



ENRICHING THE MAPPING PROCESS UTILIZING THERMAL IMAGERY

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MAPPING & GEO INFORMATION
ENGINEERING



Purpose Of Research

GOAL : Classify urban landcover types by extracting their typical thermo-spatio-temporal features

Motivation

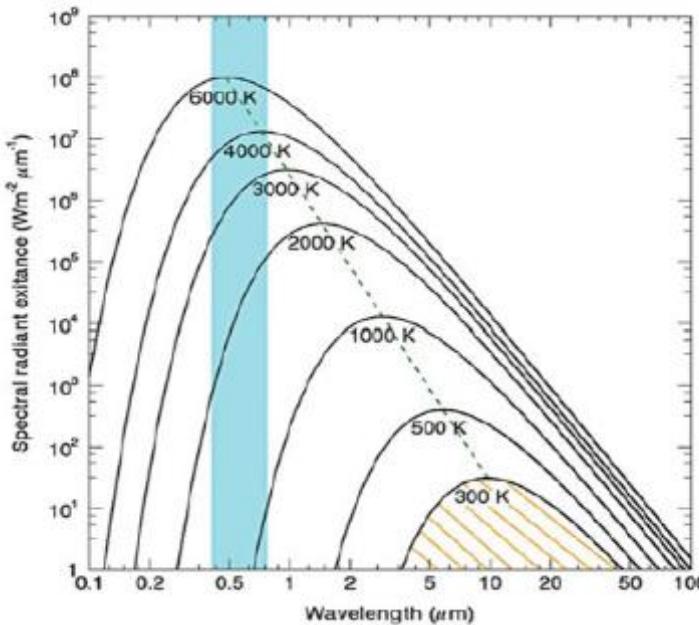
1. Thermal imagery makes remote sensing practical on certain environmental conditions in which VIS does NOT.
2. When VIS does, two objects might share same visual features, but could be distinguished by their radiant temperature values.
3. Real temperature measuring requires material properties.





Scientific Background – Thermal Radiation

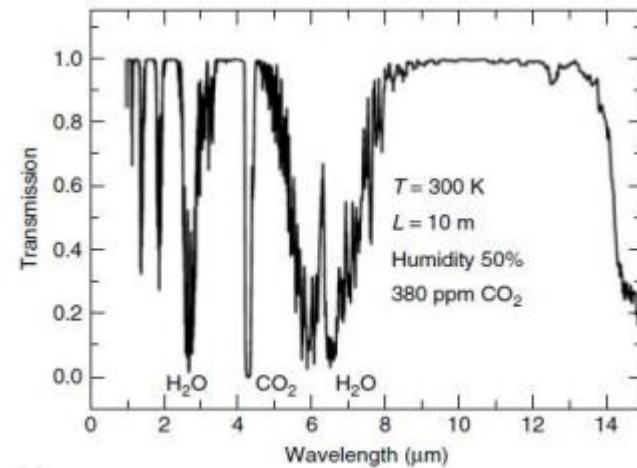
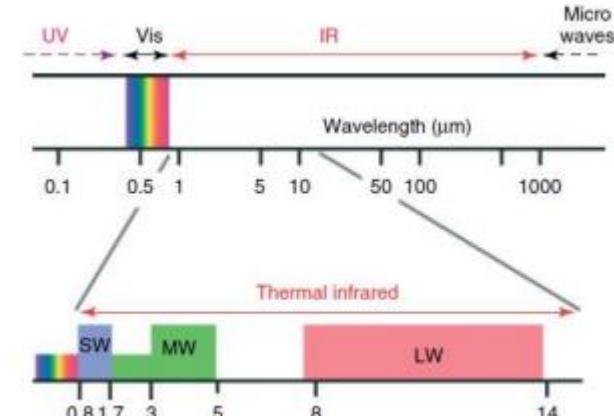
- TIR = Emitted Radiation ; VIS = Reflected Radiation
- Any object above 0 K emits radiant power,
described by Planck's Law for Blackbody at temp T and wavelength λ :



$$M(T, \lambda)_{\text{BB}} = \frac{2hC^2}{\lambda^5(e^{\frac{hc}{\lambda kT}} - 1)}$$

M_λ = spectral radiant exitance [$\text{W m}^{-2} \mu\text{m}^{-1}$]
 h = Planck's constant [$6.626 \times 10^{-34} \text{ J s}$]
 c = speed of light [$2.9979246 \times 10^8 \text{ m s}^{-1}$]
 k = Boltzmann constant [$1.3806 \times 10^{-23} \text{ J K}^{-1}$]
 T = absolute temperature [K]
 λ = wavelength [μm]

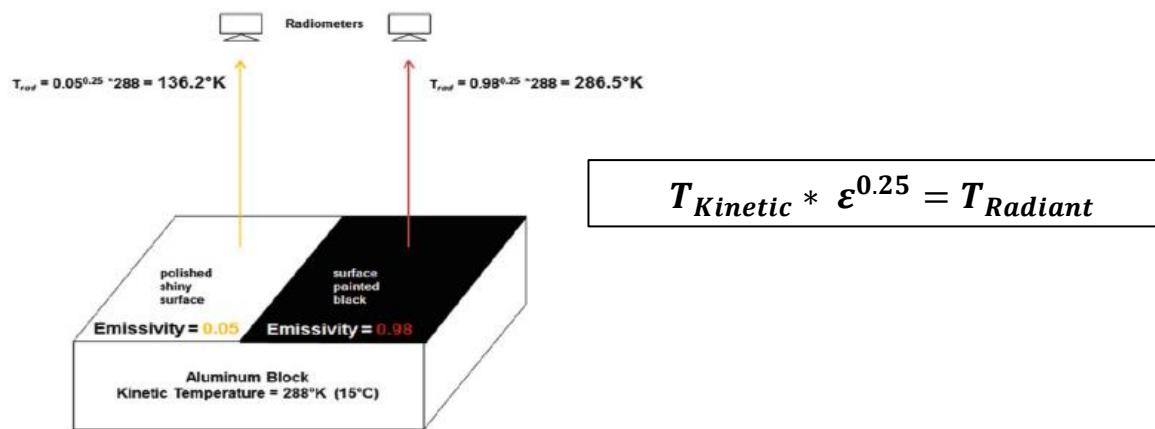
Wien's Law :
$$\lambda_{max} = \frac{C}{T}$$





Scientific Background – Radiant Vs. Kinetic Temperature

- TIR Cameras' sensors convert measured radiance into radiant temperature
 - ∞ Planck's Law mathematical inverse
- Transition to true (Kinetic) temperature requires Emissivity
 - ∞ Emissivity is defined : $\varepsilon_\lambda = \frac{R(T, \lambda)}{M(T, \lambda)_{\text{BB}}}$
 - ∞ Definite value calculation is very complicated (time, environmental variables)



Surface	Emissivity at 8–14 μm
Carbon powder	0.98–0.99
Water	0.98
Ice	0.97–0.98
Plant leaves, healthy	0.96–0.99
Plant leaves, dry	0.88–0.94
Asphalt	0.96
Sand	0.93
Basalt	0.92
White paper	0.90
Wood	0.87
Granite	0.83–0.87
Polished metals, averaged	0.02–0.21
Aluminium foil	0.036



Literature Review – Radiant Temperature Diurnal Trends

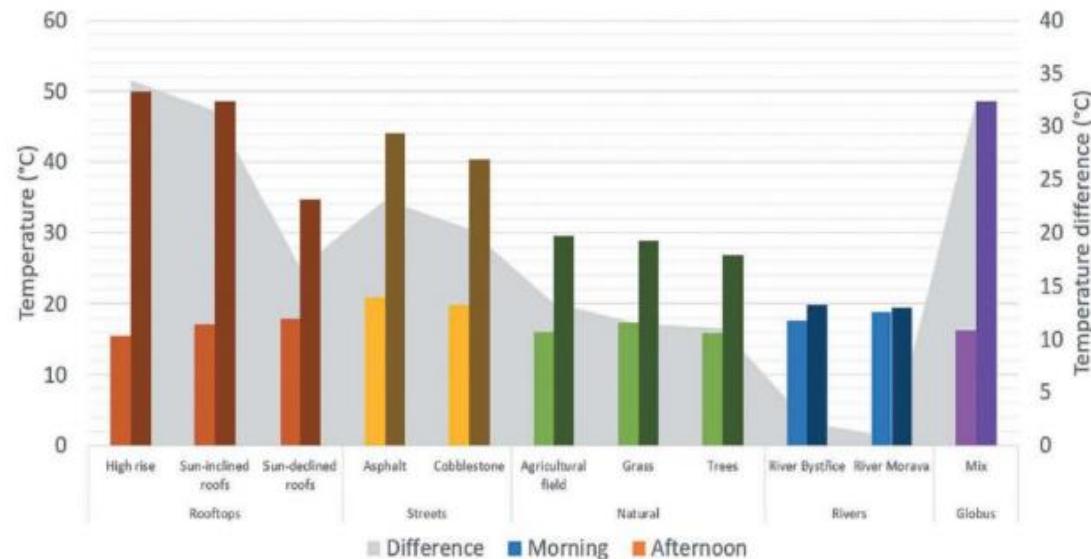


Figure : Thermal regime of urban environment land covers (Pour et al 2019)

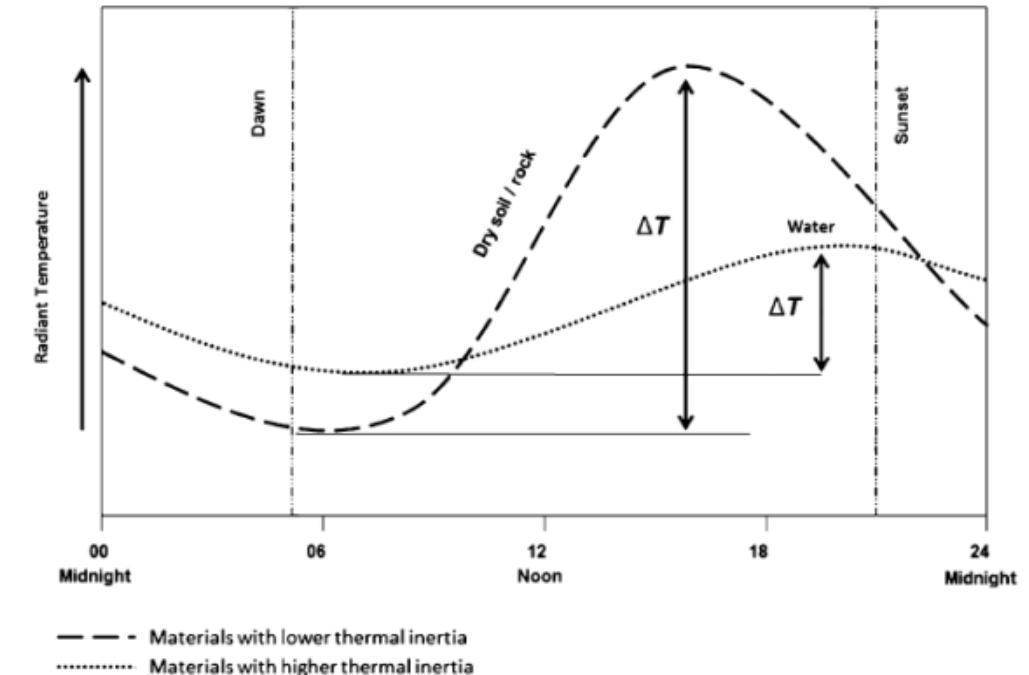


Figure : ΔT values visualization as derived from diurnal curves, for water and dry soil (Lillesand et al 2008)



Literature Review – The Spatio-Thermal Effect

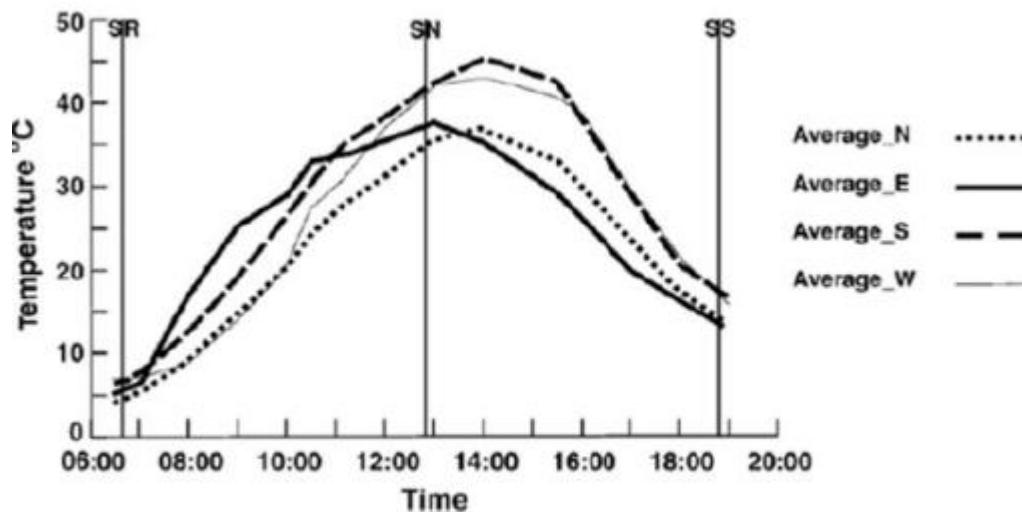
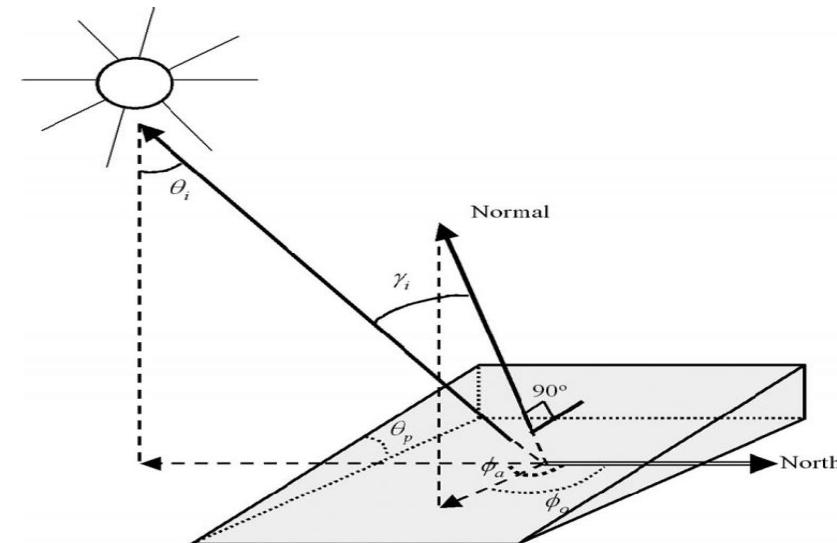


Figure : Diurnal temperature variation of desert sand depending on different aspects – east, south, west and north. (Zhang & Kuenzer 2007)



$$IL = \cos \gamma_i = \cos \theta_p \cos \theta_z + \sin \theta_p \sin \theta_z \cos (\phi_a - \phi_o)$$

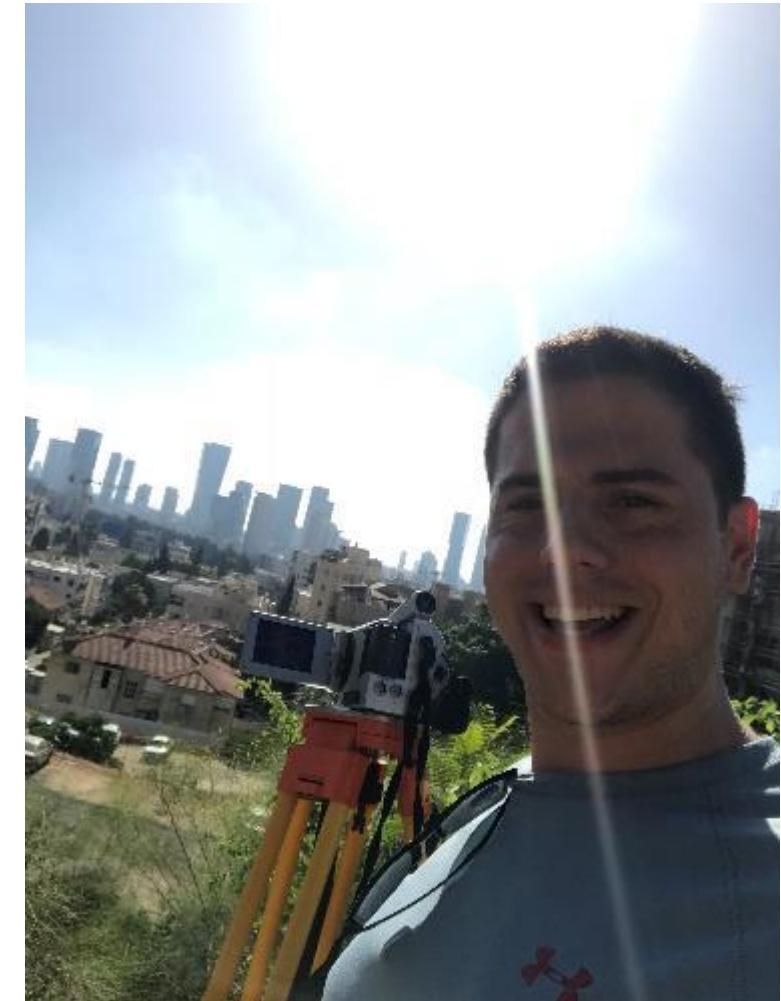
Figure : Spatial solar angles affected by topography (Riano et al 2003)



Data Collection – Field Experiment Setup

Area of Interest's Criteria – Givatayim City, Israel

- An elevated topographic POV allows full 3D scene capturing
- Land cover types variety
- E2W LOS for thermal gradient tracking (summer day)
- Dual TIR+VIS Camera (TIR resolution < 10 cm @100m pixel)





Data Collection – Image Acquisition

- Dual imagery sets had been acquired from early dawn until late night on 1 hour intervals (A-D VIS;1-4 TIR)
- Example Dual Sets from 21:00 ,15:00 ,11:00 ,05:00 are shown :



05:00 AM



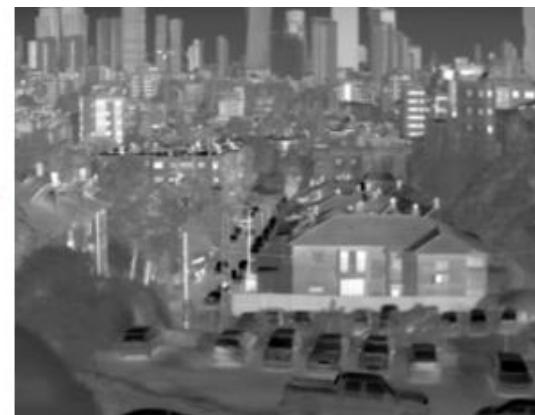
11:00 AM



15:00 PM



21:00 PM



(1)



(2)



(3)



(4)



Data Validation – Radiant Temperature Consistency

Methodology - Correspondence analysis between:

- a) Measured daily radiant temperature pattern of shaded vegetation (ambient temperature representation)
- b) Daily temperature reported for the experiment region, on the same day (by the Meteorological Service of Israel)

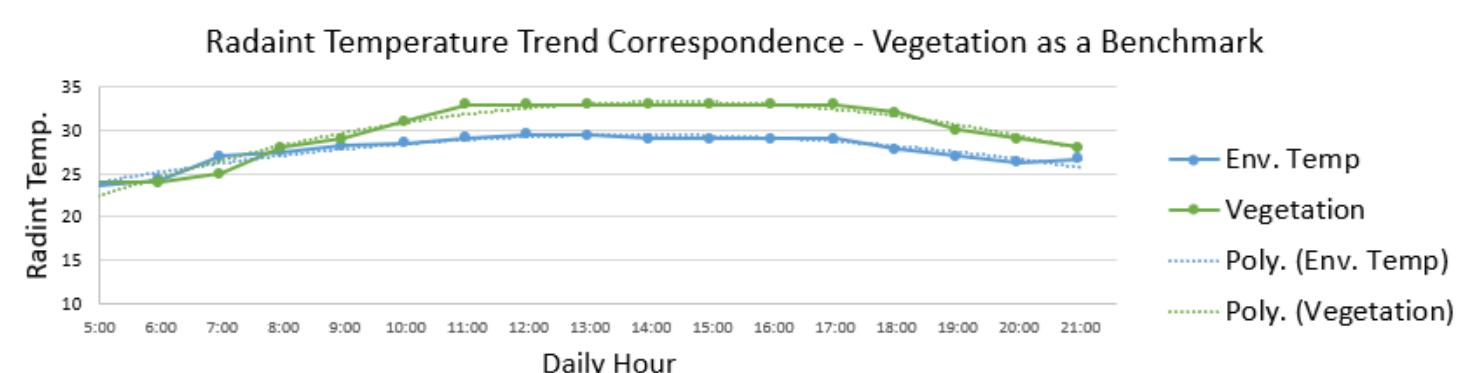
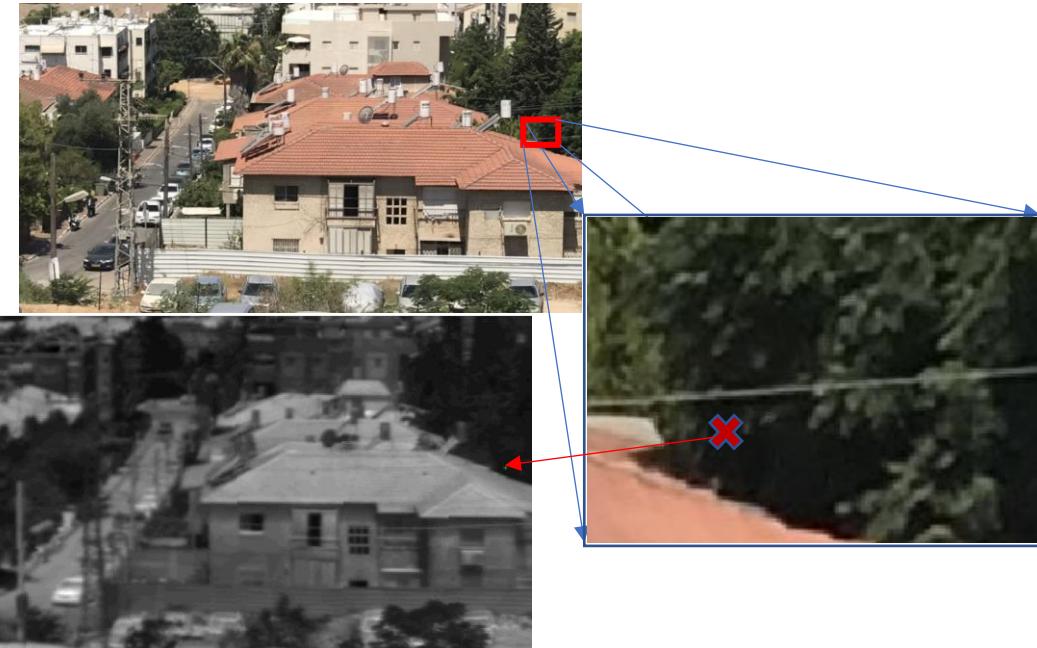
- Pearson's correlation test :

$$R = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}$$

- $R=0.95$; $p\text{-value} \approx 0$



Radiometry is consistent and reliable





Classification Model – Data Labeling

- The Train-Test Dataset was assessed based on manual RGB image interpretation
- Typical urban land cover types includes:
 1. Buildings
 2. Roads
 3. Vegetation
 4. Cars
 5. Roof Tiles
 6. Tin Fence

Pixel Labeling – 5% from image total





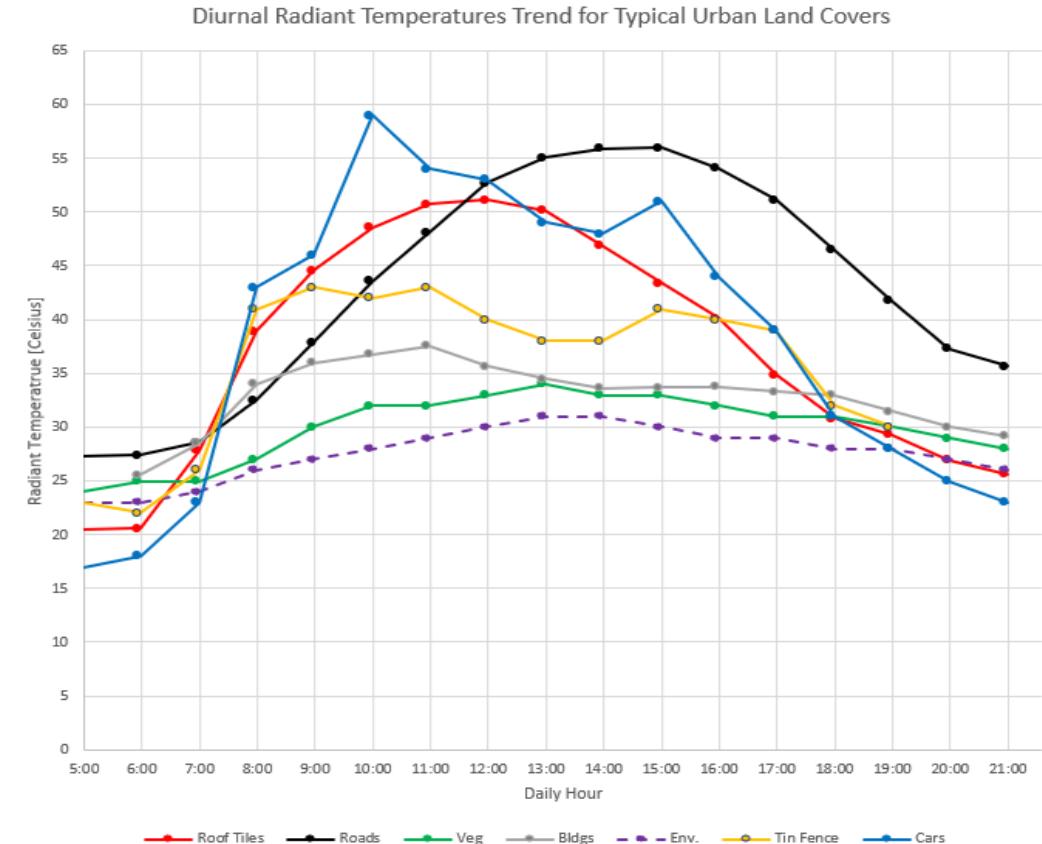
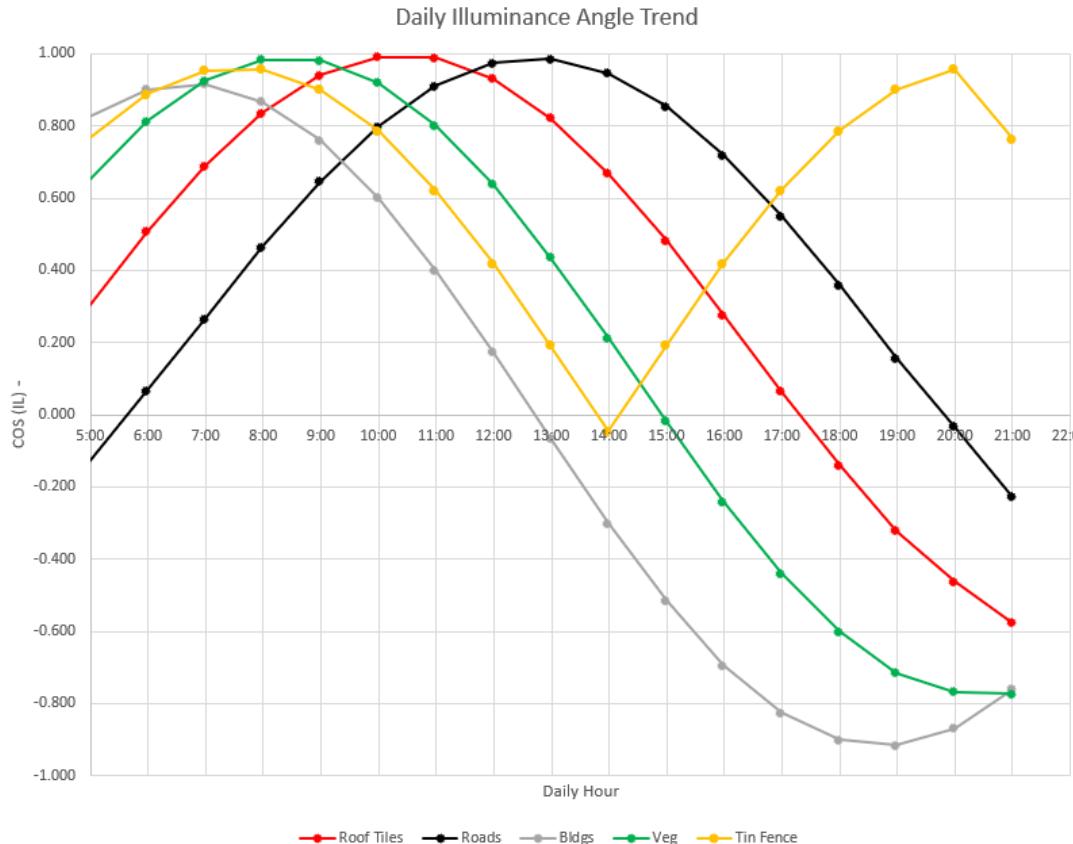
Classification Model – Feature Set Strategies



- Classification strategies included the following scenarios:
 1. All the radiant temperatures from sunrise until sunset
 2. Heating gradient-trend based only
 3. Cooling gradient-trend based only
 4. Relative parameters
 5. Three diurnal edge temperatures



Classification Model – Feature Engineering





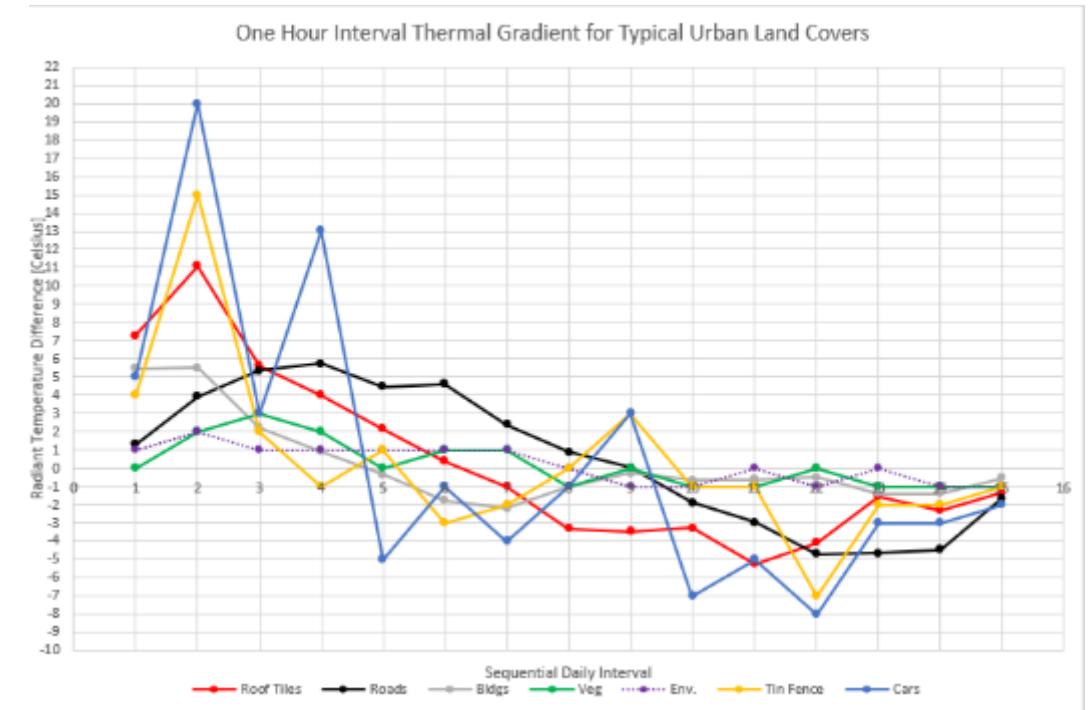
Classification Model – Feature Engineering

Sequential Thermal Gradients Patterns for different land cover types

- Transition into slopes (derivatives) space
- Description of a pattern, trend – instead of definite values

- **Thermal Gradient :**

$$\frac{\partial T}{\partial h} = \frac{T_{h_i} - T_{h_{i-1}}}{h_i - h_{i-1}}$$



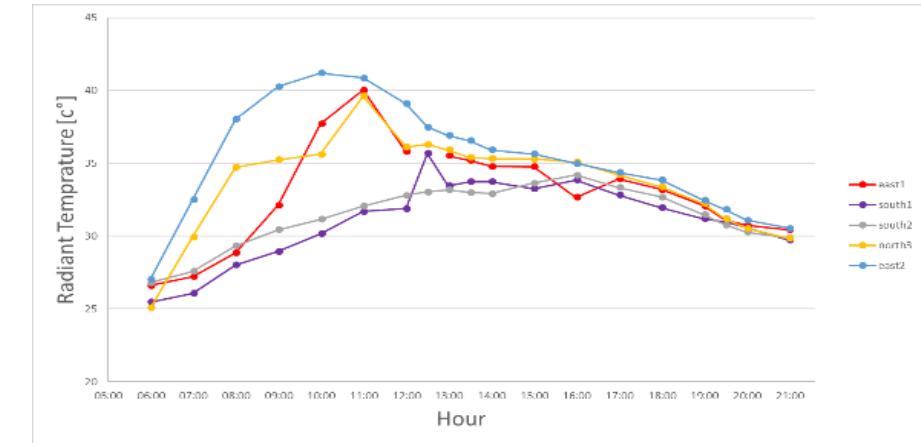


Classification Model – Feature Engineering

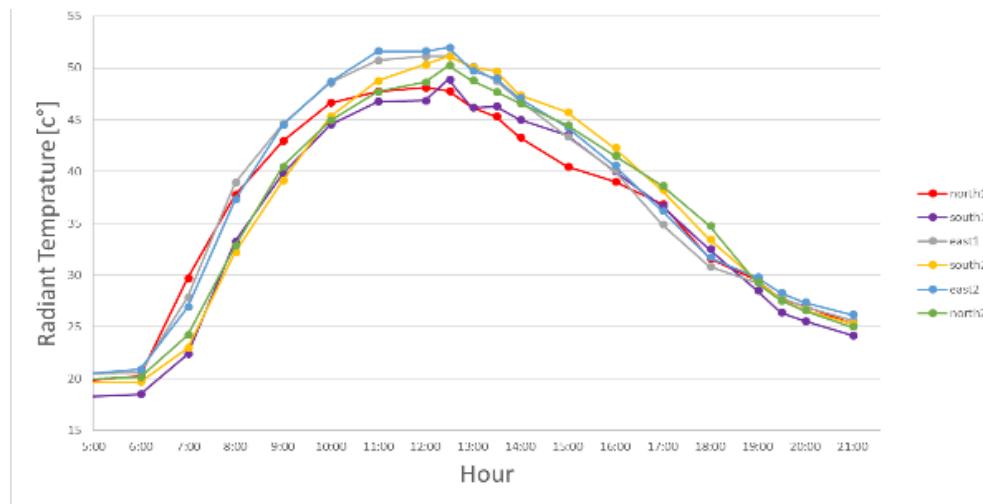
Diurnal Radiant Temperature for same land cover samples

- Bldgs – Varies pattern, Varies amplitude (highly spatial dependent)
- Roof Tiles – Similar pattern, Varies amplitude (mid spatial dependent)
- Veg – Similar pattern, Similar amplitude (low spatial dependent)

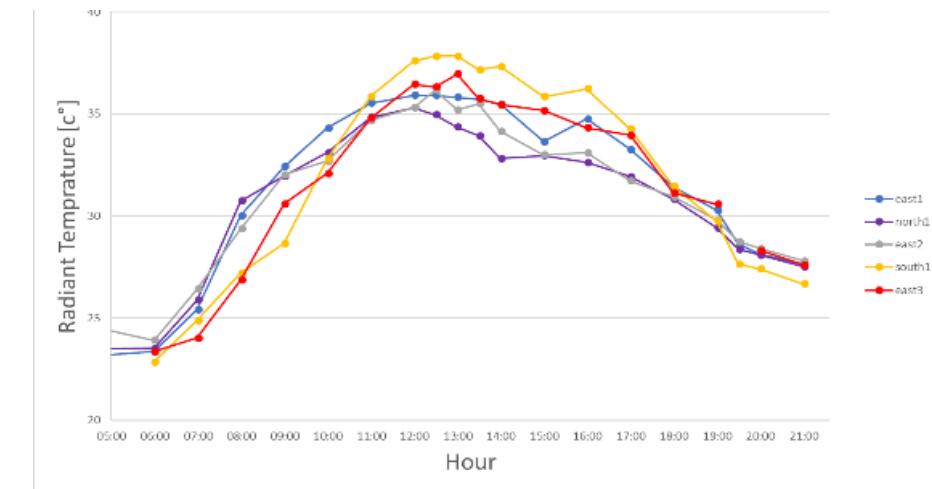
Diurnal radiant temperature patterns for several **building** landcover type observations



Diurnal radiant temperature patterns for several **Roof Tiles** landcover type observations



Diurnal radiant temperature patterns for several **Vegetation** landcover type observations





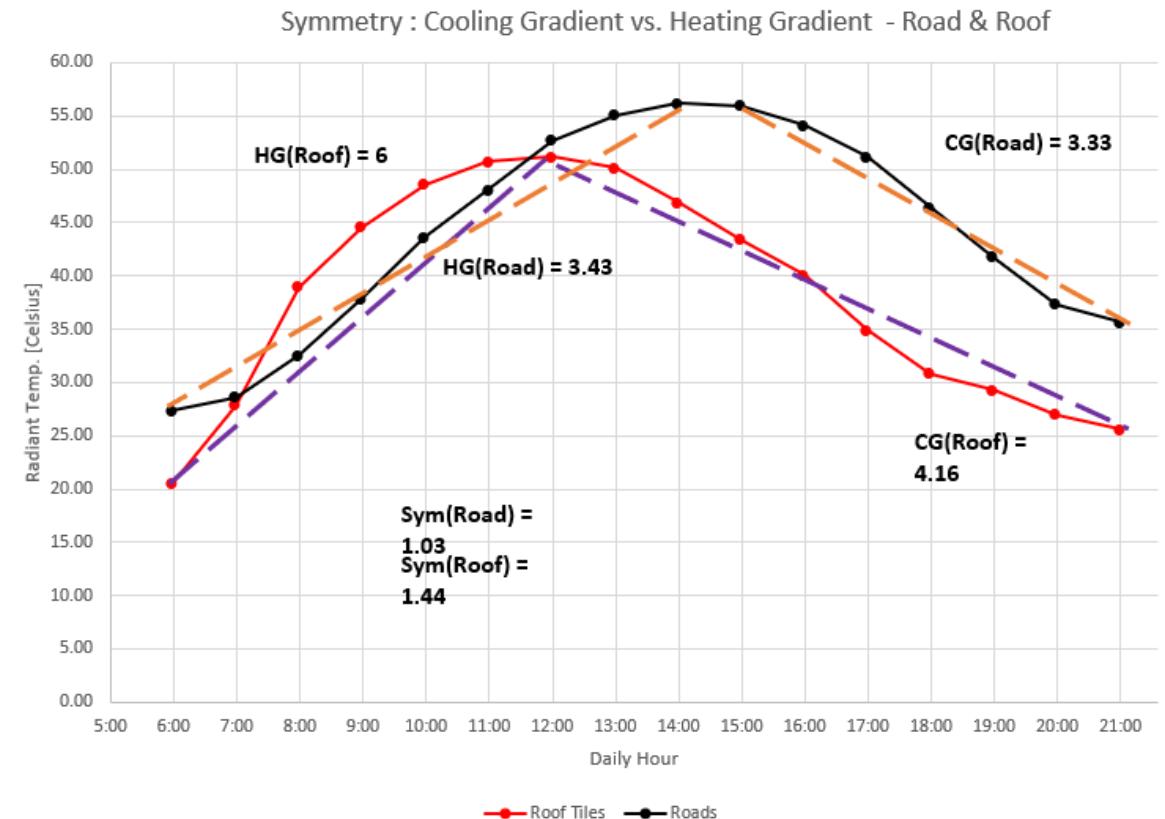
Classification Model – Feature Engineering

Heating and Cooling phenomena parametrization

- Generic modeling (all classes)
- Transformation of visual pattern into quantitative values
- Simple method that takes into account 3D spatial orientation

$$\text{Cooling Gradient}(CG) = \frac{\partial T_{cool}}{\partial h_{cool}} = \frac{T_{max} - T_s}{h_{max} - h_s} \left[\frac{^{\circ}\text{C}}{\text{hour}} \right]$$

$$\text{Symmetry} = \frac{\text{Heating Gradient}(HG)}{\text{Cooling Gradient}(CG)} = \frac{\frac{T_{max} - T_{min}}{h_{max} - h_{min}}}{\frac{T_{max} - T_s}{h_{max} - h_s}}$$





Classification Model – Feature Engineering

Amplitude values should be generalized – Relative parameter development

- Normalized Thermal Gradient Index :

$$NTGI = \frac{T_{max} - T_{min}}{T_{max} + T_{min}}$$

Label	Av_Max	Av_Min	NTGI
Veg	34.85	23.83	0.19
Roof	51.36	20.04	0.44
Build	40.42	24.87	0.24
Asphalt	53.39	26.58	0.34
Fence	42.20	22.01	0.31
Car	52.49	18.33	0.48

- APPARENT THERMAL INERTIA :

$$ATI_{new} = (1 - A)/\Delta T = \varepsilon/\Delta T = 1/\Delta T$$

ΔT : Diurnal Radiant Temperatures diff.0

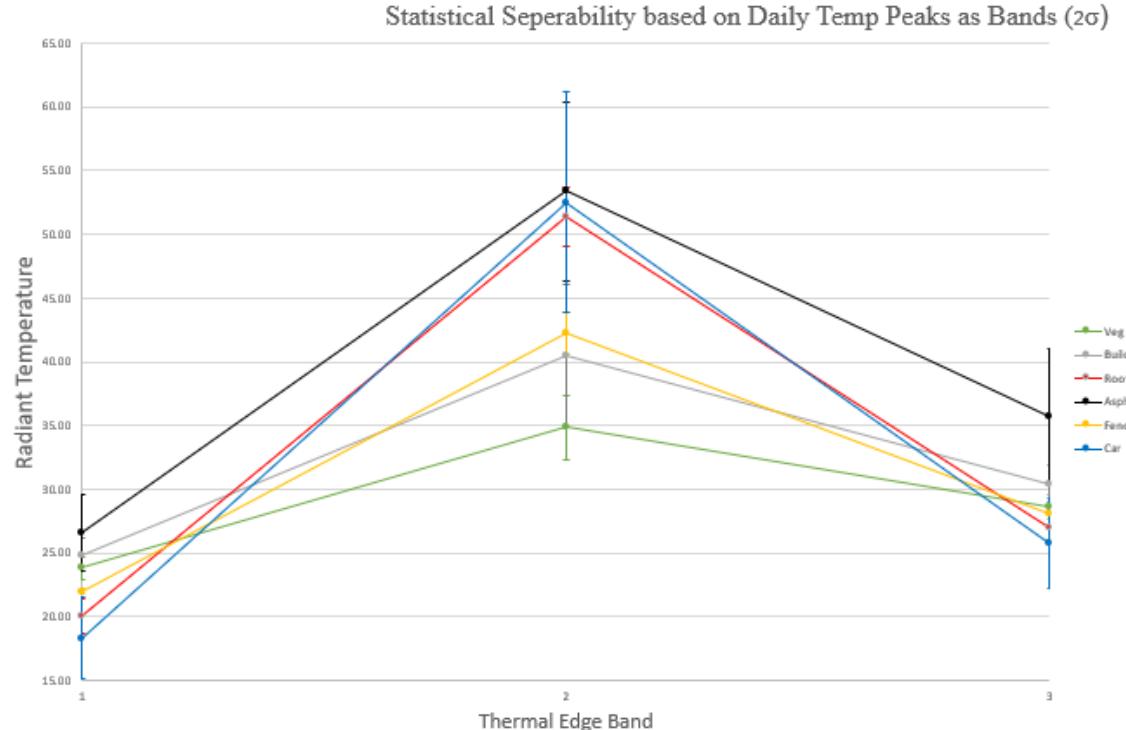
A : Albedo

ε : Emissivity (at wavelength λ)

Label	Avg_Max	Avg_Min	Std_Max	Std_Min	Avg_dT	ATI
Veg	34.85	23.83	1.26	0.43	11.02	0.091
Roof	51.36	20.04	1.15	0.67	31.32	0.032
Build	40.42	24.87	2.79	0.65	15.56	0.064
Asphalt	53.39	26.58	3.50	1.47	26.81	0.037
Fence	42.20	22.01	0.82	0.12	20.19	0.050
Car	52.49	18.33	4.32	1.60	34.16	0.029



Classification Model – Feature Engineering



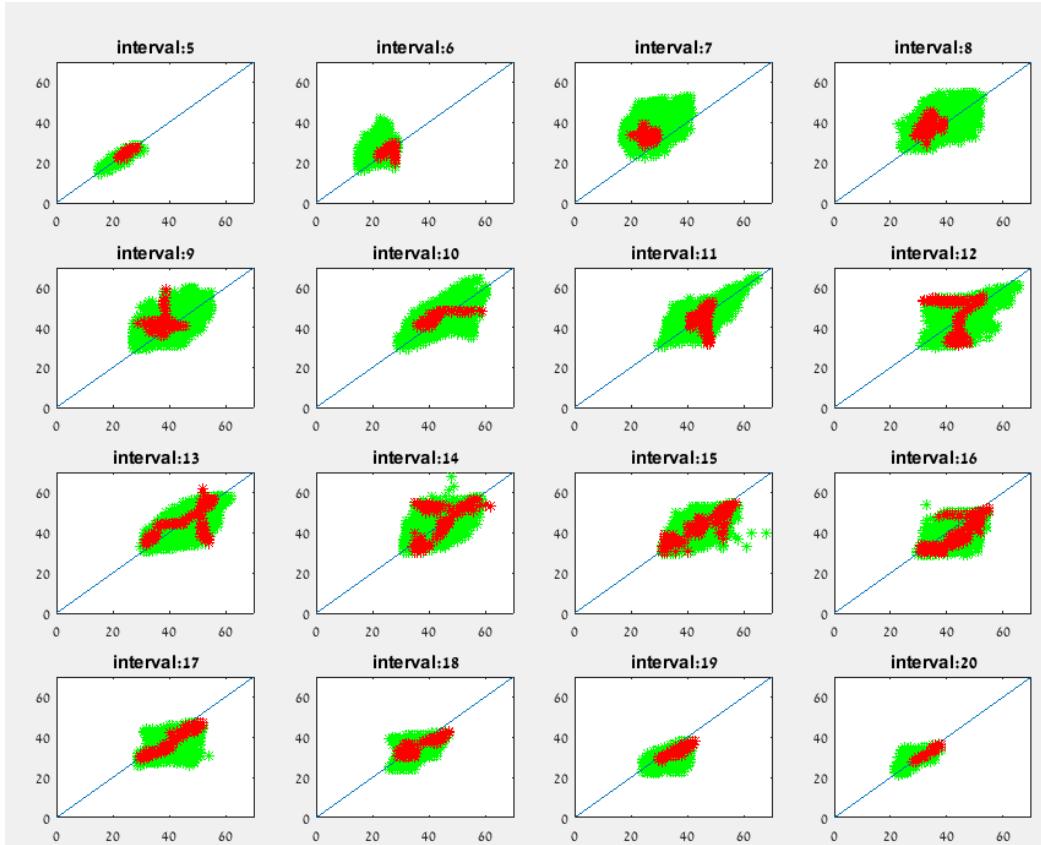
Label	Av_Max	Av_Min	Av_Ts	Std_Max	Std_Min	Std_Ts
Veg	34.85	23.83	28.61	1.26	0.43	0.50
Roof	51.36	20.04	27.04	1.15	0.67	0.55
Build	40.42	24.87	30.46	2.79	0.65	0.71
Asphalt	53.39	26.58	35.77	3.50	1.47	2.61
Fence	42.20	22.01	28.02	0.82	0.12	0.17
Car	52.49	18.33	25.77	4.32	1.60	1.80



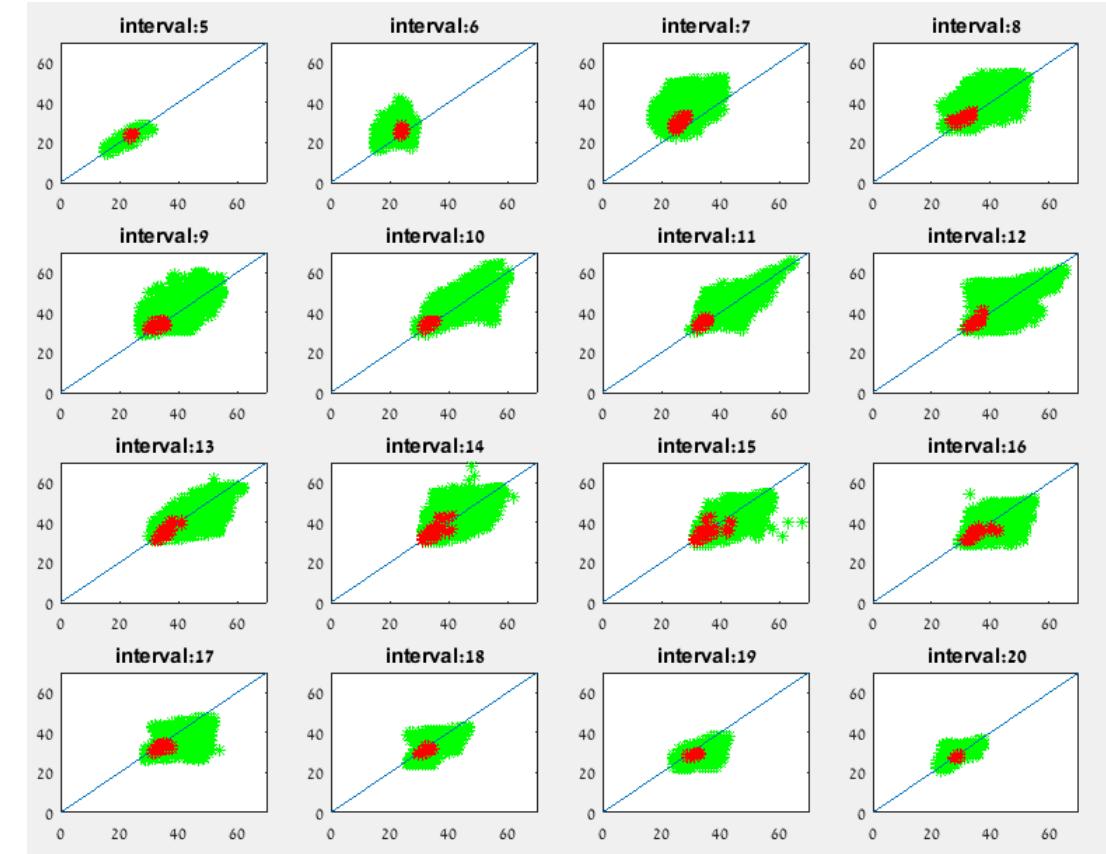
Classification Model – Time Series Analysis

Diurnal sequential gradient pairs (Green : All Pixels ; Red : Specific Land Cover Class)

Road Pixels (Dynamic-Motion)



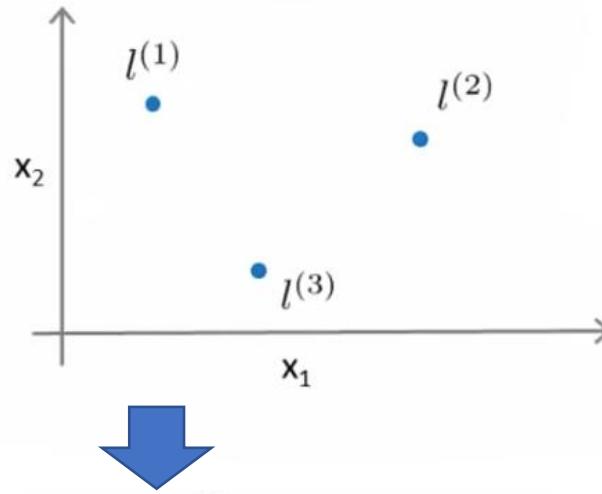
Vegetation Pixels (Static)



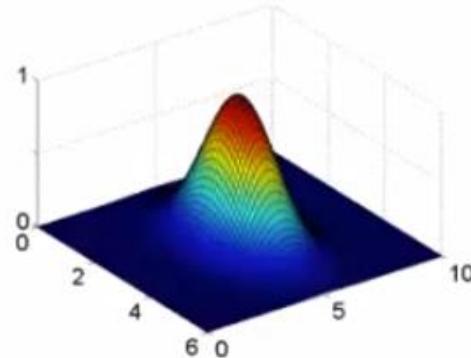


Classification Model – Algorithm / Classifier

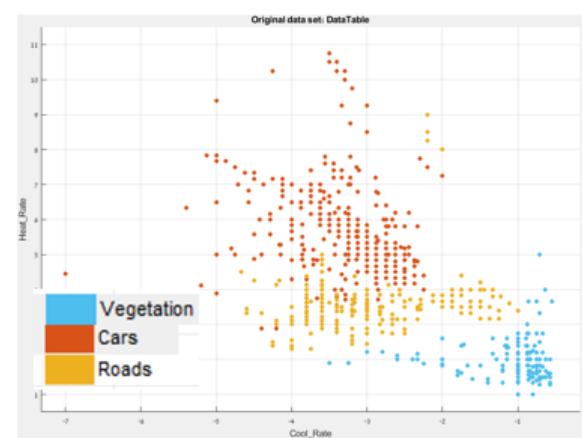
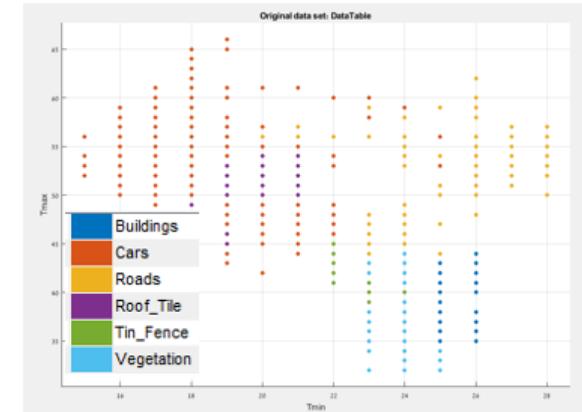
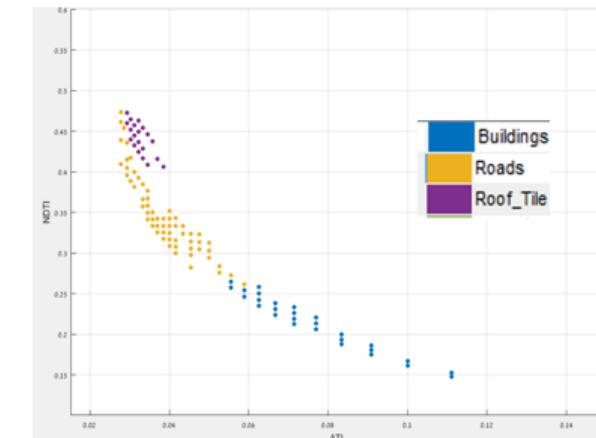
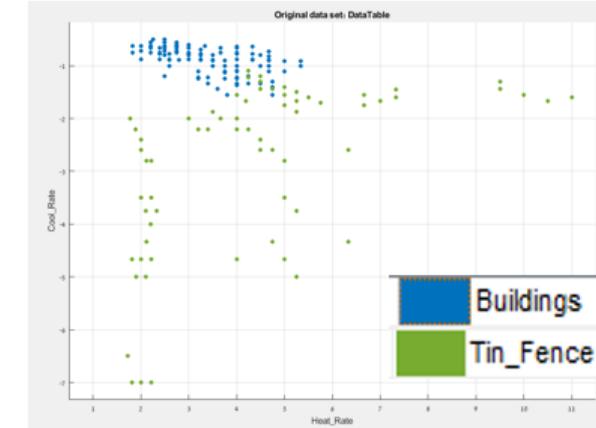
$$f_1 = \text{similarity}(x, l^{(1)}) = \exp\left(-\frac{\|x - l^{(1)}\|^2}{2\sigma^2}\right)$$



$$\sigma^2 = 1$$



SVM





Classification Model – Goodness of Fit Insights



Land Cover Type	Veg		Bldgs		Raods		Cars		Tin Fence		Root Tiles		Overall Accuracy
	Test #:	1775	Test #:	2133	Test #:	532	Test #:	541	Test #:	819	Test #:	2017	
Model Features	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	
Daily Radiant Values	1774	1	2117	16	529	3	511	30	811	8	1996	21	99%
Heating Gradient Based	1774	1	2111	22	532	0	507	34	816	3	1994	23	98%
Cooling Gradient Based	1728	47	2087	46	517	15	462	79	815	4	2012	5	97%
Relative Parameters	1707	68	2105	28	527	5	405	136	810	9	2008	9	96%
3 Edge Values	1757	18	2021	112	491	41	385	156	807	12	2003	14	93%

- Average 84% Recall and Precision (cars..)
- Highest sensitivity - FP cars classifies as roof tiles. (6%)
- Other than car, all classes holds an average of ~95%
- Confusion rates between Vegetation, Buildings. (Still >95%)
- Even though only Radiant Temperatures taken into account (no Emissivity) – high success rates thanks to TRENDS and PATTERNS

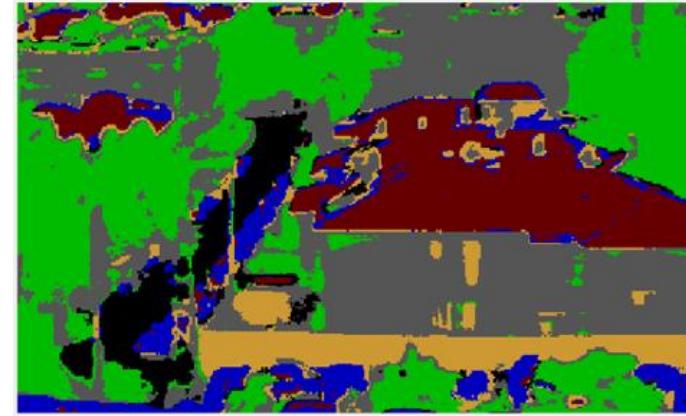


Classification Model – Fitting Results

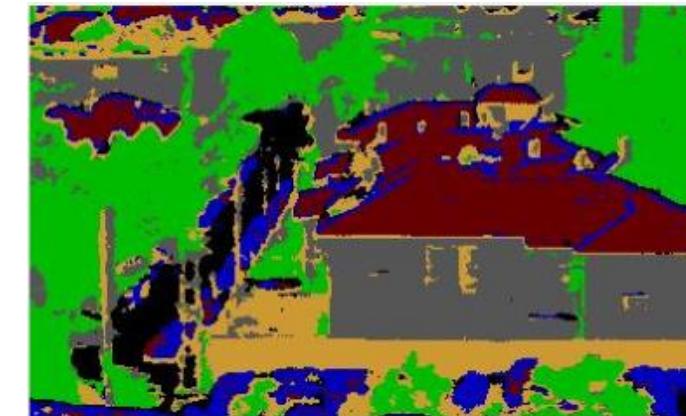
A



B



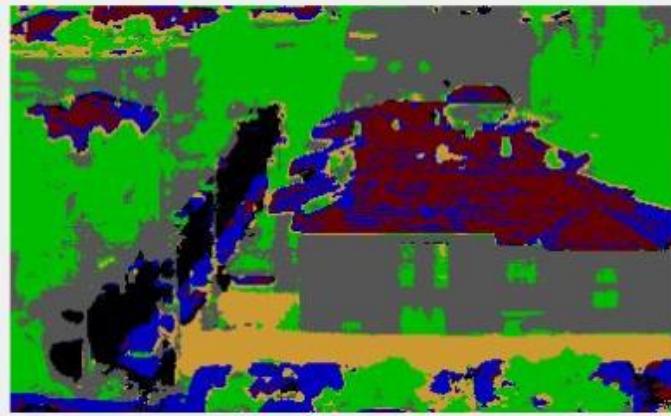
C



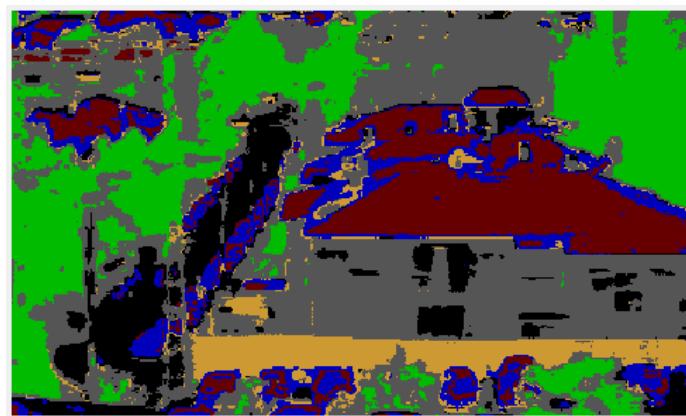
Legend :

Black	Roads
Red	Roof Tiles
Green	Vegetation
Yellow	Tin Fence
Blue	Cars
Grey	Buildings

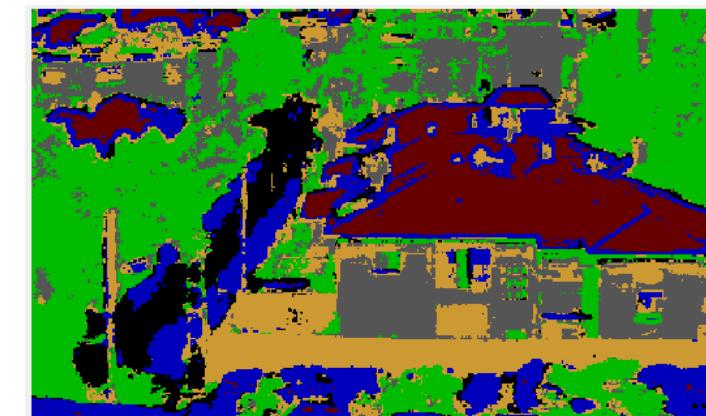
D



E



F



A) RGB Image of the scene; B) All the radiant temperatures from sunrise until sunset; C) Heating gradient-trend based only;
D) Cooling gradient-trend based only; E) Relative parameters; F) Three diurnal edge temperatures



Wrap Up & Discussion

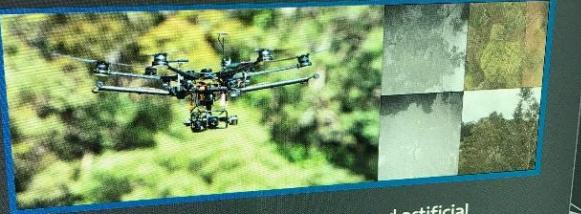


- Diurnal radiant temperature pattern facilitated reliable and unique spectral signatures for object classification, including the case of only three extreme measurements - sunrise temperature, maximum temperature and temperature at sunset.
- While heating gradient is highly affected by urban structures orientation, cooling gradient is more correlated with the ambient temperature.
- When a significant gradient is required, it is essential to analyze which of the mentioned features dominates the mapping scene.
- Relative parameters holds a great potential, by getting a robust-close solution, both accuracy and precision wise
- Supervised Thermo-Temporal 3D urban land cover classification results presented in this thesis suggest that thermal imagery may be utilized in enriching common mapping processes.

Wildlife spotting UAV:

Researchers from QUT are using unmanned aerial vehicles (UAVs) to help local councils, the government and private organizations scan for wildlife.

The notoriously shy and sleepy koala can hide in treetops for days but as their population dwindles councils and researchers are keen to know more about these reclusive, fluffy guys.



Using infrared thermal imaging and artificial intelligence algorithms, the QUT Remote Airborne sensing drones are scanning bushland, conducting test flights over wildlife and koala habitats around South East QLD and Northern NSW.

The project has already proved the technology can save government, companies and councils valuable time. In one test, it took humans more than three hours to conduct the same survey a UAV took just 30 minutes to complete.



Thank You



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