Understanding perception of different urban thermal model visualizations

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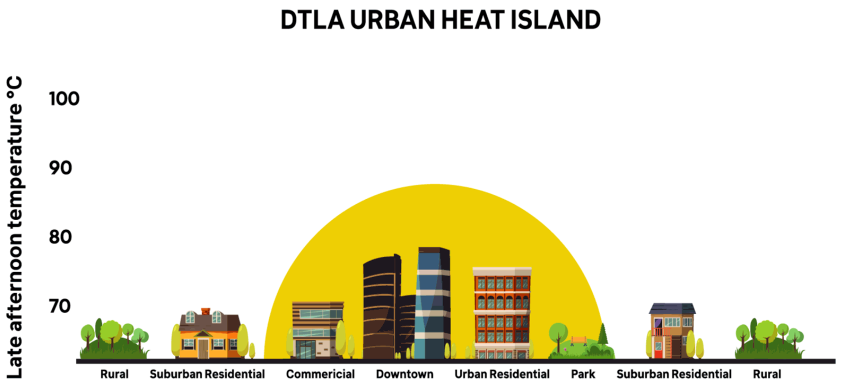
Urban heat island effect

The Urban Heat Island Effect (UHIE) is the phenomenon of increased temperature in urban areas compared to the surrounding rural areas, first described in Howard, 1818 for London.

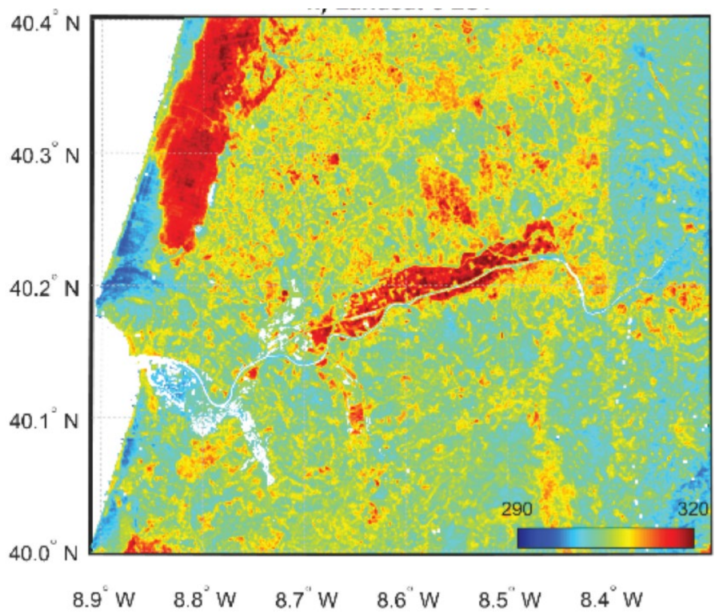
The average temperature of cities in 2100 is projected to increase 2°C *above that of* a global temperature increase, compared to a 2006-2015 baseline, and expose 2.3 billion people to severe heatwaves (UNEP, 2021).

It is the number one weather-related cause of death averaged over the past several decades (Lee, 2014; Sheridan and Allen, 2018).

A variety of satellites including Landsat, MODIS, and others can indirectly measure temperature through infrared emissions.



Source: climateplans.la/dtla/



Surface Temperature (Kelvin) algorithmic estimation from Landsat-8 shown for central Portugal, distributed via Google Earth Engine. From Ermida et al. 2020, Figure 4.

Mapping for equity and social justice

Heat exposure disproportionately impacts marginalized communities (Klinenber, 2003)

The problem of heat in neighborhoods and the social justice aspects of heat distribution may not be immediately apparent to residents (Lim et al., 2022)

Gap in data availability and how such information can be incorporated to respond to heat threats (Wilson, 2020)

Gap in extreme heat impact understanding prevent planners and residents to translate scientific knowledge of urban heat to reduce its impact (Lim et al., 2022)

Make sure maps that display such information must be made as accessible and comprehensible as possible

Increased engagement can help achieve a better decision-making process for community resilient heat planning

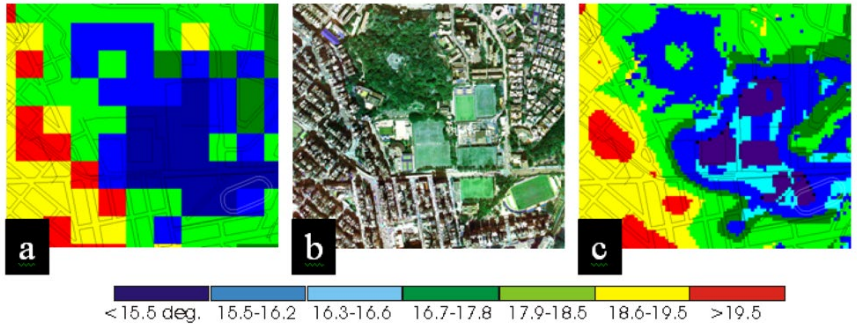
Improving estimates of urban heat

Interpolation can be used to improve spatial resolution.

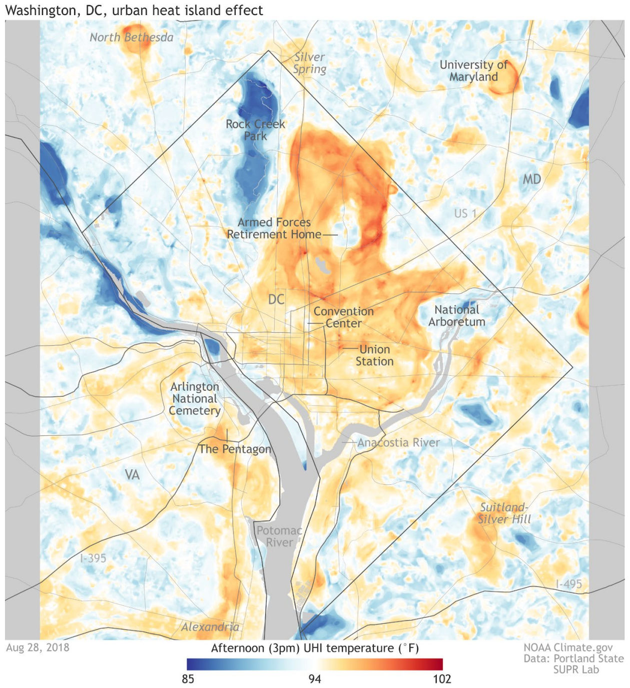
The **National Integrated Heat Health Information System - Climate Adaptation Planning and Analytics (NIHHIS-CAPA) Urban Heat Island Mapping Campaign** has been providing funding since 2017 to produce high-resolution air temperature maps of cities.

The approach adopted an approach where volunteers were outfitted with a small instrument mounted on a vehicle that recorded temperature 5-6 feet from the ground.

A Random Forest Regression model was applied to the collected temperature and humidity readings combined with satellite imagery to produce city-wide estimates

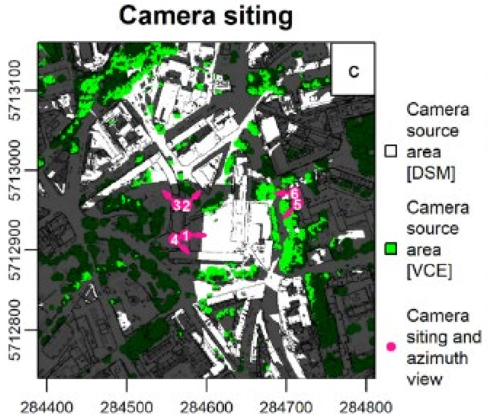


(a) ASTER 90 m thermal data combined with land cover classes derived from (b) RGB imagery to create (c) an interpolated 10 m surface temperature estimate for Hong Kong (from Nichol and Wong, 2009).



Improved measurements of urban heat

Ground-based thermography



6 static LWIR cameras were used to observe urban surface temperatures (Morrison et al., 2021)

UAV-based urban thermography

Naughton & McDonald (2019) used DJI Matrice 100 quadcopter for LST variability

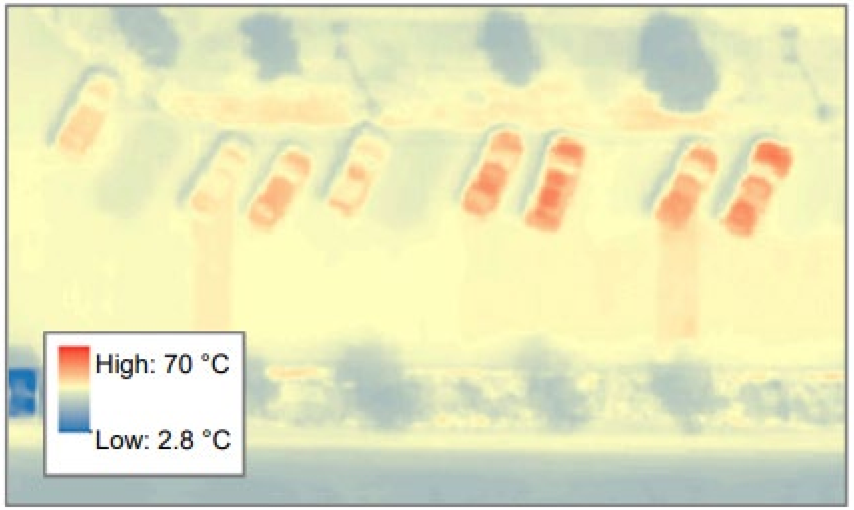
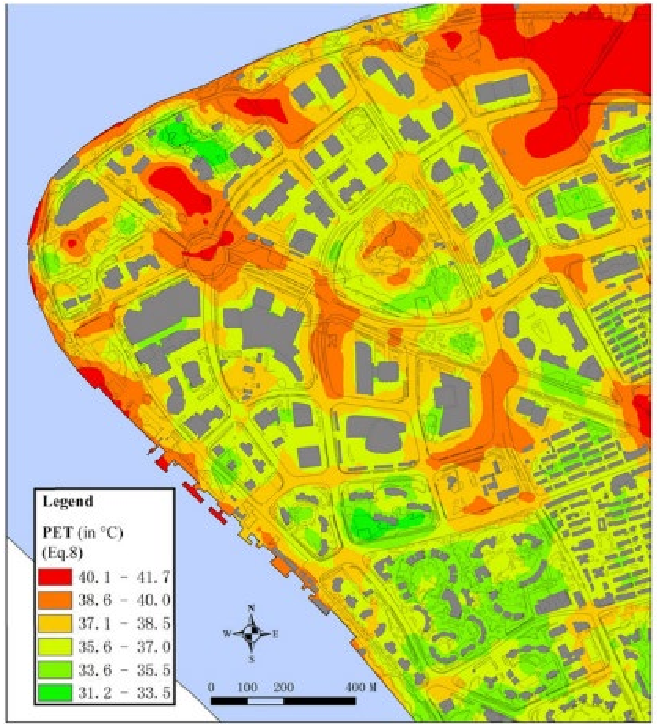
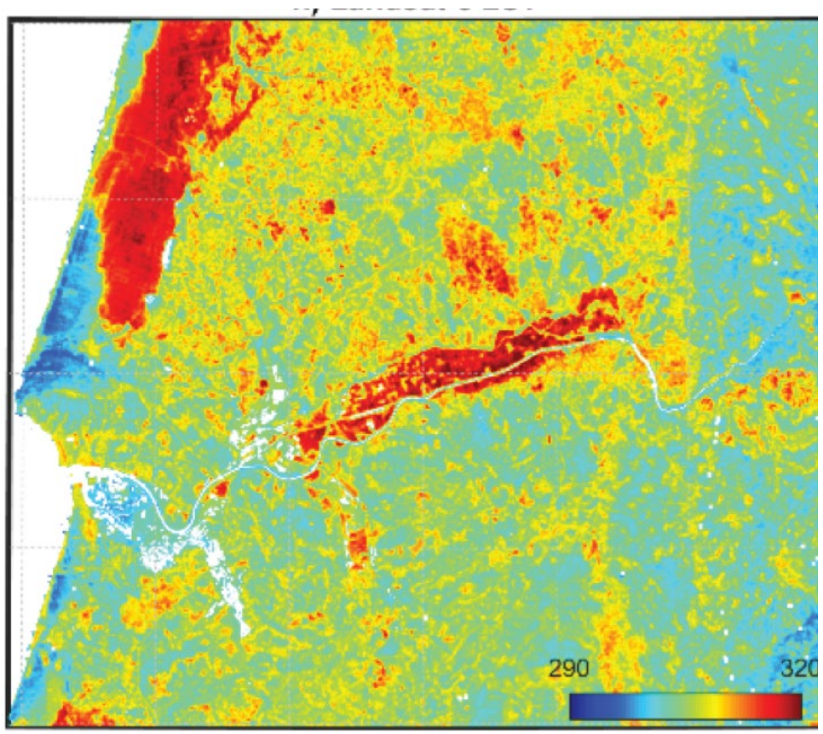


Figure from Naughton and McDonald (2019) Figure 6

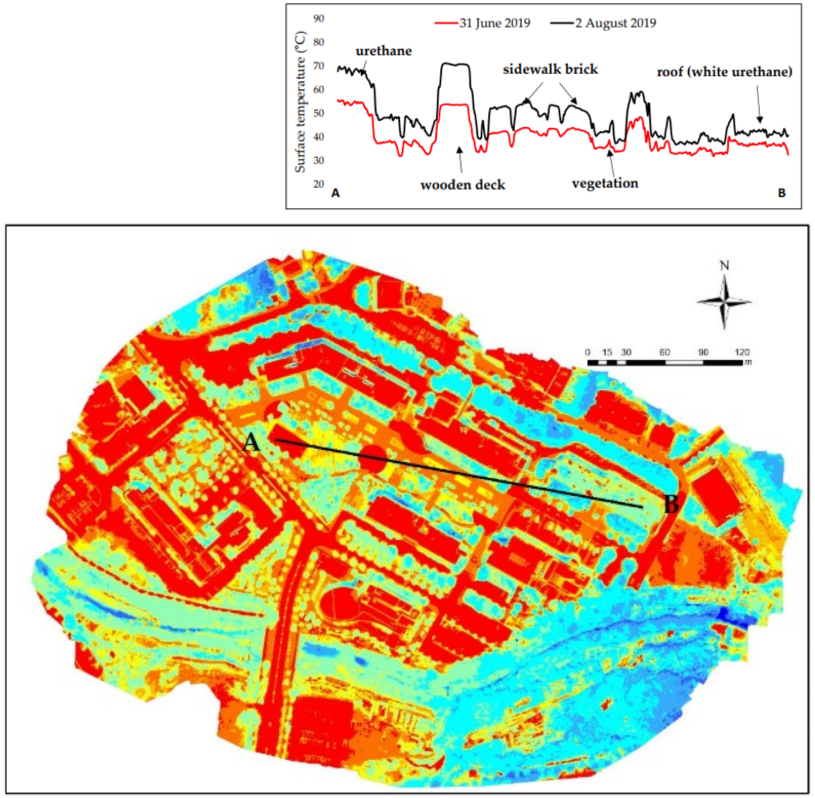
Visualizations of urban heat in scientific literature



A summer daytime thermal atlas of Shanghai CBD showing the temperature in a Red-Yellow-Green diverging colormap (Yang & Chen 2016)

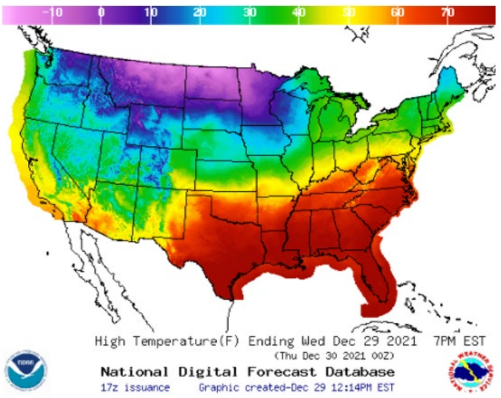


Surface Temperature (Kelvin) algorithmic estimation from Landsat-8 shown for central Portugal, distributed via Google Earth Engine. Map is shown in a rainbow colormap (Ermida et al. 2020)

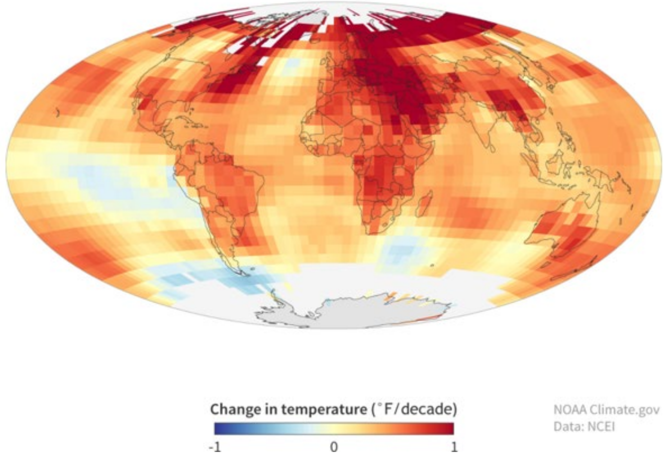


Land Surface Temperature (Celsius) distribution estimated with a Thermal Infrared Camera lifted on a UAV in Changwon, South Korea. Map is using a rainbow colormap (Song & Park 2020)

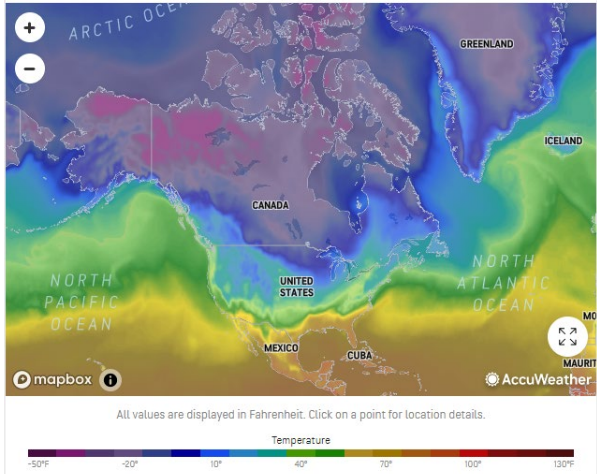
How do meteorologists and climate scientists visualize temperature?



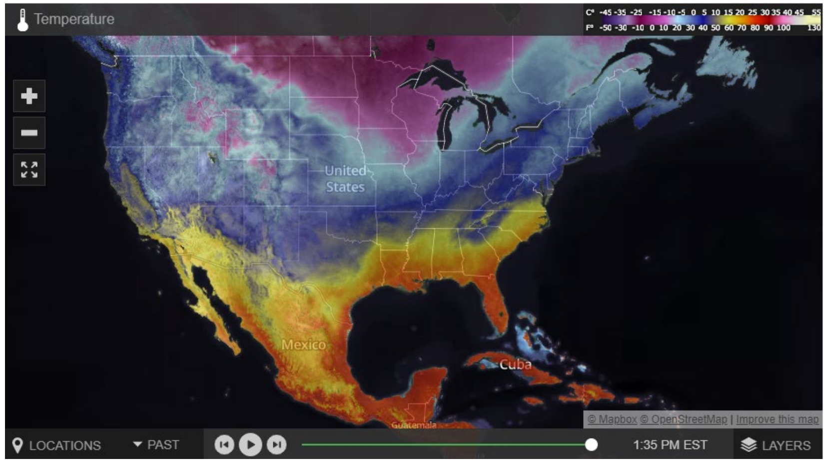
Daily high-temperature values from weather.gov



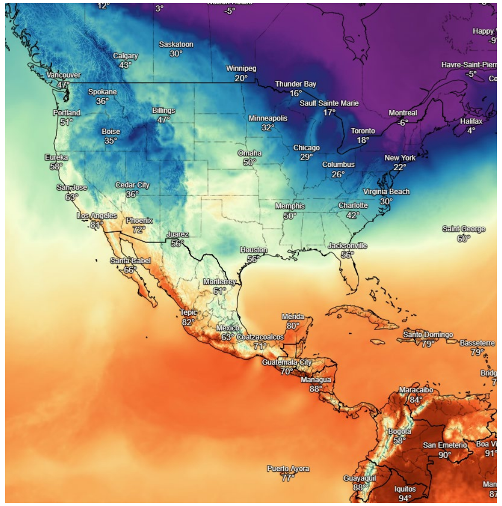
Global thermal anomalies from climate.gov



Accuweather

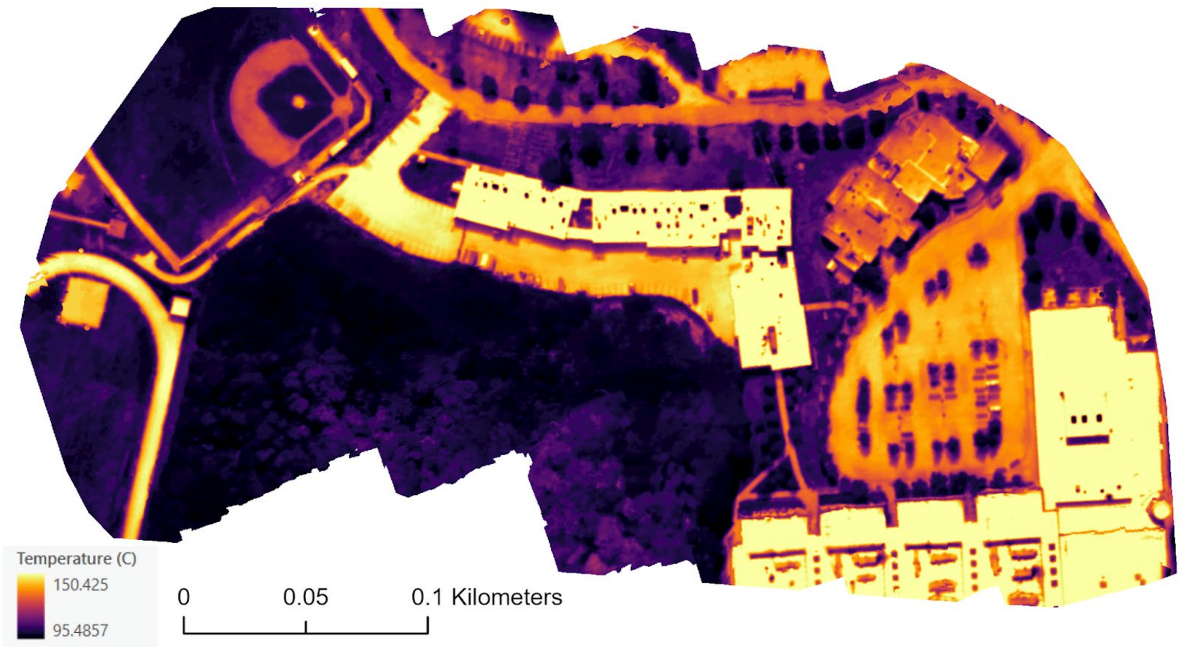


NBC12



Dark Sky

Necessity of visualizing urban heat island effect in high-resolution



Thermal image orthomosaic constructed from images taken during a flight in Roanoke, VA using Mavic Pro Duo thermal camera. Visualized with “inferno” colormap.

<u>UAVs can</u>

- Can collect high-resolution data (Laliberte et al., 2011)
- Shorter time intervals (Vasterling & Meyer, 2013)
- Can change speed, direction and, altitude as needed (Villa et al., 2017)
- 3D models can be reconstructed using the SfM technique (Kniaz & Mizginov, 2018).
- Improvements in spatial resolution of thermal imagery make buildings, trees, and sidewalks directly visible in the scene

The unexplored research areas

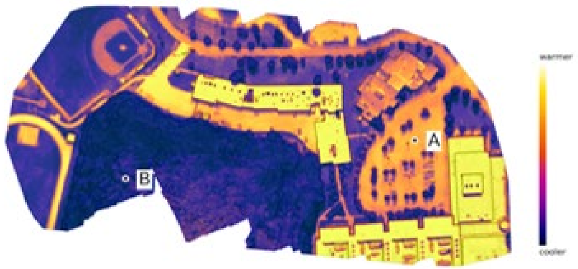
Colormaps affect users' ability to <u>quickly</u> and <u>accurately</u> understand the thermal properties of a scene

Resolution from the different image sources (satellite vs. drone) affect understanding of intra-urban thermal variability

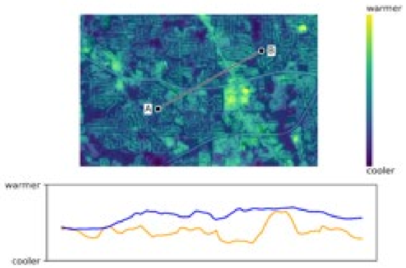
Cartographic augmentations like shading affect how easily and well images are interpreted

The Experiment

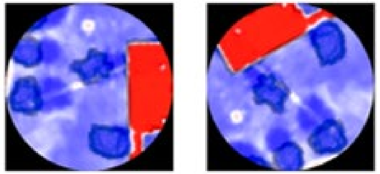
- n = 66
- Three Map Tasks*
  - A-B Pairwise Comparison (50 Q)
  - Profile Estimation (50 Q)
  - Map Rotation (50 Q)
- Three independent variables:
  - Colormap, Source, and Shading enhancement
- Response Time and Accuracy
- Post-task questionnaire
- Administered with PsychoPy
- Analyzed with repeated measures ANOVA in JMP
  - Log(RT)
  - Least squares (marginal) means shown
- Approved by IRB (Case #22-299)



Task 1: Pairwise (A to B) comparison



Task 2: Profile estimation



Task 3: Map rotation

*Tasks were significantly different with respect to both accuracy and (especially) response time.

Data Sources

A **DJI Mavic 2 Enterprise Dual drone** with a thermal camera was used to collect imagery in Roanoke, VA during summer of 2021. This imagery was processed using Pix4D Structure from Motion (SfM) software to create a thermal orthoimage and a 3D point cloud and mesh of the surface. The output resolution was 15 cm.

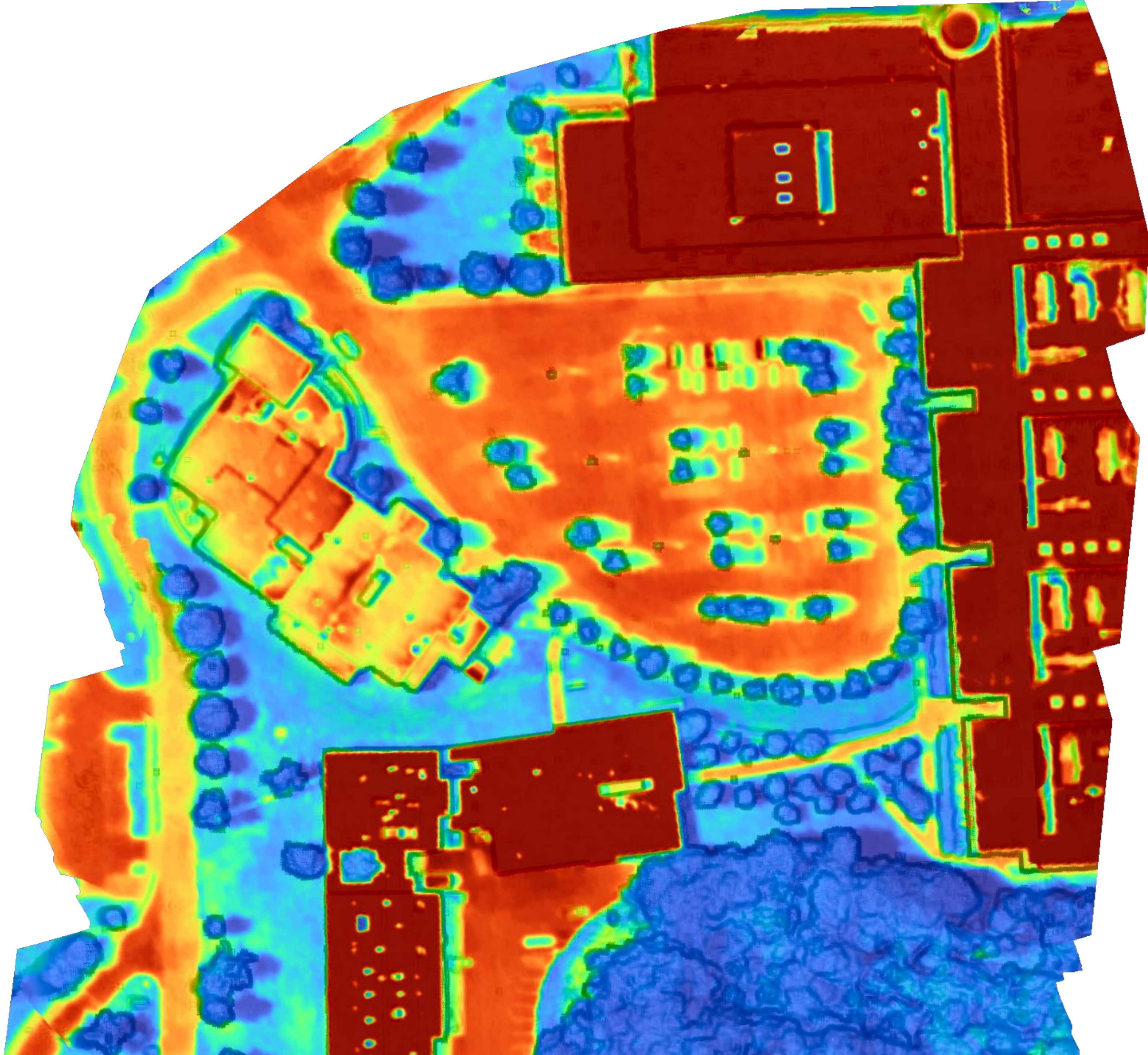
A **Landsat-8 Analysis Ready Data (ARD)** source layer of surface temperature was collected for an area around Atlanta, Georgia during summer. The nominal resolution of this data was 30 m, but visualized over a larger extent

Thermal data was visualized using one of five colormaps:

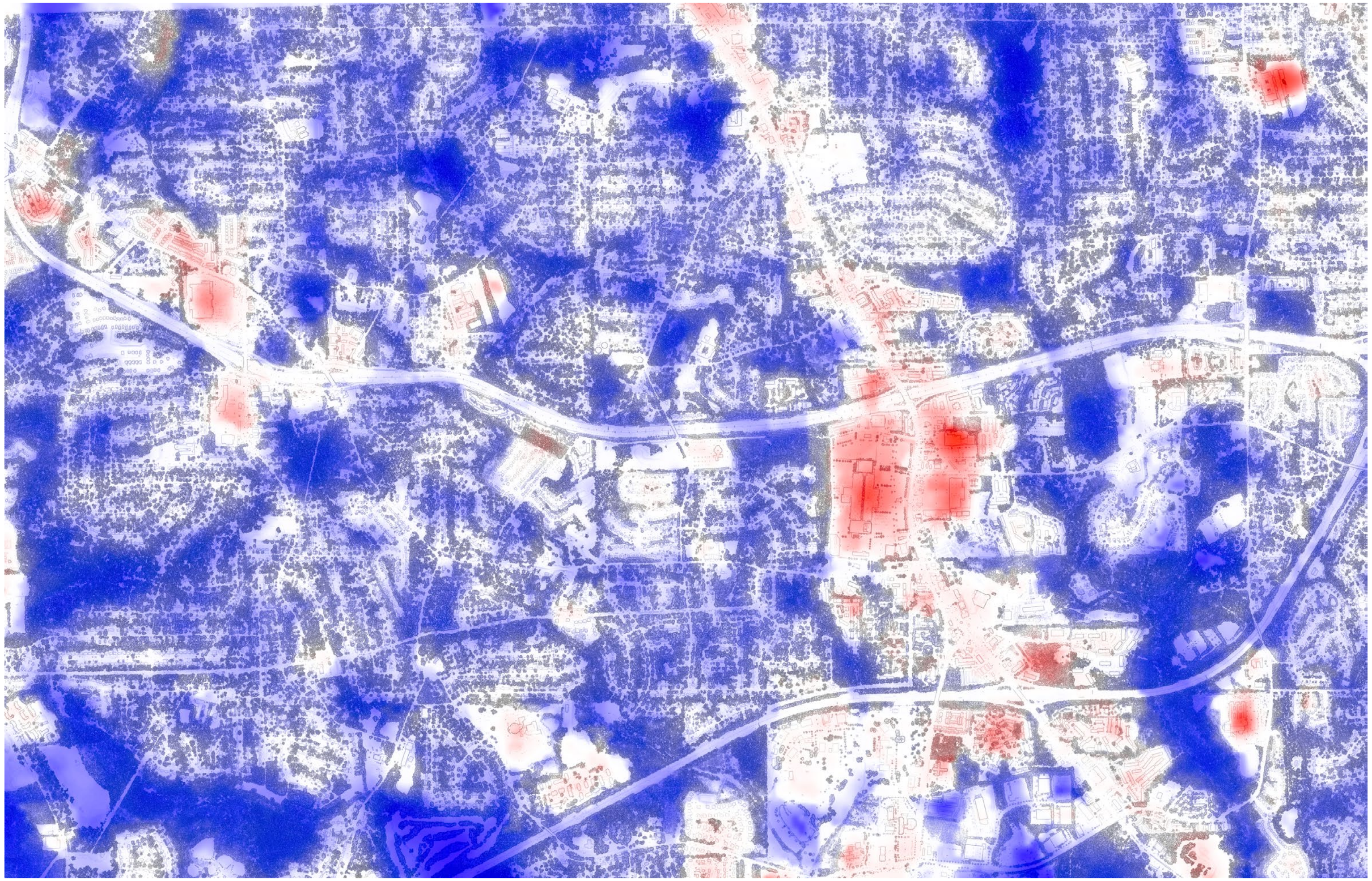
A) Blue-White-Red (BWR)
B) Esri's Temperature Colormap
C) Ironbow, used by FLIR
D) Viridis
E) Turbo, a more perceptually uniform version of "jet"

The Digital Surface Model (DSM) derived from the SfM reconstruction was used to add shading.

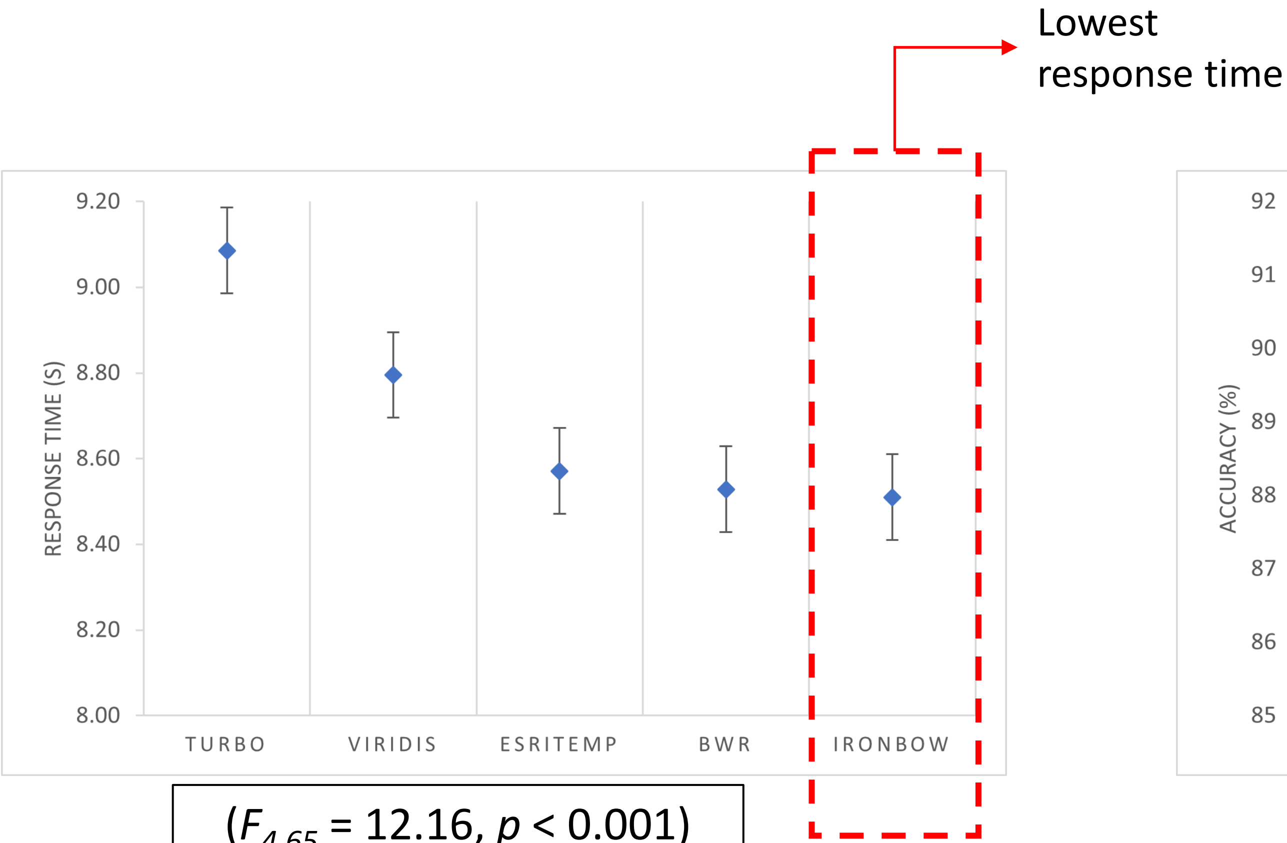
In this way, trees, cars, buildings, and other forms of landcover more clearly stand out.



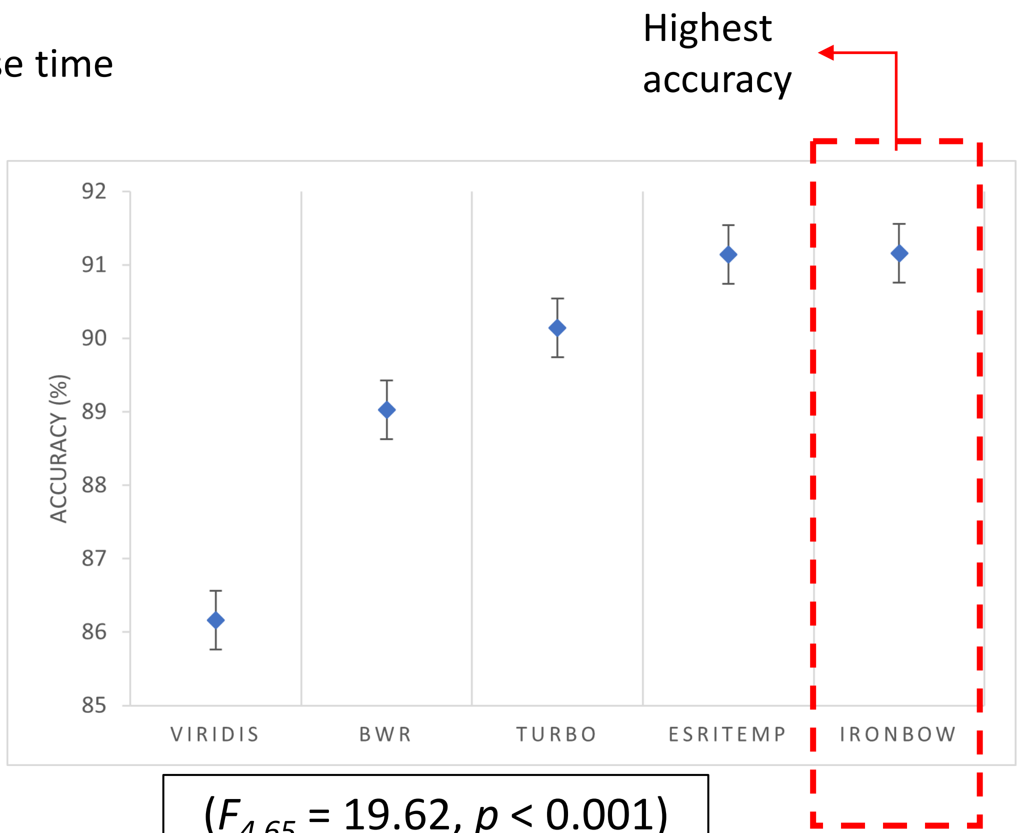
A similar process (using lidar) was used to shade the Landsat-8 / city-scale image.



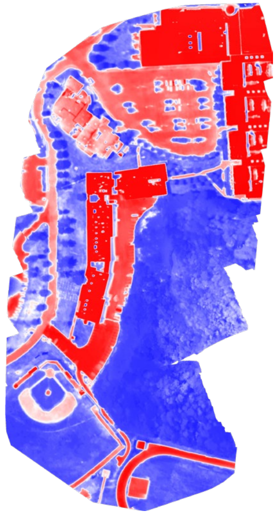
Ironbow colormap has lower response time and better accuracy



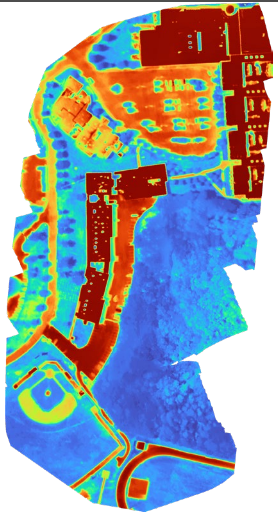
($F_{4,65}$ = 12.16, p < 0.001)



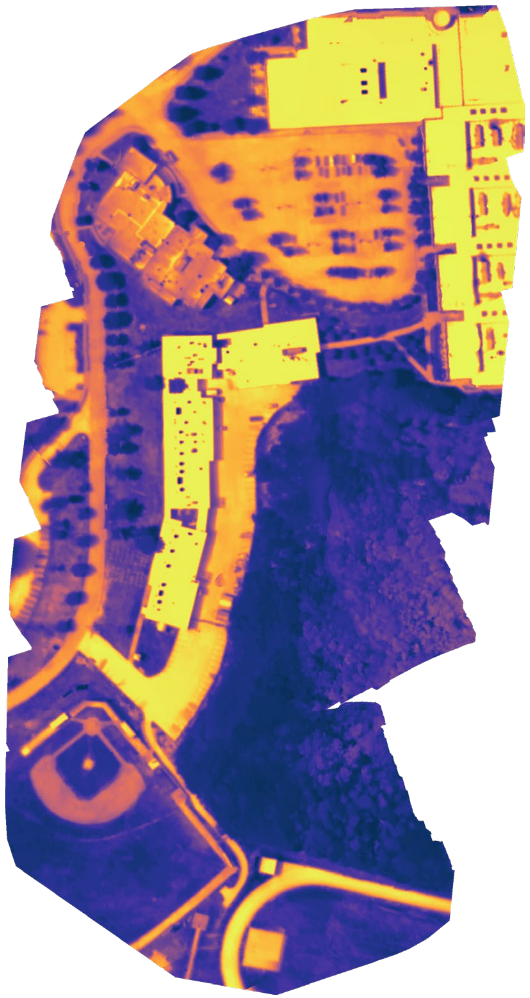
($F_{4,65}$ = 19.62, p < 0.001)



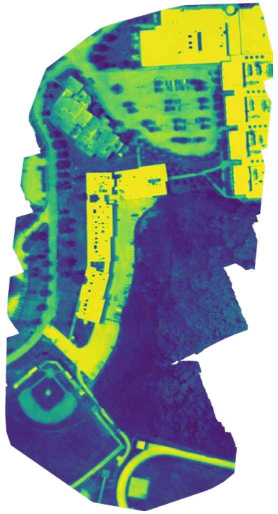
BWR



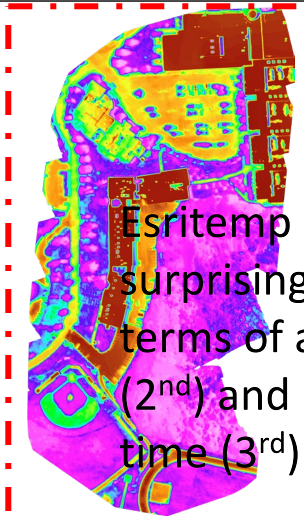
Turbo



Ironbow has the lowest response time and the highest accuracy



Viridis



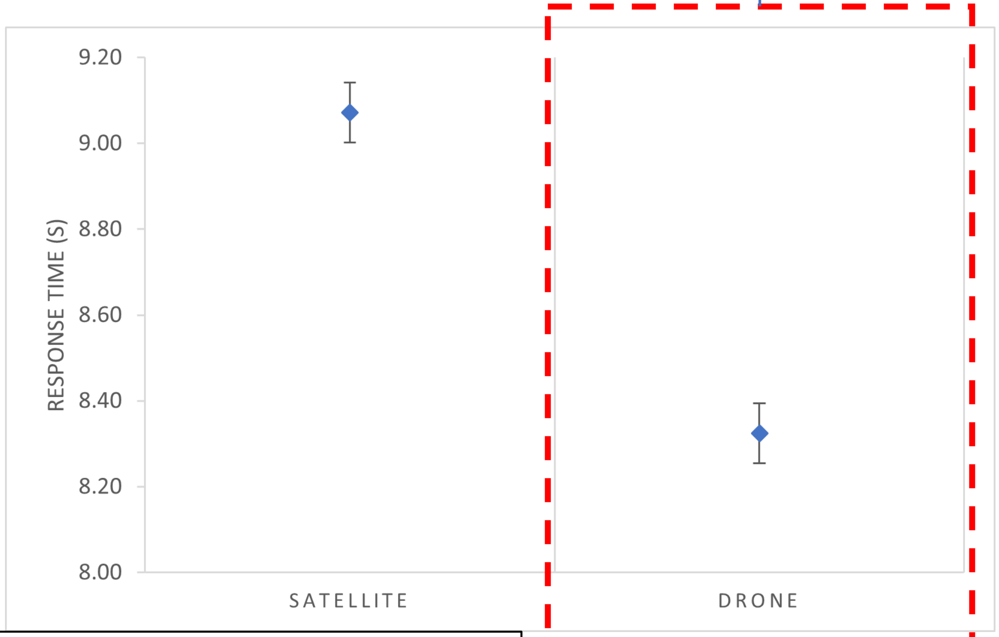
Esritemp performed surprisingly good in terms of accuracy (2nd) and response time (3rd)

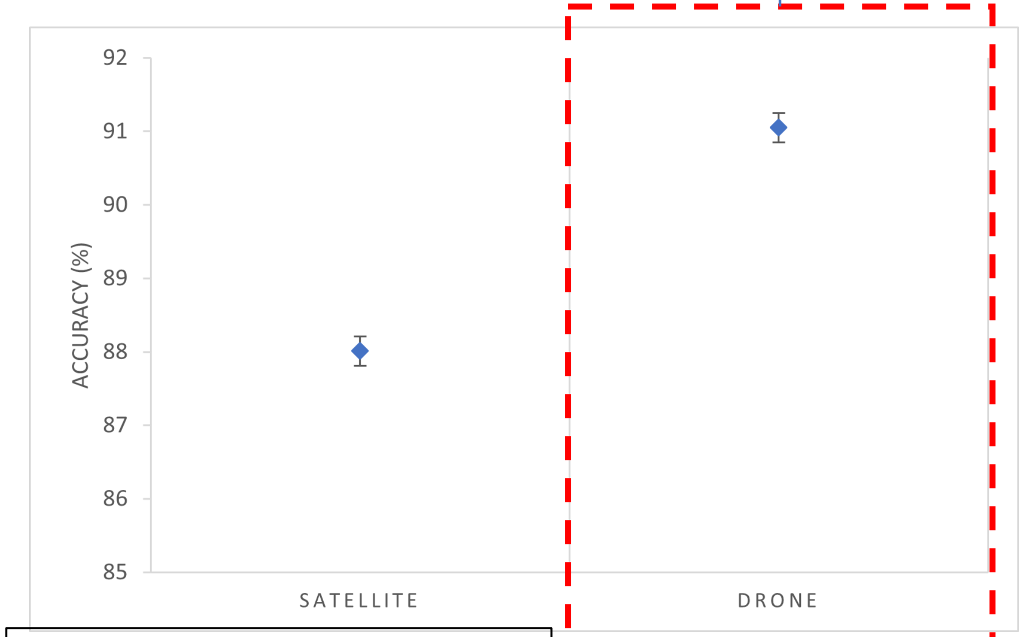
Esritemp

Drone images have better accuracy

Lower
Response time

Higher Accuracy

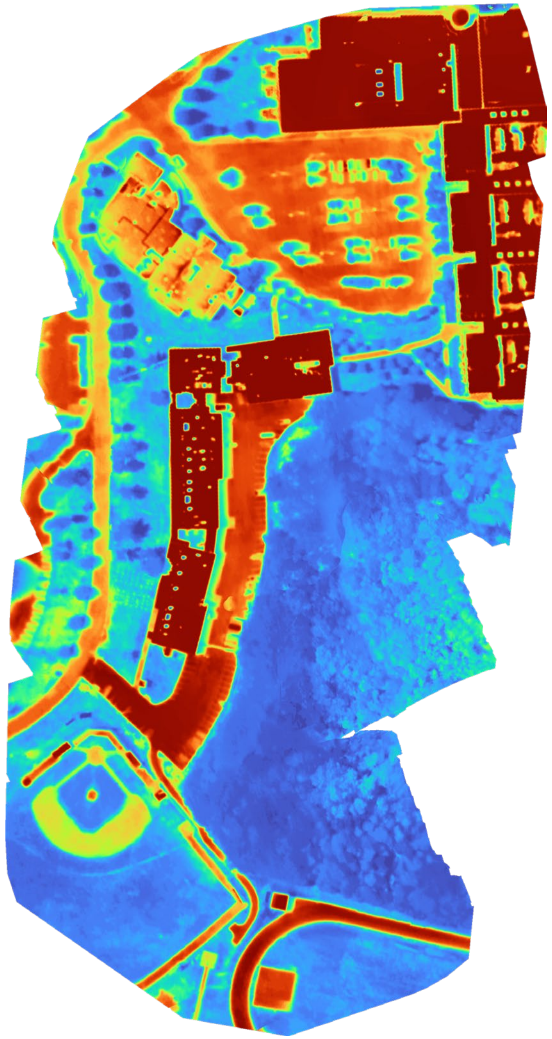




($F_{1,65} < 0.01$, $p = 0.96$)**

($F_{1,65} = 52.80$, $p < 0.001$)

**The difference is not significant

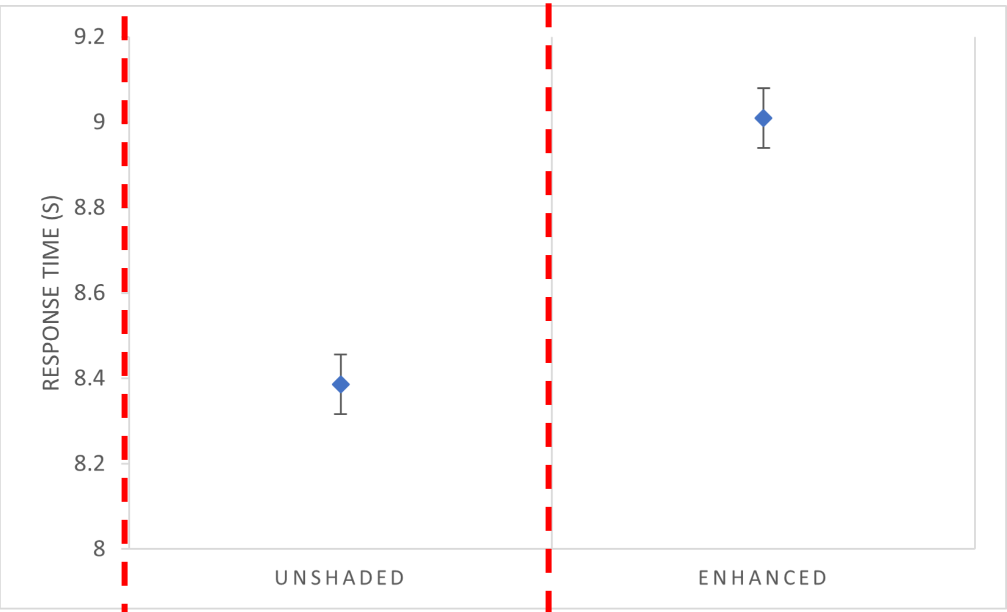


Judgements made from drone-sourced images are more accurate

Unshaded images have lower response time

Lower response time

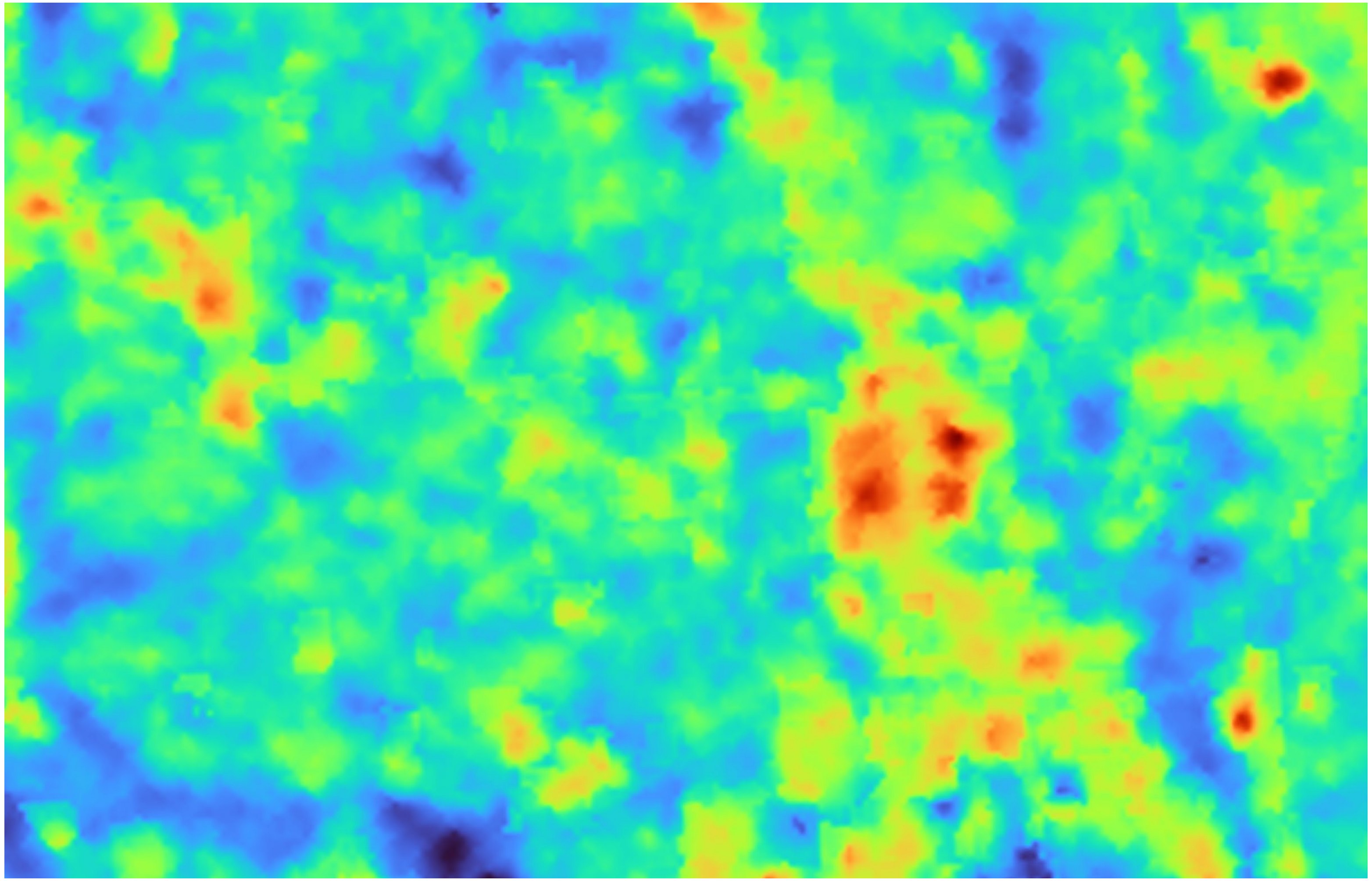
Higher accuracy



($F_{1,65}$ = 128.77, p < 0.001)

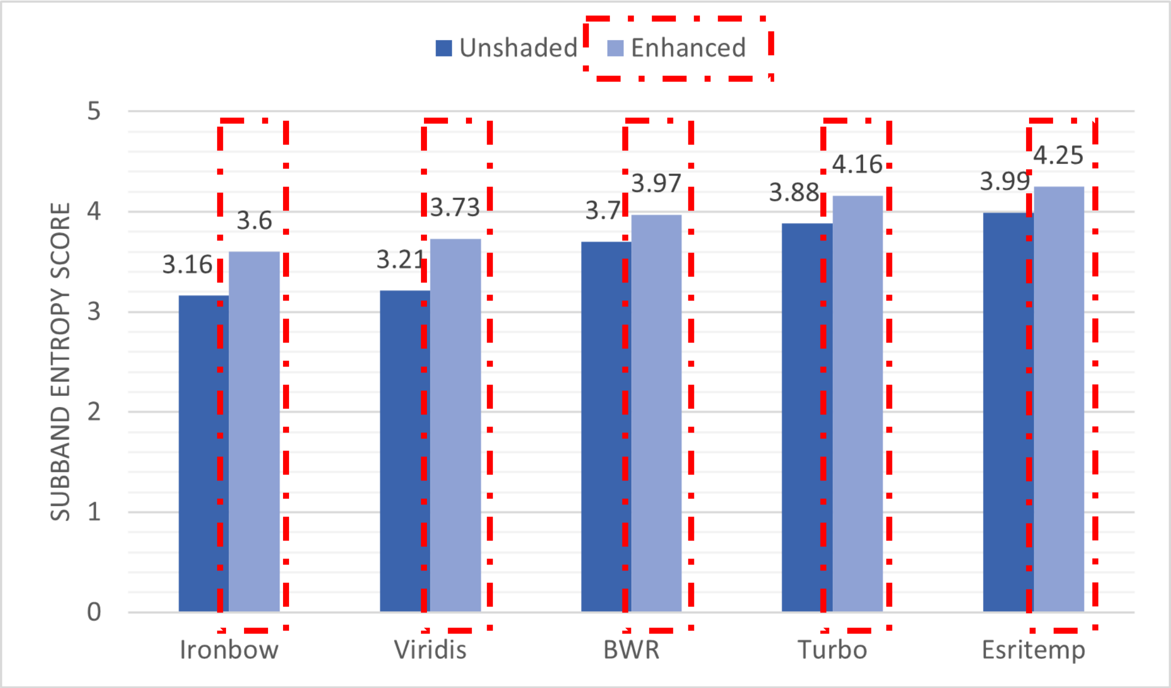
($F_{1,65}$ = 2.92, p = 0.09)**

**The difference is not significant



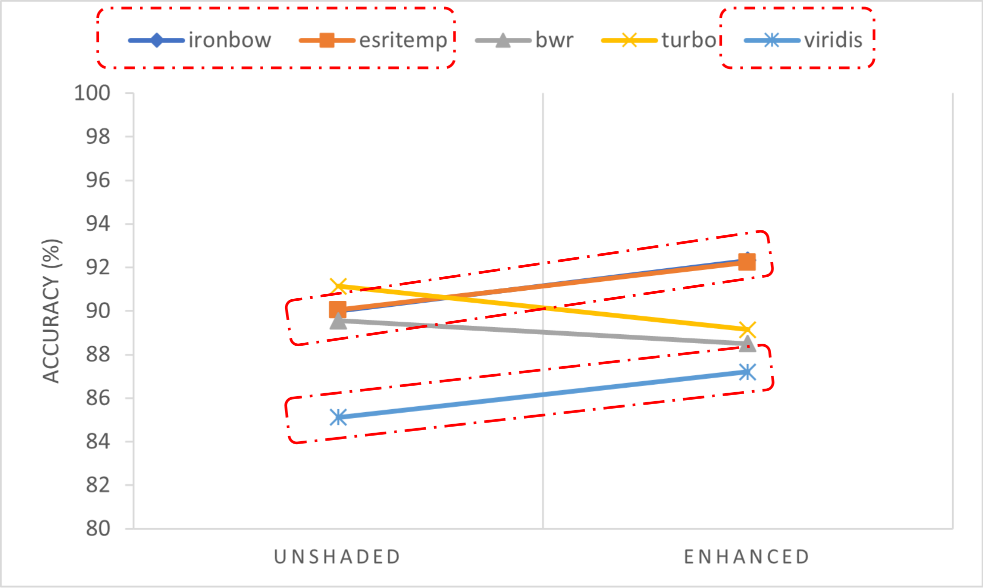
Unshaded images are faster to interact with.

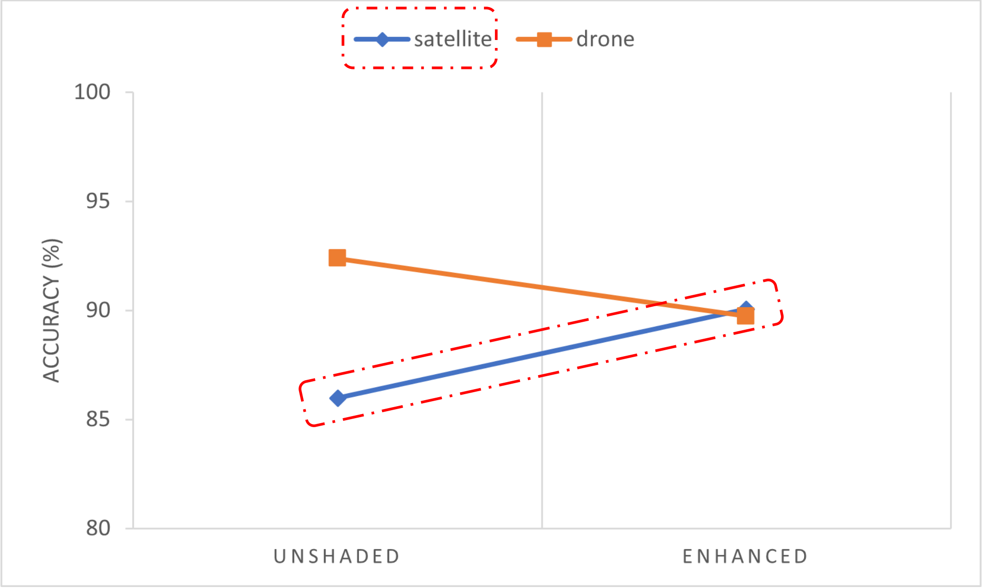
Visual Clutter



- Visual clutter is the state where excess items, or their representation in a visual lead to degradation of performance at some task
- Subband Entropy is a measure of visual clutter that is related to the number of bits needed for subband image coding
- Enhanced images contain more information to interpret, that's why they are 'cluttered'
- Users had **longer response time** to interpret the information but that resulted in **higher accuracy**

Results: Shading interaction with colormaps and sources

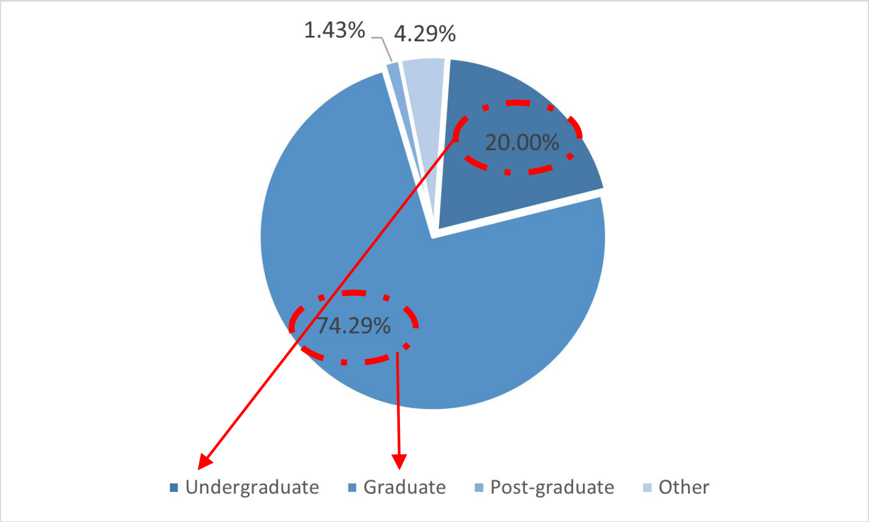




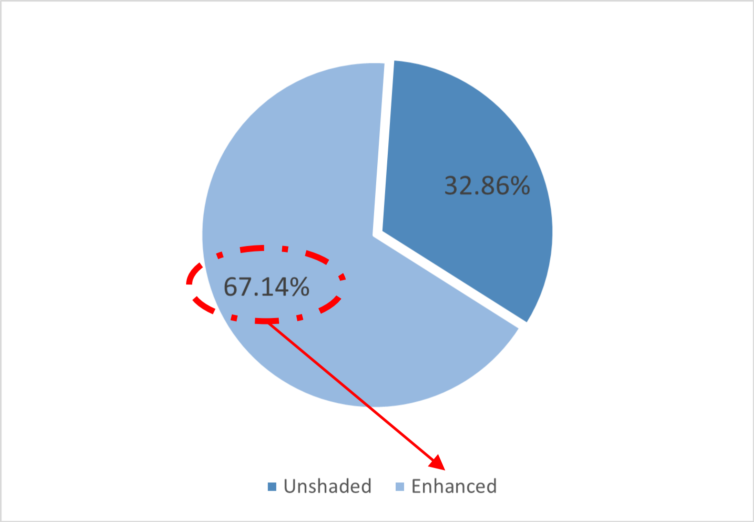
Enhancement increased accuracy for Ironbow, Esritemp and Viridis colormaps

Enhancement increased accuracy for satellite images and decreased for drone images

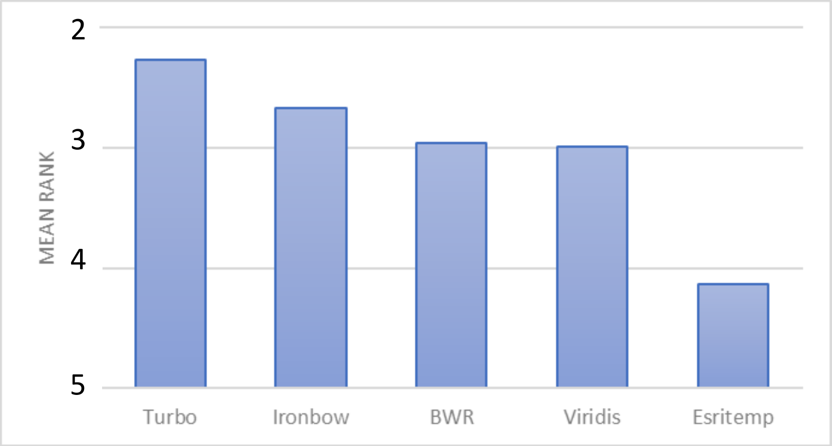
Results: Preferences



Education level of participants



Preference for enhancement



Mean rank of colormaps

Conclusions

- Performance matters, but so does preference.
  - People are more likely to be engaged with images they find preferable (Lefkoff-Hagius & Mason, 1993).

- <u>Colormaps</u> were significantly different in performance and preference
  - Ironbow was a strong performer and was well-liked.
  - Esritemp was a strong performer but was not well-liked.
  - Viridis is a poor performer overall

- <u>DSM Shading</u> was well-liked, but performance less clear
  - Some of the performance difference may be attributable to increased visual clutter

- <u>Source</u> matters, as judgements made from drone-sourced images were faster and more accurate.

Thank you!

I am now open for your questions and comments.