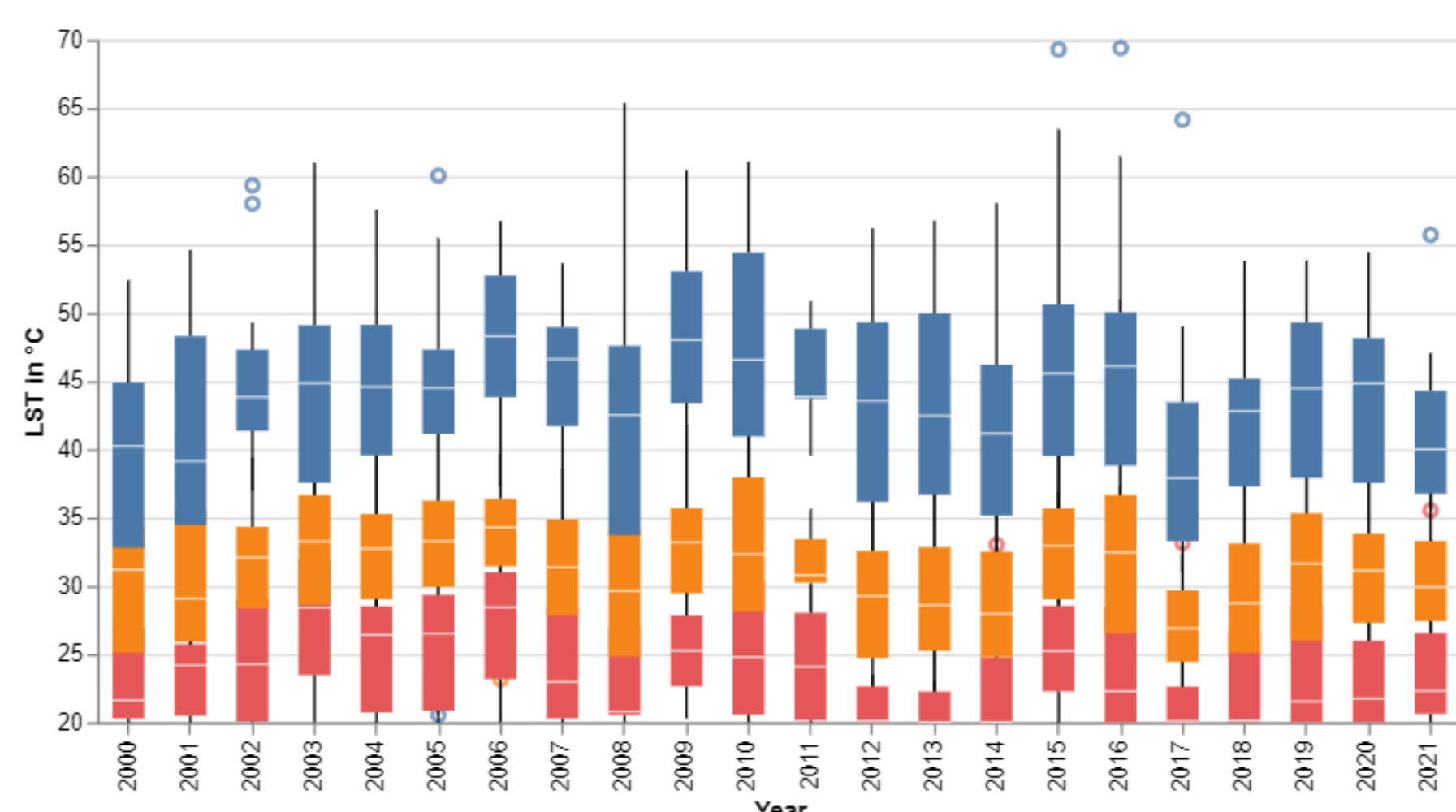


Figure 3: Yearly minimum, mean & maximum LST

- Overall range is 20 – 70 °C, cyclic pattern
- Maximum LST having the widest range
- 2003, 2008, 2015 and 2016 have wider range
- Presence of outliers denotes extreme values

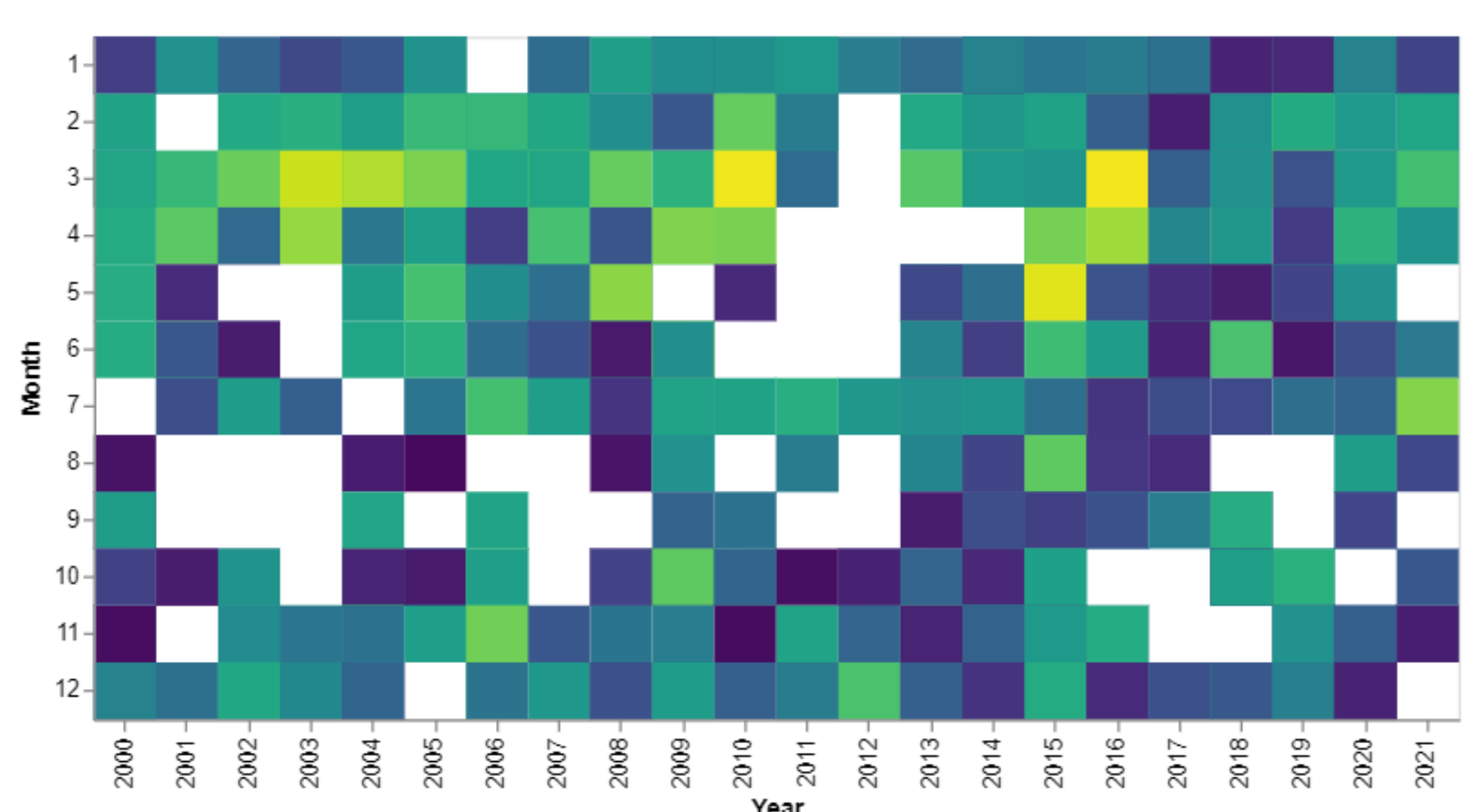


Figure 4: Calendar heatmap of mean LST

- White boxes inside the figure represents no data
- November – April: dry season
- Recurrence of high temperature in every 6th or 7th year (March- 2003, 2010, 2016)

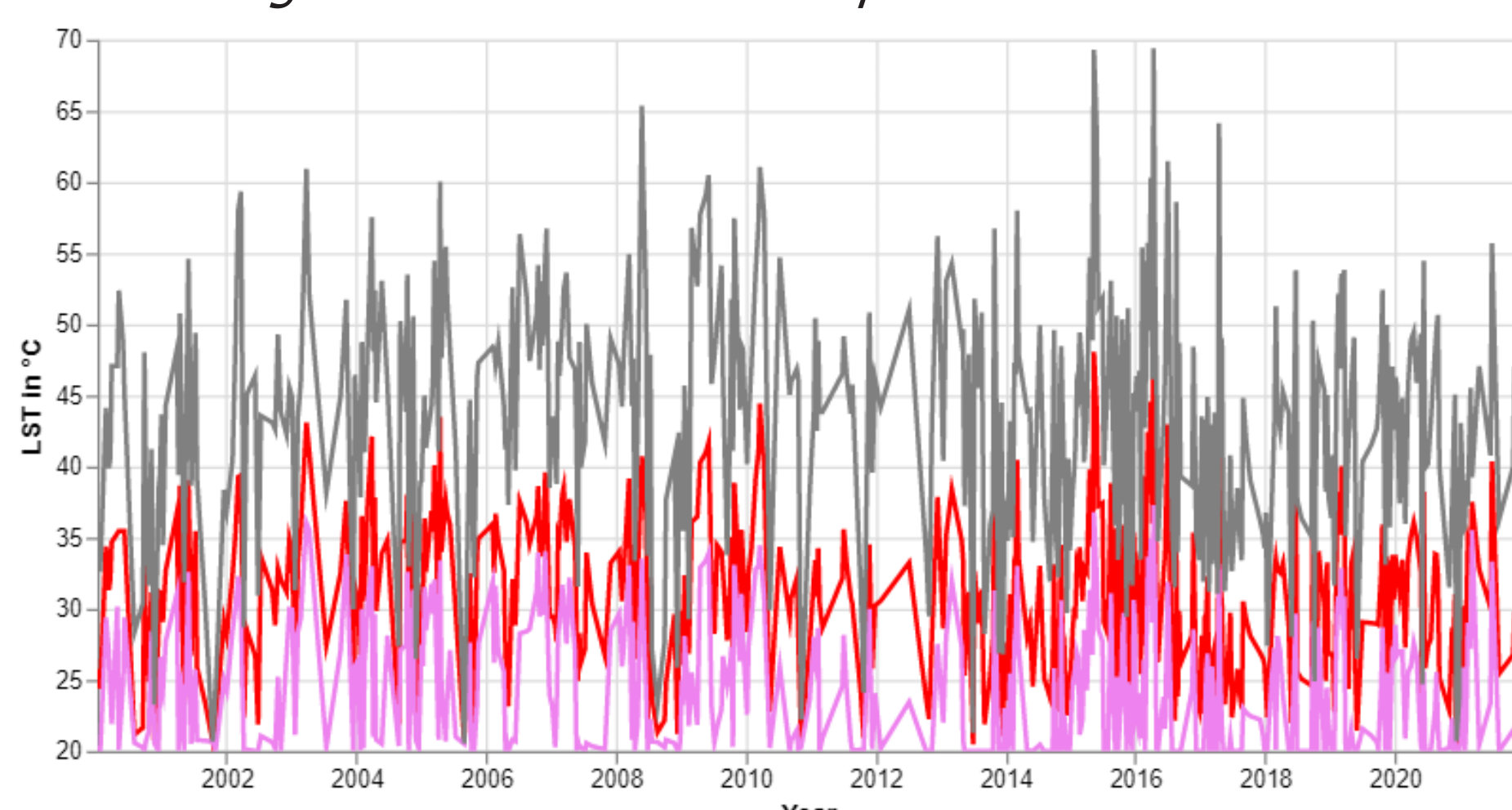


Figure 5: Total time series of minimum, mean & maximum LST (2000 - 2021)

- 20 °C flatline at the bottom due to temperature mask
- Regular fluctuation due to seasonal variation
- No long-term trend
- Symmetrical spikes

### Material & methods

Remote sensing data primarily included Collection-1: Tier 1 data from Landsat 5, 7, and 8. Due to the region's susceptibility to cloud presence, a maximum 60% cloud filter was applied, resulting in 462 images from 2000 to 2021 selected for the study. Google Earth images were used to compare LST and LULC changes visually.

A general overview of the methodological workflow is given below (Figure 2).

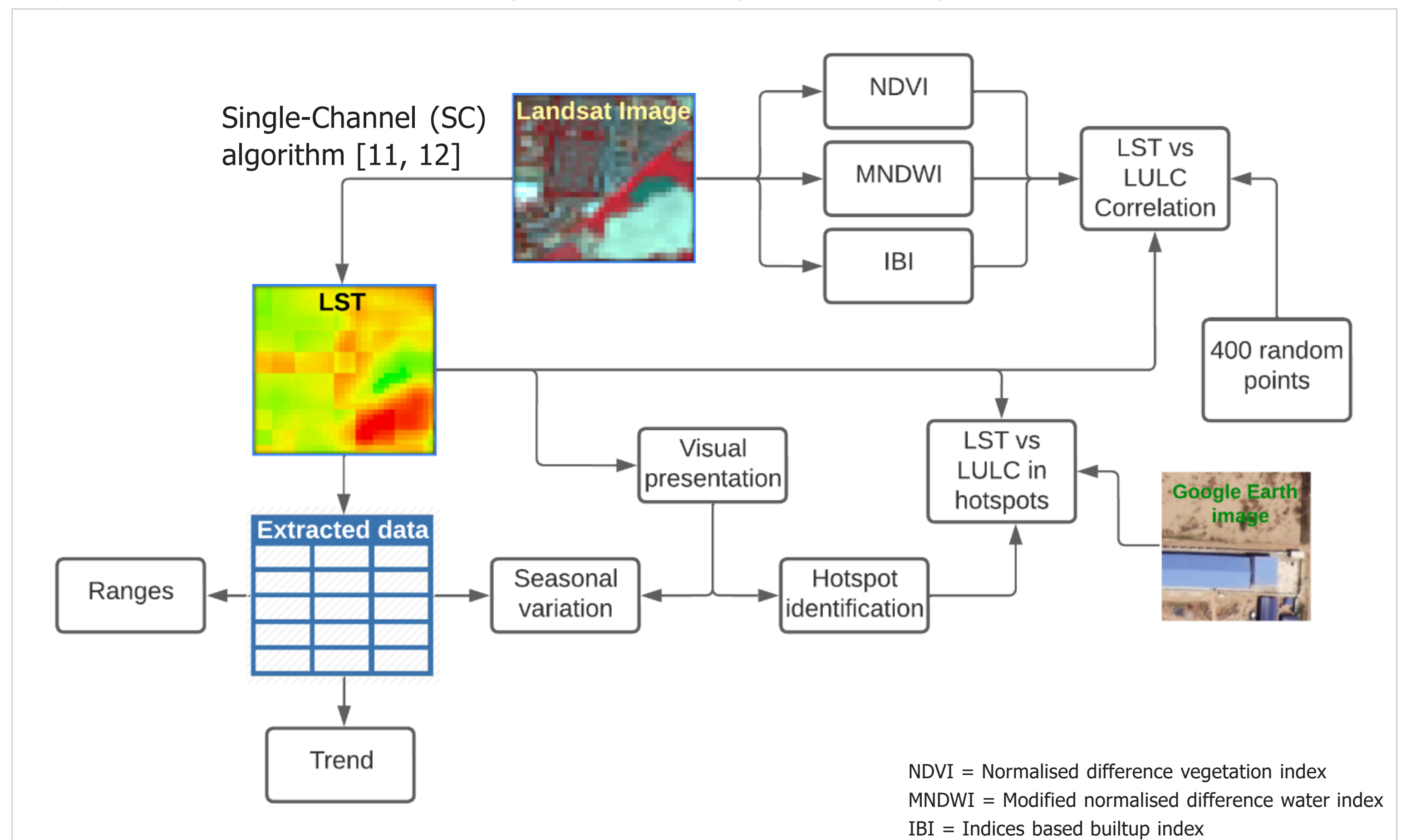


Figure 2: Graphical overview of methodical workflow

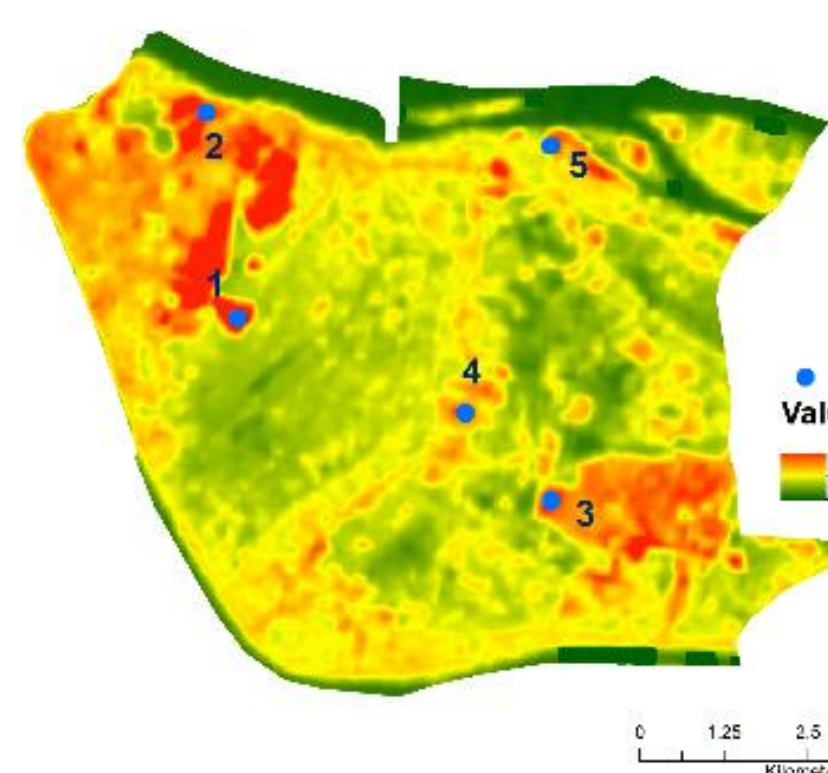


Figure 6: Identified hotspots (background image from LST (in °C) January 2015)

- Marked five points on the maps are consistently warmer spots which are identified as hotspots
- Point 4 is elaborated further as an example how LST responds to different LULC within the study period

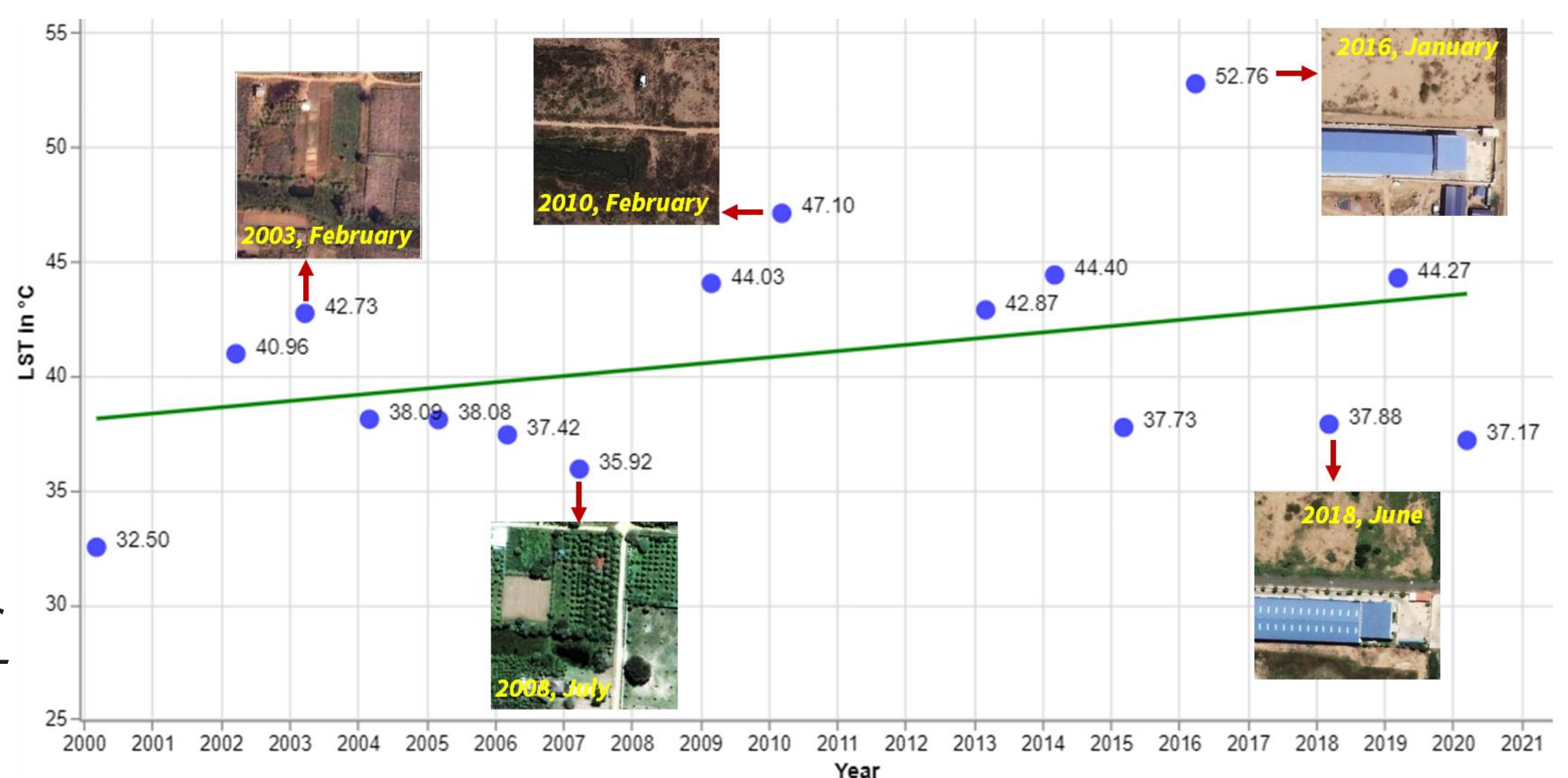


Figure 7: LST and LULC changes in hotspot 4

- LST changes are visibly connected to LULC changes
- LST decreased 2008 noticeably when the area was covered with trees and vegetation
- The area showed the highest LST in 2016 when it converted into built-up area and bare soil

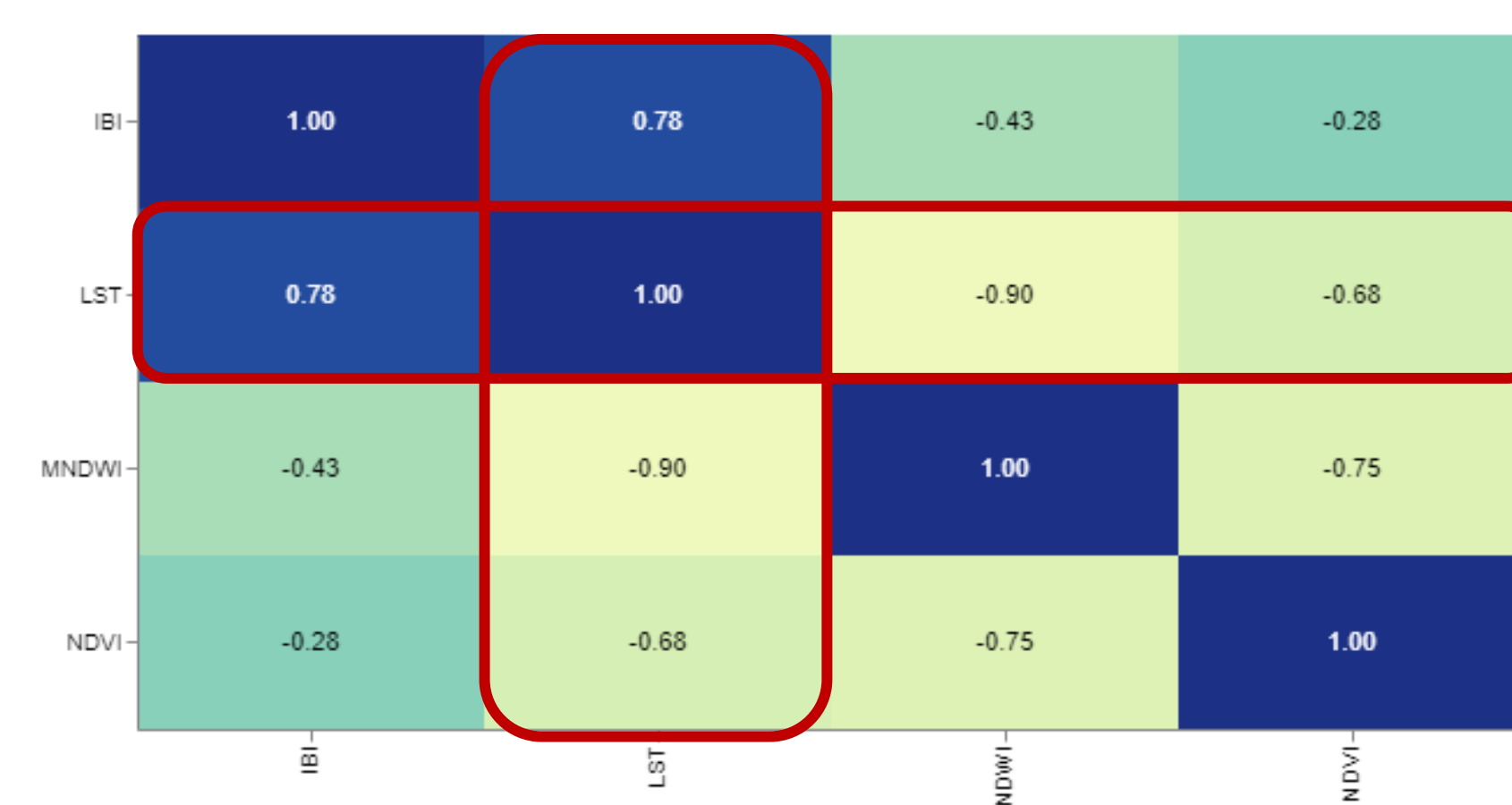


Figure 8: Correlation matrix between LST and spectral indices

- Built-up area, water and vegetation are represented by the spectral indices- IBI, MNDWI and NDVI respectively
- Strong positive correlation between the built-up area and LST
- Strong negative correlation between LST
- Strong negative correlation between LST between vegetation

This study offers insights into the spatiotemporal patterns of LST in the specified area and its observed empirical relationship with LULC changes using remote sensing. It underscores the importance of considering seasonal variability, LST trends, and how LST responds to LULC variations in particular areas. These findings enhance our understanding of the LST-LULC dynamic and its implications for urban planning. Despite a few limitations, the study's methodology can be adapted to other contexts and paves the way for future inquiries into LST dynamics in different environments.

### Acknowledgement

This research was funded by the Build4People Project under the funding priority SURE, Sustainable Development of Urban Regions, of the German Federal Ministry of Education and Research (BMBF), funding support code (FKZ): 01LE1908D1.



References