DINING LIU

INTERNET OF OPEN SPACE

LANDSCAPE RESEARCH AND DESIGN PORTFOLIO, 2016 - 2018

1

GRADUATE THESIS

SUPERVISOR:

IRYNA DRONOVA, JOHN RADKE, PAUL WADDELL

UC BERKELEY, 2017 - 2018

CROWDSOURCING

Using Geotagged Photos to Analyze
the Relationship between Cultural Ecosystem Services
and Site Specific Features of Urban Green Space
in San Francisco

MOTIVATION Cultural ecosystem services (CES), known as non-material benefits human obtain from ecosystems including aesthetic, recreational value, and sense of identity, is the dominant category of benefits provided by urban green space (UGS). Lack of spatial explicit data, the mapping and assessment of city-wide CES, however, is underdeveloped. Crowdsourced data from mobile devices, especially geotagged photos collected from photo-sharing platforms, cost-effective without spatial and temporal limitation, tend to be attractive source of information to evaluate CES.

GOALS AND METHODS This study used geotagged photos from Instagram and Flickr to investigate the spatial pattern of CES provided by UGS in San Francisco during the summer of 2017. The relationship between CES provision and five categories of site-specific features of UGS was analyzed through an automated photo content analysis and a regression analysis testing the hypotheses made based on observations and literature review.

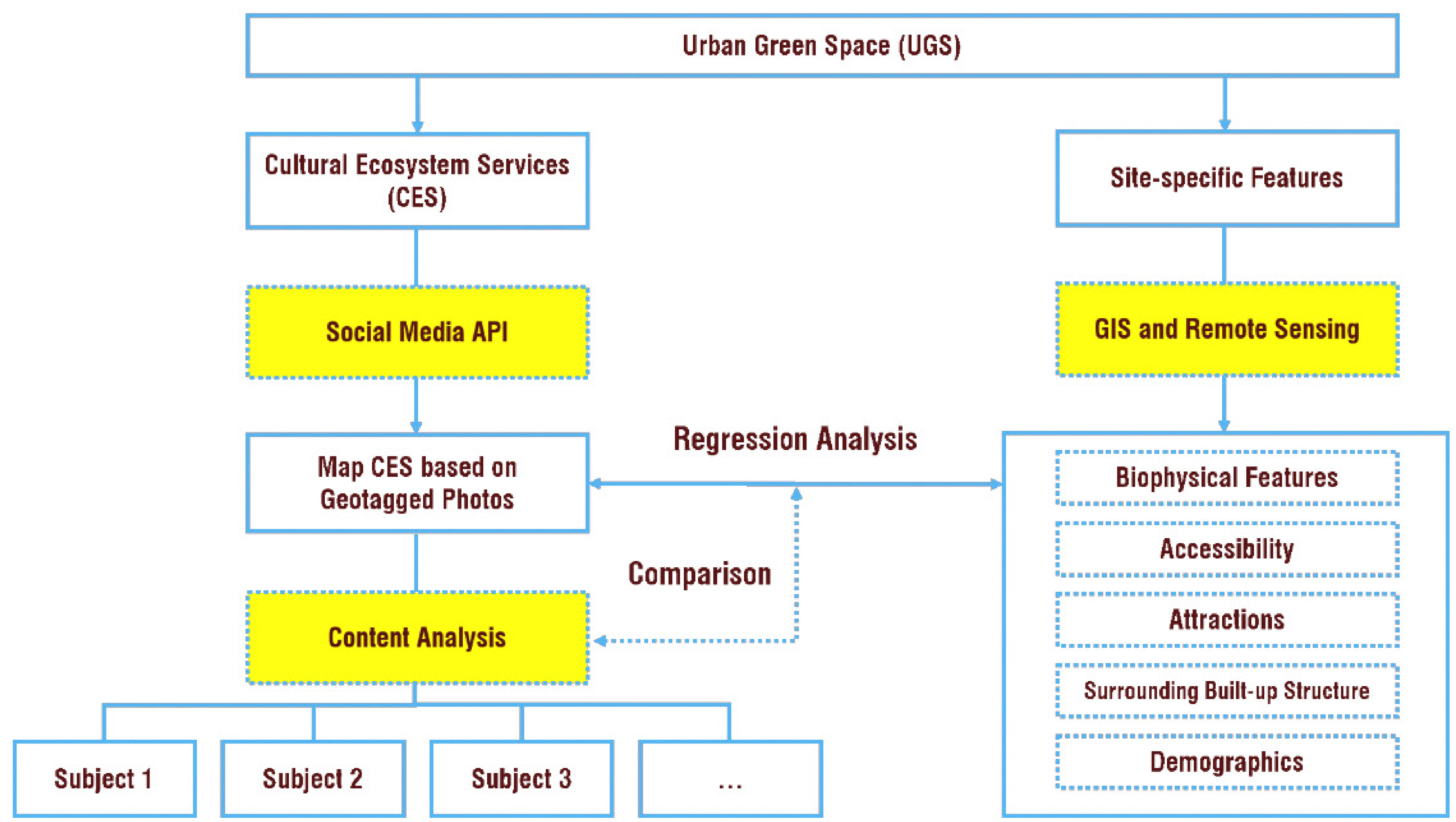


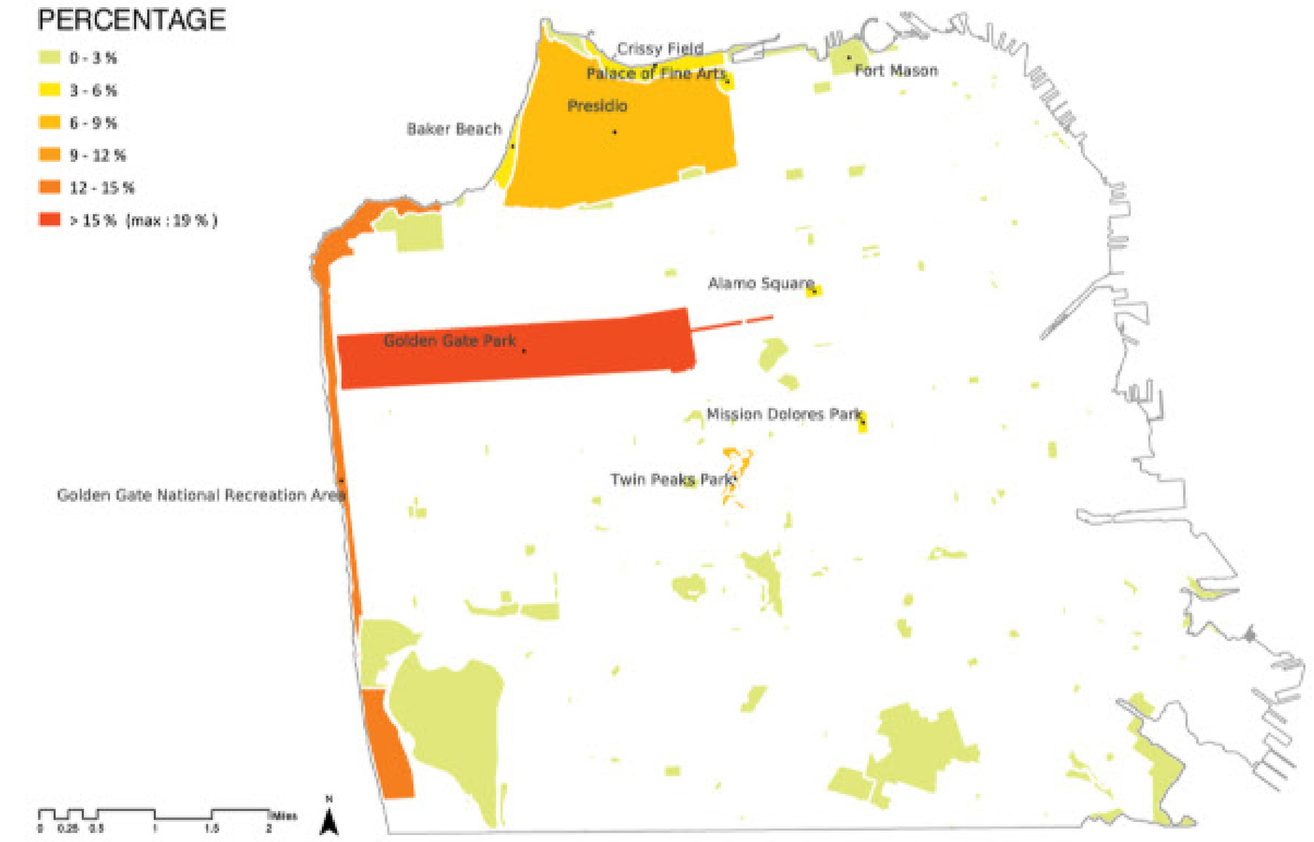
FIG. METHODOLOGY OF THE STUDY

RESULTS Findings showed that the spatial patterns of CES quantified by photo counts and photo counts per hectare in UGS were quite different while both meaningful and necessary for assessing CES. The composition of CES across all UGS in San Francisco varied a lot due to different site-specific features, shown by diverse subjects of photos. UGS located in less dense area with a larger size, more disaggregated shape, more landmarks, waterbody, cultural and recreation spots, as well as a potential sea view were probably to get more photo counts; UGS with waterbody, higher building and population density in surrounding neighborhoods could have more photo counts per hectare in San Francisco.

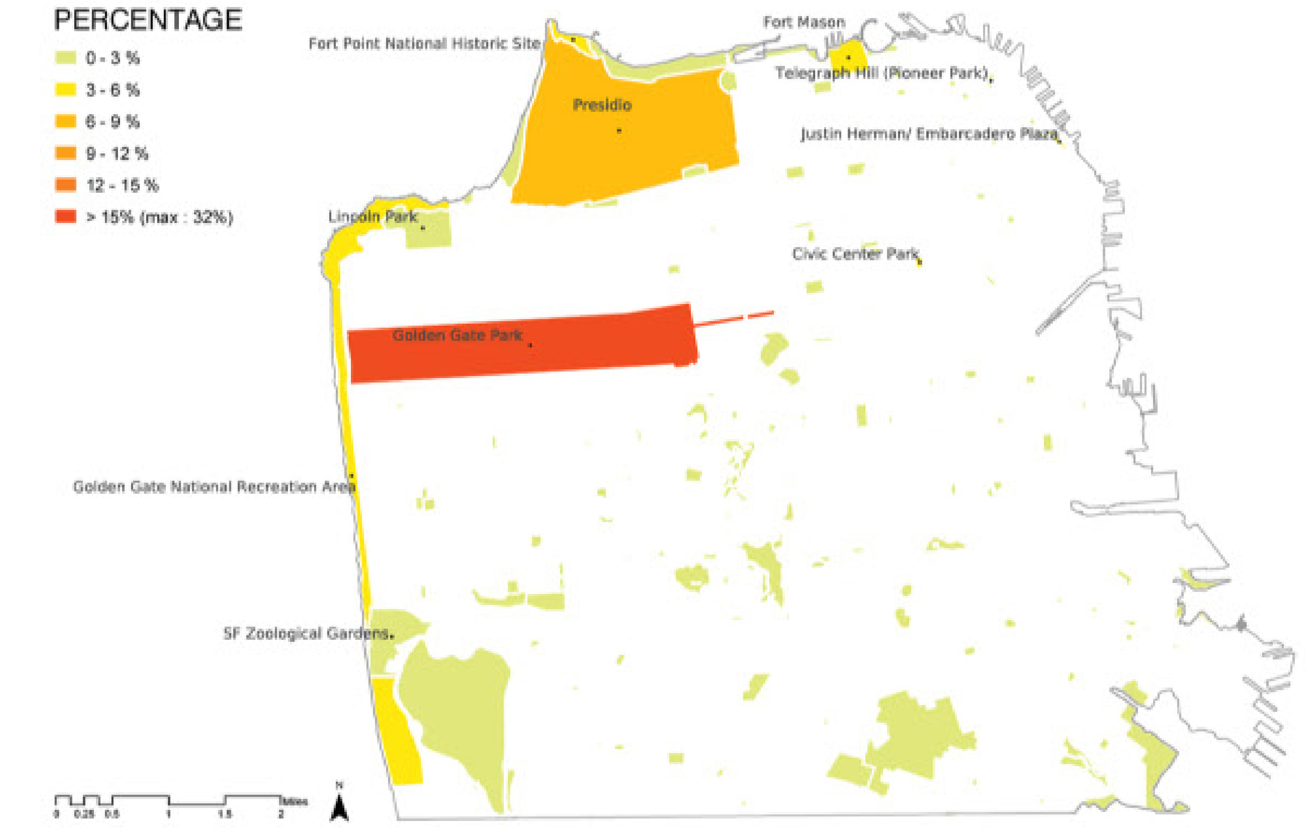
CONTRIBUTION These results could be used by environmental planners to understand citizens' preferences and behaviors in UGS on a large scale with a lower cost compared to traditional approaches, and compare the trade-offs across different options of site-specific feature changes.

The right shows three ways to map cultural ecosystem services (CES) provided by urban green space (UGS) in San Francisco using geotagged photos. Maps on the left are based on Instagram geotagged photos, and the right part are based on Flickr geotagged photos. The first pair (a) (b) are choropleth maps showing percentage of total photo counts in San Francisco UGS during the summer of 2017; the second pair (c) (d) visualize photo counts per hectare for all UGS; the third pair (e) (f) visualizes percentages of the total number of likes gained by photos across all UGS. The top 10 UGS are annotated in each map.

Instagram | **Flickr**



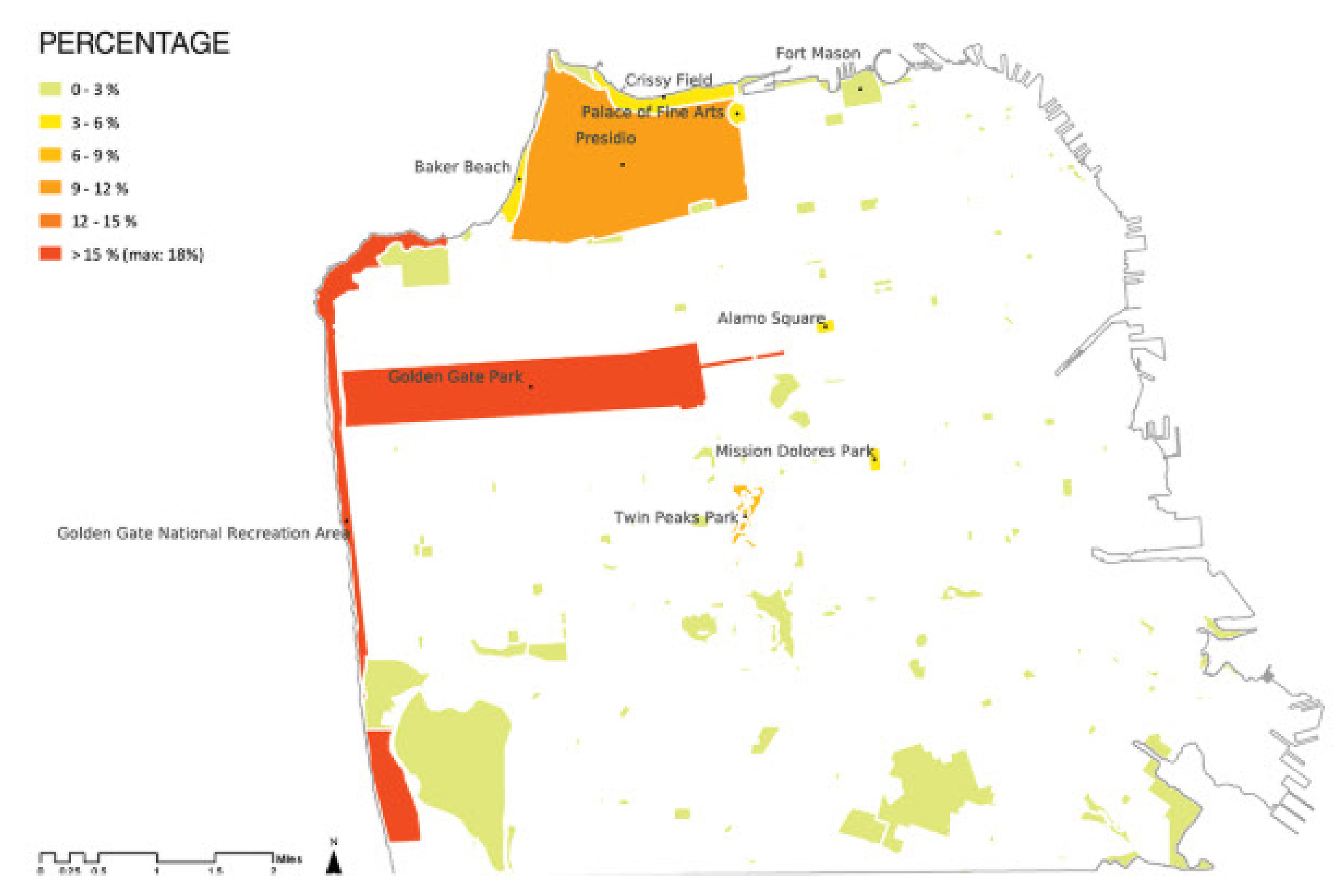
(a) Percentage of total Instagram geotagged photo counts



(b) Percentage of total Flickr geotagged photo counts

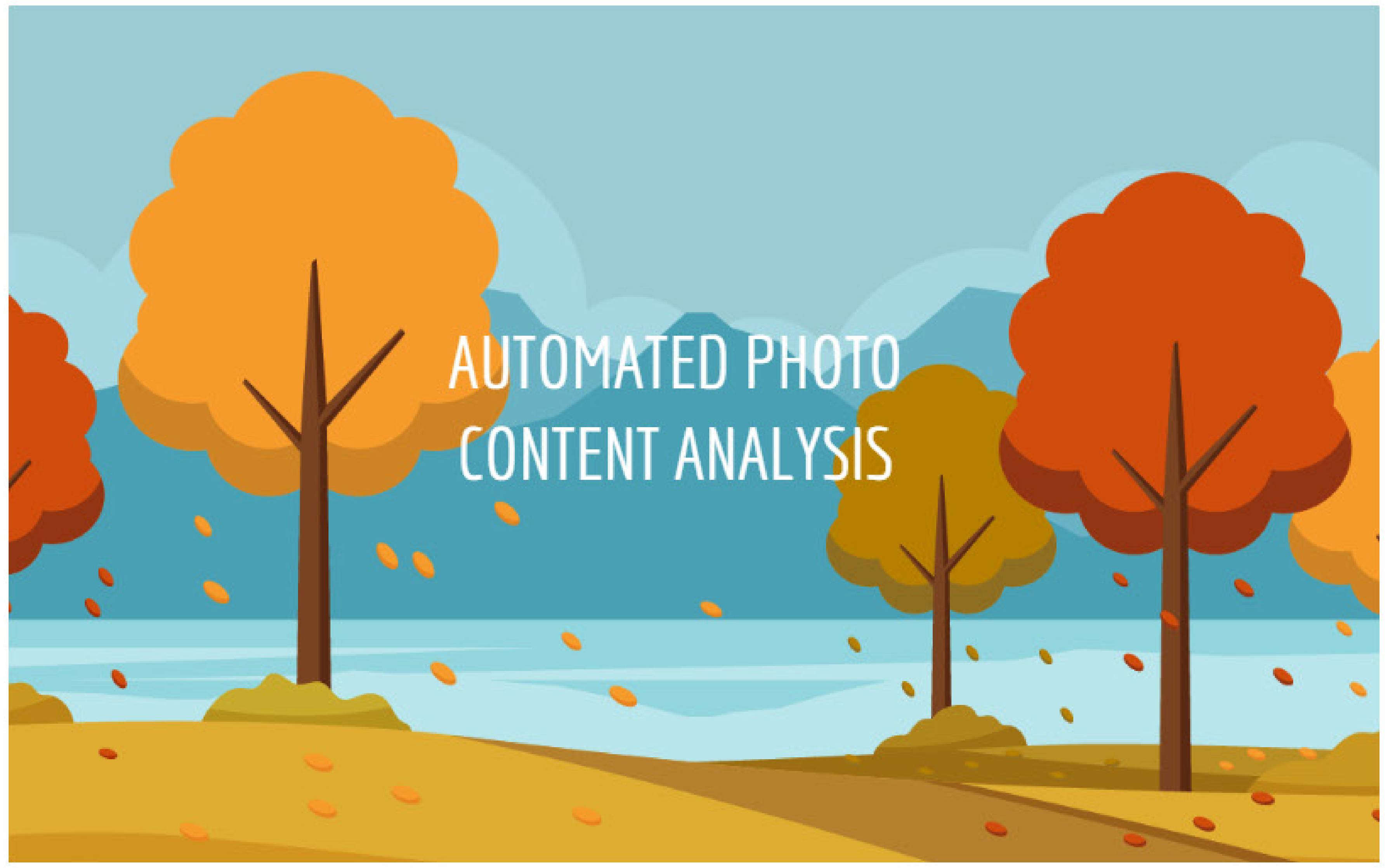
(c) Total Instagram geotagged photo counts per hectare

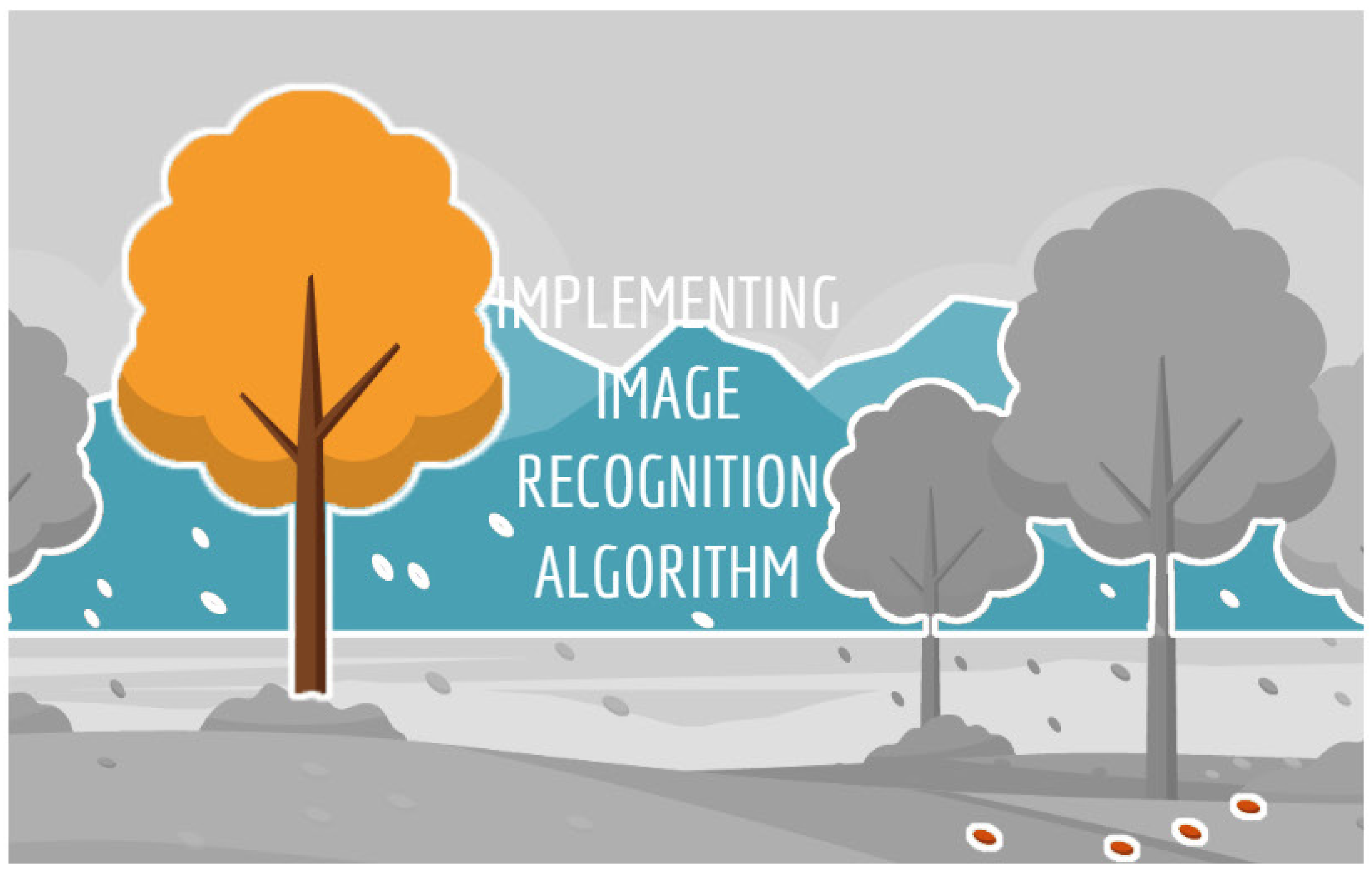
(d) Total Flickr geotagged photo counts per hectare

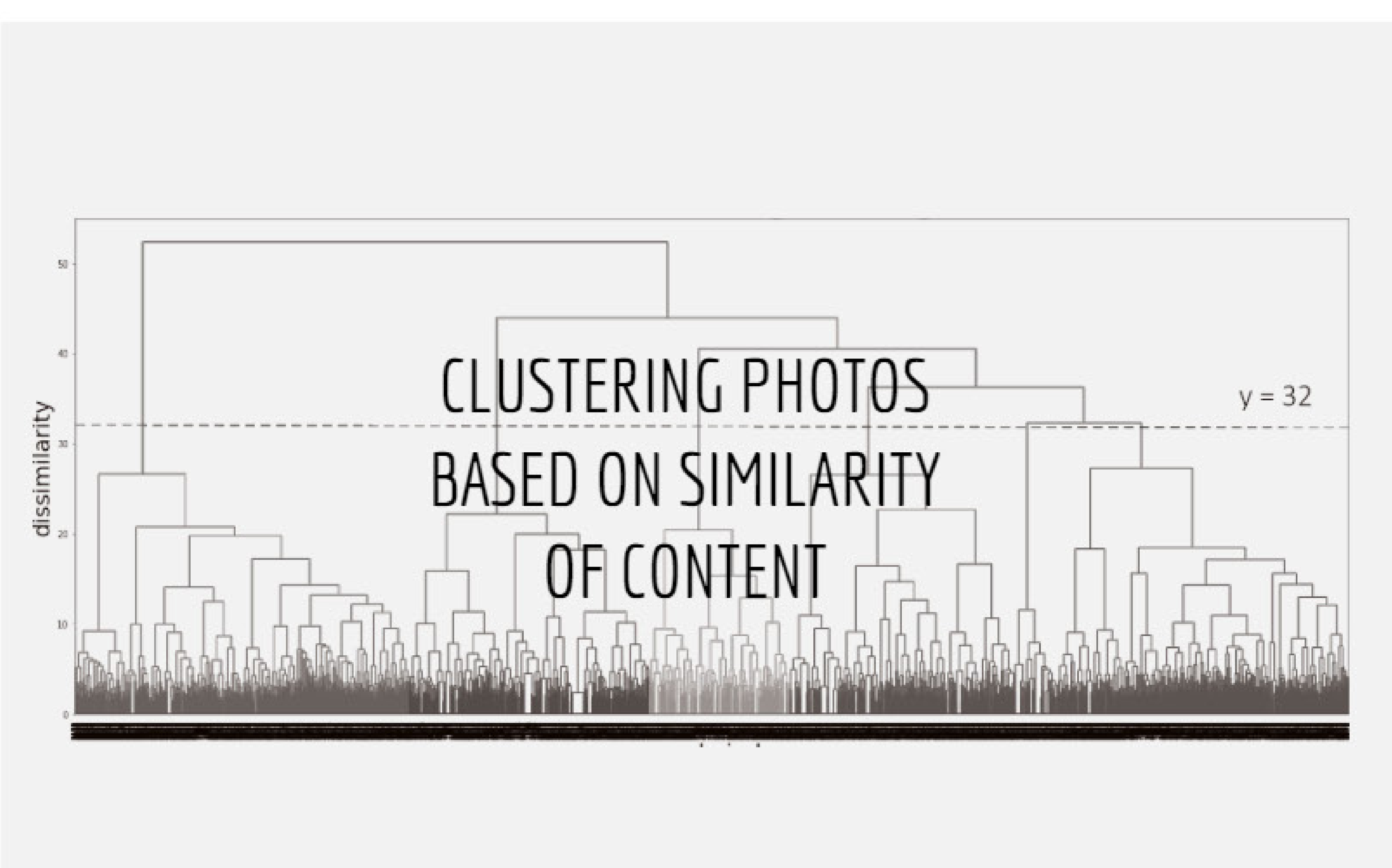


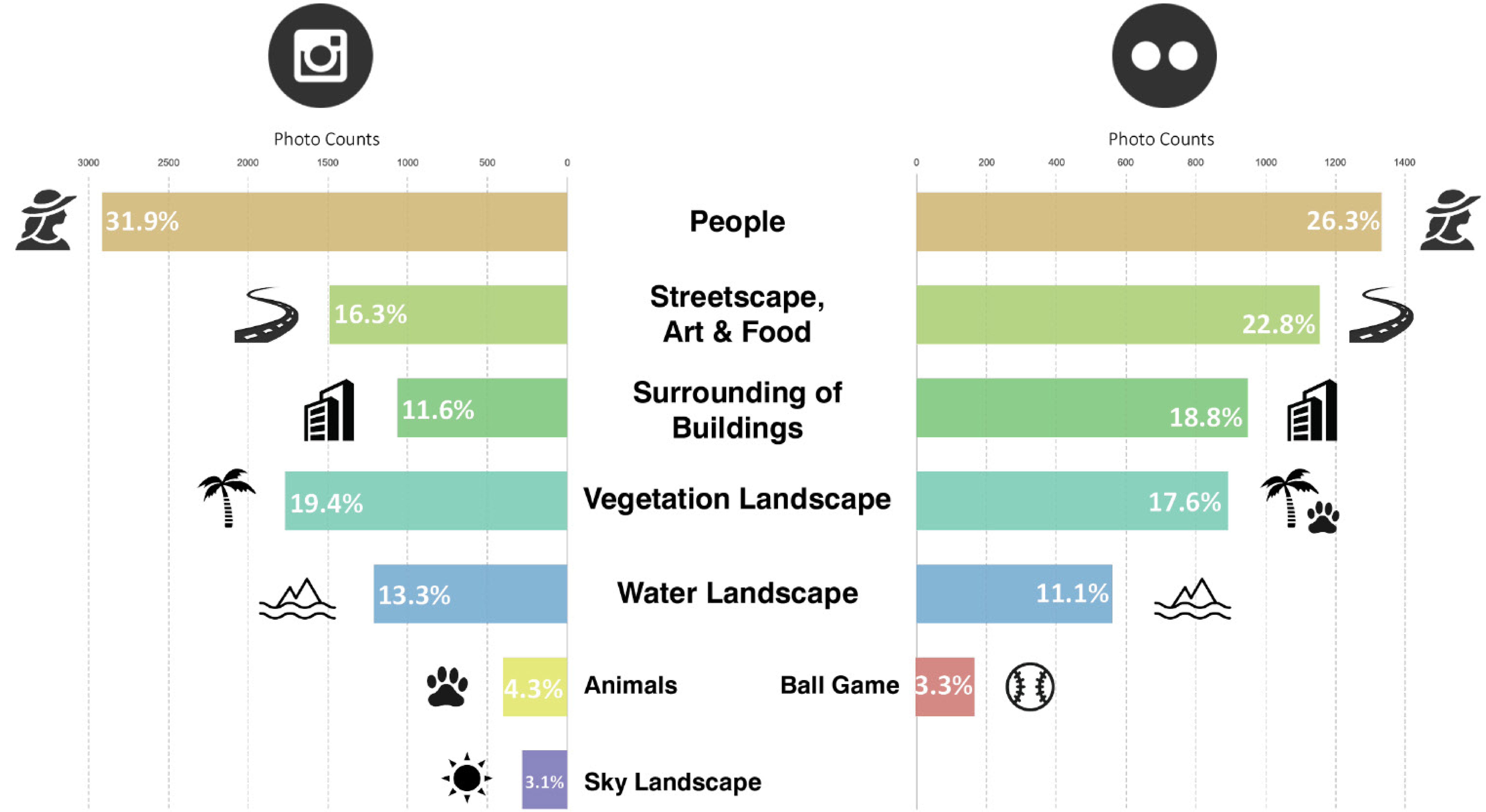
(e) Percentage of total number of likes of Instagram geotagged photos

(f) Percentage of total number of likes of Flickr geotagged photos









SUBJECTS OF CLUSTERED FLICKER AND INSTAGRAM GEOTAGGED PHOTOS

The subjects of clustered Flickr and Instagram photos in the summer of 2017 were quite similar, though there were subtle differences about small subjects. “People” was the most popular subject, about 30% in both Flickr and Instagram groups. “streetscape, art and food” “surroundings of buildings” “vegetation landscape” “water landscape” and “animals” all presented in two groups, while in Flickr group “animals” subject was less conspicuous and mixed with “vegetation landscape” subject. There was a special small subject “sky landscape” in Instagram group which related to sunset, dusk, dawn and nightscape. “Ball game” was a particular subject in Flickr group which was mostly about people playing baseball game. The subjects of posted photos reflected what types of landscape might have more aesthetic and recreation value.

2

PERSONAL PROJECT

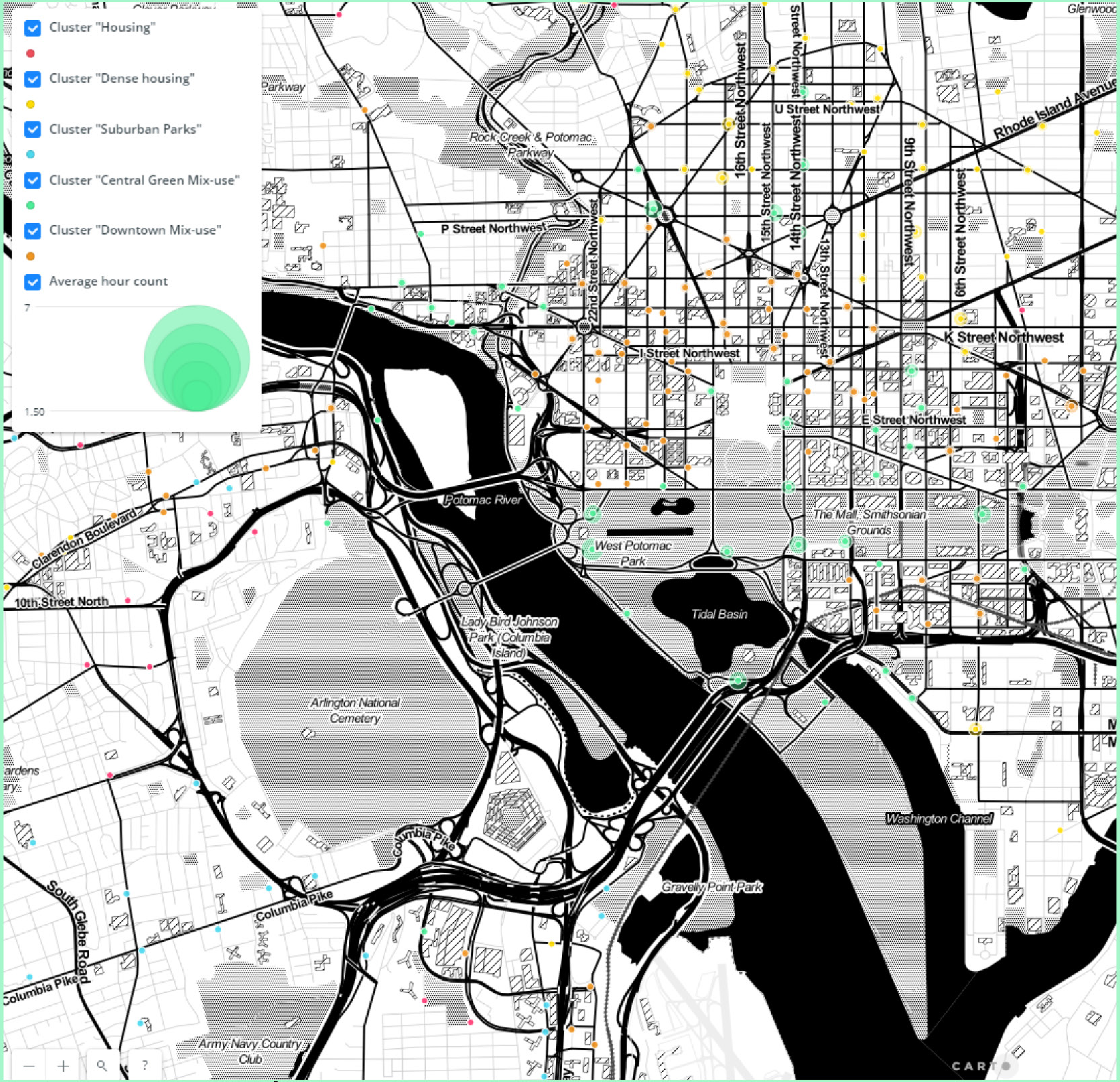
DS 100 PRINCIPLES AND TECHNIQUES OF DATA SCIENCE

SUPERVISOR: FERNANDO PEREZ, JOSH HUG

UC BERKELEY, 2018

DATA MINING

Bike Sharing System Usage in Washington D.C.



METHODOLOGY

1. BIKE STATION DATA COLLECTION AND PRE-PROCESSING

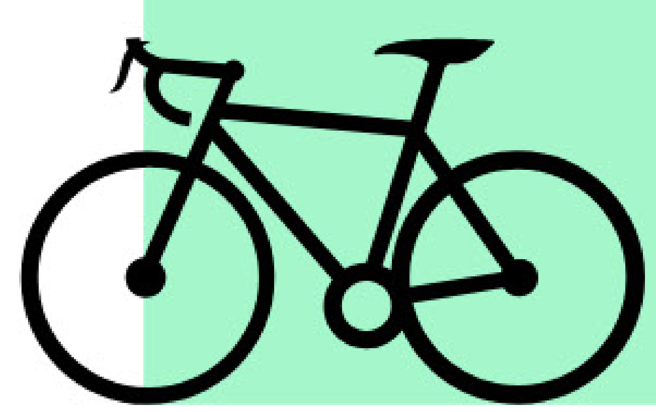
2. EXPLORATORY DATA ANALYSIS (EDA)

3. CREATE COUNT TIME SERIES OF STATIONS

4. CALCULATION OF THE SIMILARITY BETWEEN COUNT TIME SERIES

5. CLUSTERING STATIONS BASED ON SIMILARITY OF USAGE PROFILE

6. INTERPRETATION OF CLUSTERS OF STATIONS CONSIDERING SOCIO-ECONOMIC CONDITIONS



MOTIVATION

Bicycle sharing systems (BSS) provide people with free or rental bicycles suitable for short-distance trips in urban areas, thus reducing traffic congestion, air pollution and noise. Many cities all over the world have introduced and implemented BSS as a way of sustainable transport. These systems generate large amount of transportation data, the mining of which is useful to understand the underlying city dynamics. This project aims to develop a method analyzing BSS usage data to reveal urban mobility patterns with Washington D.C. as a case study.

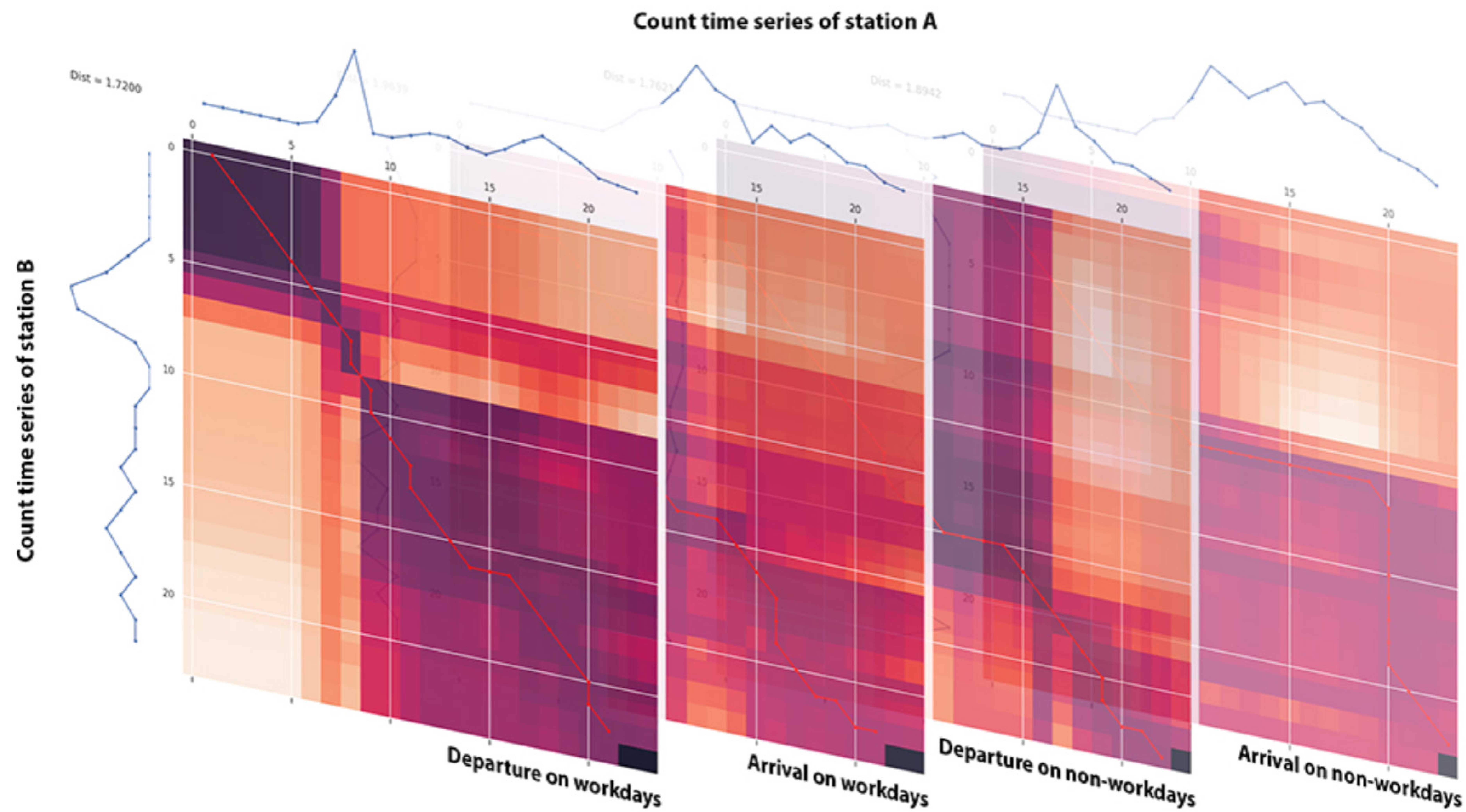
CREATE COUNT TIME SERIES OF STATIONS

the vector describes the departure and arrival activity of station s for both workday w1 and non-workday w0 for each hour (h0 – h23), therefore, the length of the vector is 96. I used the median of each hour count across all workdays / non-workdays to mitigate the effect of temporary social events.

$$\mathbf{X}_{swh} = (\underbrace{\underbrace{X^{start}_{sw1h0}, \cdots, X^{start}_{sw1h23}}_{24\ departure\ counts}, \underbrace{X^{end}_{sw1h0}, \cdots, X^{end}_{sw1h23}}_{24\ arrival\ counts}}_{workday}, \underbrace{\underbrace{X^{start}_{sw0h0}, \cdots, X^{start}_{sw0h23}}_{24\ departure\ counts}, \underbrace{X^{end}_{sw0h0}, \cdots, X^{end}_{sw0h23}}_{24\ arrival\ counts}}_{non-workday})$$

CALCULATION OF THE SIMILARITY BETWEEN COUNT TIME SERIES

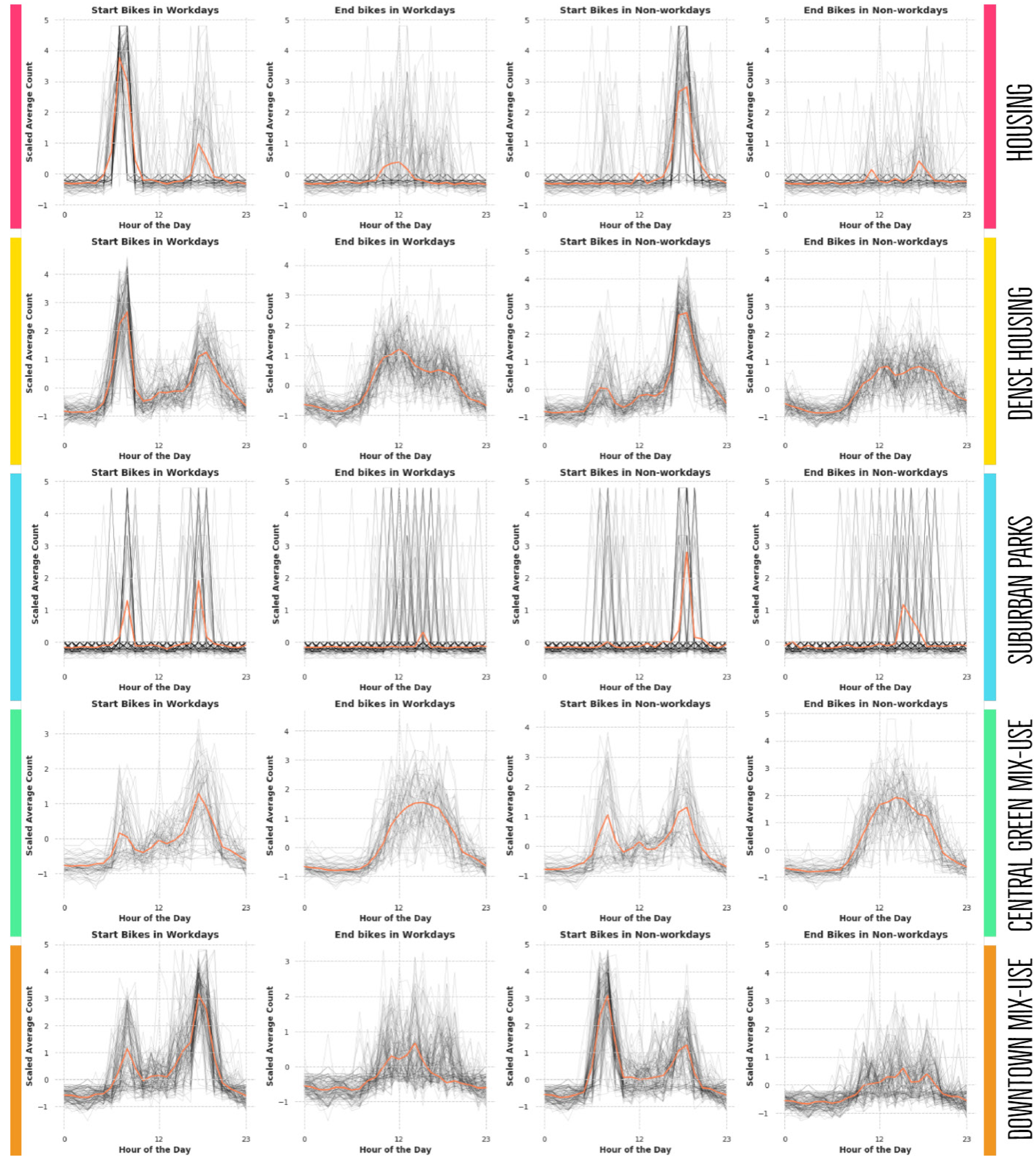
Dynamic time warping (DTW) finds the optimal non-linear alignment between two time series compared with the Euclidean distance method. Given the assumption that the four 24-hour time series in the vector are independent, I need to reshape the vector into a 4 x 24 matrix before comparison. It is noticeable that some stations show similar trend while the amplitude are quite different due to the capacity and location of stations. Therefore, to deal with amplitude scaling issue, I transformed all time series so that their mean and standard deviation in each dimension is 0 and 1. The right Fig. shows the basic idea of calculating similarity between two time series of 4 dimensions in this case.



INTERPRETATION OF CLUSTERS OF STATIONS CONSIDERING SOCIO-ECONOMIC CONDITIONS

Cluster name	Inhabitants / acre	Jobs / acre	Retail and entertainment jobs / acre	Proportion of block group within 0.25 mile of transit stops
"Housing"	**27**	12	2	13%
"Dense Housing"	**39**	23	5	27%
"Suburban Parks"	16	25	4	12%
"Central Green Mix-use"	17	**101**	**15**	36%
"Downtown Mix-use"	33	**160**	**17**	**54%**

Table. Mean of each cluster with respect to population density (number of inhabitants per acre), employment density (number of jobs per acre), retail and entertainment service (number of related jobs in grocery stores, restaurants, etc. per acre), and public transportation accessibility (proportion of block group within 0.25 mile of transit stops).



3

GROUP PROJECT, CHIEF DESIGNER
LA 201 ECOLOGICAL FACTORS IN URBAN DESIGN
SUPERVISOR: KRISTINA HILL, NATE KAUFFMAN
UC BERKELEY, 2016

RESILIENT BY DESIGN

A Resilient Canal District in San Rafael, CA

SEA LEVEL RISE

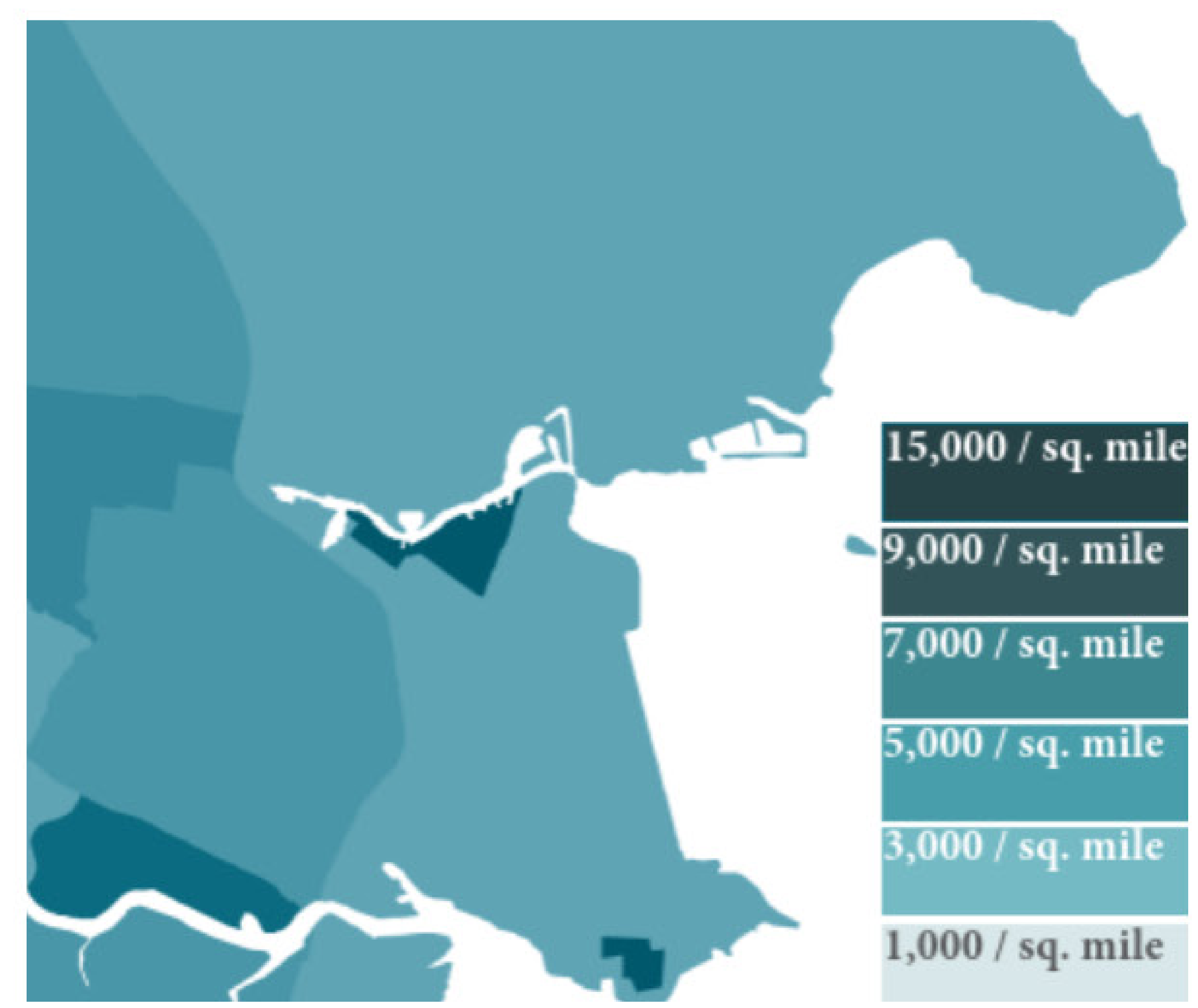
GOALS

1. Meet immediate housing, infrastructure, and open space needs: serve as a template for an **EVOLVING DISTRICT** & region
2. Multi-benefit water management, habitat, and public spaces: **CELEBRATE RESILIENT DESIGN**
3. Provide for hazard **ADAPTATION,** mitigation, and preparedness

SITE FACILITES

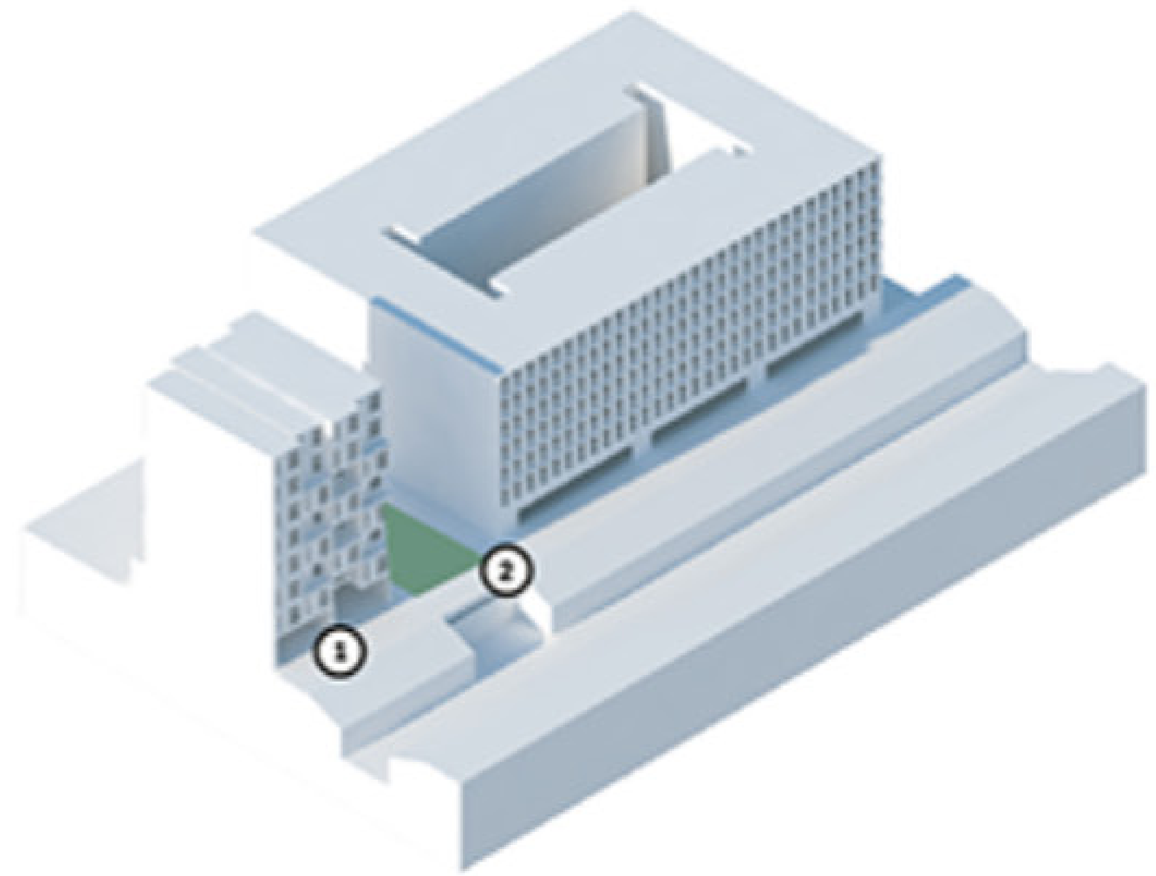
LAND USE

POPULATION DENSITY



HOUSEHOLDS BELOW POVERTY LINE

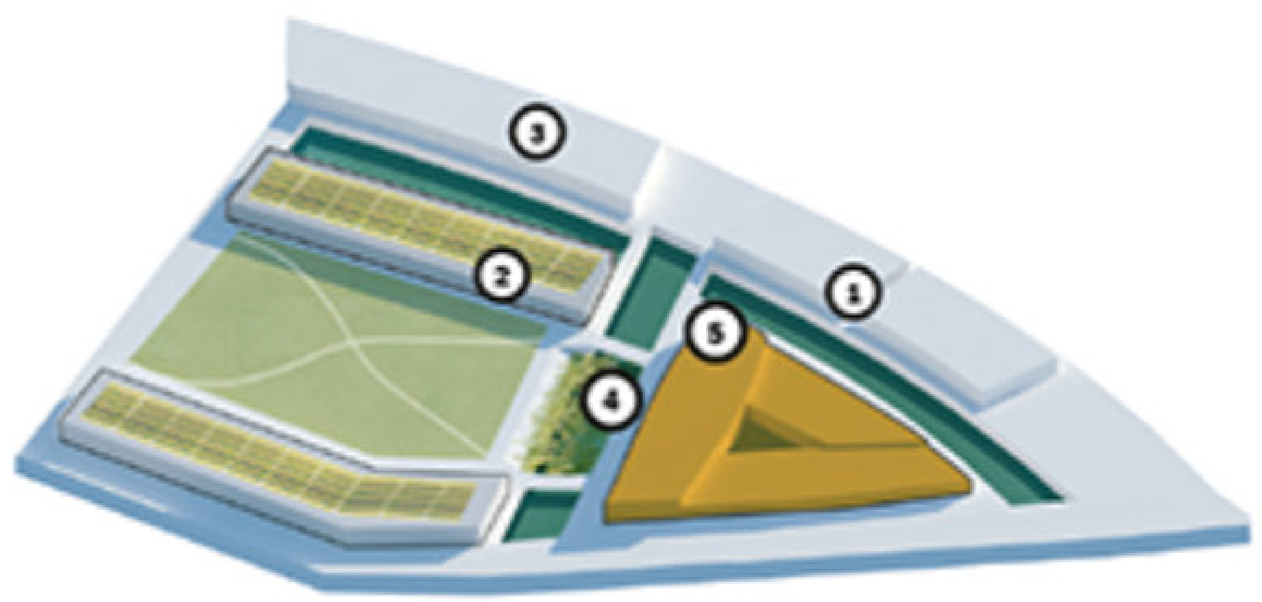
URBAN CANALS

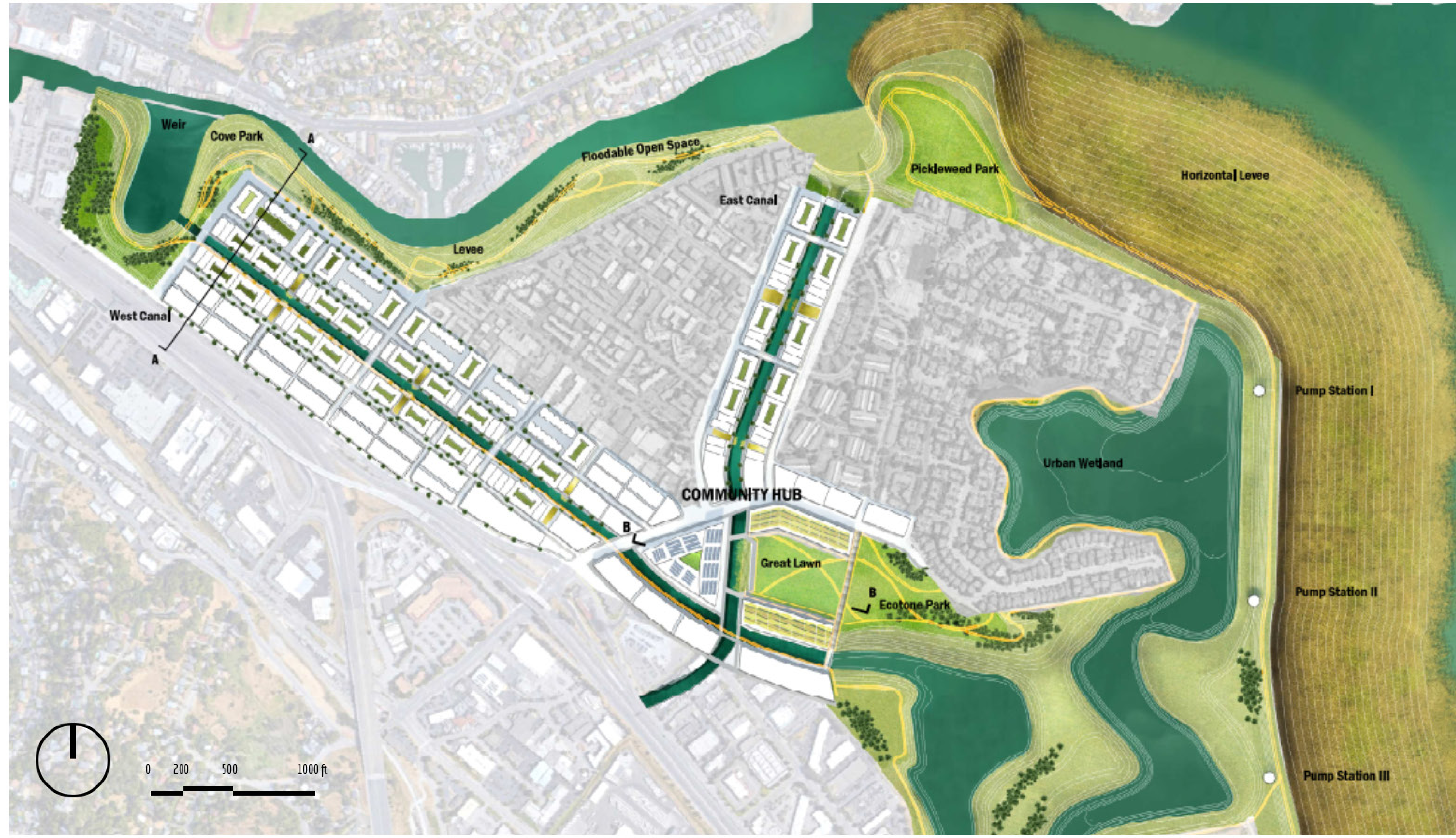


1. CANAL DISTRICT PROMENADE WITH RETAIL FRONTAGE
2. CANAL PLANTING FILTERES

COMMUNITY HUB

1. RESILIENCY CENTER/ MICROGRID / COMMUNITY CENTER
2. COMMUNITY GREEN WITH ALTERNATE USES FOR DISASTER PREPAREDNESS
3. RELOCATED SCHOOL / DAYCARE CENTER
4. URBAN VERTICAL FARM / GROCERY STORE
5. URBAN CANAL PARK



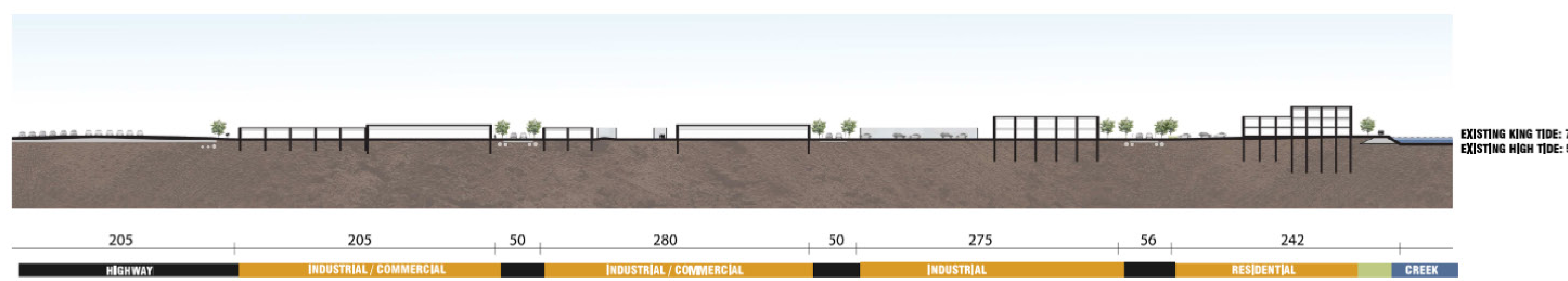


PHASE I

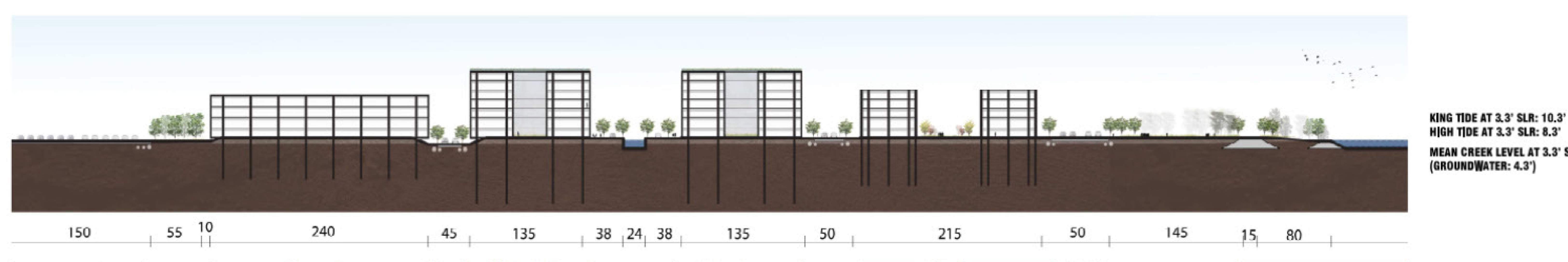
1.6' SEA LEVEL RISE 3' GROUND WATER TABLE

SITE AREA:	675 ACRES
CONSTRUCTED WETLANDS:	193 ACRES
WATER STORAGE:	488.3 ACRE FEET
NEW HOUSING UNITS:	13,148
COMMERCIAL/MIXED USE:	1.6 MILLION SF
INDUSTRIAL/MIXED USE	1.4 MILLION SF

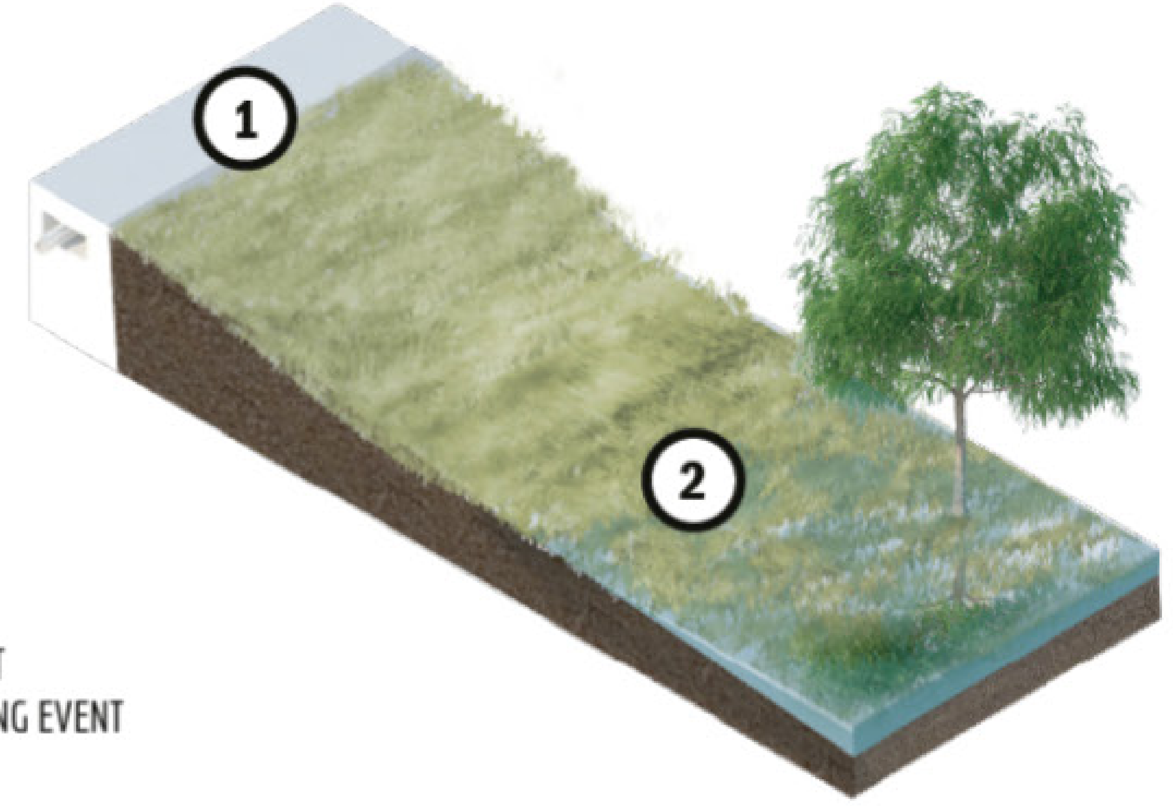
A. EXISTING



A. PHASE 1

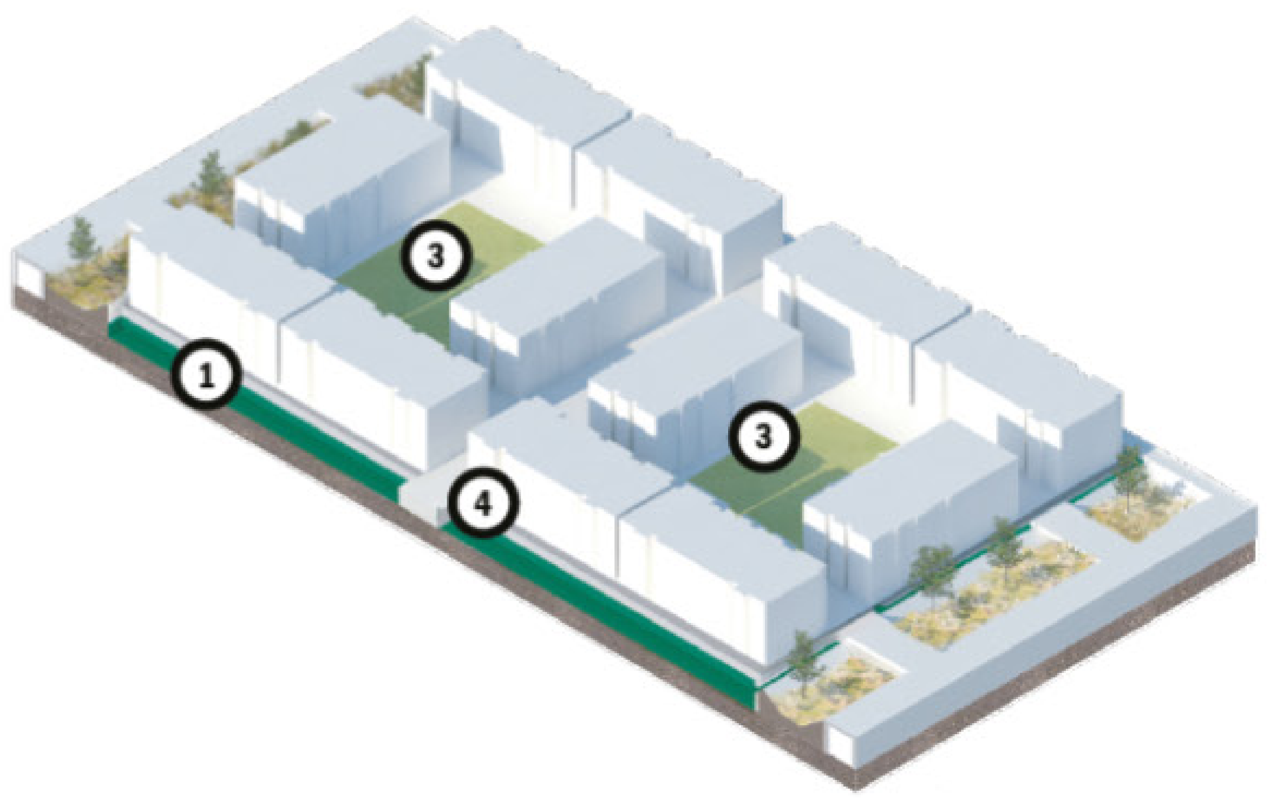


FLOODABLE PARK



1. CONNECTION TO ROAD NETWORK ON LEVEE
2. PUBLIC OPEN SPACE THAT CAN COLLECT STORM WATER DURING MAJOY FLOODING EVENT

FLOATING BLOCKS



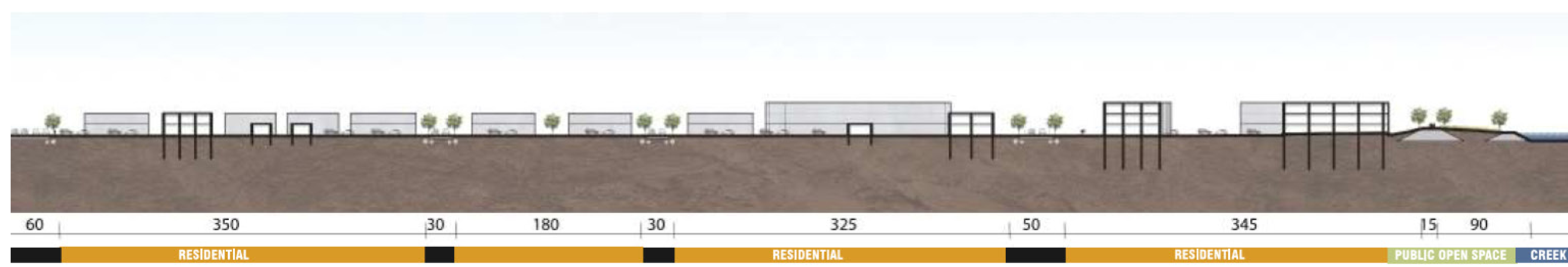
1. LIGHT WEIGHT CONCRETE IN AN ARTIFICIAL POND
2. BIOSWALE AND EMERGENCY STORAGE
3. SHARED OPEN SPACE
4. HINGE RAMP INTEGRATED WITH UTILITY LINE CONNECTIONS

PHASE II

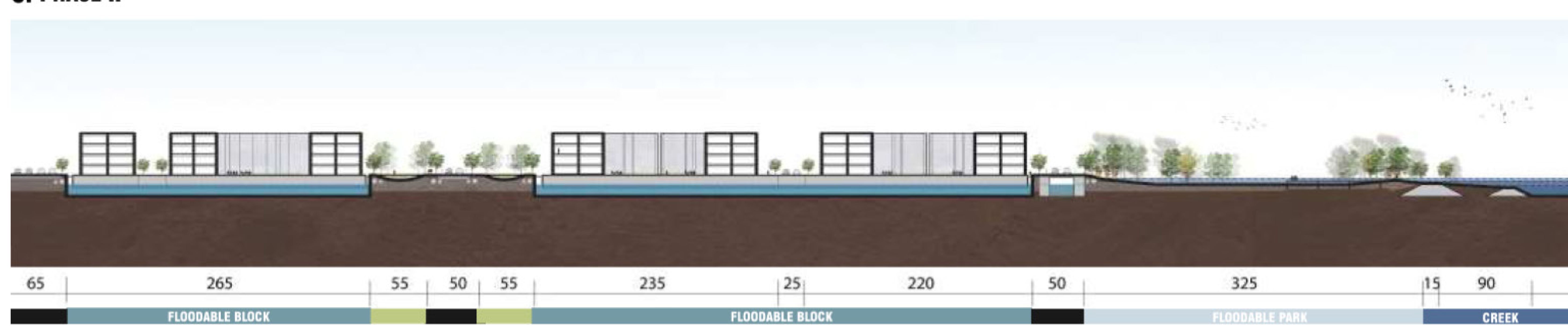
10' SEA LEVEL RISE 11' GROUND WATER TABLE

TOTAL HOUSING UNITS:	16,262
PUBLIC OPEN SPACE:	45 ACRES
PRIVATE OPEN SPACE	44 ACRES
WATER STORAGE:	1,811 ACRE FEET

C. EXISTING



C. PHASE II

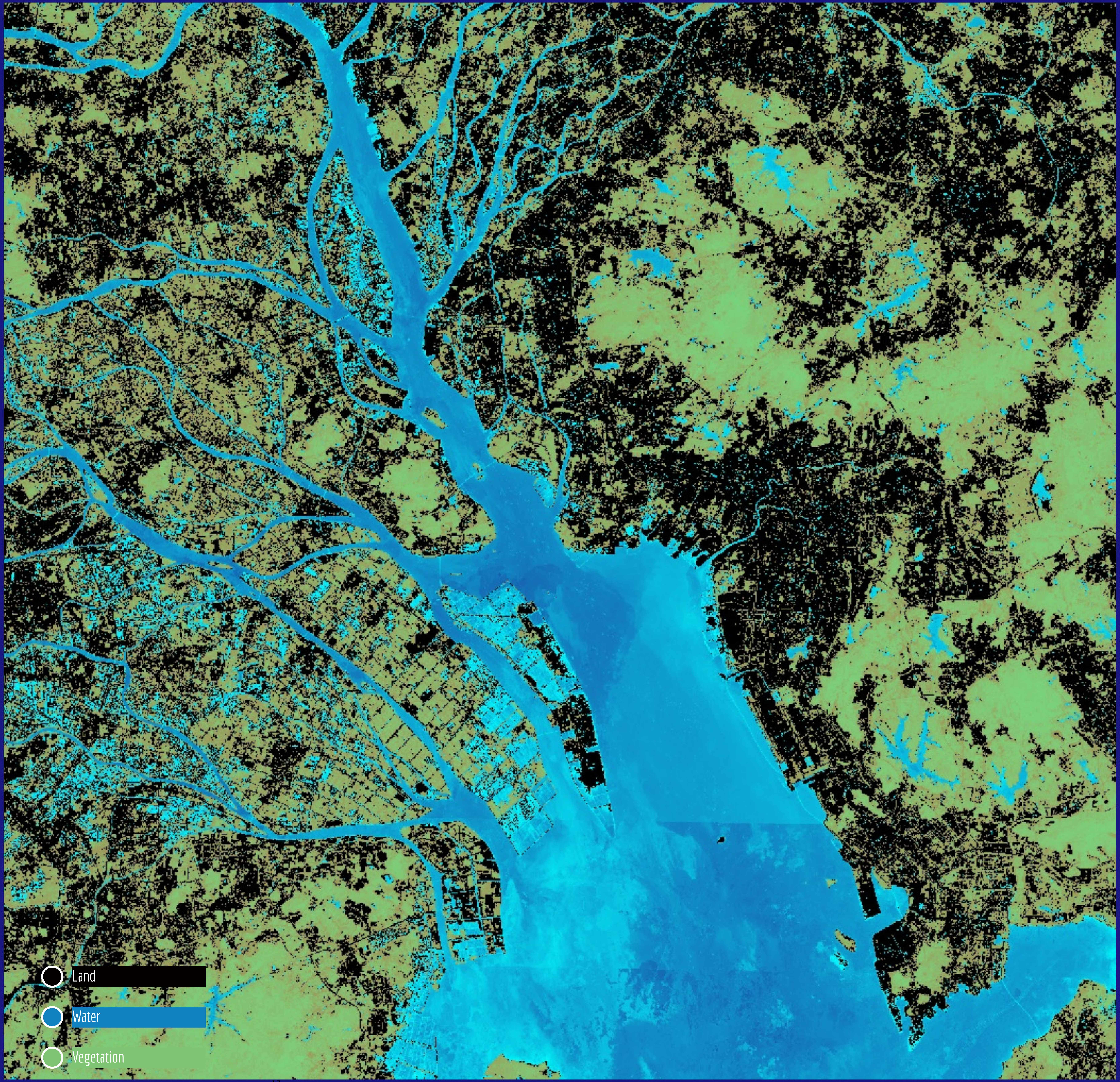


4

PROFESSIONAL PROJECT
RESEARCH ASSISTANT, HKU, 2018-NOW
WORKING WITH MICHAEL KOKORA,
IVAN VALIN, SUNNIE LAU

DATA-POOR REGION MAPPING

Physical Landscape Element Extraction and Mapping in Pearl River Delta, China



```
// Map the function over one year of
data and take the median.
// Load Sentinel-2 TOA reflectance
data.
var sentinel = ee.ImageCollection
('COPERNICUS/S2')
.filterDate('2018-01-01', '2018-06-30')
// Pre-filter to get less cloudy
granules.
.filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE',
20))
.map(maskS2clouds);
// Temporally reduce the image using
mean().
var composite = sentinel.median();
//Make a handy variable of visualiztion
parameters.
var visParams = {bands: ['B4', 'B3',
'B2'], max:0.3};
// Create the NDVI and NDWI spectral
indices.
var ndvi = composite.normalizedDifference
(['B8','B4']);
var ndwi = composite.normalizedDifference
(['B3','B8']);
// Add two bands to simple composite
image
var composite_n = composite.addBands
([ndvi, ndwi]);
// Display the composite map
Map.addLayer(composite_n, visParams,
'median composite');
Map.setCenter(113.677368, 22.758458,
11);
name: 'over 90% occurrence water mask'
});
Map.setCenter(113.677368, 22.758458,
11);
```

IMAGE COLLECTION

IMAGE FILTERING

COMPOSITE IMAGE

BAND MATH

ADD NEW BANDS

MAP VISUALIZATION

GIS data in Pearl River Delta is **INCOMPLETE, INACCESSIBLE, OR OUT-DATED,** which sets up obstacles on sustainable urban planning and design. Focusing on coastal flooding, the greatest environmental threat in PRD due to climate change, I have tried to use over 800 Landsat satellite images to study the change of water from 1984 to 2018. I am working in Google Earth Engine processing those images in Javascript to generate latest datasets of physical elements such as water, vegetation and topography based on theories of remote sensing. The left is just a simple example to basically tell difference between vegetation, water and urbanized area shown in the previous page.

Water (water occurrence > 90%)

Not water

High water occurrence

Low water occurrence

No water occurrence

No change

Loss

Gain

Not water

Permanent

New permanent

Lost permanent

Seasonal

Ephemeral seasonal

New seasonal

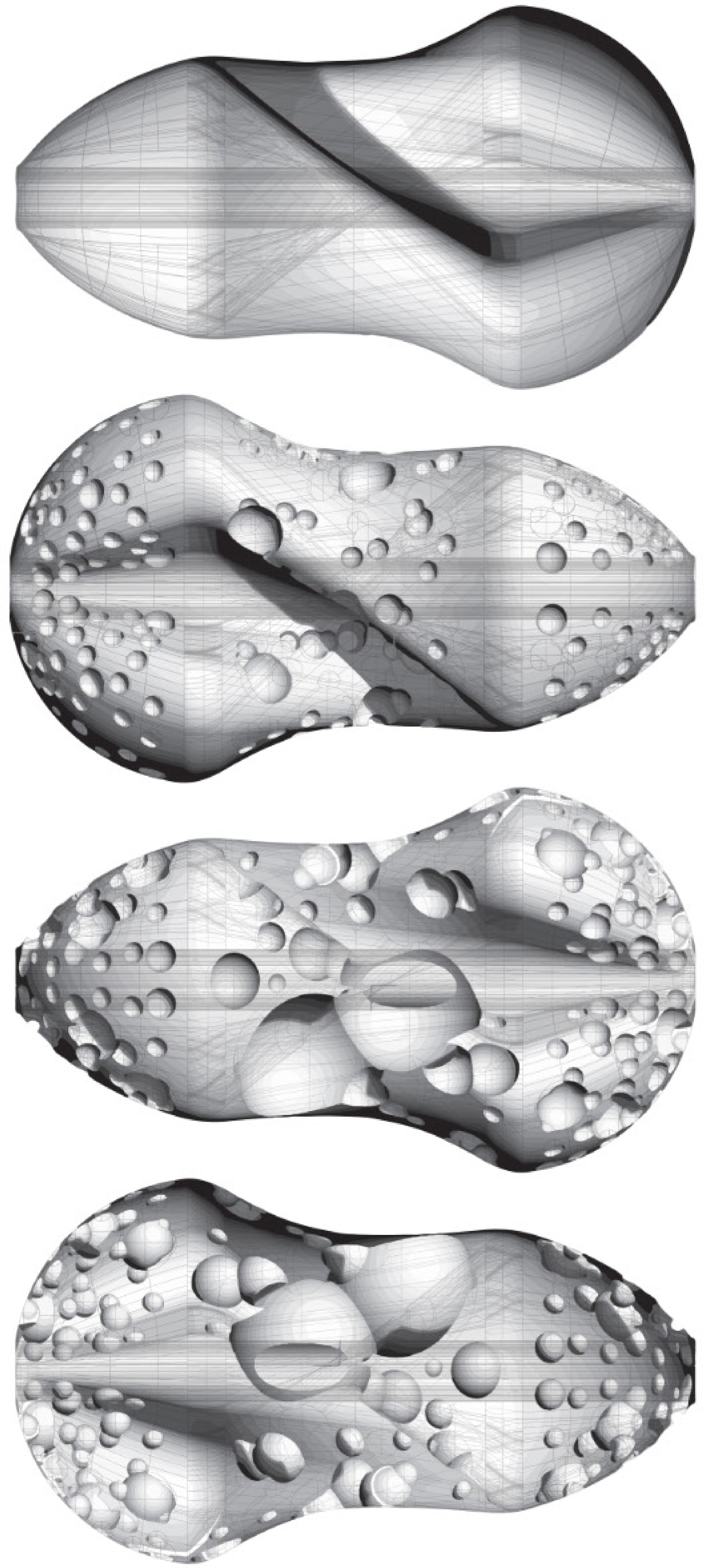
Lost seasonal

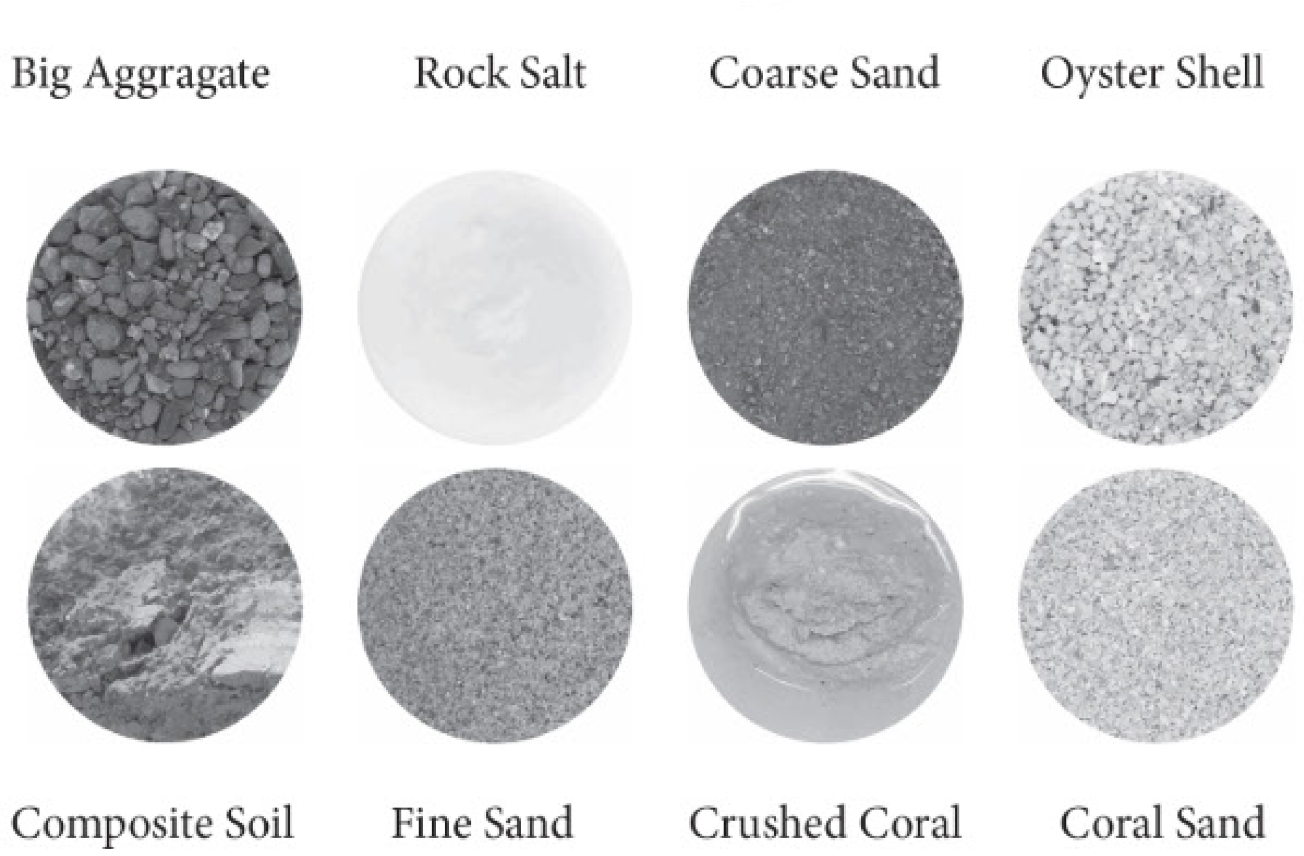
Seasonal to permanent

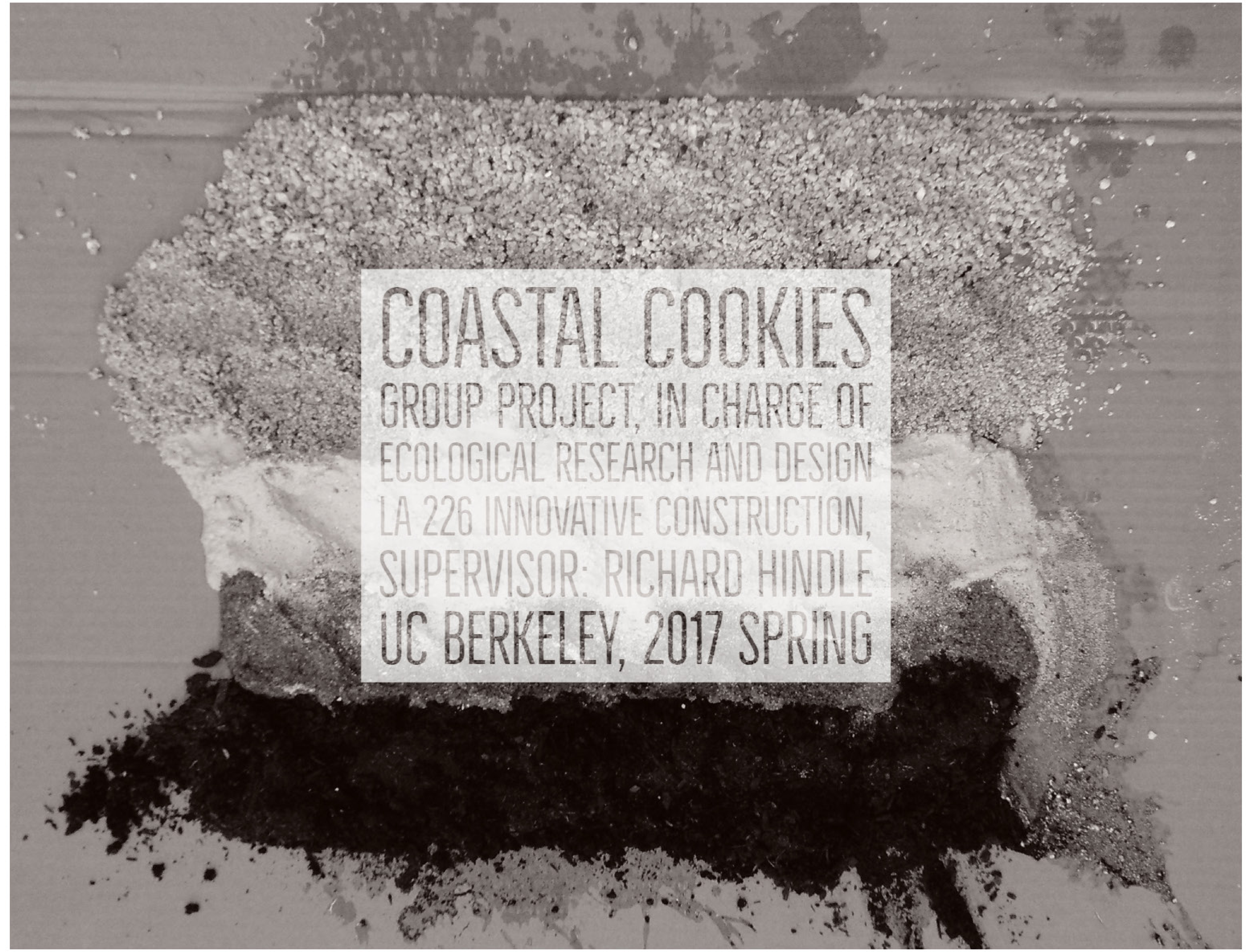
Permanent to seasonal

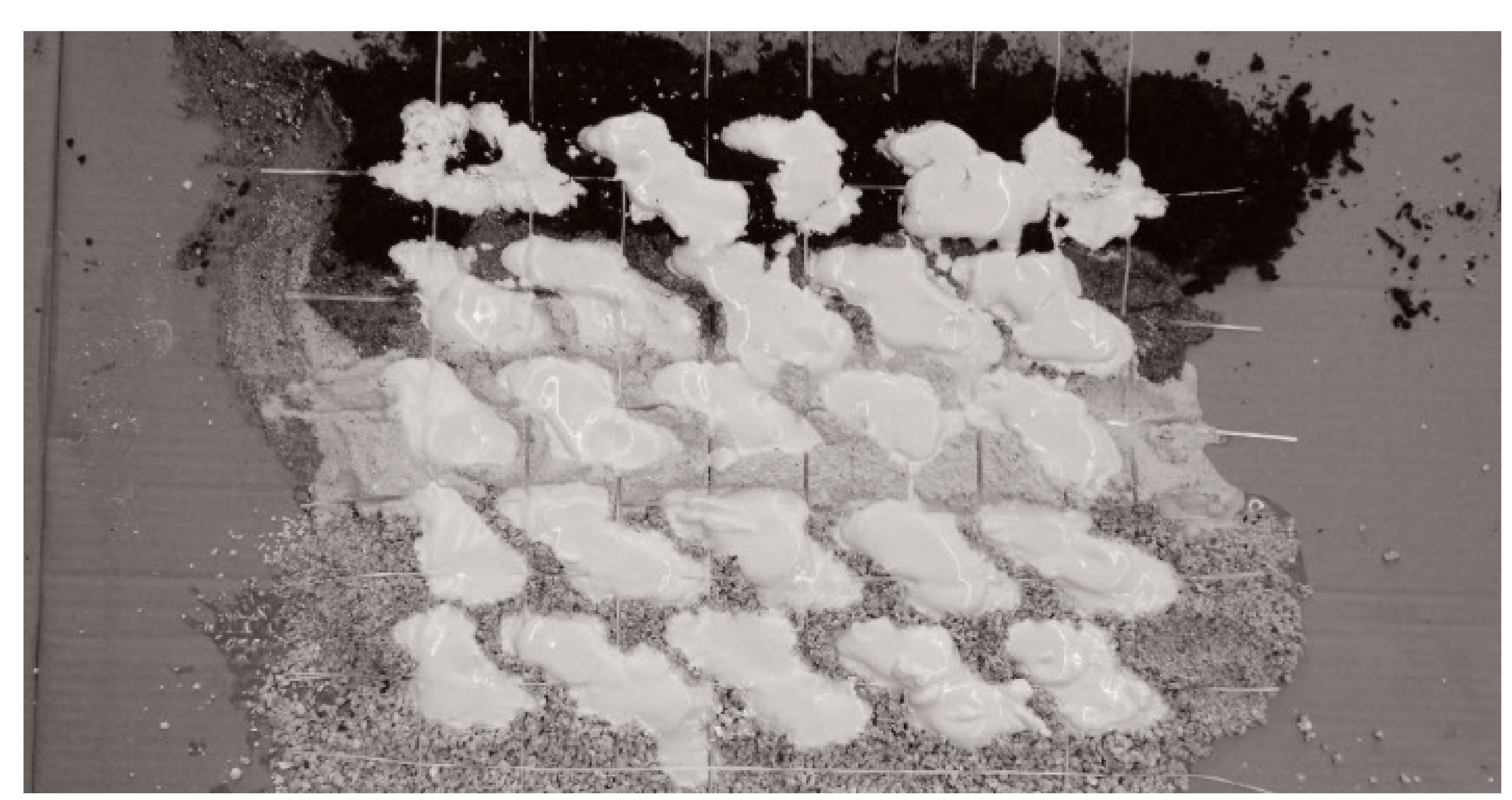
Ephemeral permanent

Types	Width of Zone	Pits Spacing $0.14in^2$	Pits Spacing $1.2in^2$	Pits Spacing $8in^2$
Upland Zone	33ft			
Mudflat Zone	65ft	$/2in^2$	$/9in^2$	
Intertidal Zone	100ft	$/2in^2$	$/9in^2$	$/81in^2$
Subtidal Zone	100ft	$/2in^2$	$/9in^2$	$/81in^2$

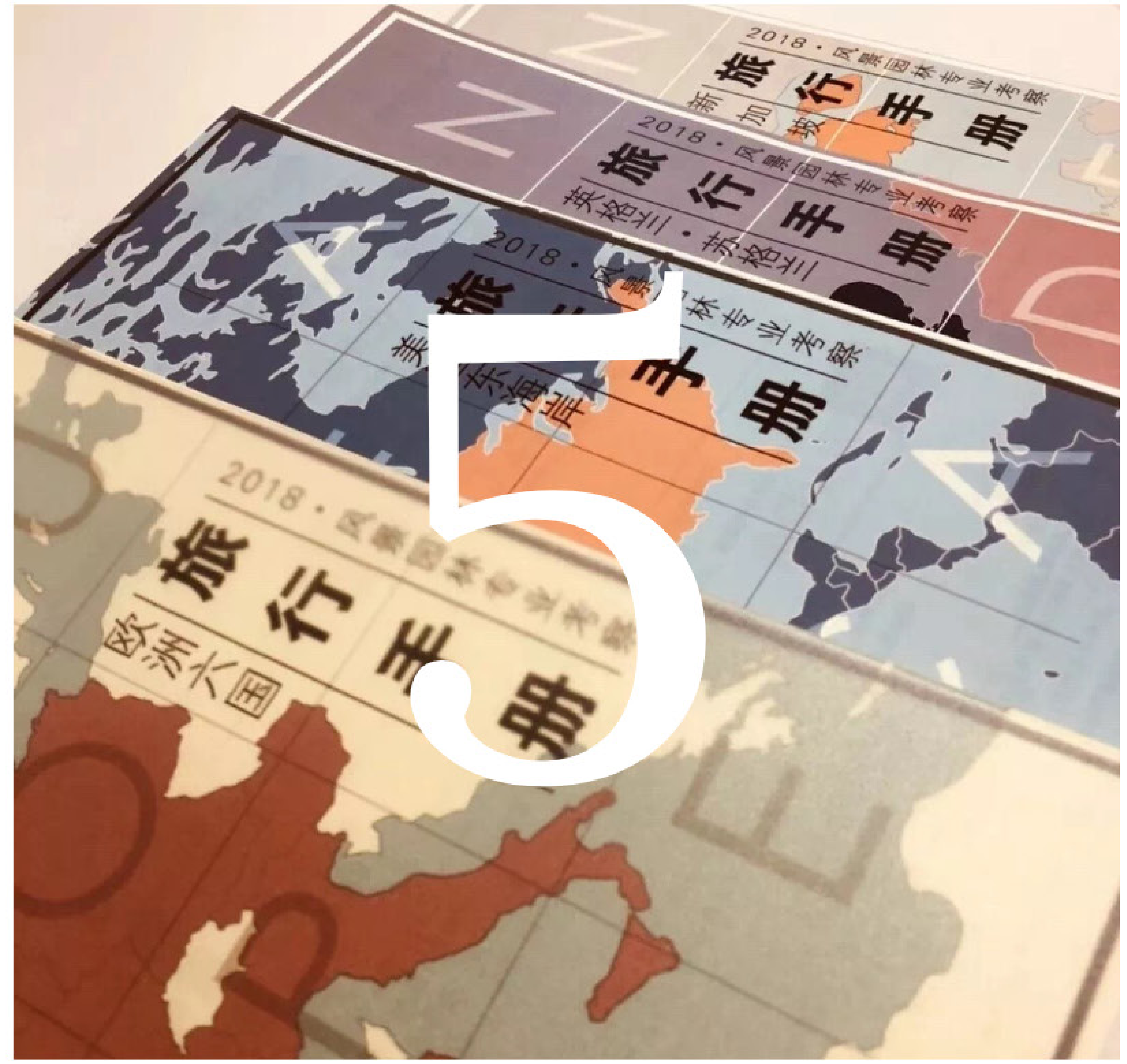








Modelling of Aero Island, Denmark, 2018



Eight Outer Temples, Chengde, China 2015

Fenghuang Ancient Town, 2013

5

OTHER WORKS

Treasure Island Cultural Park, San Francisco, 2018