Los Angeles County Drought & Wildfire Monitoring

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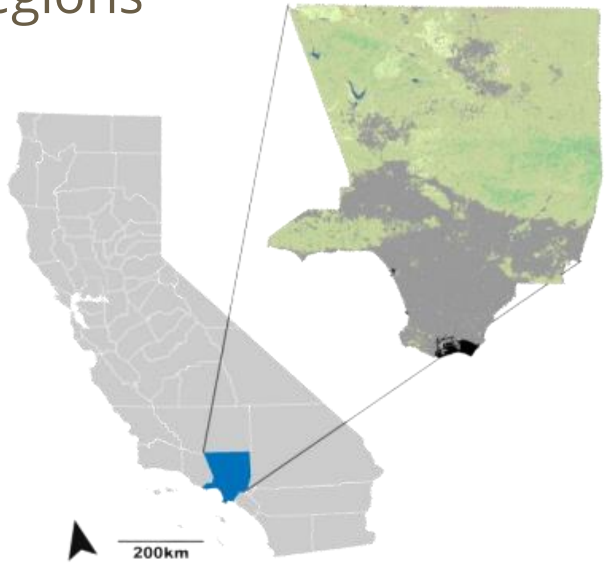
Background

- Los Angeles County is the most populous county in the United States
- Wide urban area surrounded by mountainous regions
- Almost 10 million residents
- Droughts and wildfires affect people state-wide



Background

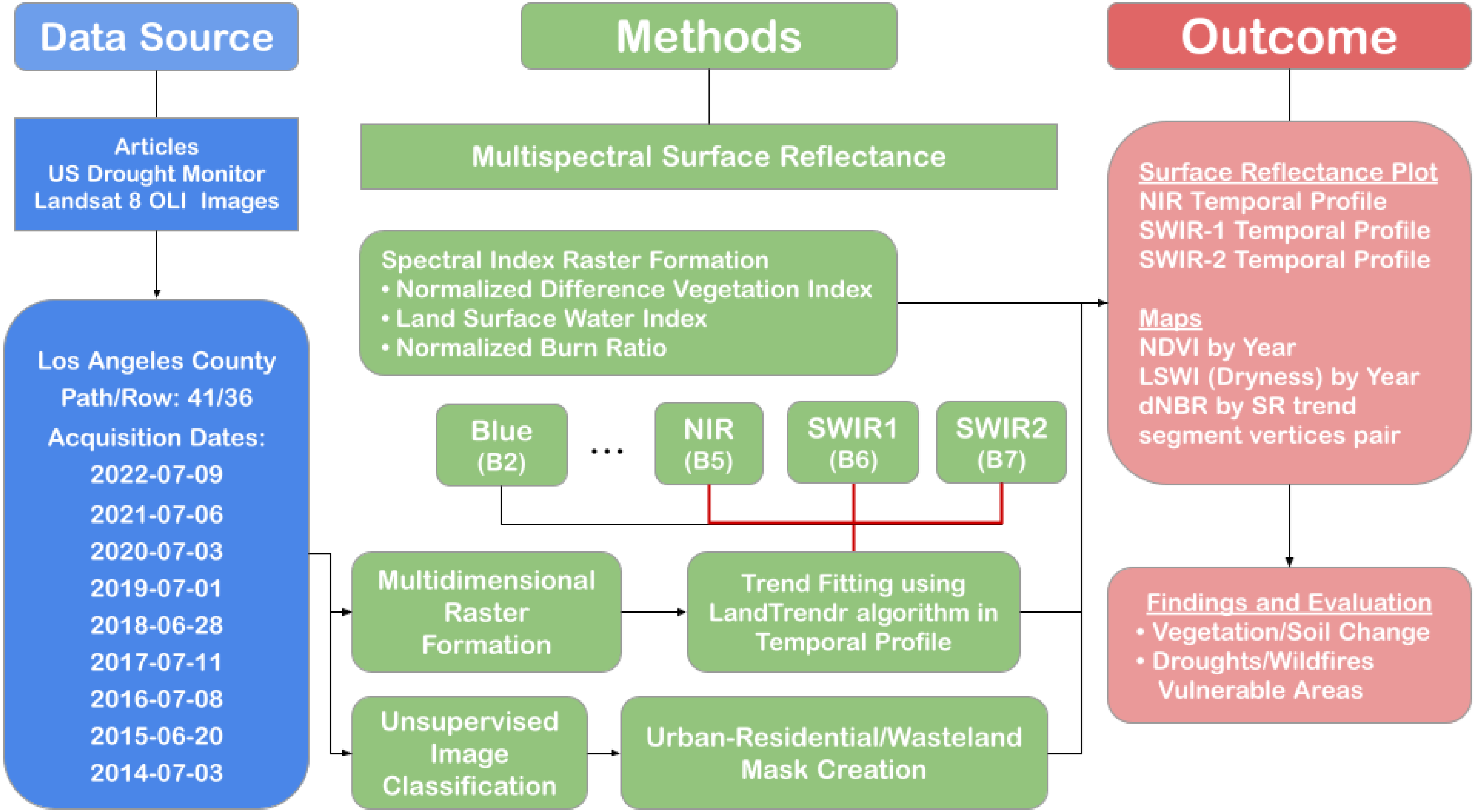
- Droughts in California led to a $3.5 billion decline in food processing and manufacturing
- 12,000 agricultural jobs lost

Image Source: Progressive Farmer

Research Questions and Objective

- Monitor water levels using remote sensing
- Collect agricultural data such as biomass vigour, supporting soil, and in-vegetation moisture content
- **We expect that the areas affected by droughts will increase over time**

Image Source: The Guardian


Data Source
Methods
Outcome
Articles
US Drought Monitor
Landsat 8 OLI Images
Multispectral Surface Reflectance
Surface Reflectance Plot
NIR Temporal Profile
SWIR-1 Temporal Profile
SWIR-2 Temporal Profile
Spectral Index Raster Formation
• Normalized Difference Vegetation Index
• Land Surface Water Index
• Normalized Burn Ratio
Maps
NDVI by Year
LSWI (Dryness) by Year
dNBR by SR trend segment vertices pair
Los Angeles County
Path/Row: 41/36
Acquisition Dates:
2022-07-09
2021-07-06
2020-07-03
2019-07-01
2018-06-28
2017-07-11
2016-07-08
2015-06-20
2014-07-03
Blue (B2)
...
NIR (B5)
SWIR1 (B6)
SWIR2 (B7)
Multidimensional Raster Formation
Trend Fitting using LandTrendr algorithm in Temporal Profile
Findings and Evaluation
• Vegetation/Soil Change
• Droughts/Wildfires Vulnerable Areas
Unsupervised Image Classification
Urban-Residential/Wasteland Mask Creation

Data Source

Articles
US Drought Monitor
Landsat 8 OLI Images

Los Angeles County
Path/Row: 41/36
Acquisition Dates:
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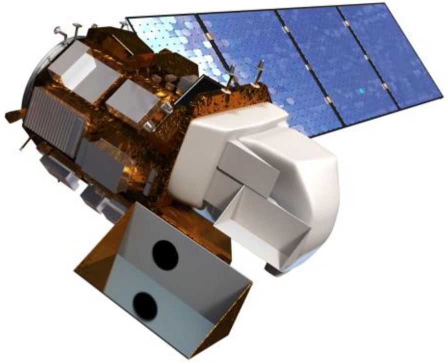
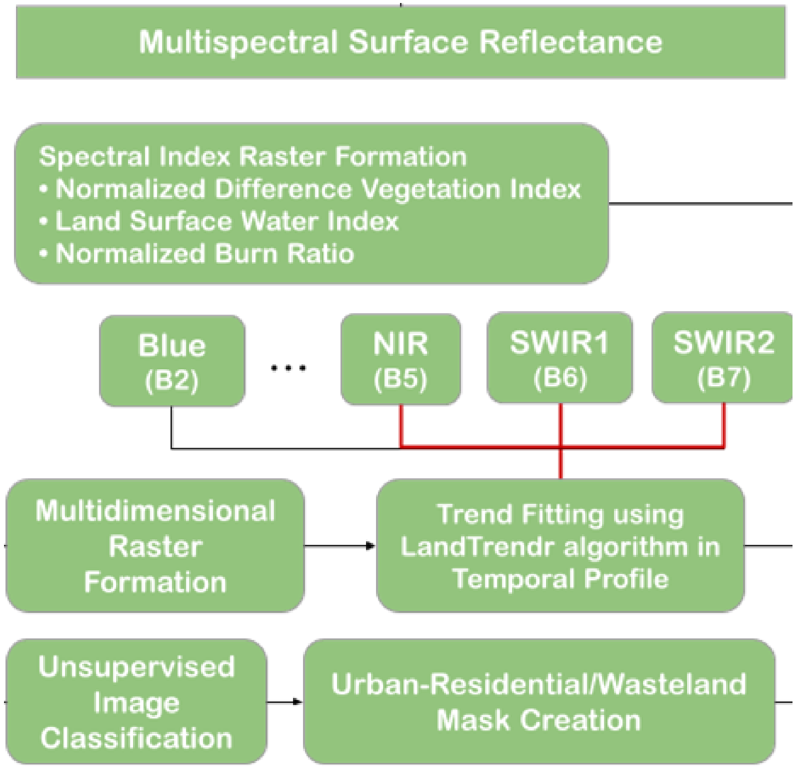
2014-07-03

- Landsat 8 Operational Land Imager
- **July 2014 - July 2022**
- This timespan has estimated dry years and years with no droughts
- 2011-2017: California drought



Landsat 8 image: https://www.usgs.gov/media/images/landsat-8

Methods



NDVI

General biomass vigour

LSWI

Soil moisture content

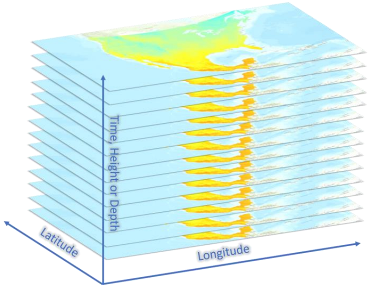
NBR

Burn ratio of area

LandTrendr

Tool for detecting and analyzing changes in land cover over time-series satellite imagery

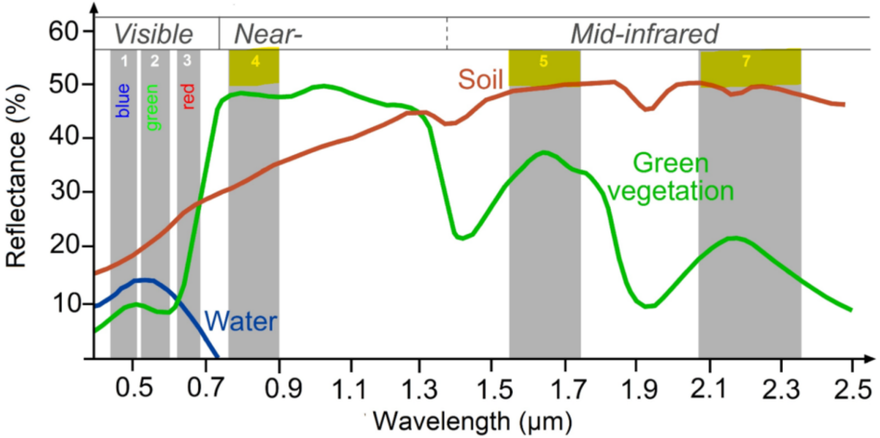
(Requires Multidimensional Raster)

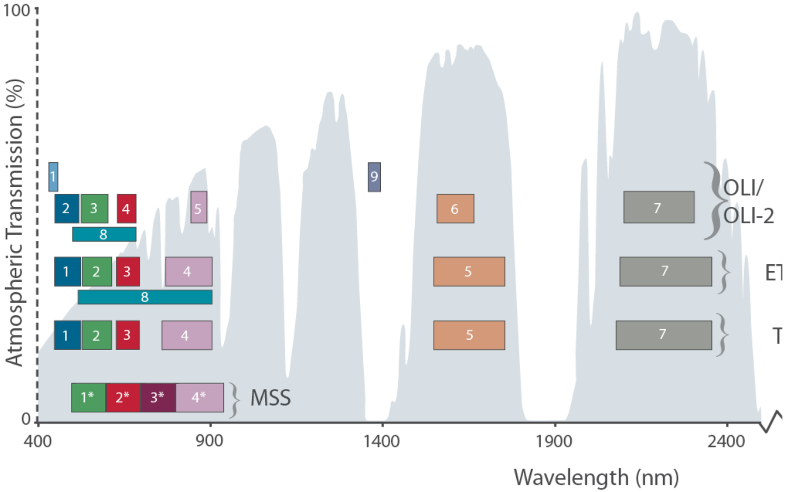


Methods

- NIR - high digital number when reflecting vegetation
    - Used for spectral indices involving vegetations

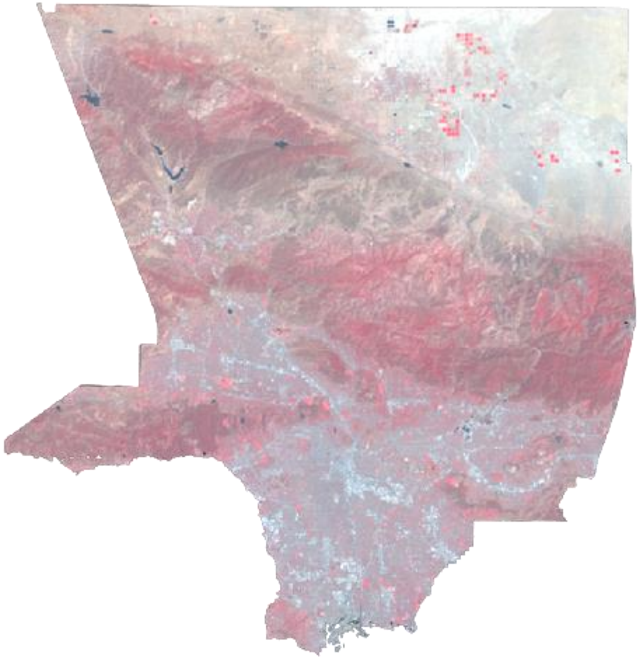
- SWIR - sensitive to changes in the vegetation and soil caused by fire
    - Low moisture results in lower SWIR reflectance, especially approx. 2.08 - 2.35 µm



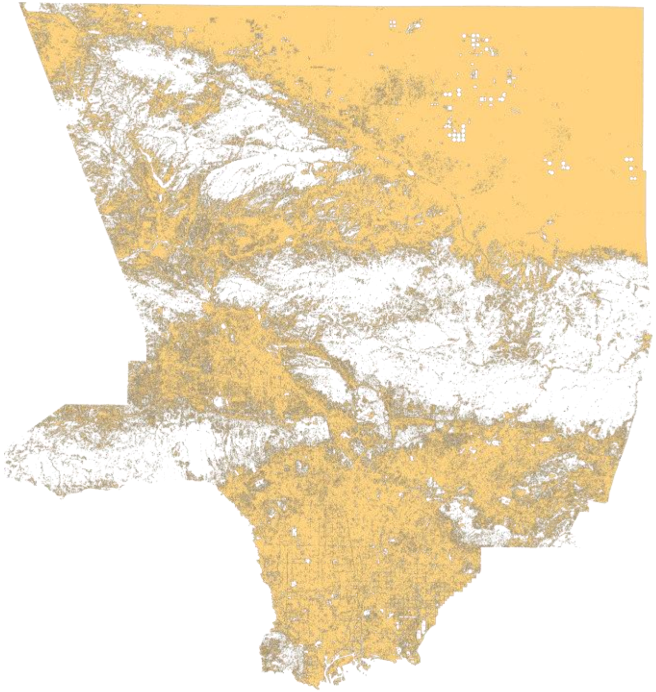


Mask Creation for Non-Urban Highlighting Layer Image Classification

Highlighter Mask Creation - FCC Image Classification



Unsupervised Classification



Classified all the subclasses formed, and merged as
Non-Urban and Urban/Barren land/ Wasteland
(The classes are binary at the end, except Unclassified)

Highlighter Mask Creation - Accuracy Assessment

ERROR MATRIX

Reference Data

Classified Data		Mountain/V	Urban/Resi	Row Total
Mountain/Ve	0	13	5	18
Urban/Resid	0	6	26	32
Column Total	0	19	31	50

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Mountain/Ve	19	18	13	68.42%	72.22%
Urban/Resid	31	32	26	83.87%	81.25%
Totals	50	50	39		

Overall Classification Accuracy = 78.00%

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.5283

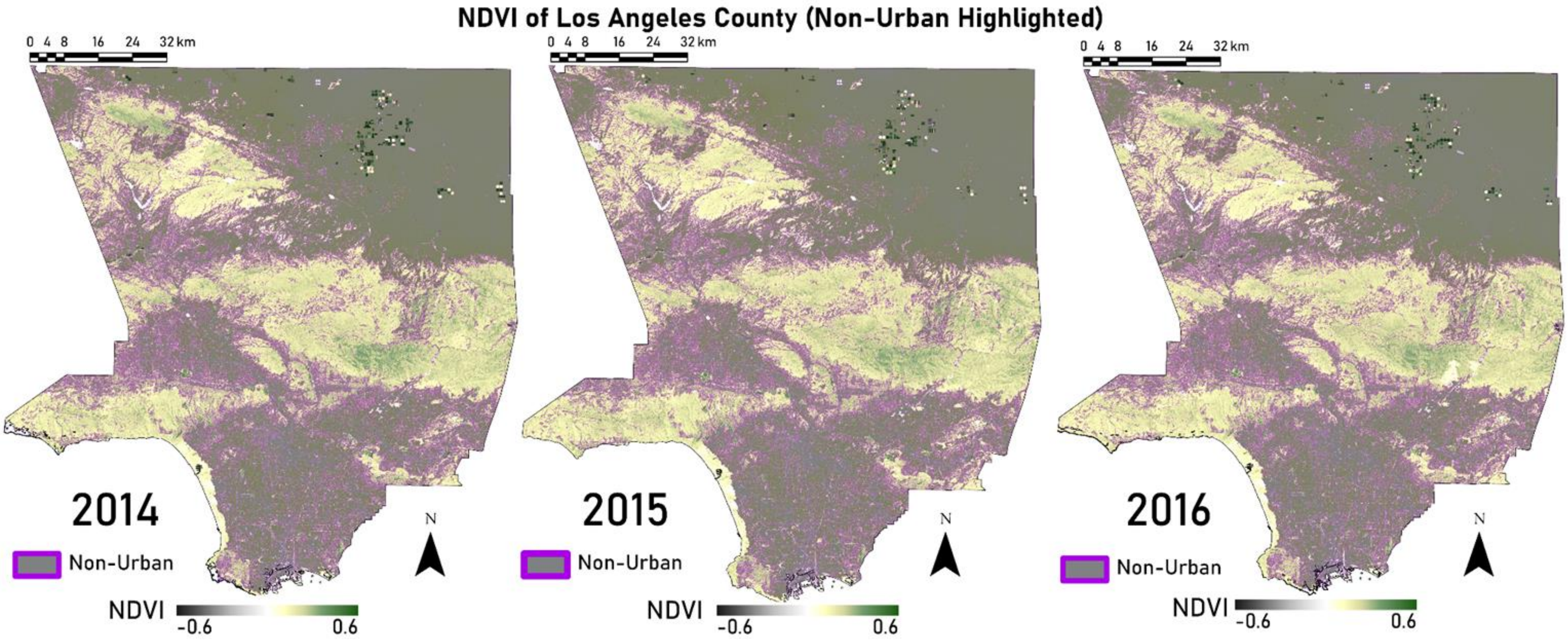
Conditional Kappa for each Category.

Class Name	Kappa
Mountain/Ve	0.5520
Urban/Resid	0.5066

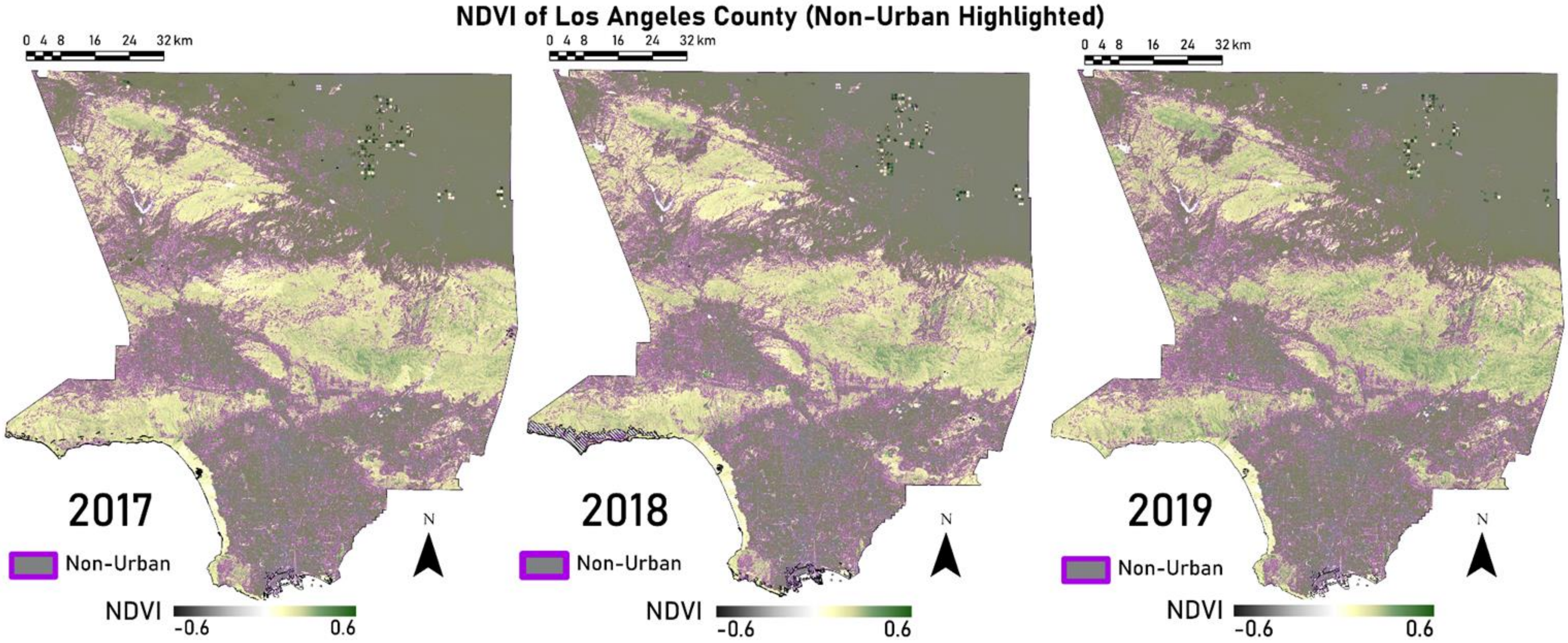
- Moderate level of agreement
- Higher PA & UA in *Urban/Resid*
- Use *Urban/Resid* as mask for display instead of extracting from *Mountain/Ve*

NDVI
Normalized Difference Vegetation Index

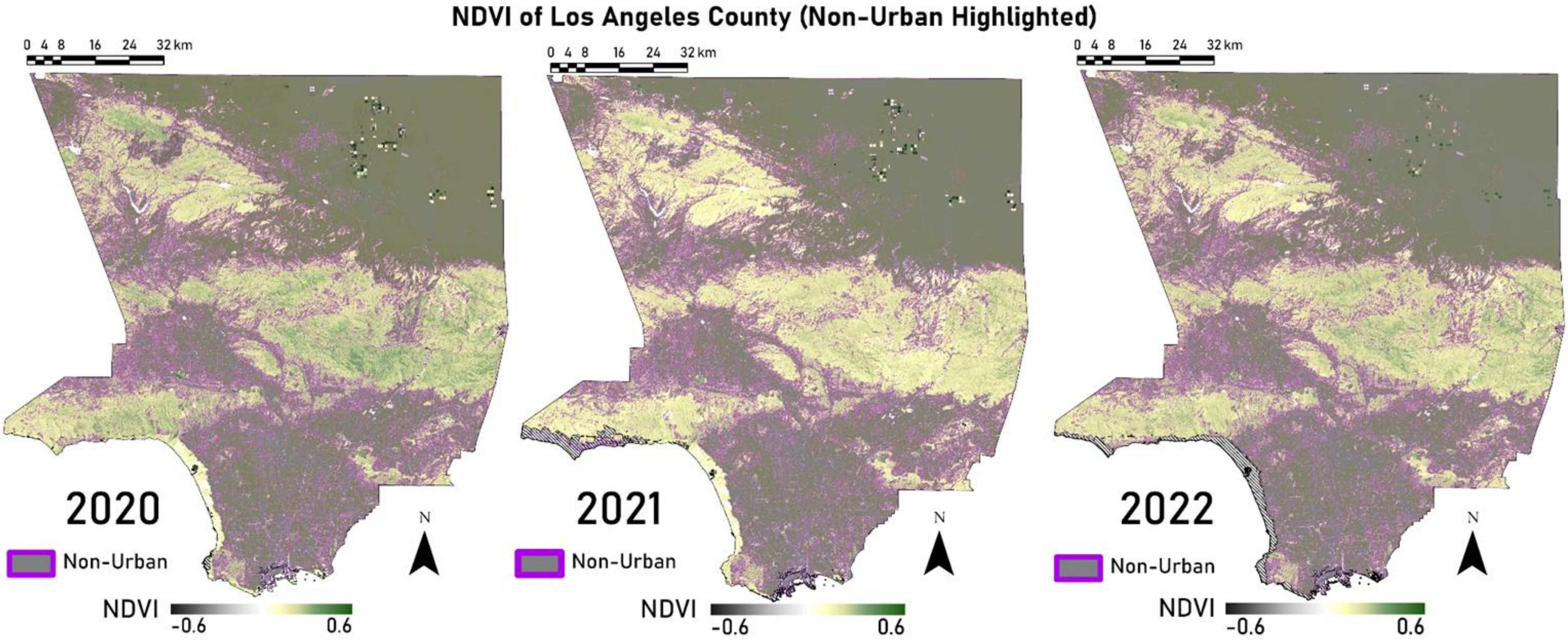
NDVI for Vegetation Vigor 2014 - 2016



NDVI for Vegetation Vigor 2017 - 2019

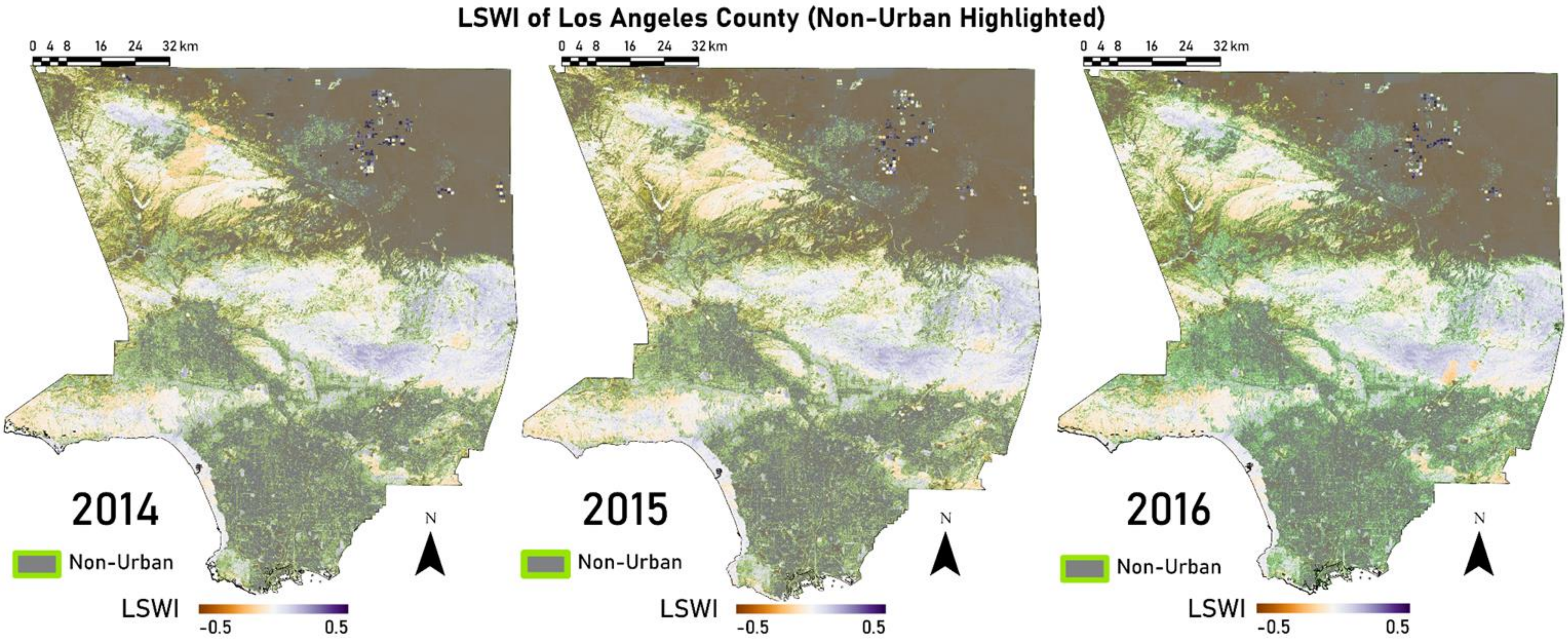


NDVI for Vegetation Vigor 2020 - 2022

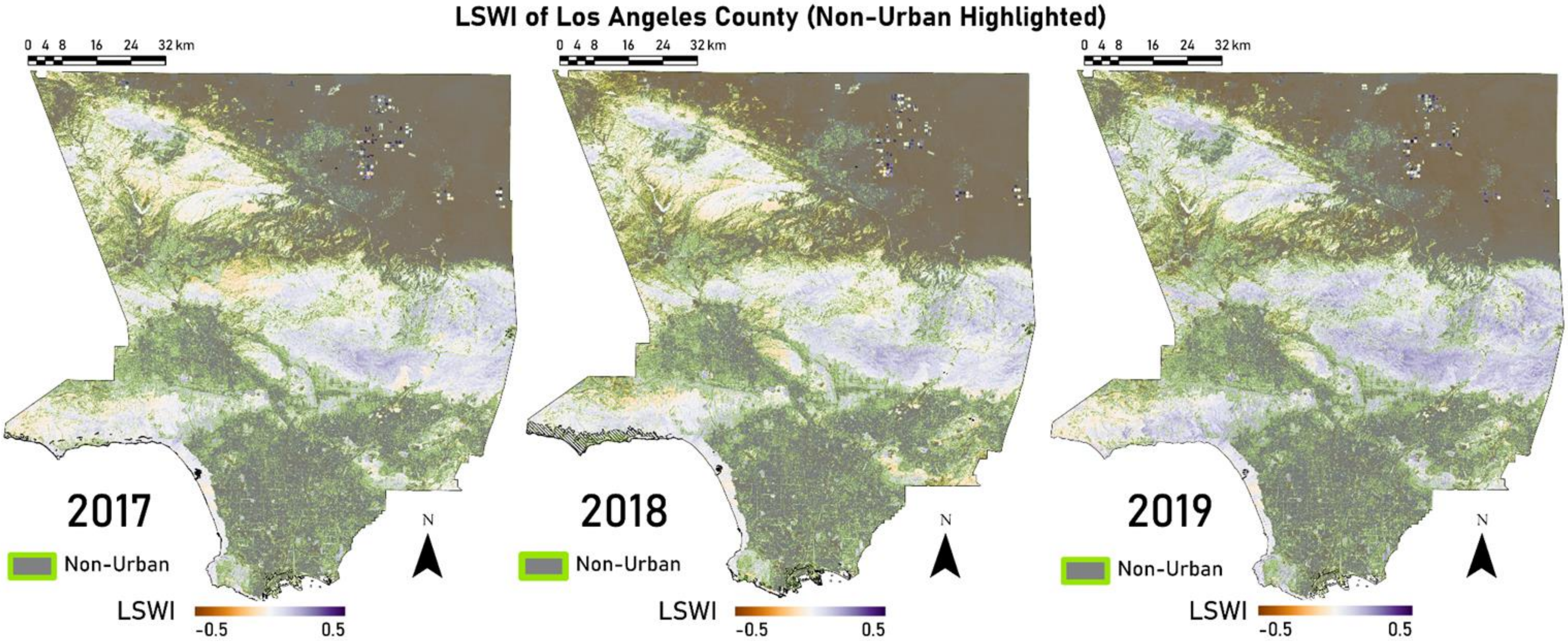


LSWI
Land Surface Water Index

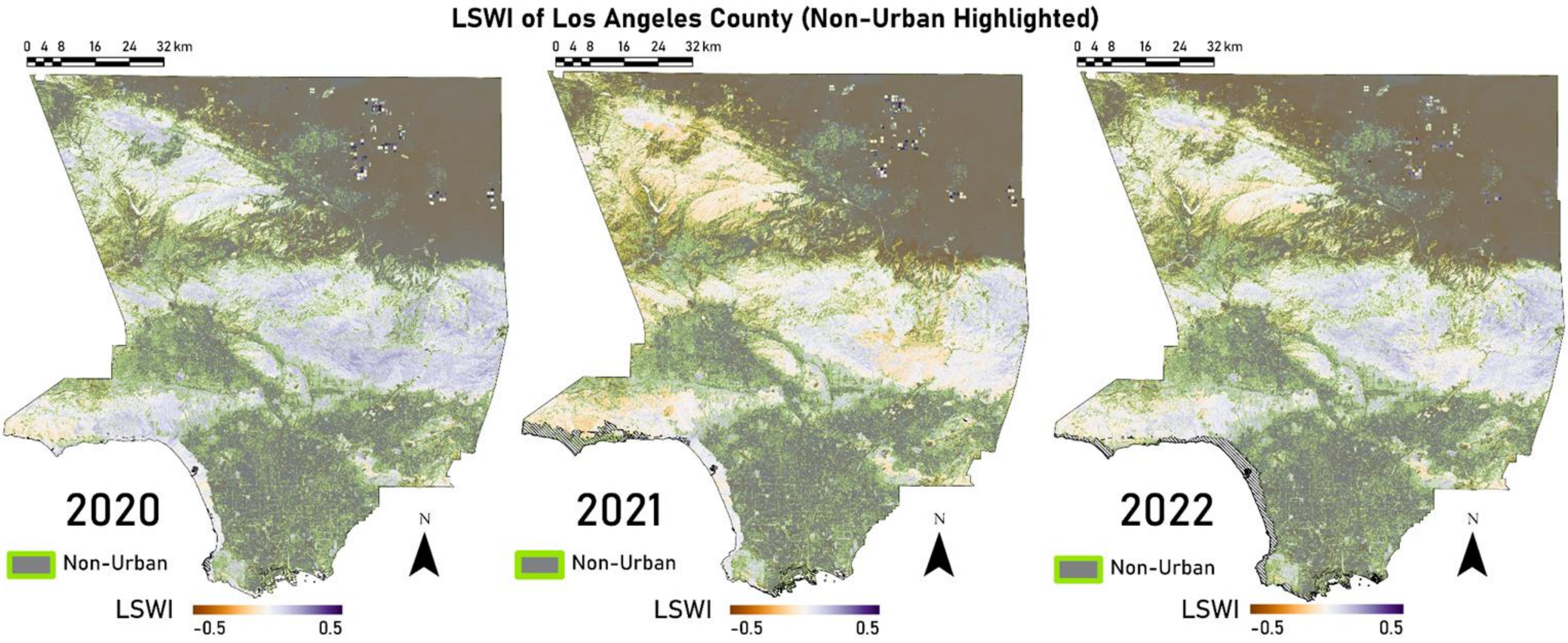
LSWI for In-Vegetation/Soil Moisture 2014 - 2016



LSWI for In-Vegetation/Soil Moisture 2017 - 2019

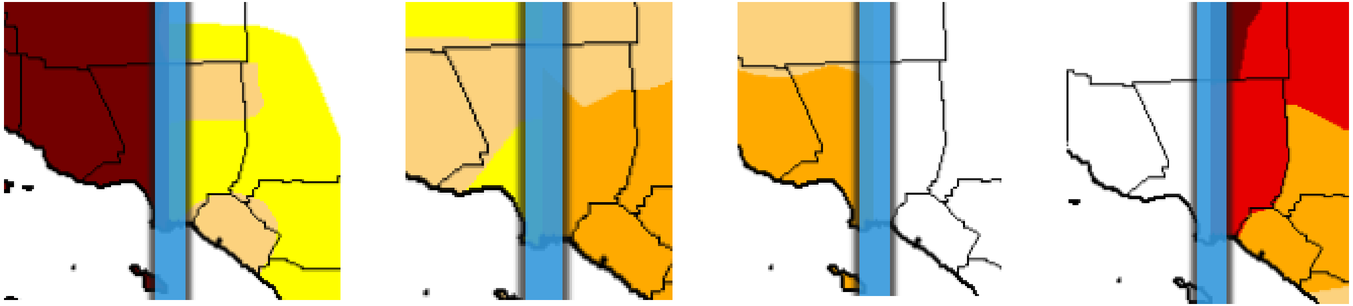


LSWI for In-Vegetation/Soil Moisture 2020 - 2022



Key Results from Surface Reflectance Trend Inspection

- Changes in SWIR *(short wave infrared)* reflectance
  - 2016 - 2017 decline
  - 2017 - 2018 rise
  - 2018 - 2020 decline
  - 2020 - 2021 rise
- SWIR (band 7) is the most sensitive to fire hotspots
  - Indicates burned or actively burning regions



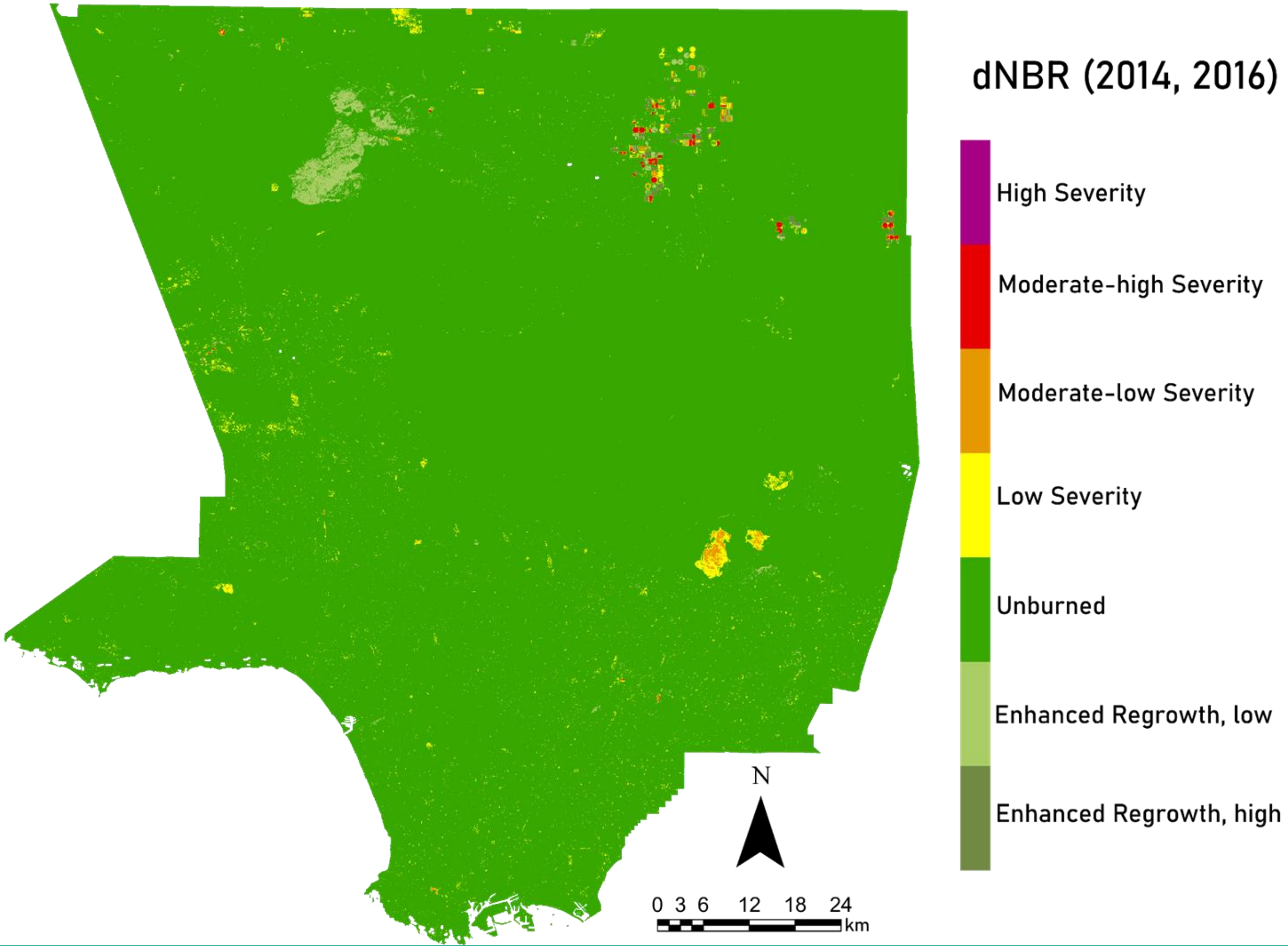
Source: US Drought Monitor

dNBR
Difference Normalized Burn Ratio

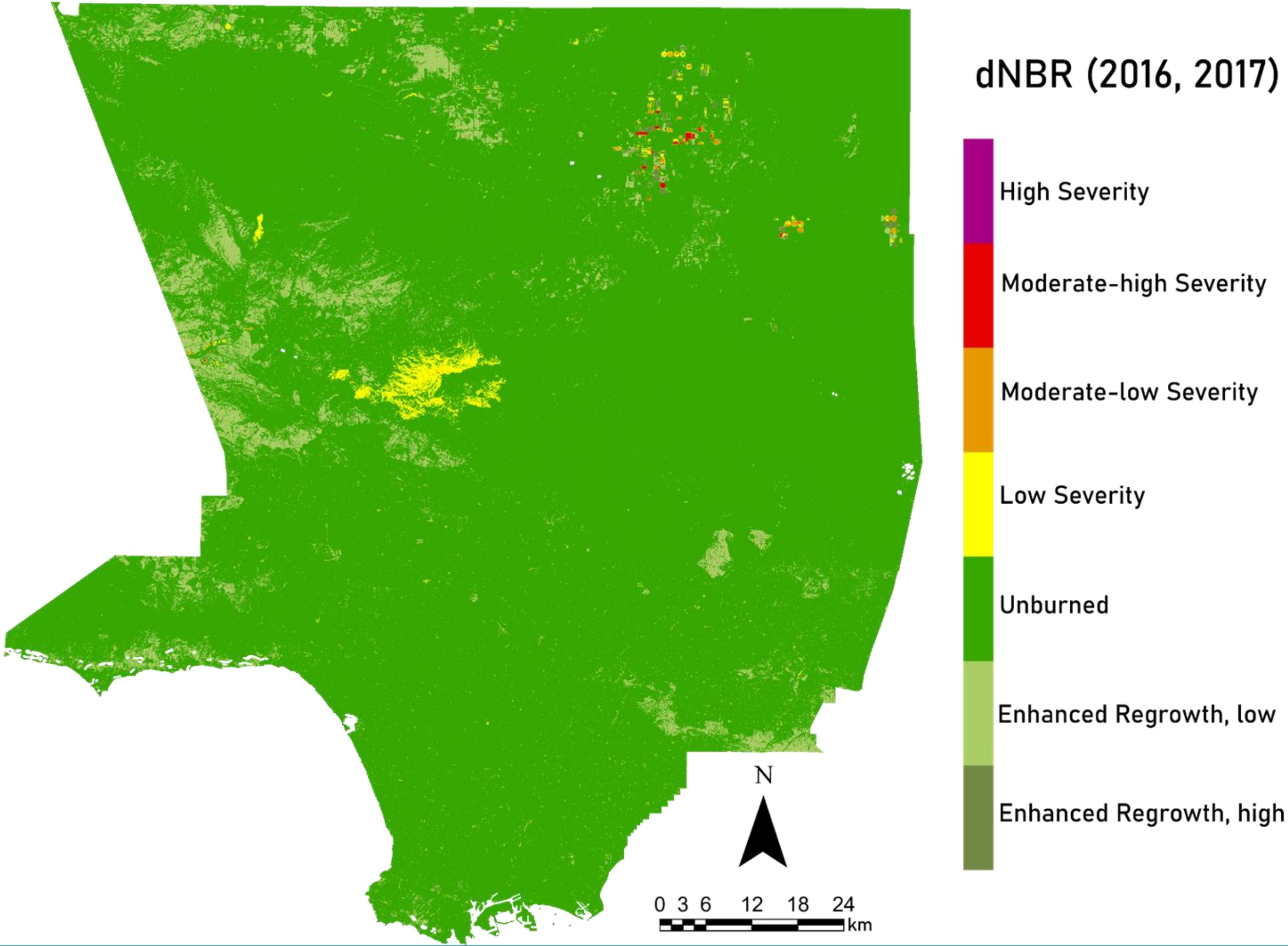
Severity Level	dNBR Range (scaled by 10^3)	dNBR Range (not scaled)
Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-250 to -101	-0.250 to -0.101
Unburned	-100 to +99	-0.100 to +0.99
Low Severity	+100 to +269	+0.100 to +0.269
Moderate-low Severity	+270 to +439	+0.270 to +0.439
Miderate-high Severity	+440 to +659	+0.440 to +0.659
High Severity	+660 to +1300	+0.660 to +1.300

Burn severity levels obtained calculating dNBR, proposed by USGS

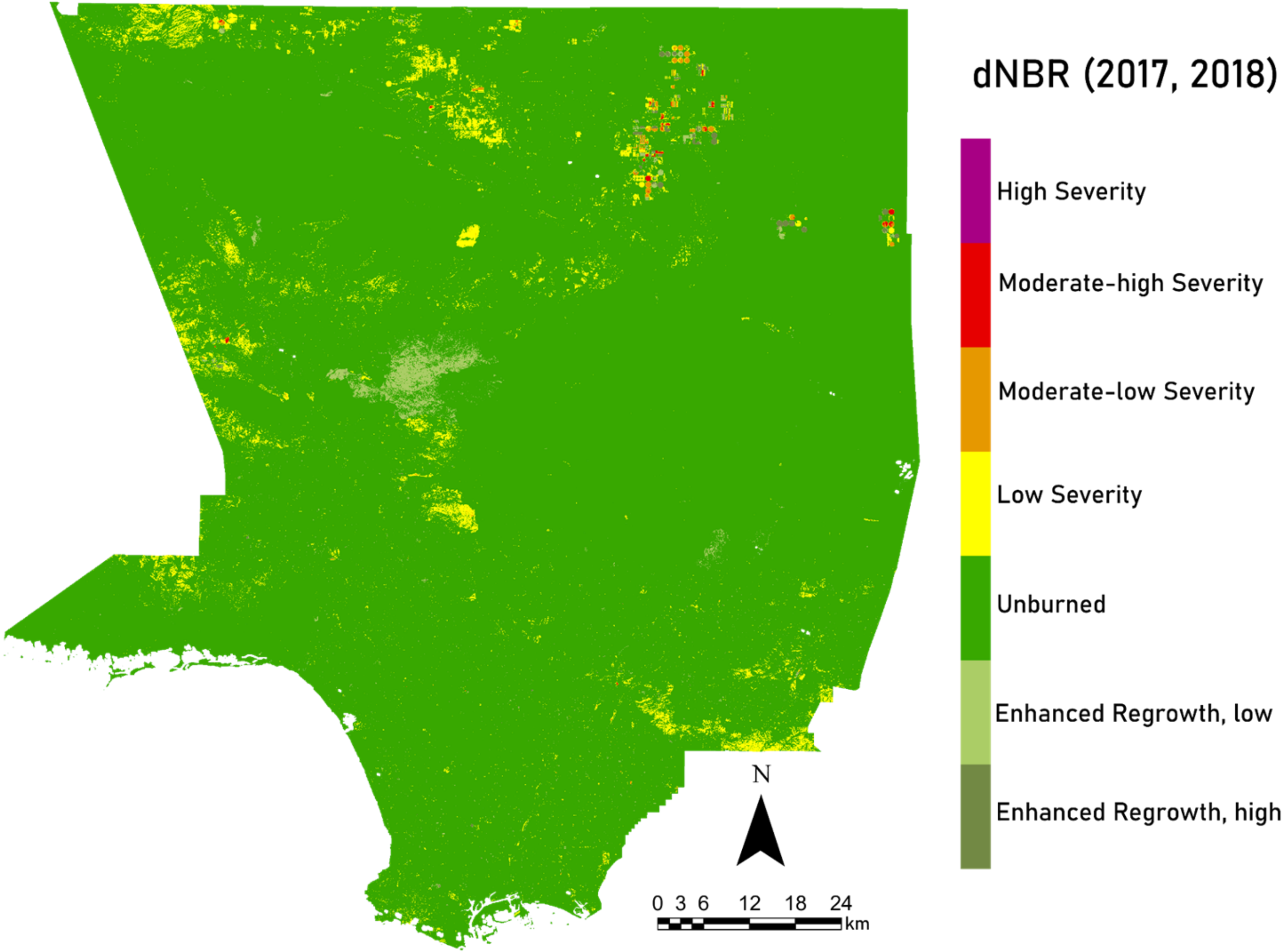
dNBR for 2014 - 2016



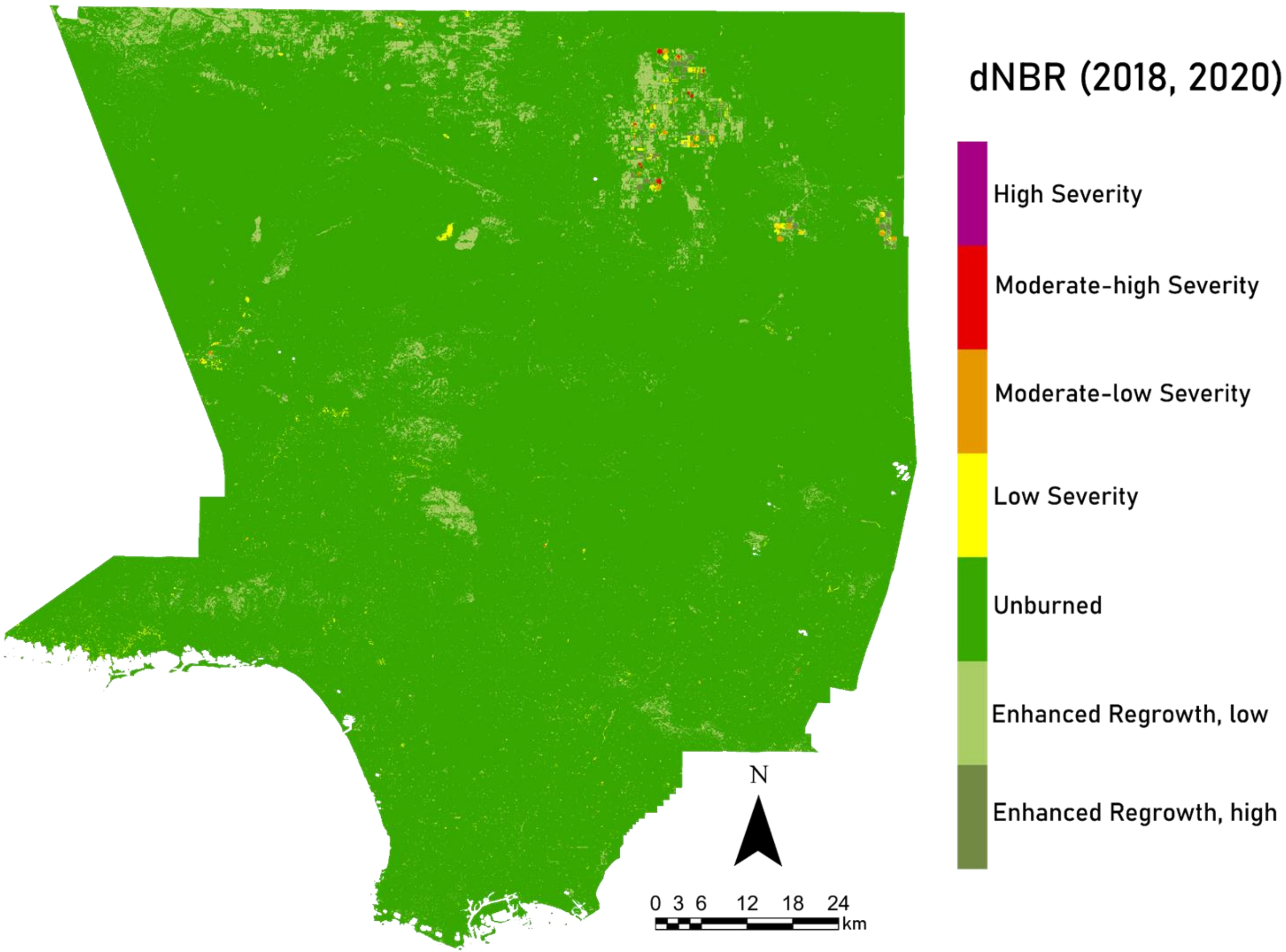
dNBR for 2016 - 2017



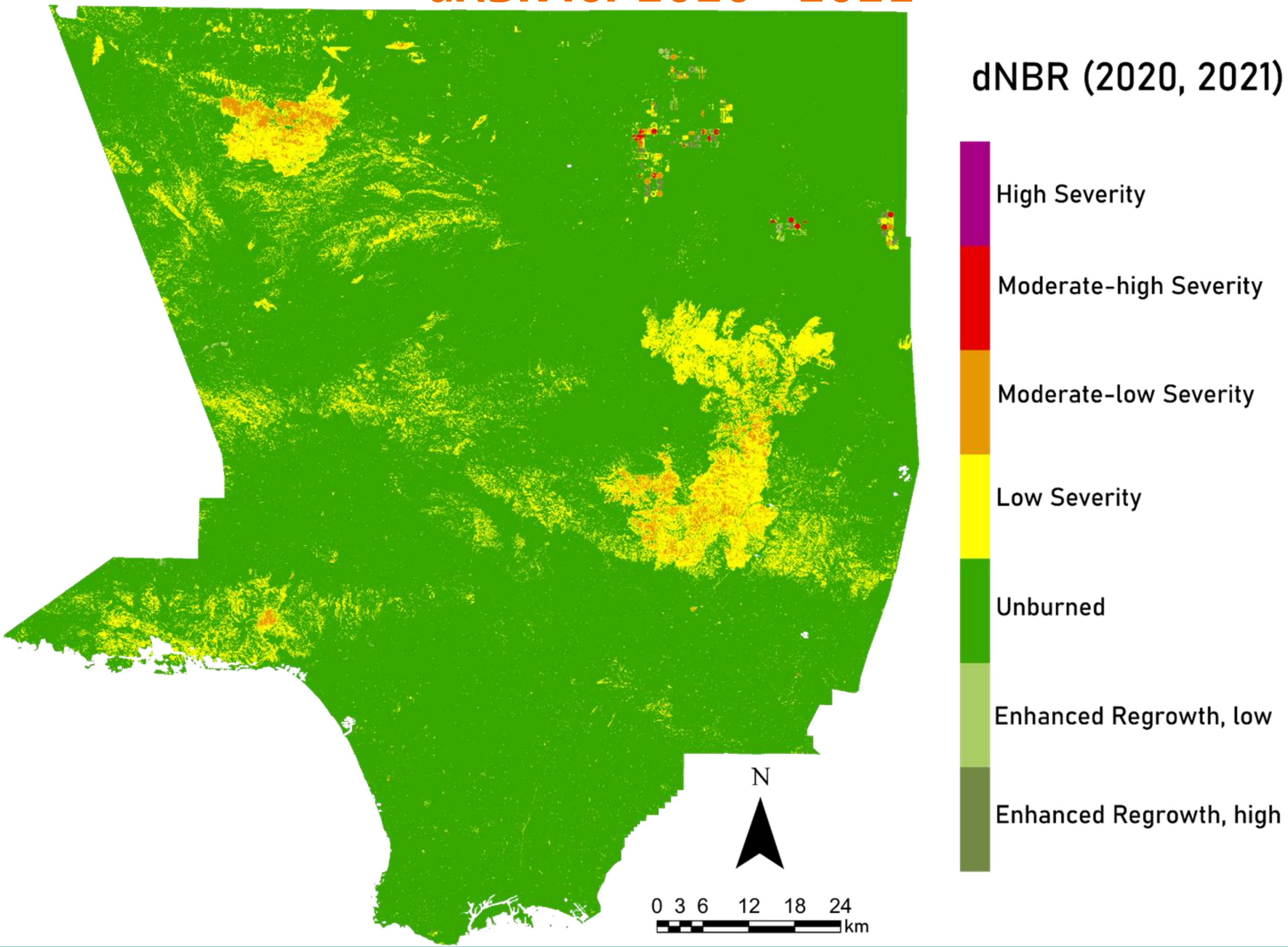
dNBR for 2017 - 2018



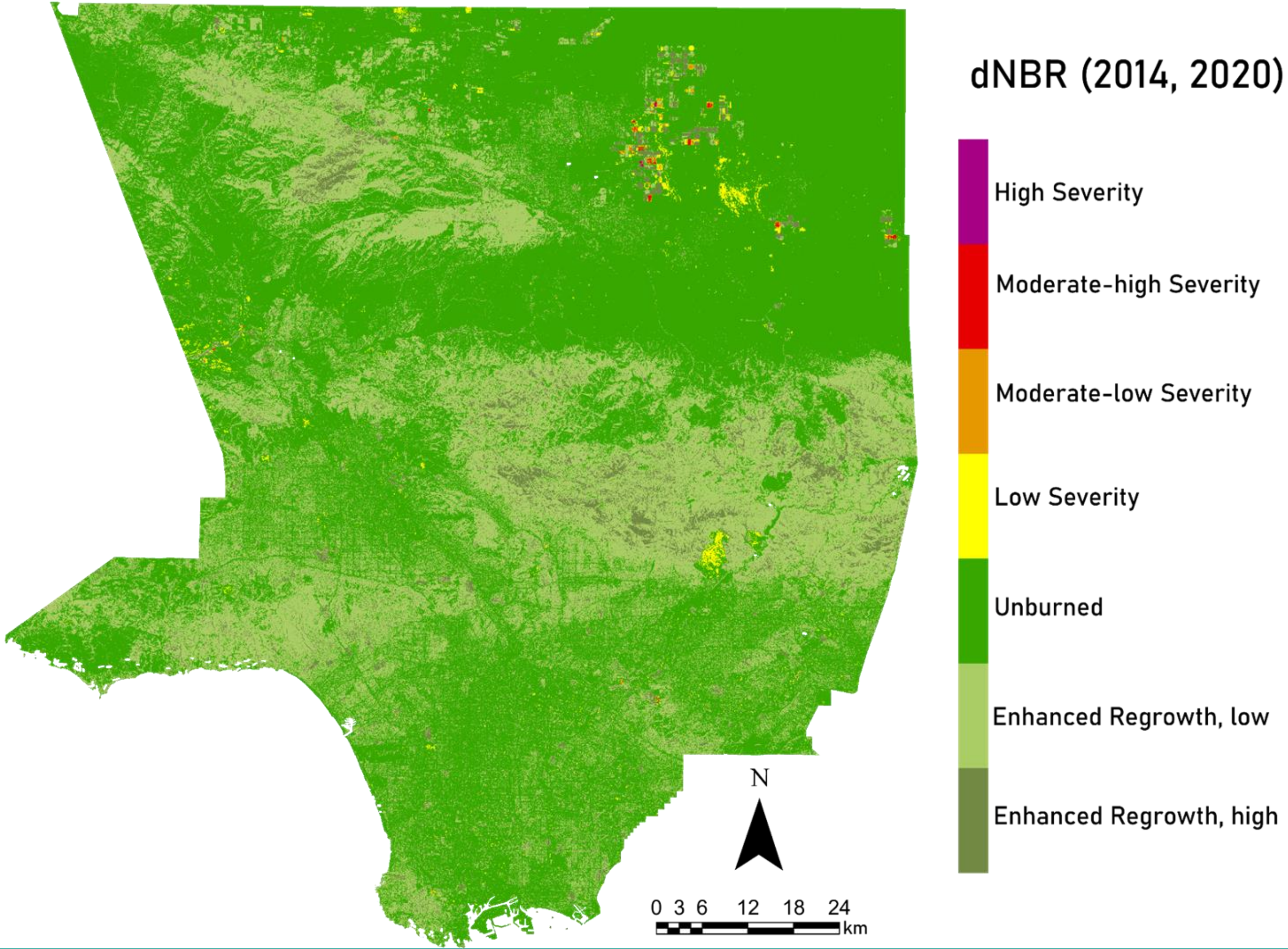
dNBR for 2018 - 2020



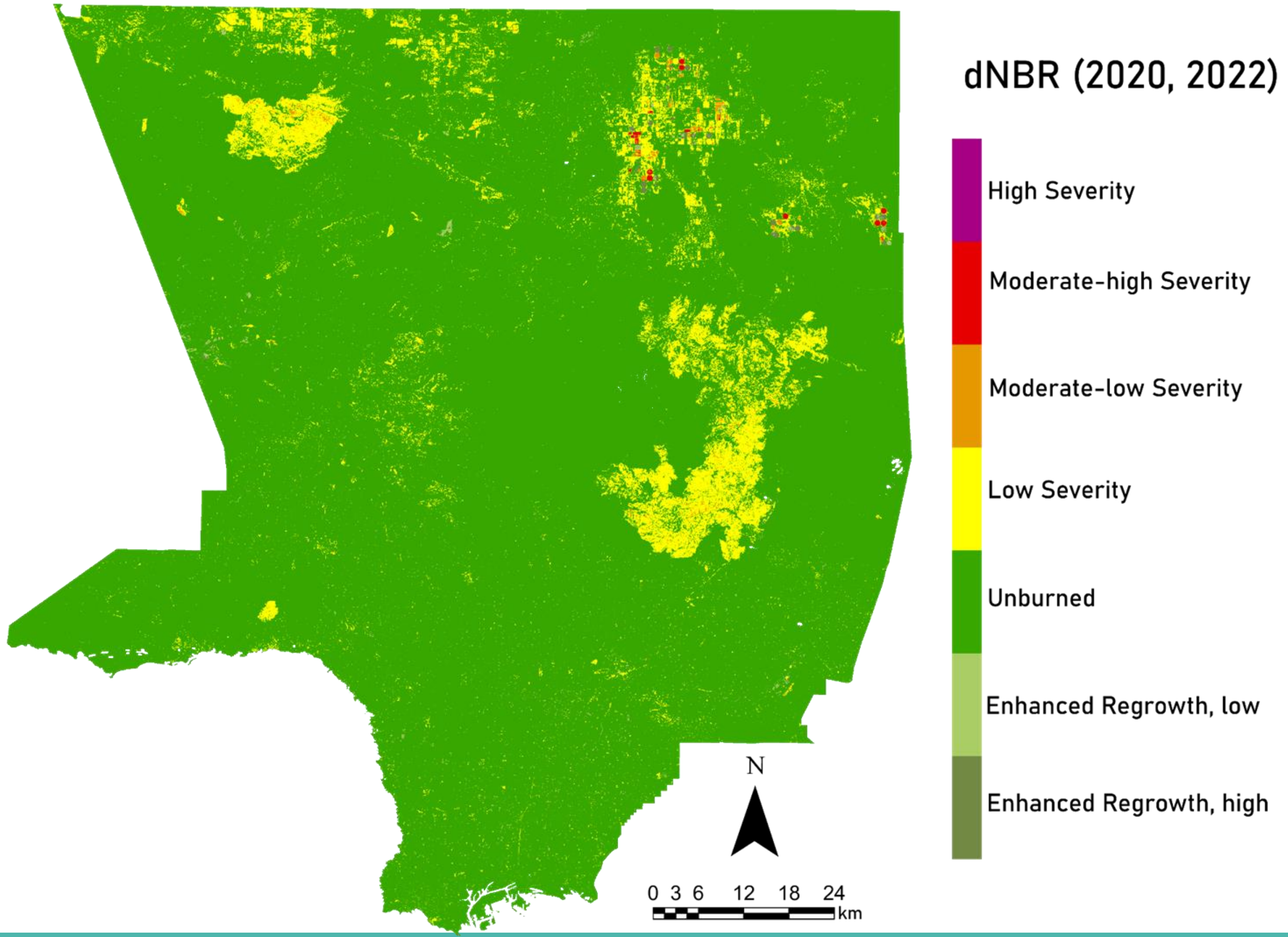
dNBR for 2020 - 2021



dNBR by Overall Disturbance Trend on Vertex: 2014-2020

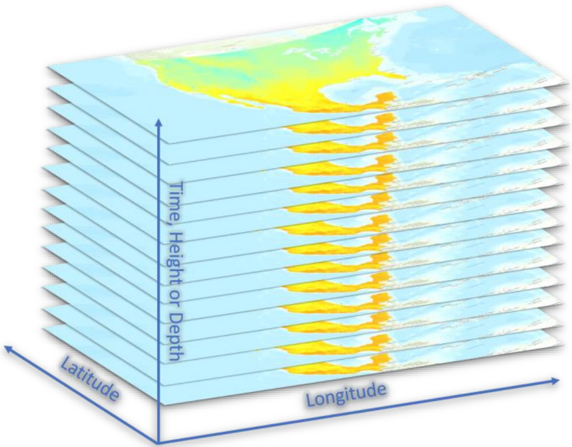


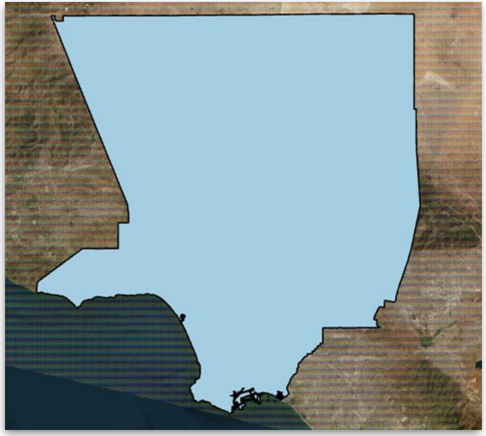
dNBR by Overall Recovery Trend on Vertex: 2020-2022

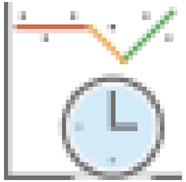


Pixel Time Series Change Explorer
Surface Reflectance Trend Fitting with LandTrendr

Disturbance & Recovery - Surface Reflectance Trend





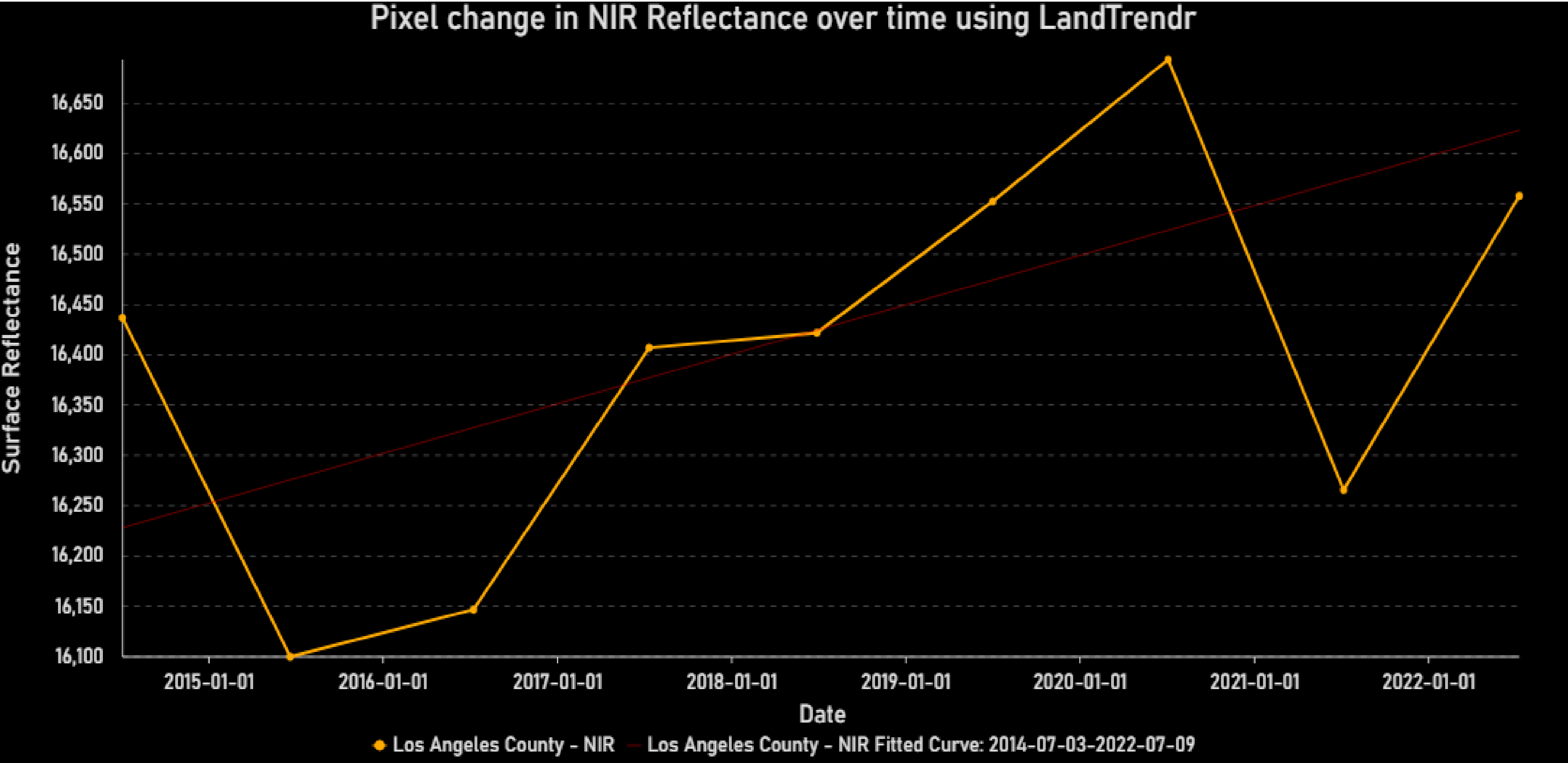


Multidimensional Raster Layer
(Jul 2014 - Jul 2022)

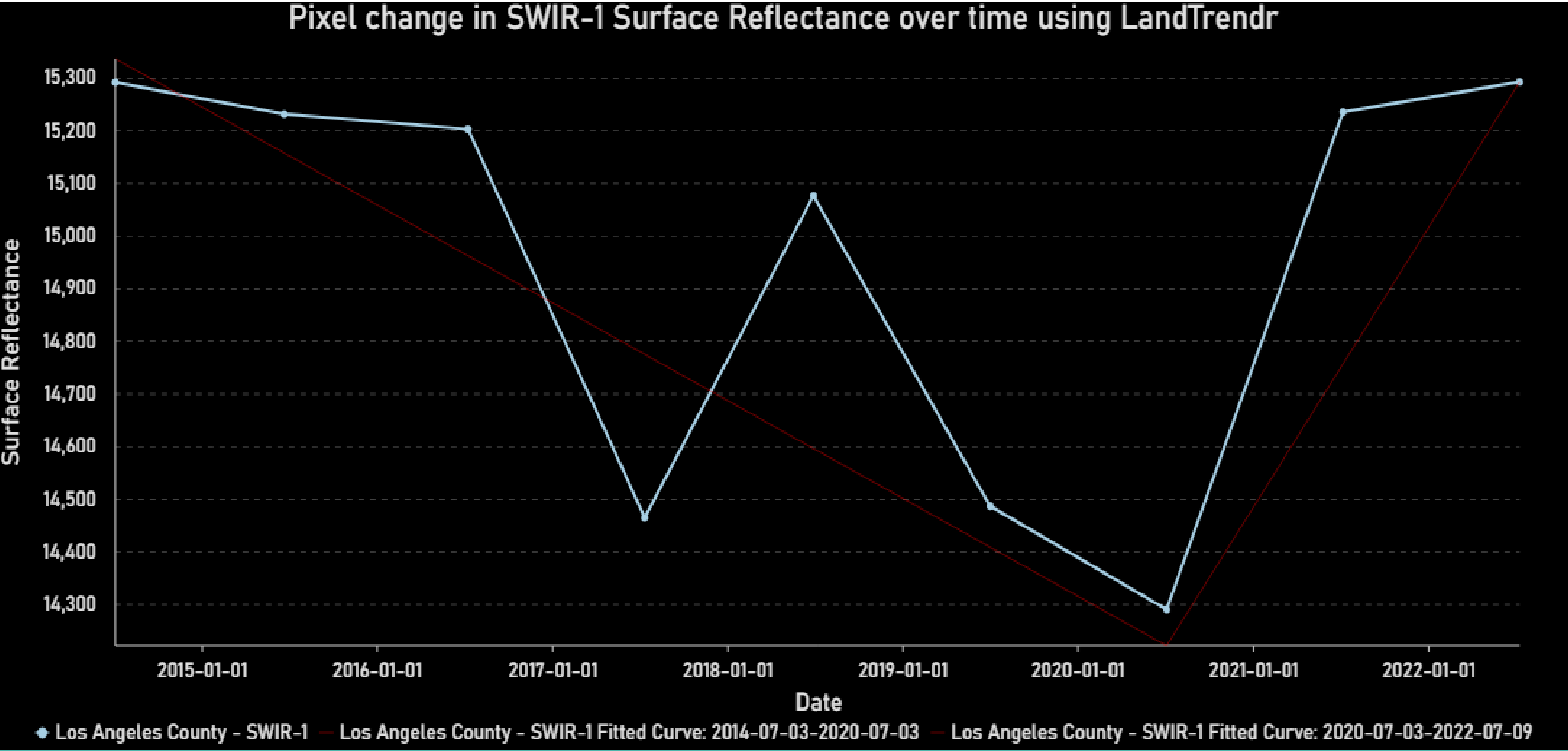
Selection of Area of Interest
(Los Angeles County)

Creation of Chart by Band

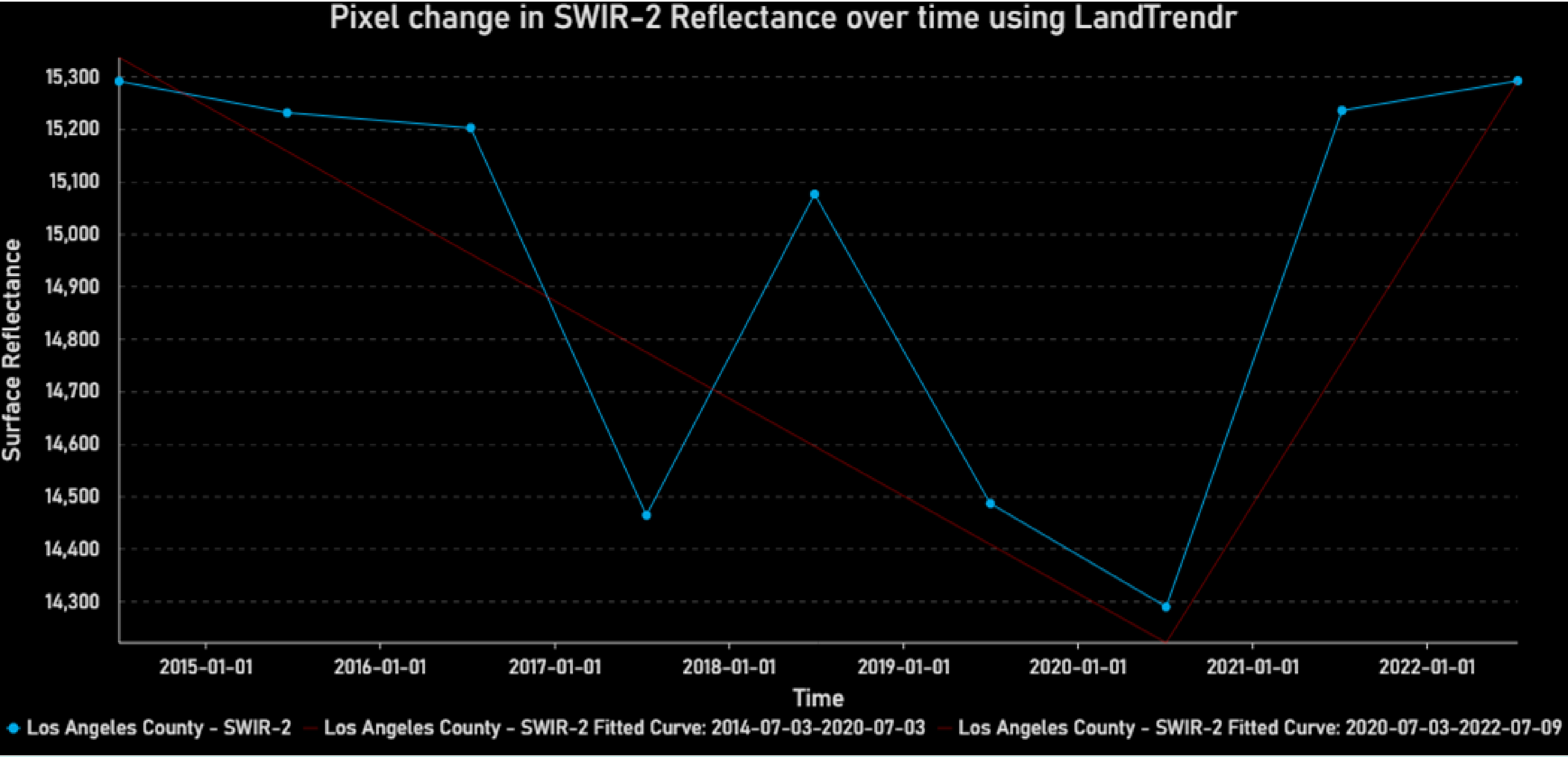
Surface Reflectance Trend (NIR)



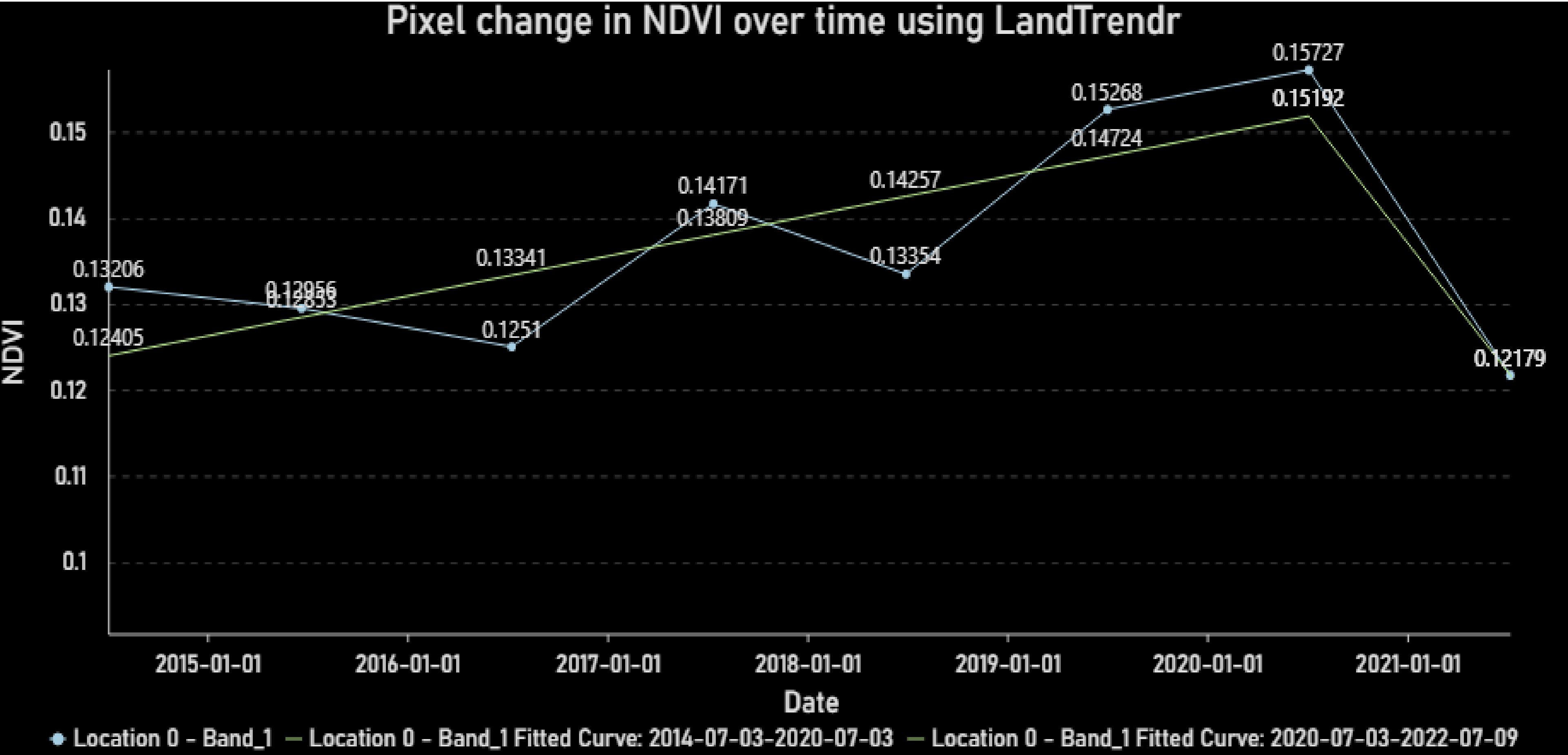
Surface Reflectance Trend (SWIR-1)



Surface Reflectance Trend (SWIR-2)



Surface Reflectance Trend - NDVI



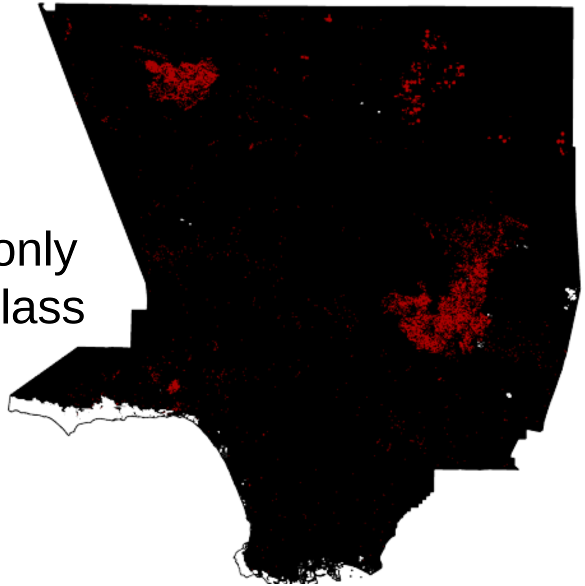
Weighted Average of dNDVI at Disturbance Segments

dNDVI (2014,2016)
NDVI 2014 – NDVI 2016 x 15%

dNDVI (2017,2018)
NDVI 2017 – NDVI 2018 x 25%

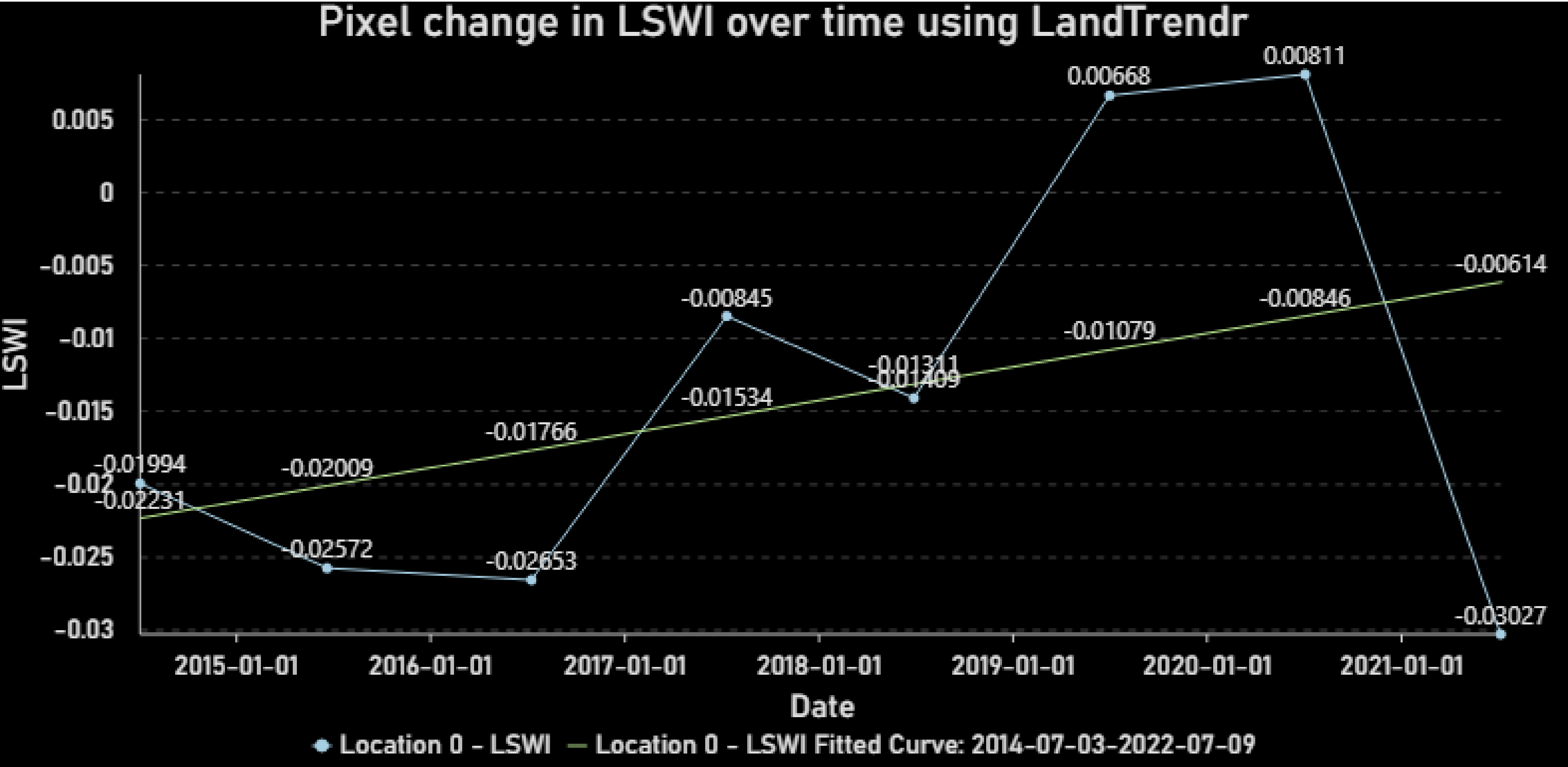
dNDVI (2020,2021)
NDVI 2020 – NDVI 2021 x 60%

Average and Classify only Highest Sum dNDVI Class



Potential Vegetation-loss Vulnerable Areas

Surface Reflectance Trend - LSWI

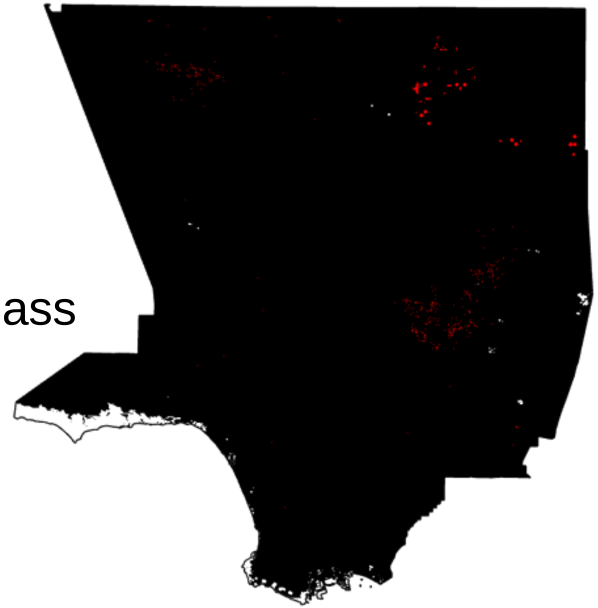


Weighted Average of dLSWI at Disturbance Segments

dLSWI (2017,2018)
LSWI 2017 – LSWI 2018 x 25%

dLSWI (2020, 2021)
LSWI 2020 – LSWI 2021 x 75%

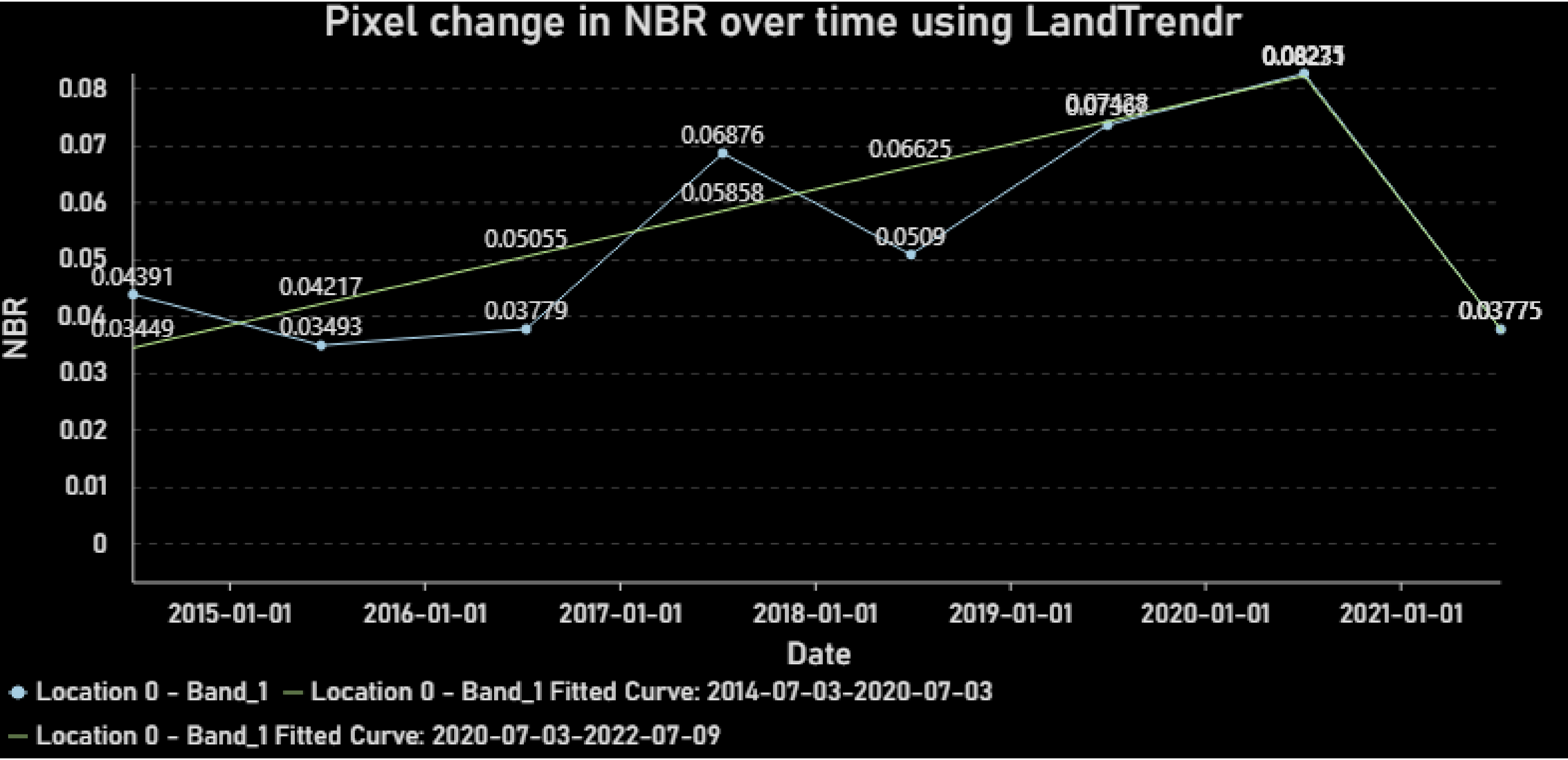
Average and Classify
Highest Sum dLSWI Class



Potential Water-Stress Vulnerable Areas

0.101 - 0.247

Surface Reflectance Trend - NBR



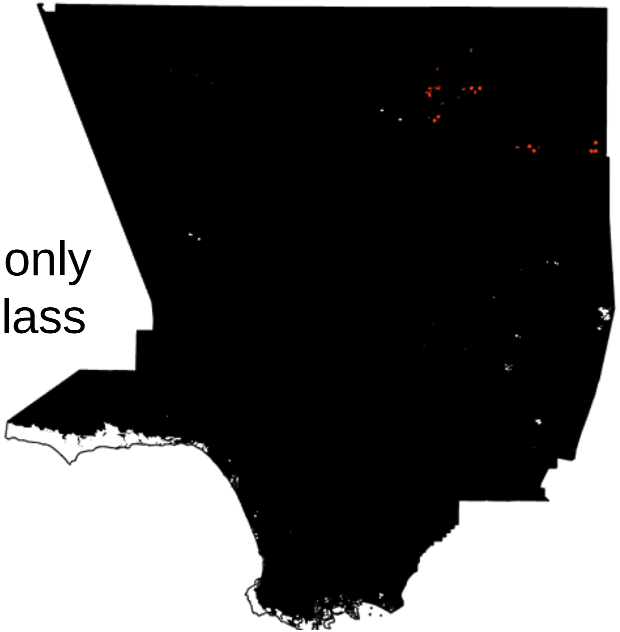
Weighted Average of NBR at Disturbance Segments

dNBR (2014,2016)
NBR 2014 – NBR 2016 x 10%

dNBR (2017,2018)
NBR 2017 – NBR 2018 x 20%

dNBR (2020,2021)
NBR 2020 – NBR2021 x 70%

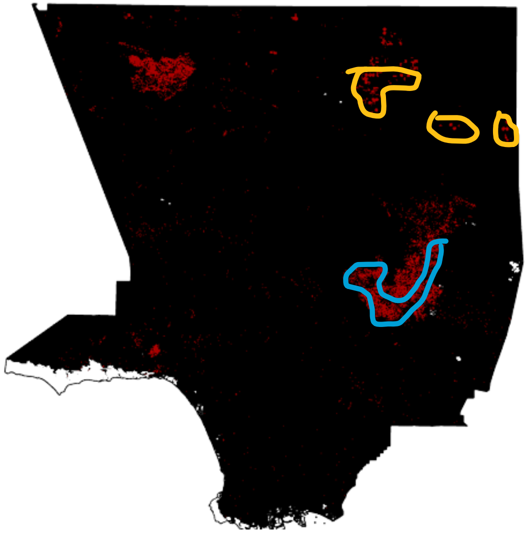
Average and Classify only Highest Sum dNBR Class



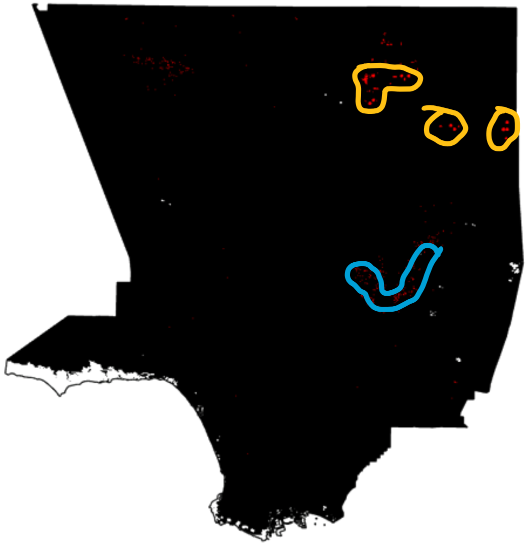
Potential Wildfire Vulnerable Areas

0.101 - 0.567

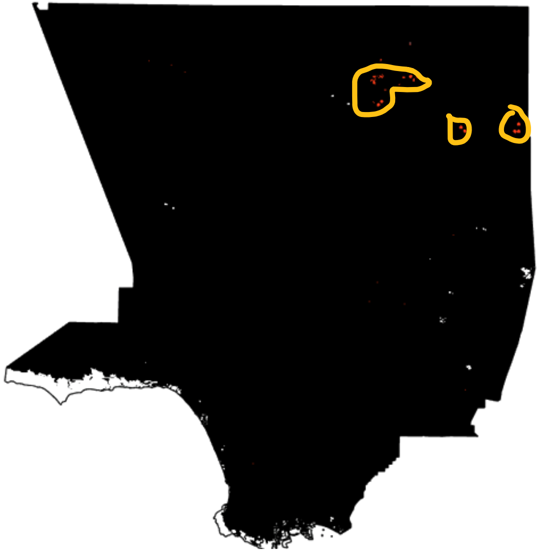
Key Results



Frequent (over decade)
Vegetation-loss Areas



Frequent (over decade)
Water-Stress Areas



Frequent (over decade)
(Wildfire) Burnt Areas

Yellow Area: Vegetation-loss, Water-stress, and Wildfire have been frequently occurring over decade

Blue Area: Vegetation-loss and Water-stress have been frequently occurring over decade

Conclusion

- By observing the significance of each spectral band and indices from the satellite images over the decade, it was possible to detect the trend of repetition of disturbance and recovery of vegetations
- After catching the disturbance vertices, Difference-Indices could be evaluated and weighted averaged to find the frequently (Vegetation-loss/Water-Stress/Burn Damage) occurring areas
- The areas labelled Yellow should be prioritized for wildfire & drought vulnerability
- The areas labelled Blue should also consider their drought vulnerability along with its mountainous vegetation-loss
- LA County Government or any possible stakeholders may consider for intensive monitoring as the half of the labelled areas were croplands, referring to TCC/FCC images
- Mountainous areas generally have less spreadability, however, LA County had many residential and agricultural areas on the edge of the blue-labelled mountainous areas, so intensive monitoring on those areas should be considered to prevent further damage/loss

Limitations

- Number of data points (dates of images) were not sufficient enough to precisely fit the trend of each surface reflectance. (Fitting using CCDC requires number of data points more than 12)

- Urban region mask by each year could not be used to extract only non-urban areas due to complex landscape of Los Angeles, especially the borderlines of mountainous region and urban area, having mixture of barren lands and bare soils.
  - With more accuracy on the mask, better noise surface reflectance removal such as urban/wasteland/barren lands would be possible