

Projecting the Urban Heat Island Effect Using Historical Weather Patterns and Land Cover

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Abstract

An Urban Heat Island is a metropolitan area with higher air and surface temperatures than surrounding areas. The Urban Heat Island Effect (UHIE) is a relative measure of the heat in urban heat islands. This research study investigates how developed land cover and weather trends can be used to forecast the UHIE with two distinct modeling frameworks. Projections of future conditions can prepare scientists and communities to take greener initiatives and adapt their lifestyle to preserve the Earth. The study focuses on the Greater Austin Region (TX, USA) for initial feasibility, but aims to extend these methods to a national or global scale. The first technique uses machine learning (Keras sequential model) to identify correlations between factors closely linked to the UHIE. The tested factors were air and surface temperature, relative humidity, soil moisture, and population growth. Evident correlations were found and used to begin training a predictive model (artificial neural network). The second technique uses developed softwares in QGIS Modules for Land Use Change Evaluation (MOLUSCE), high resolution satellite imagery provided by Multi-Resolution Land Characteristics land cover/land use data, and distance from roadways and inland water bodies data in order to accurately predict the possible changes in 2022 to the Greater Austin Region. Major limitations throughout the research process include regional & temporal data inconsistencies, the narrow scope of factors and geographic region, and the time constraint of the NASA SEES internship. Given ample time and data, these analyses can be used in green efforts to moderate and reduce the causes of UHIE. They can also aid in further investigating water contamination, energy consumption, and human health, and make larger scale environmental simulations possible.

Projecting the Urban Heat Island Effect Using Historical Weather Patterns and Land Cover

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An Urban Heat Island is a metropolitan area with higher air and surface temperatures than surrounding areas. The Urban Heat Island Effect (UHIE) is a relative measure of the heat in urban heat islands. This research study investigates how developed land cover and weather trends can be used to forecast the UHIE with two distinct modeling frameworks. Projections of future conditions can prepare scientists and communities to take greener initiatives and adapt their lifestyle to preserve the Earth. The study focuses on the Greater Austin Region (TX, USA) for initial feasibility, but aims to extend these methods to a national or global scale.

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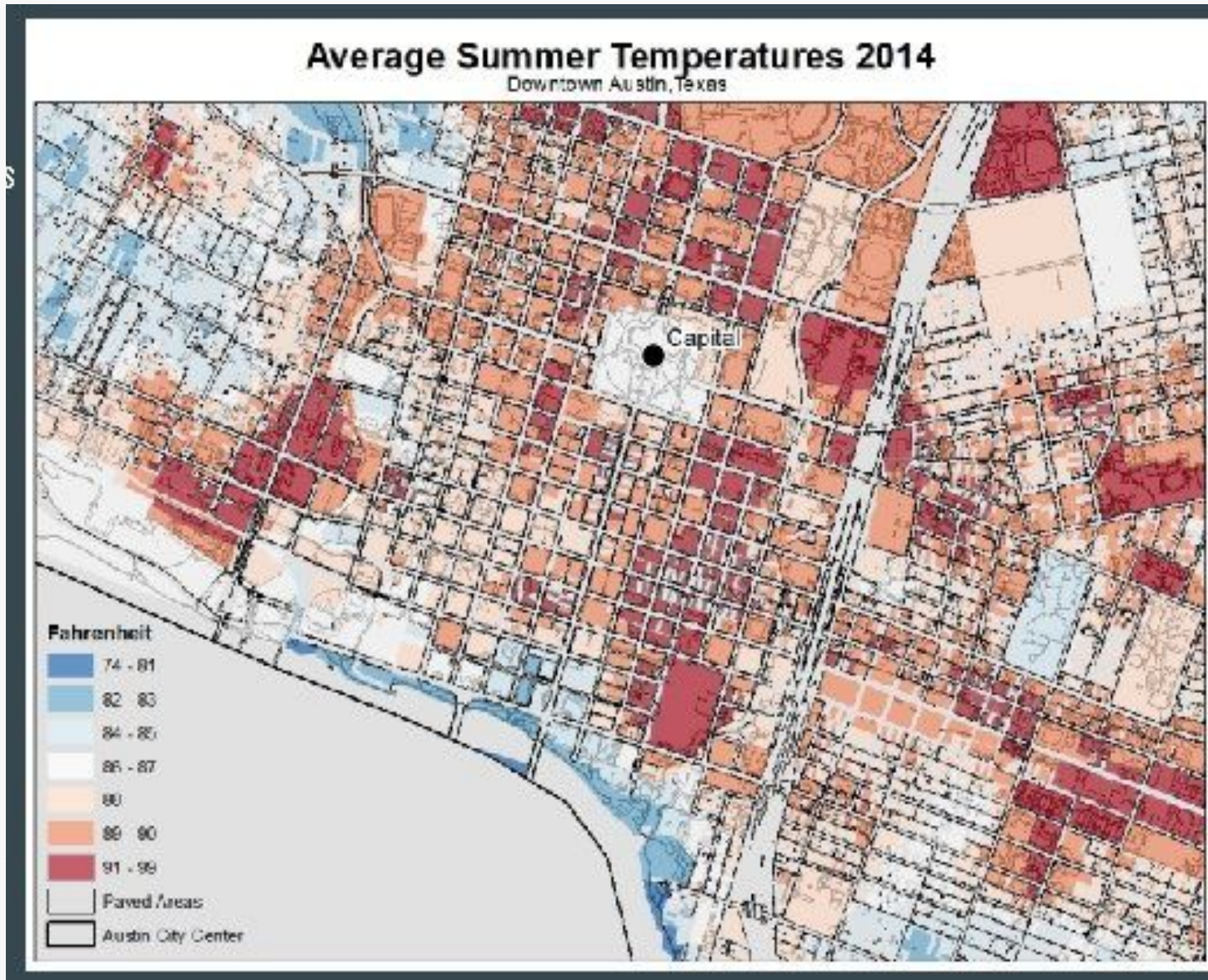
An aerial photograph of a city skyline, likely Chicago, at sunset. The sky is a mix of orange, pink, and blue, with some clouds. The city buildings are visible in the foreground and middle ground, with the Lake Michigan shoreline in the distance.

Research Question

How can **developed land cover**
and **weather trends** be used to
forecast the **Urban Heat Island**
Effect?

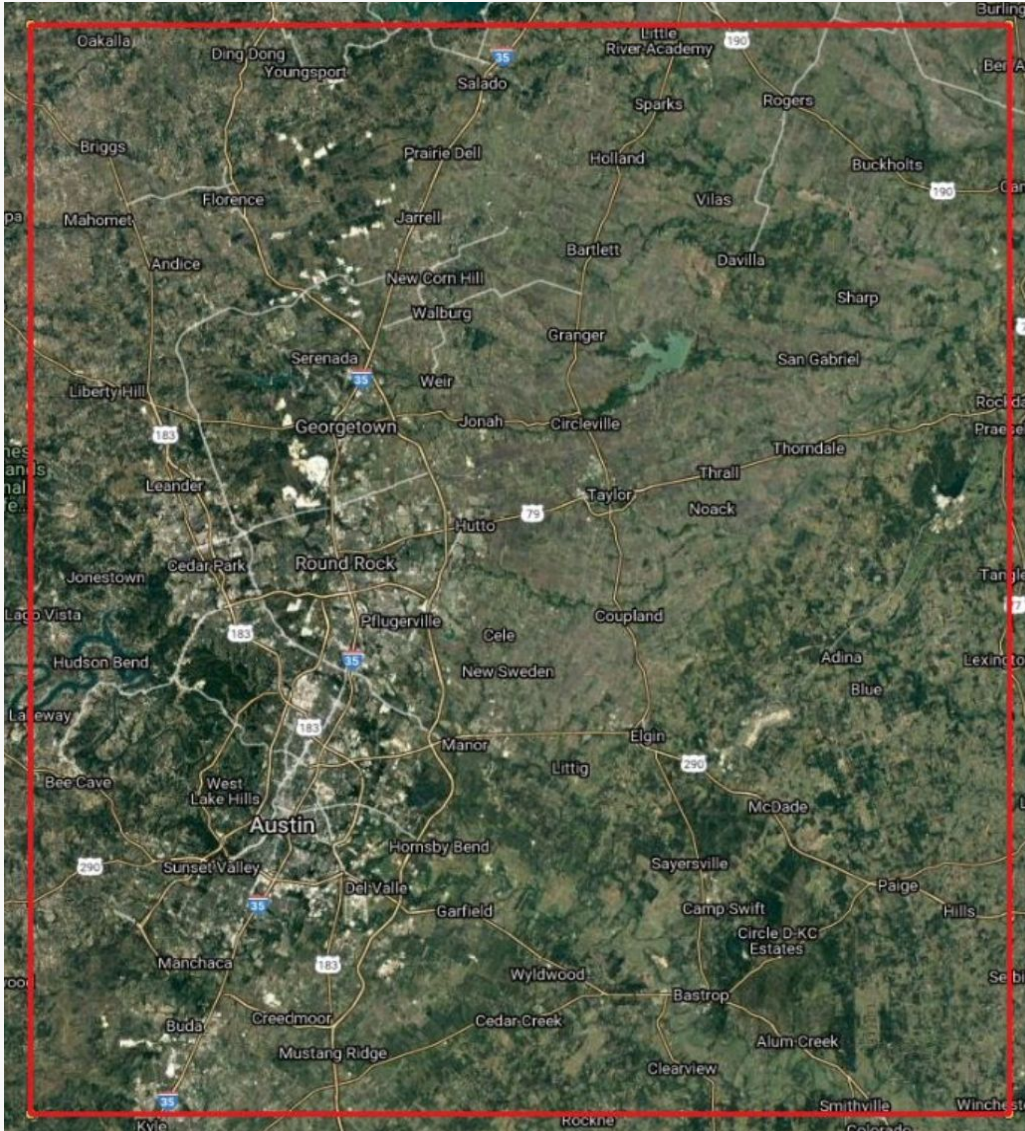
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Introduction



- ❑ Urban Heat Islands
- ❑ Trend changes with Urban Sprawl
- ❑ Hayhoe et al., 2014

Study Site



Greater Austin Region (TX, USA)

Climate

- ❑ Köppen Climate Classification
 - ❑ Humid Subtropical Climate
- ❑ Evenly distributed precipitation
 - ❑ May, October, June Peaks
- ❑ Southerly winds
- ❑ Low stratus clouds at night
- ❑ Hottest year: 2017, coldest: 1899
 - ❑ Progressive Increase

Google Maps

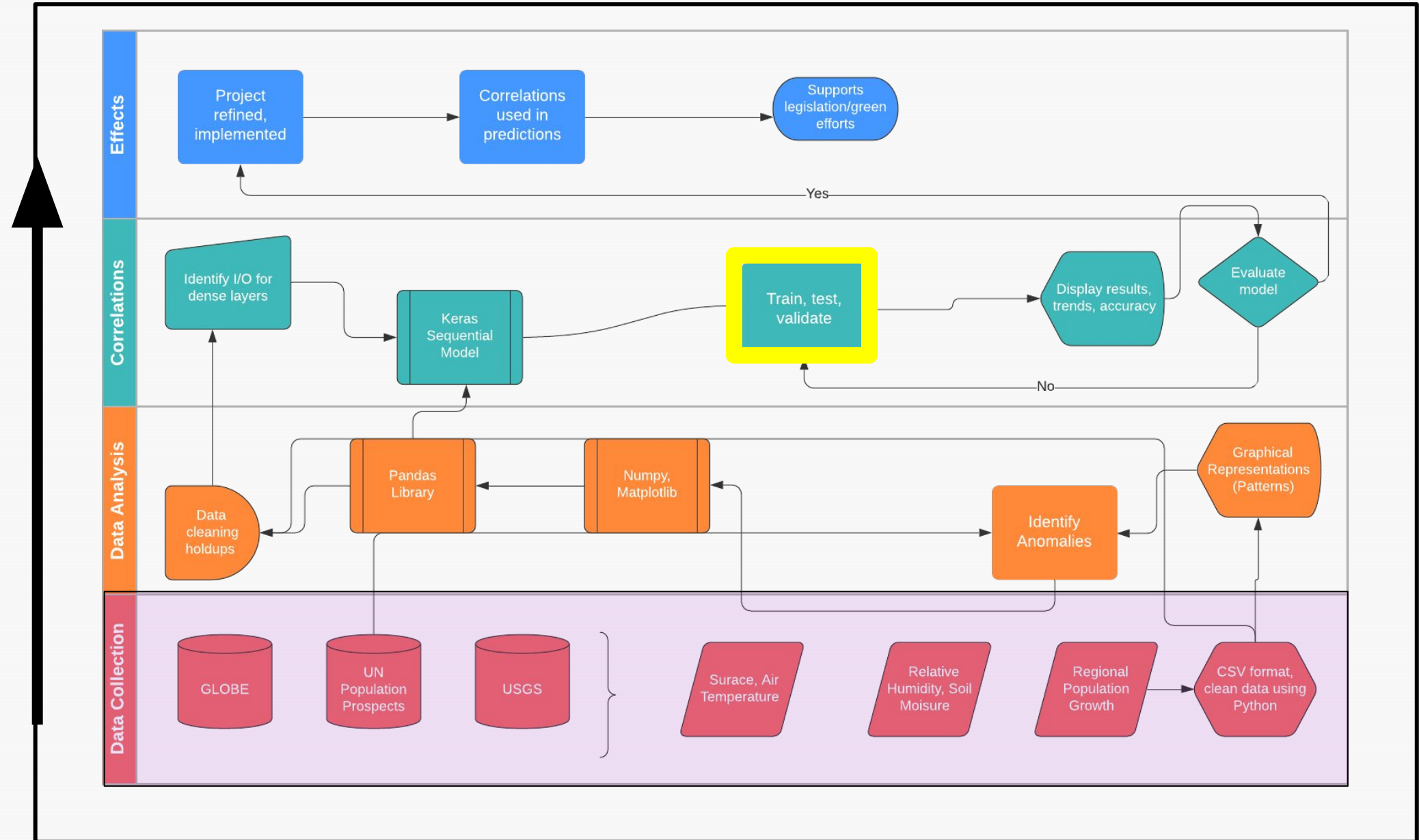




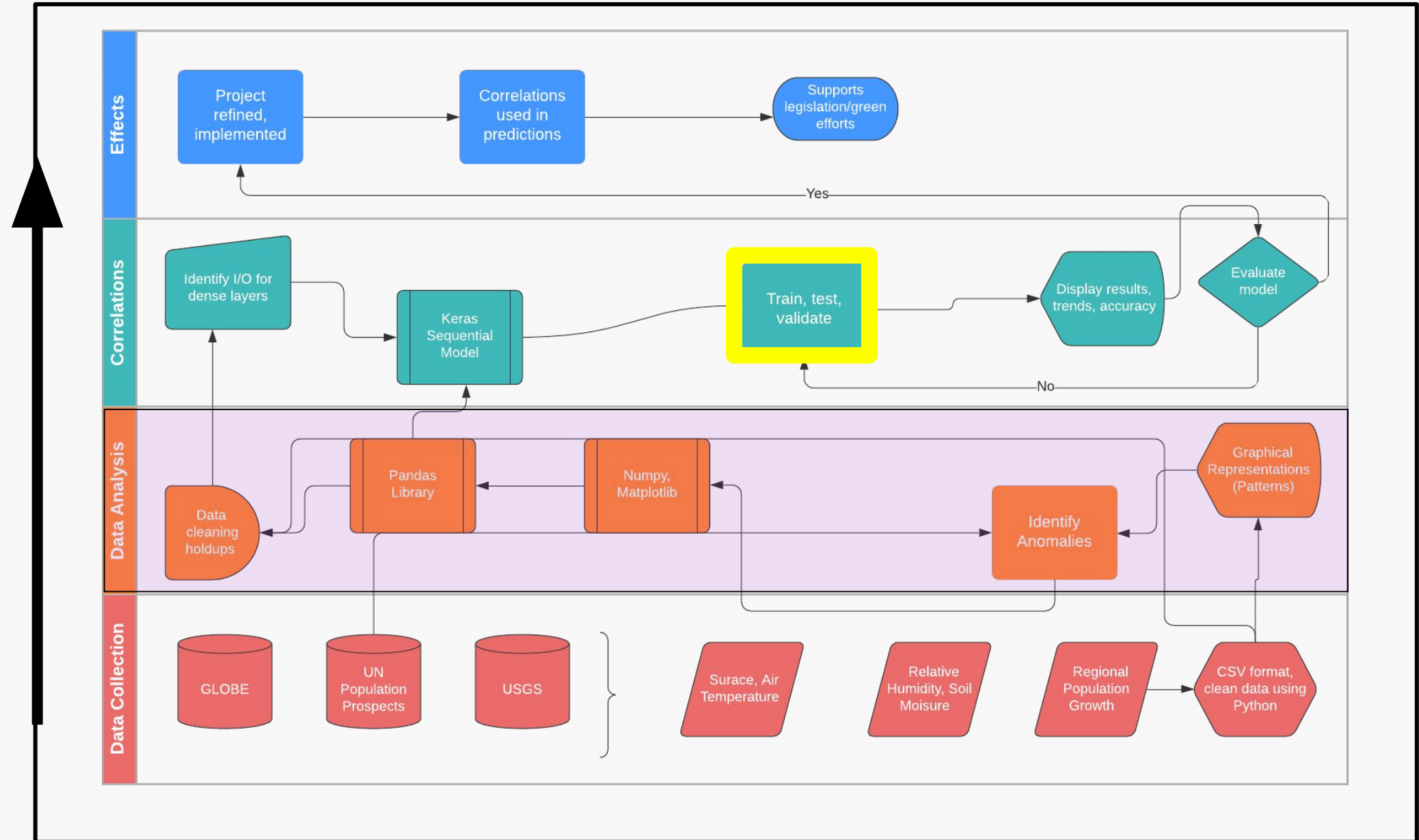
Identifying Correlations Between Environmental Factors

Part 1: Computational Modeling

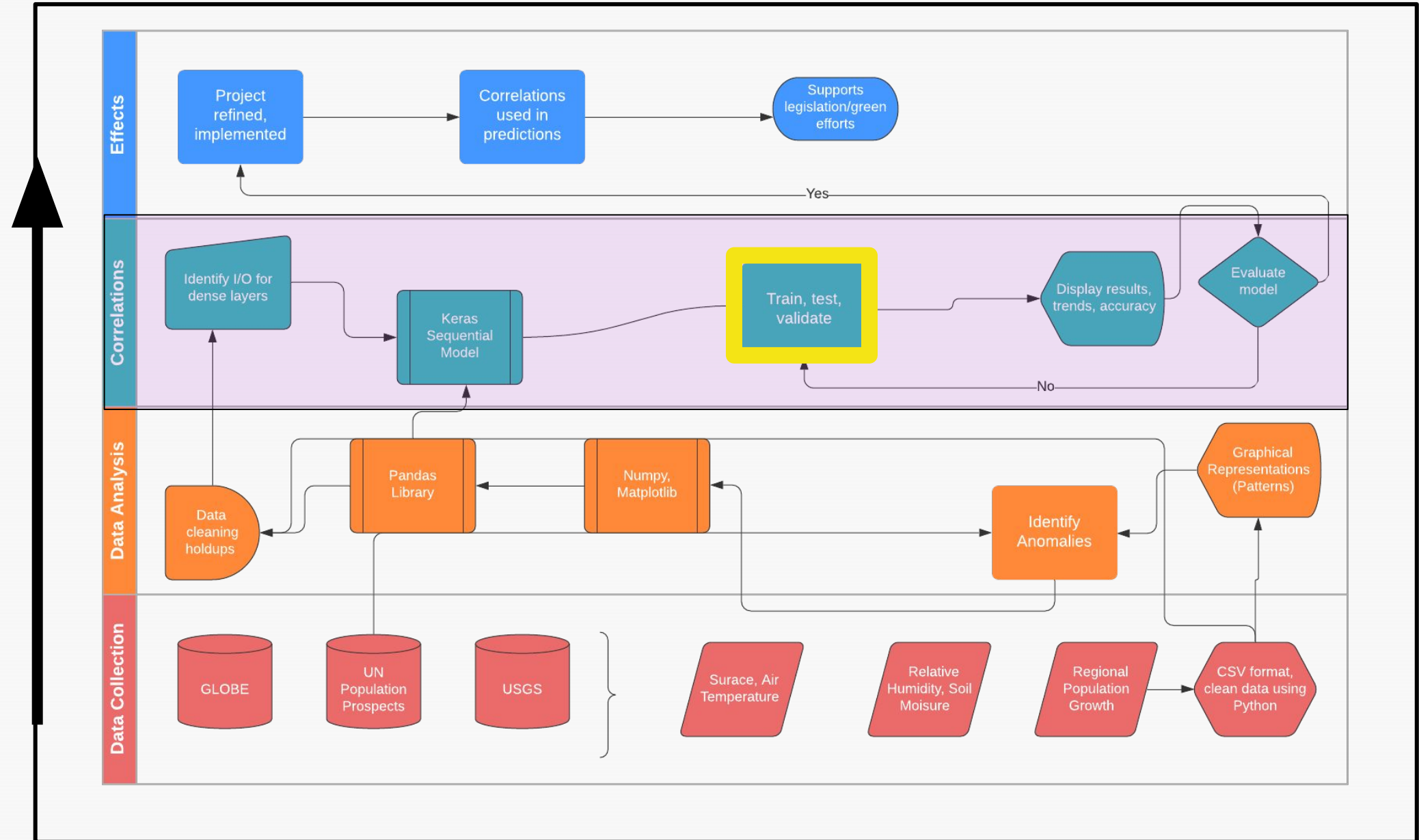
Research Methods: Planning



Research Methods: Planning



Research Methods: Planning



Results

Correlations, precision & recall

Real Output <==> Predictions (First 10 values)

```
[10.2] <==> [10.19517]
[10.2] <==> [10.24102]
[9.4] <==> [10.206987]
[10.4] <==> [11.291314]
[10.4] <==> [11.104922]
[9.8] <==> [10.973987]
[13.7] <==> [11.557368]
[13.8] <==> [10.897681]
[11.9] <==> [11.373532]
[11.9] <==> [12.201732]
```

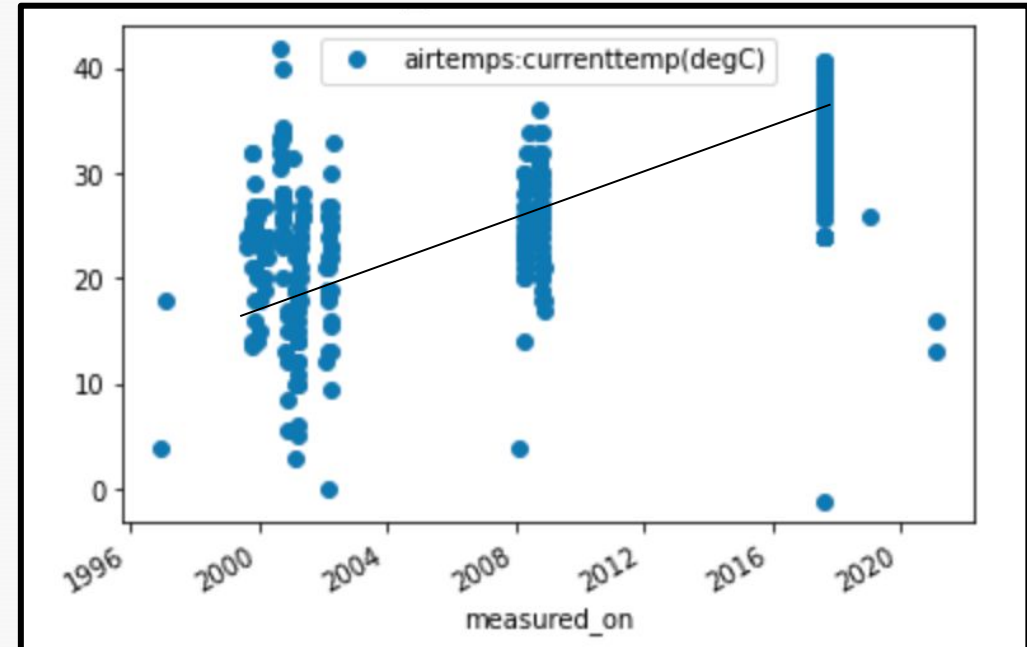
Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 32)	96
dense_1 (Dense)	(None, 10)	330
dense_2 (Dense)	(None, 1)	11

Total params: 437

Trainable params: 437

Non-trainable params: 0



Upward trend in median air temperature in study site

Research Methods: Data

```
atemp.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
Int64Index: 571 entries, 1 to 571
```

```
Data columns (total 14 columns):
```

#	Column	Non-Null Count	Dtype
0	organization_id	571 non-null	object
1	org_name	571 non-null	object
2	site_id	571 non-null	object
3	site_name	571 non-null	object
4	latitude	571 non-null	object
5	longitude	571 non-null	object
6	elevation	571 non-null	object
7	measured_on	571 non-null	datetime64[ns]
8	airtemps:user_id	571 non-null	float64
9	airtemps:measuredat	571 non-null	object
10	airtemps:solarmeasuredat	571 non-null	object
11	airtemps:currenttemp(degC)	571 non-null	float64
12	airtemps:comments	342 non-null	object
13	airtemps:globeteams	0 non-null	float64

```
dtypes: datetime64[ns](1), float64(3), object(10)  
memory usage: 66.9+ KB
```

Pandas Dataframe Summary



GLOBE Visualization System

Discussion

Importing Keras and Modelling

```
from oauth2client.client import GoogleCredentials

# Keras requirements
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.callbacks import EarlyStopping

from google.colab import drive

Requirement already satisfied: gast==0.2.2 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.2.2)
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.15.0)
Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.16.4)
Requirement already satisfied: protobuf>=3.8.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (3.8.0)
Requirement already satisfied: scipy=1.2.2; python_version < "3" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.2.2)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.15.0)
Requirement already satisfied: wheel; python_version < "3" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.36.2)
Requirement already satisfied: wrapt>=1.11.1 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.11.2)
Requirement already satisfied: keras-preprocessing>=1.1.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.1.0)
Requirement already satisfied: backports.weakref>=1.0rc1; python_version < "3.4" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.0.post1)
Requirement already satisfied: tensorflow-estimator<2.2.0,>=2.1.0rc0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (2.1.0)
Requirement already satisfied: keras-applications>=1.0.8 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.0.8)
Requirement already satisfied: functools32>=3.2.3; python_version < "3" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (3.2.3.post2)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.1.0)
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.7.1)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (2.3.2)
Requirement already satisfied: tensorboard<2.2.0,>=2.1.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (2.1.0)
Requirement already satisfied: google-pasta>=0.1.6 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.1.7)
Requirement already satisfied: enum34>=1.1.6; python_version < "3.4" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.1.6)
Requirement already satisfied: mock>=2.0.0; python_version < "3" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (2.0.0)
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Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.4.1)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.15.5)
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Requirement already satisfied: cachetools>=5.0,>=2.0.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (4.1.0)
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Requirement already satisfied: rsa<4.6; python_version < "3.6" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (4.7.1)
Requirement already satisfied: urllib3<1.25.0,>=1.25.1; python_version < "3" in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (1.25.1)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (3.0.2)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (2019.9.11)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (2.8.0)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (3.1.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.1 in /usr/local/lib/python2.7/dist-packages (from tensorflow-gpu) (0.4.1)
Reading package lists... Done
Building dependency tree
Reading state information... Done
graphviz is already the newest version (2.40.1-2).
0 upgraded, 0 newly installed, 0 to remove and 40 not upgraded.
```

Real Output <==> Predictions

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Model: "sequential"
```

Model's validation losses
(discrepancy between
verified data and
predicted output) < 4%



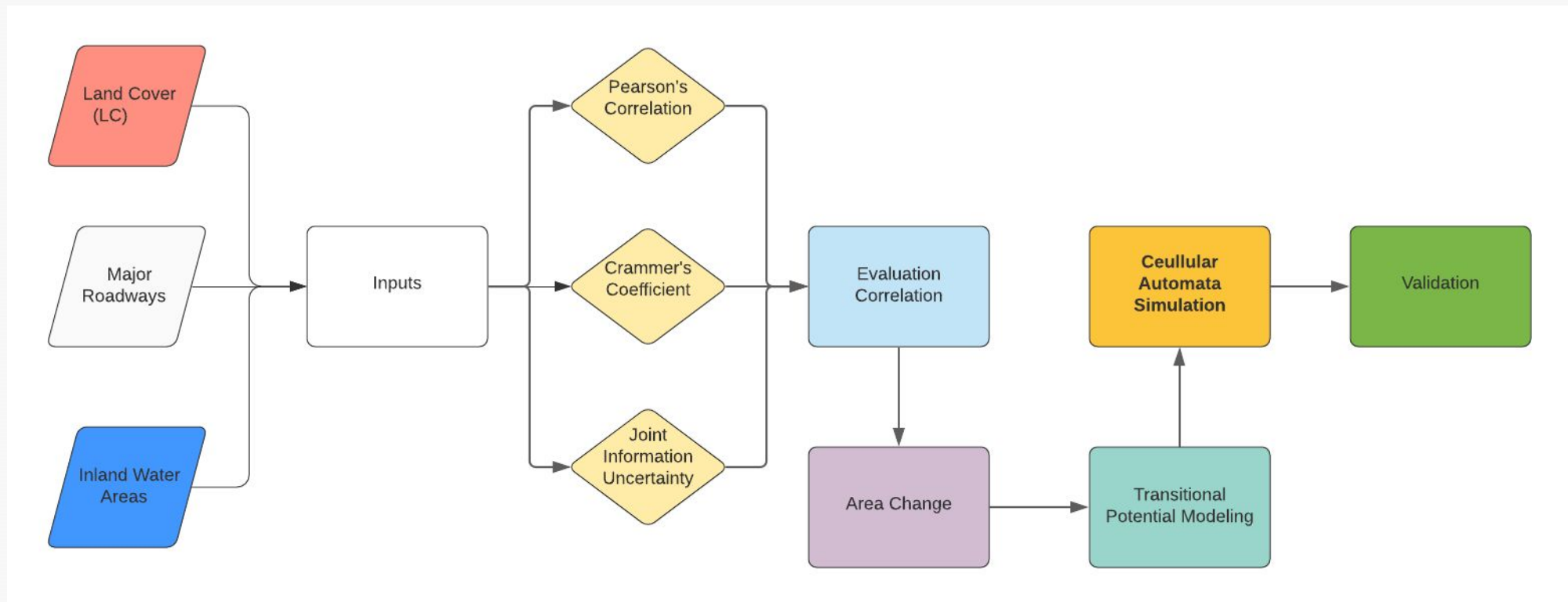
Predicting Future Land Use/Land Cover

Part 2: Satellite Imagery

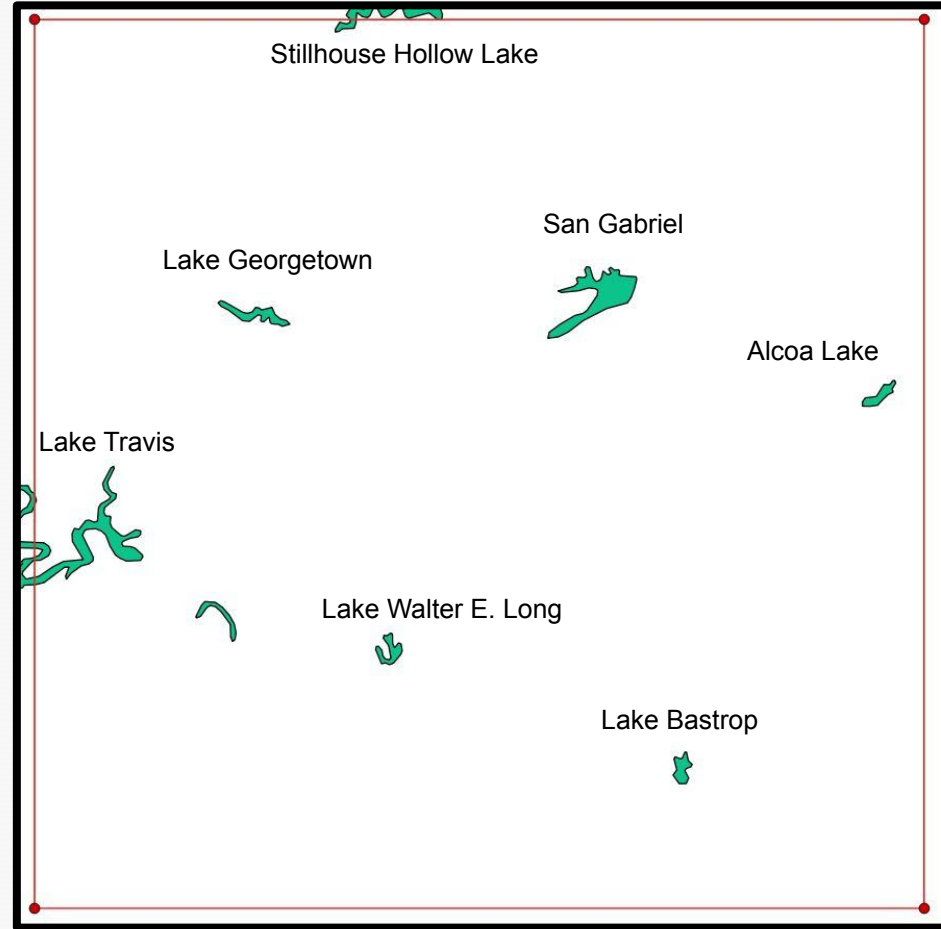
Modules for Land Use Change Simulations (MOLUSCE)



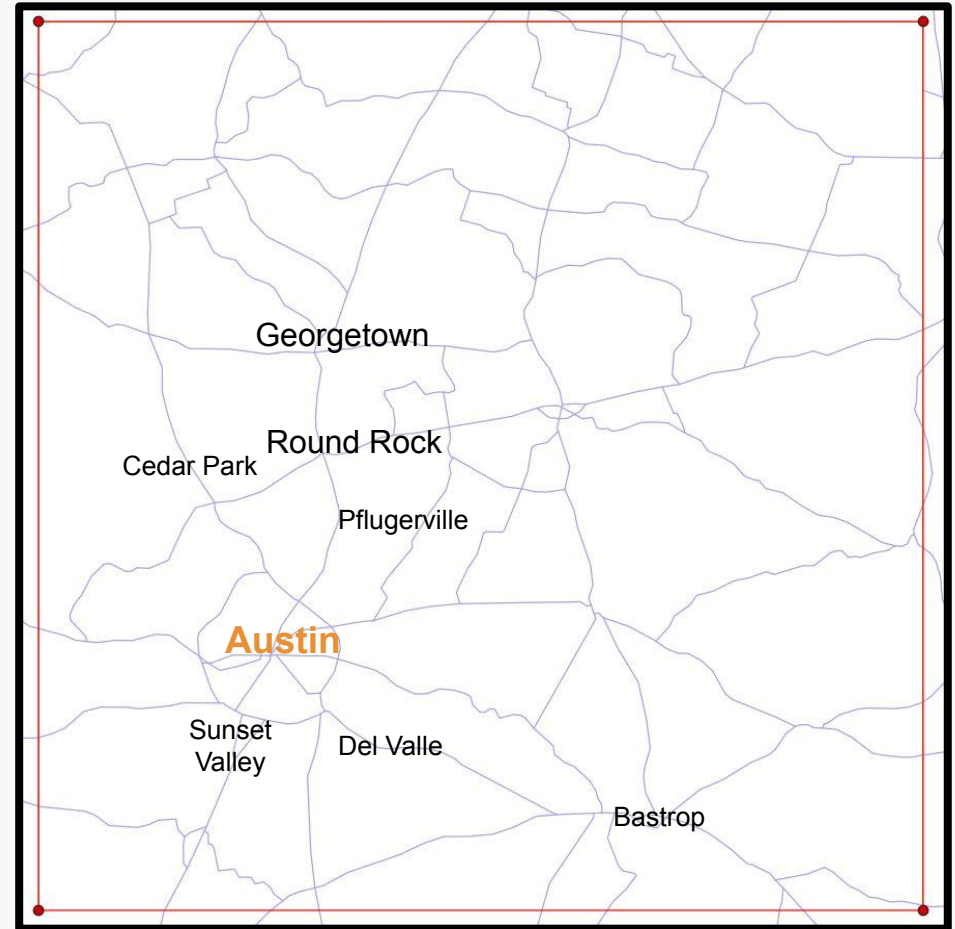
Prediction Model Process



Inputs

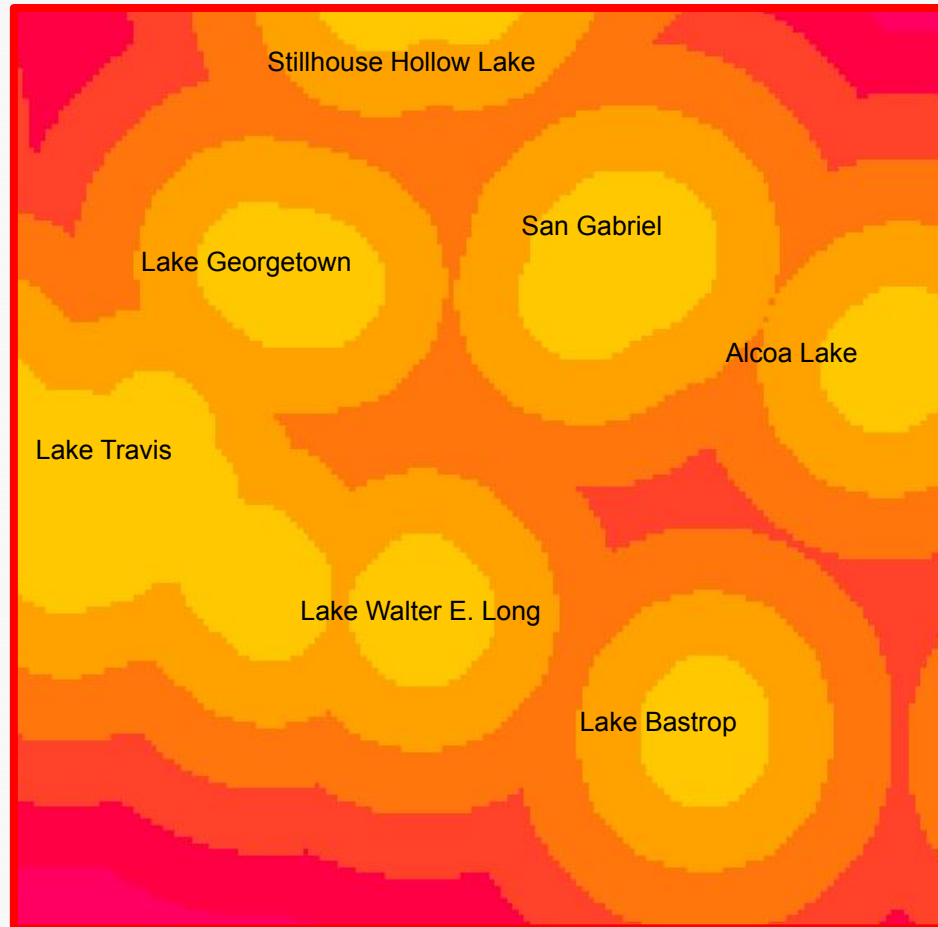


Inland Water Input

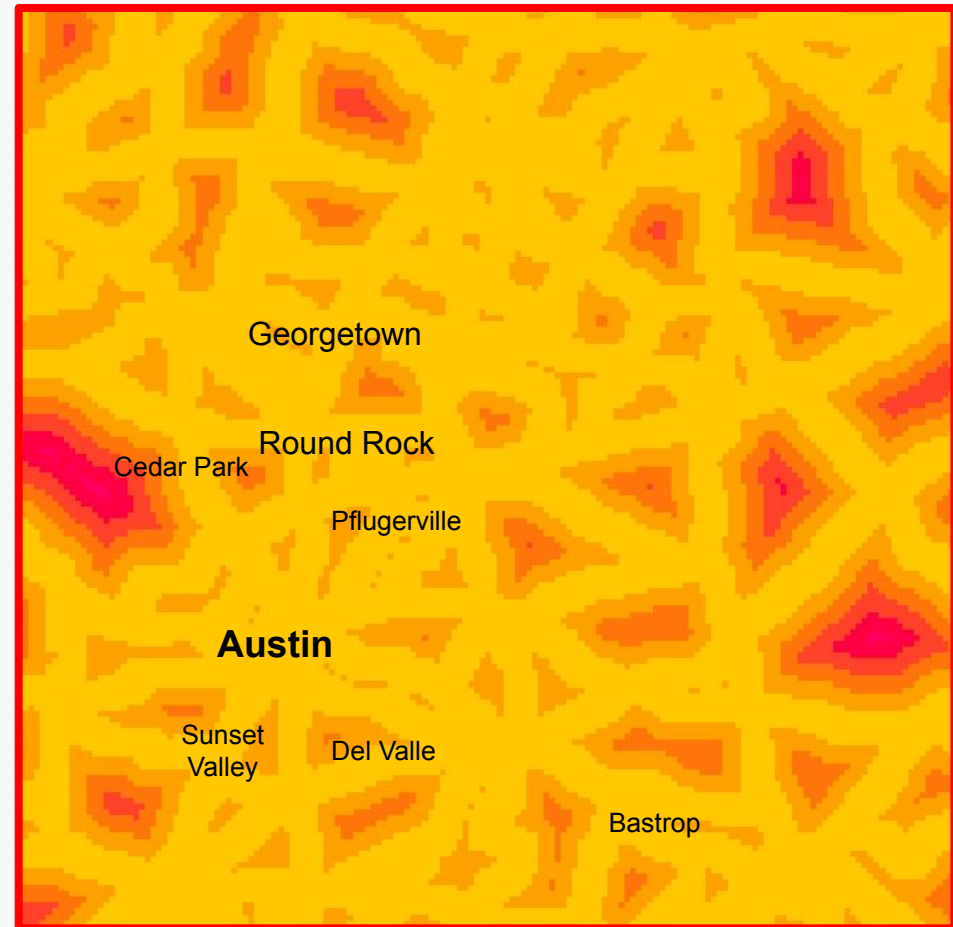


Major Roadways

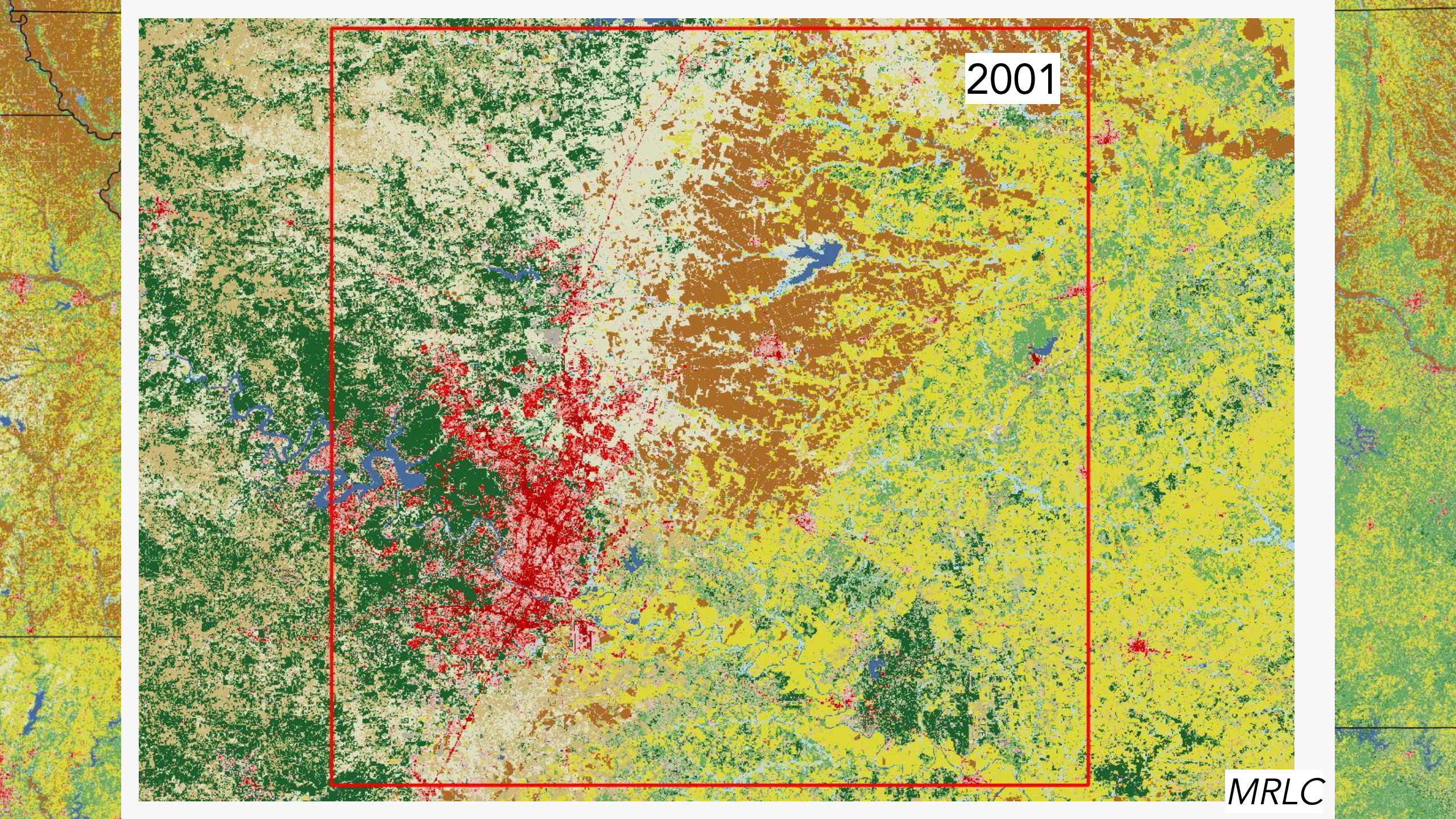
Euclidian Distance From



Distance From Water



Distance From Road



2001

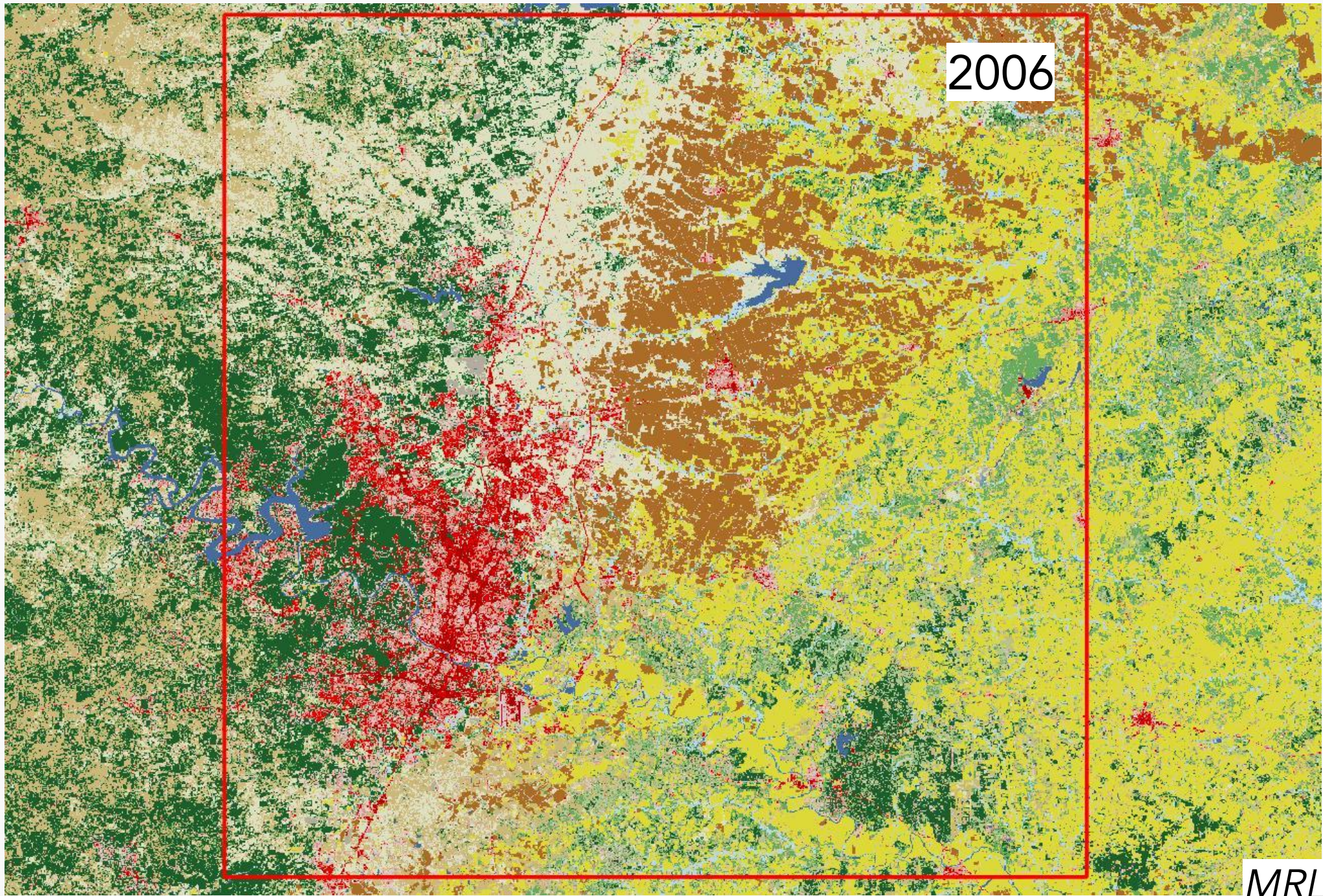
MRLC

2004

MRLC

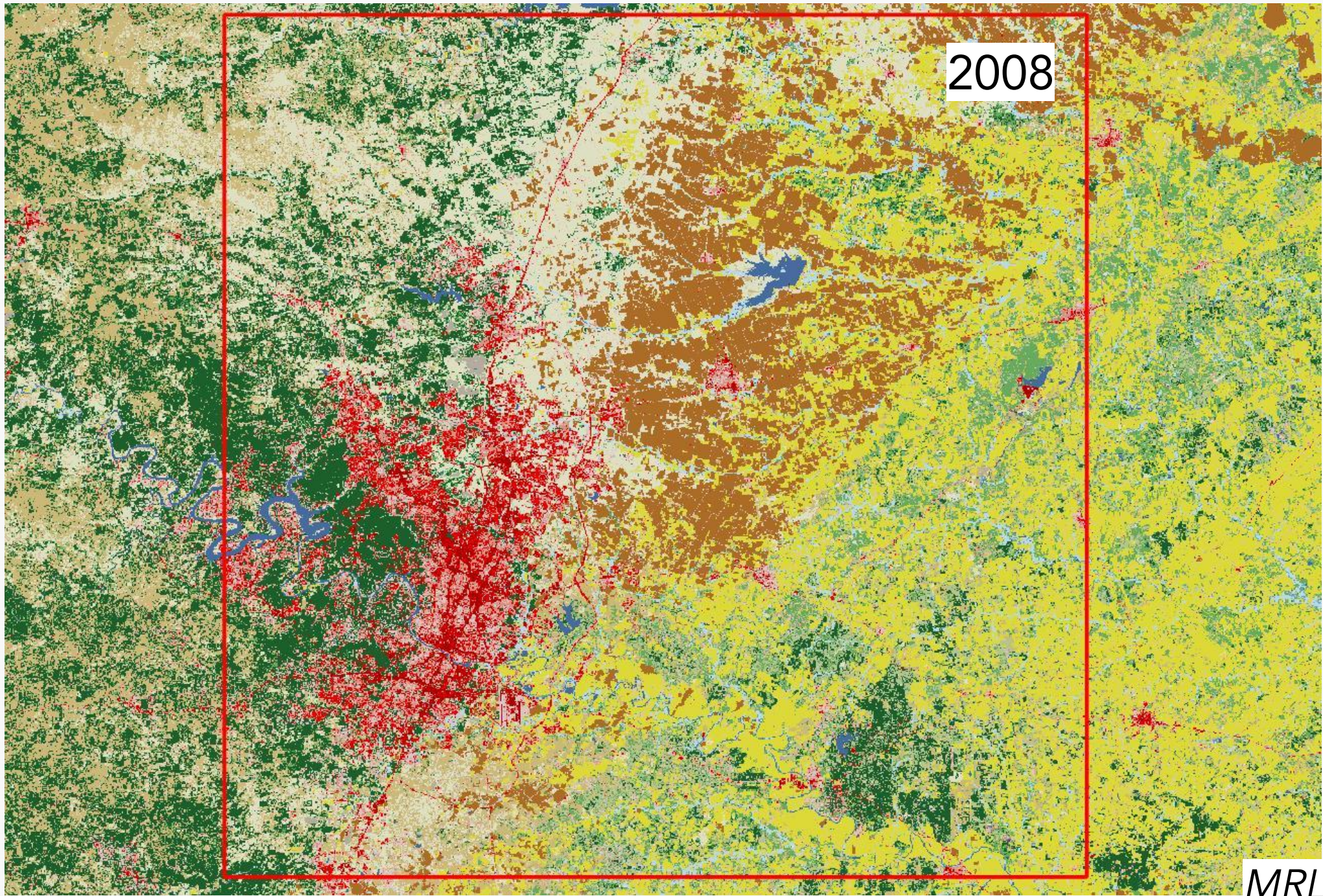
2006

MRLC



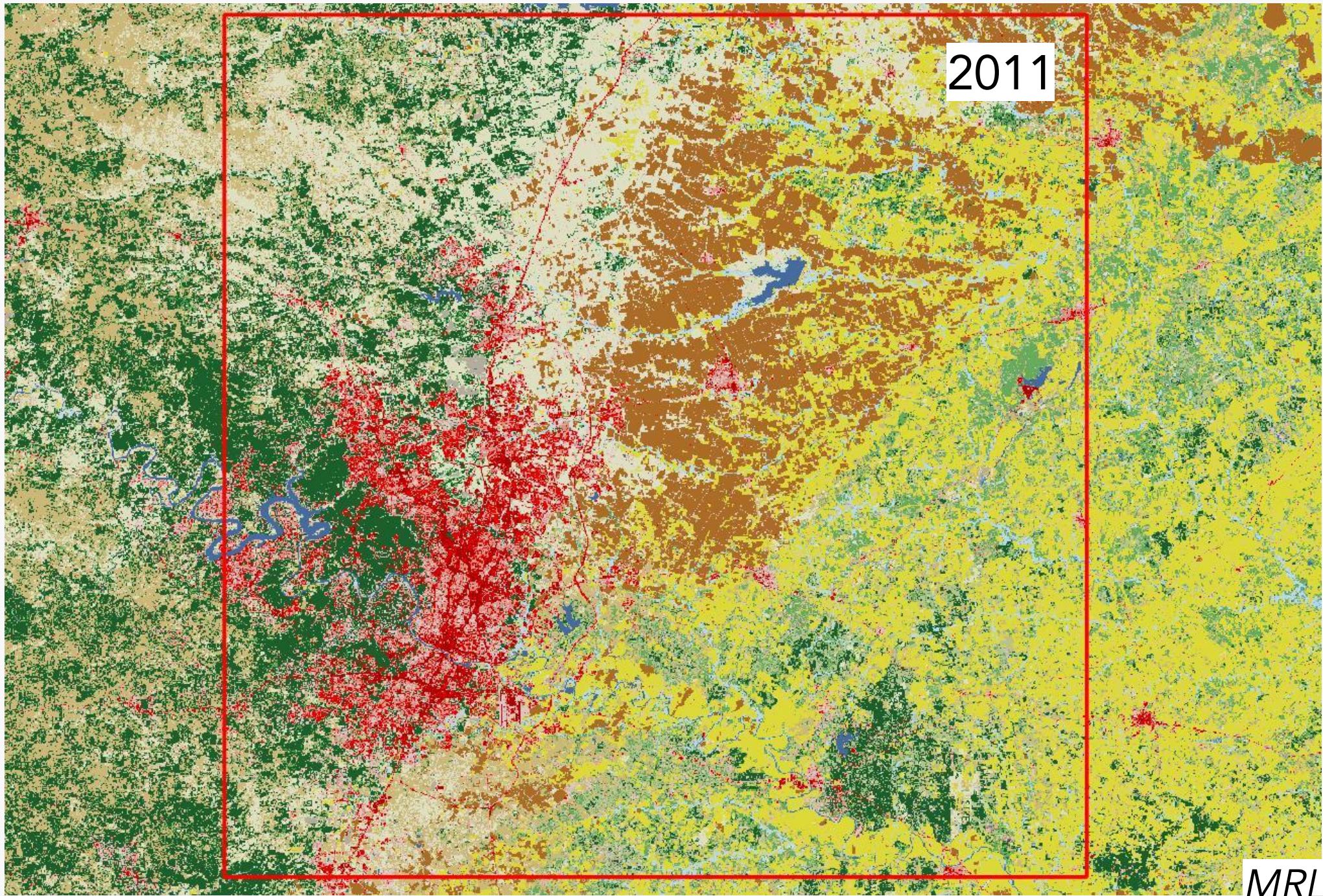
2008

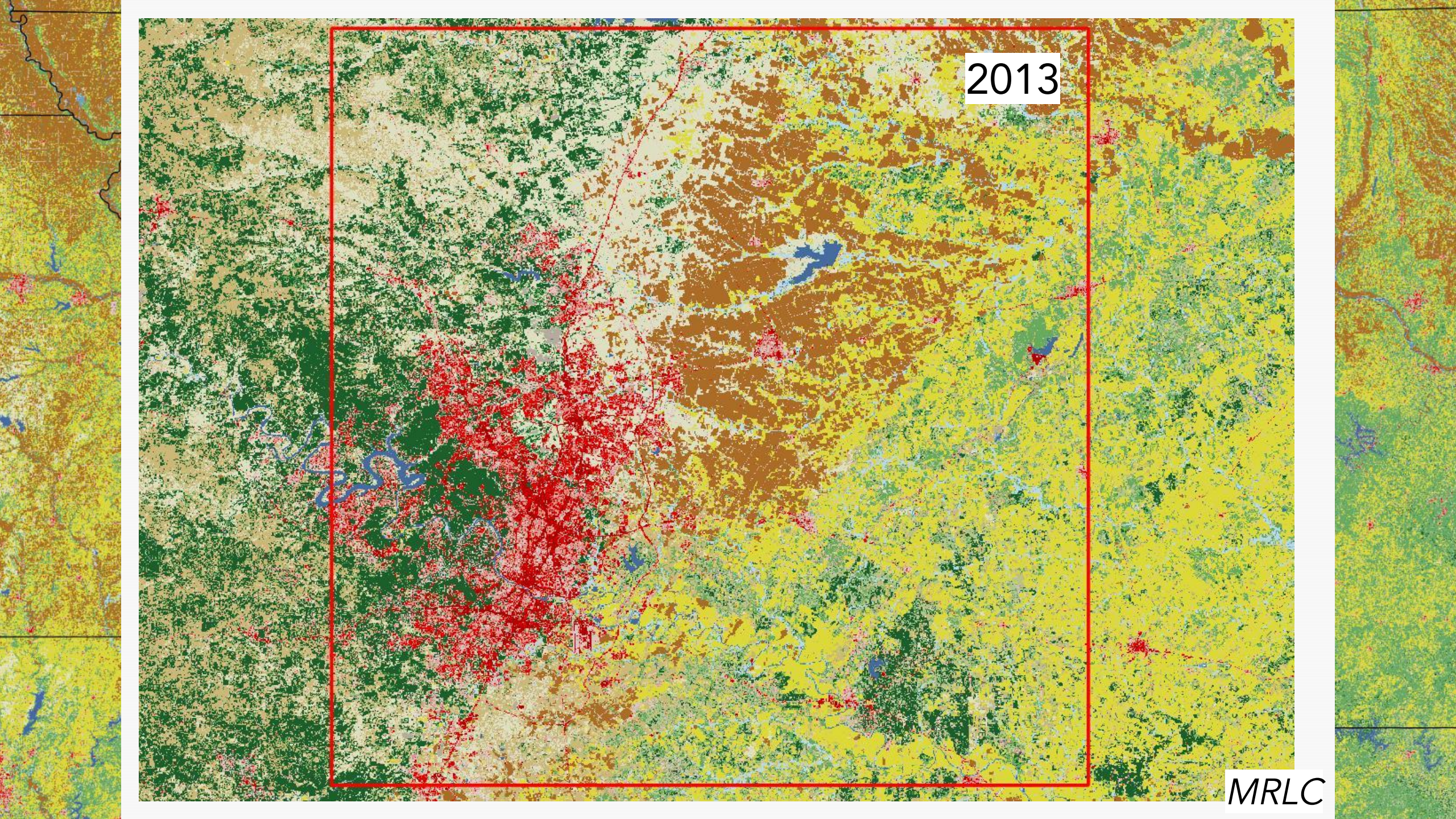
MRLC



2011

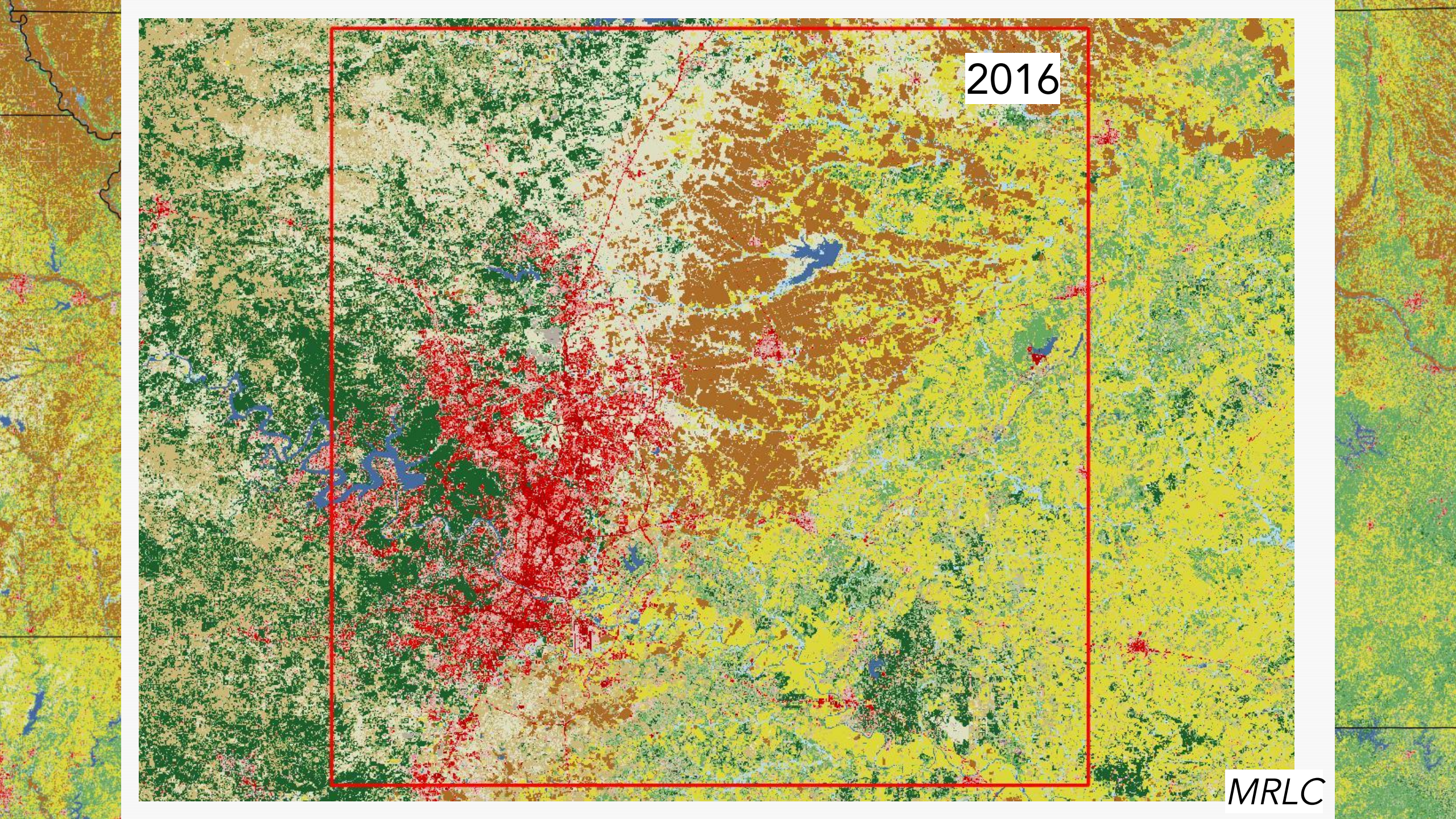
MRLC





2013

MRLC

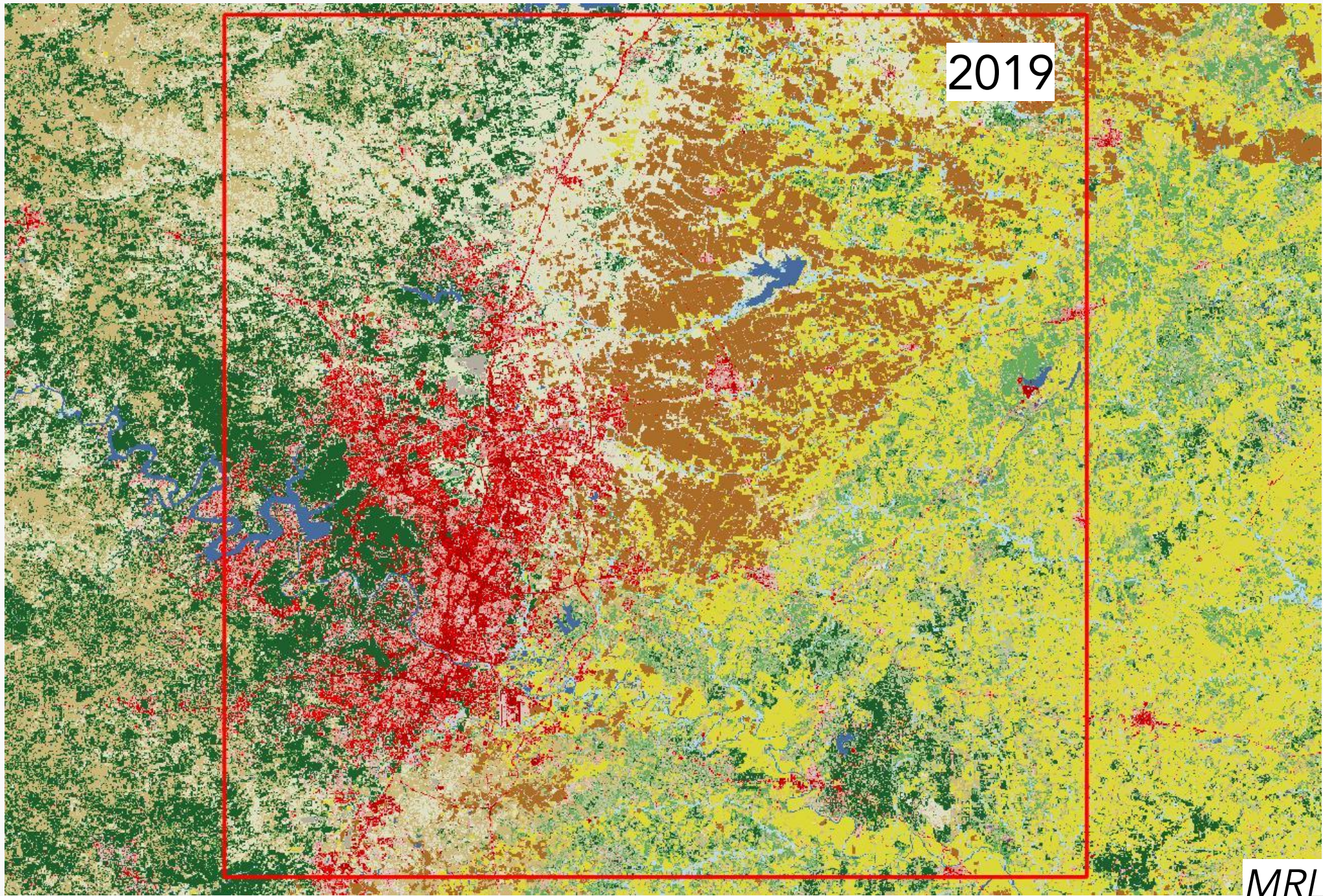


2016

MRLC

2019

MRLC

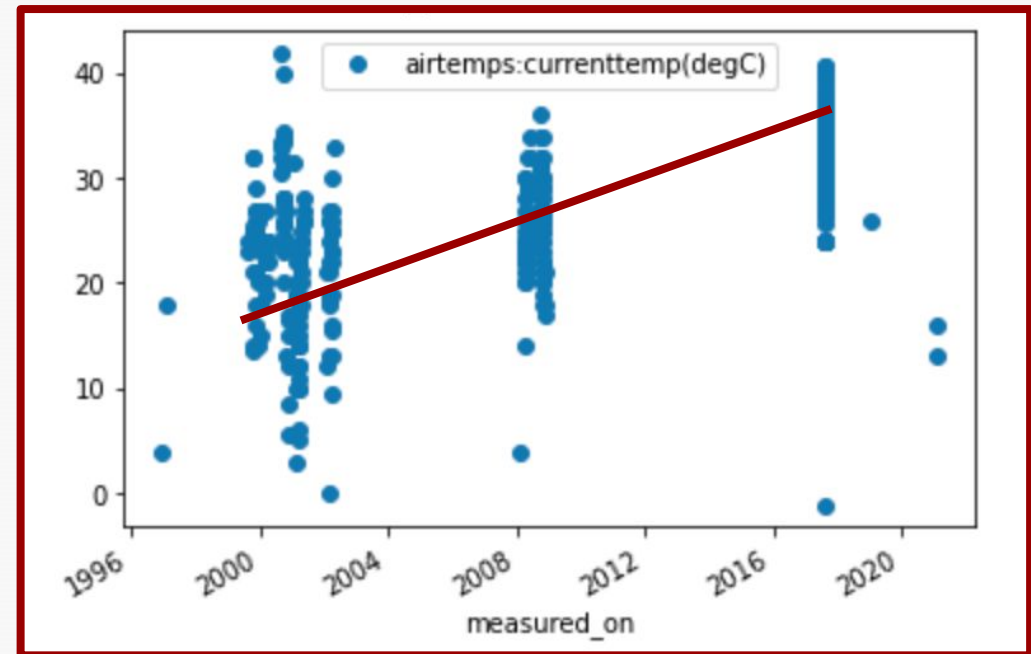
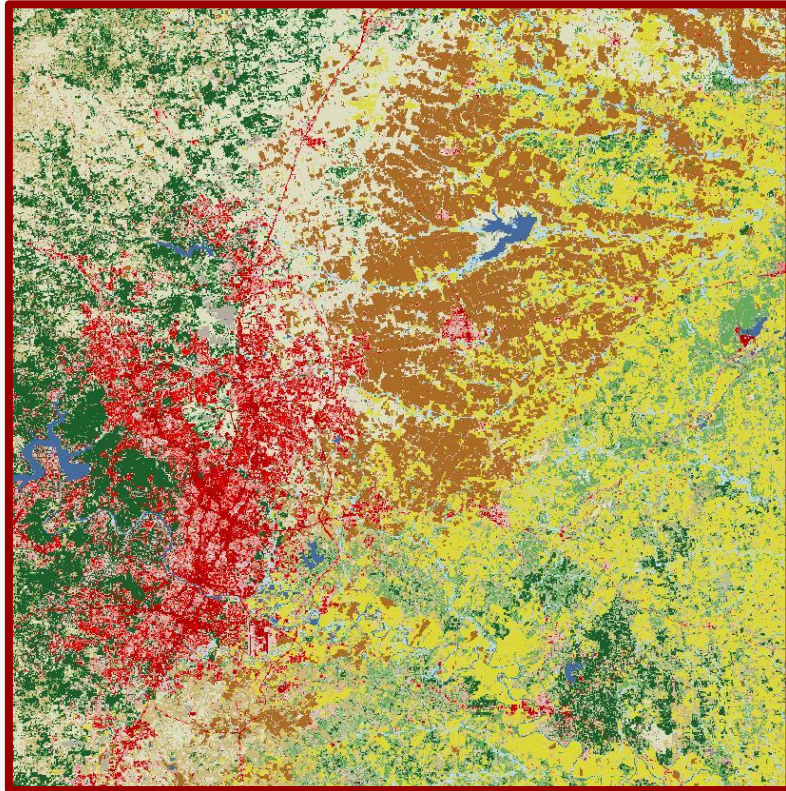


An aerial photograph of a landscape, possibly a wetland or coastal area, with a red rectangular boundary. The map is overlaid with a color-coded pattern: green for vegetation, yellow for open land or water, and red for a specific feature, possibly a road or boundary. The text "2022 (Predicted)" is in the top right, and "MRLC" is in the bottom right.

2022
(Predicted)

MRLC

Combining Parts



Potential Use



Green Efforts

References

- Guidigan, M. L. G., Sanou, C. L., Ragatoa, D. S., Fafa, C. O., & Mishra, V. N. (2019). Assessing land use/land cover dynamic and its impact in Benin Republic using land change model and CCI-LC products. *Earth Systems and Environment*, 3(1), 127-137.
- Myrup, L. O. (1969). A numerical model of the urban heat island. *Journal of Applied Meteorology and Climatology*, 8(6), 908-918.
- Rahman, M. T. U., Tabassum, F., Rasheduzzaman, M., Saba, H., Sarkar, L., Ferdous, J., ... & Islam, A. Z. (2017). Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh. *Environmental monitoring and assessment*, 189(11), 1-18.
- Rangarajan, S. (2021). Predicting the Future Land Use and Land Cover Changes for Bhavani Basin, Tamil Nadu, India Using QGIS MOLUSCE Plugin.