

Large-Scale Geo-Data Mining for Good

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Agenda

Big Geo-Data Remote Sensors: an eye on our planet across the spectrum I

Urban Forests:
a source of wellbeing that deserves attention & planning II.a

Klein, Zhou, Albrecht ([ICML 2021](#)), Albrecht et al. ([IGARSS 2022, accepted](#)),
Klein, Albrecht, Marianno ([2022 ESA Living Planet Symposium](#))

Archeology top-down:
discover traces of and learn from our ancestors keeping intact the environment II.b

Albrecht et al. ([IEEE BigData 2019](#)), Albrecht & Pankanti ([2020 AAAS symposium](#)),
students of Albrecht group @ Zhu lab ([2022 German-Israeli archeology challenge winners](#))

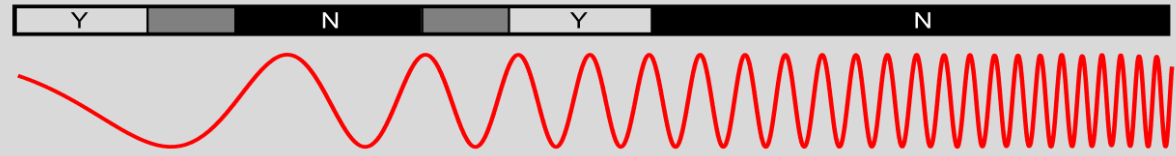
Earth Observation analytics: challenges & perspectives III

plenum & discussion IV

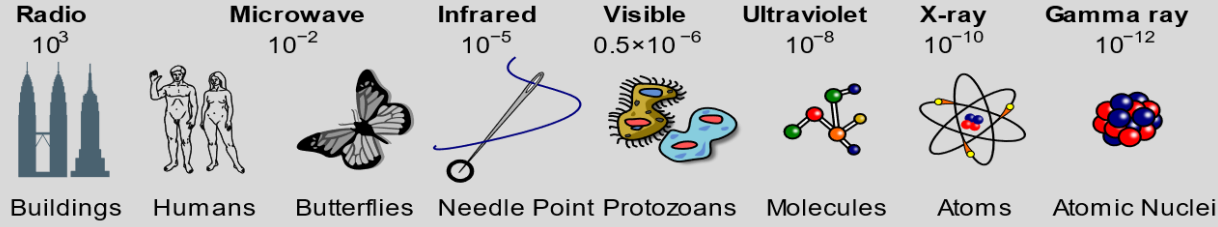


I Big-Geo Data Remote Sensors: eye on our planet across the spectrum

Penetrates Earth's Atmosphere?



Radiation Type
Wavelength (m)
Approximate Scale of Wavelength

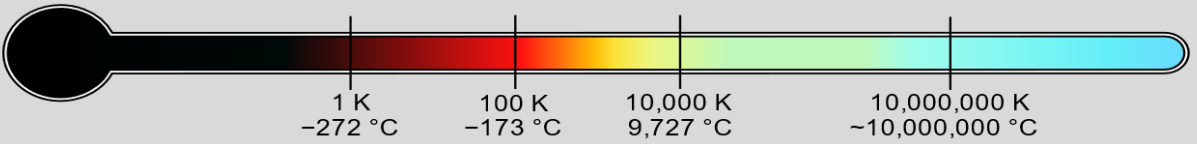


source of figure elements:
<https://wikipedia.org> and
<https://svs.gsfc.nasa.gov/13114>

Frequency (Hz)



Temperature of objects at which this radiation is the most intense wavelength emitted

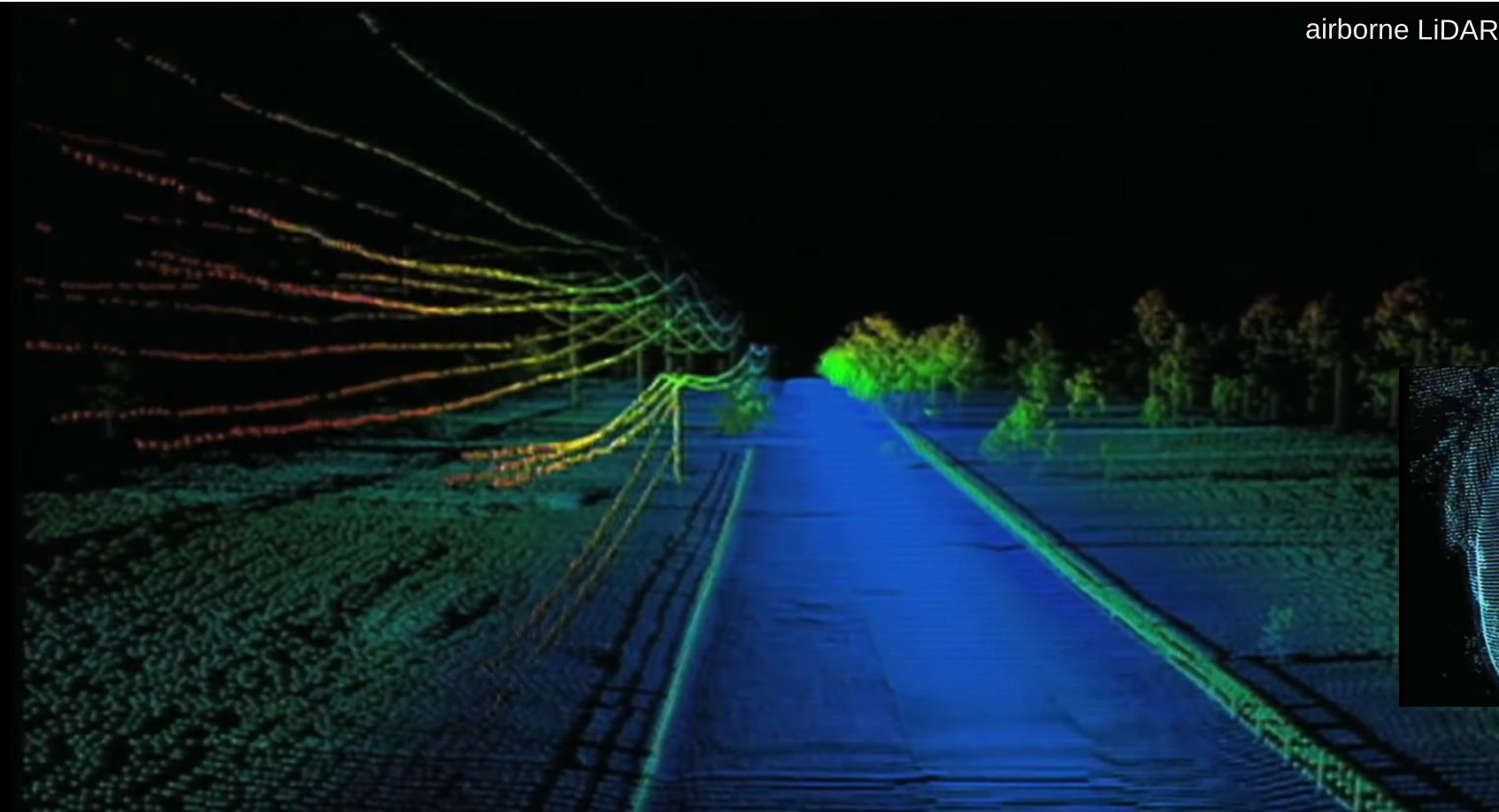


Radar: record phase and amplitude of microwave-like generated signal bouncing off Earth's surface (including its polarization)



optical: multi- & hyperspectral imaging by absorption of sunlight reflected by Earth's surface (including infrared and thermal radiation)

I Big-Geo Data Remote Sensors: LiDAR laser technology in the arts

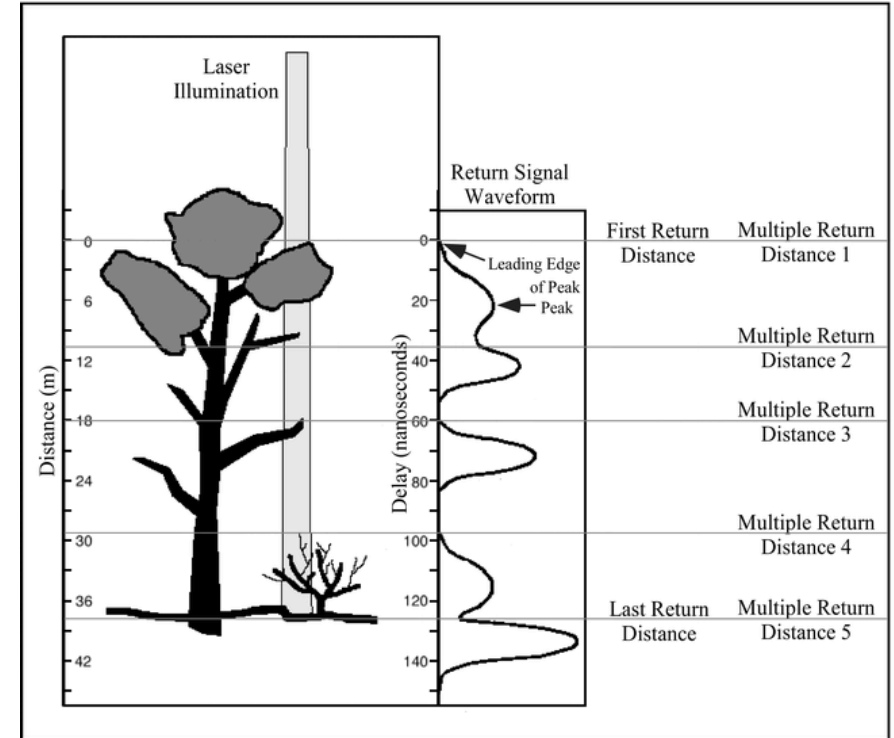


airborne LiDAR



car-mounted(-like) LiDAR

I Big-Geo Data Remote Sensors: LiDAR worth the effort?



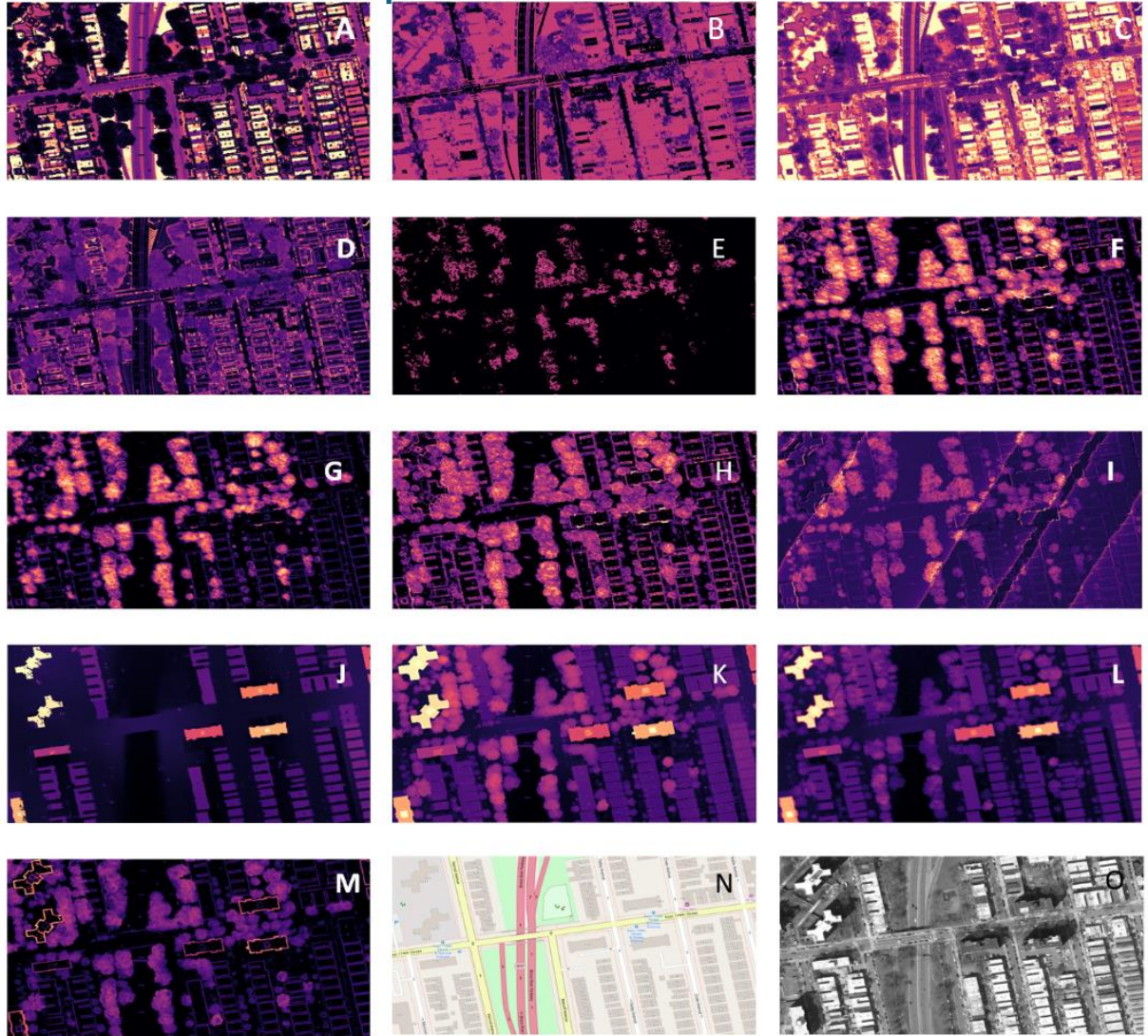


view onto Manhattan with Central Park, New York City, as in my seat after take-off from EWR ...

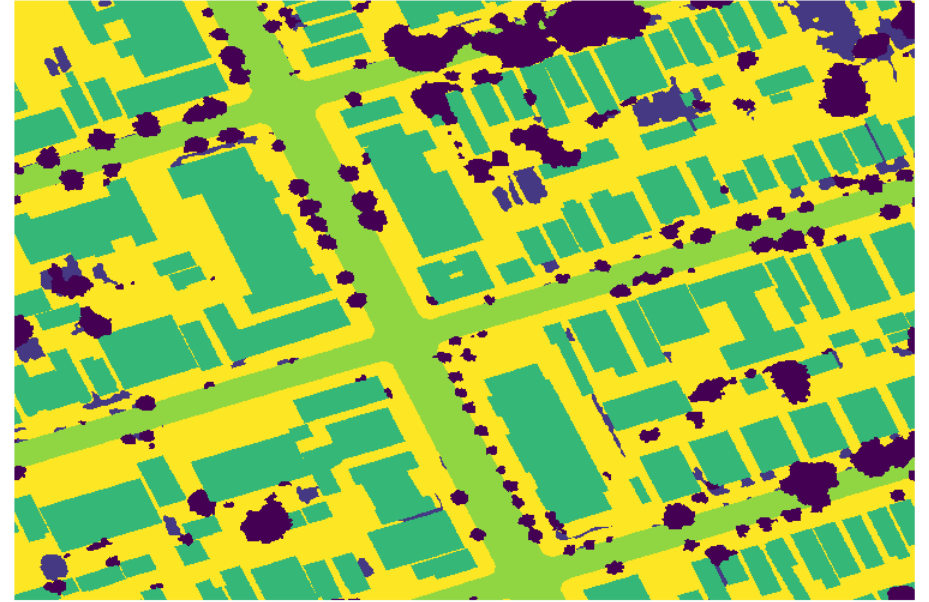
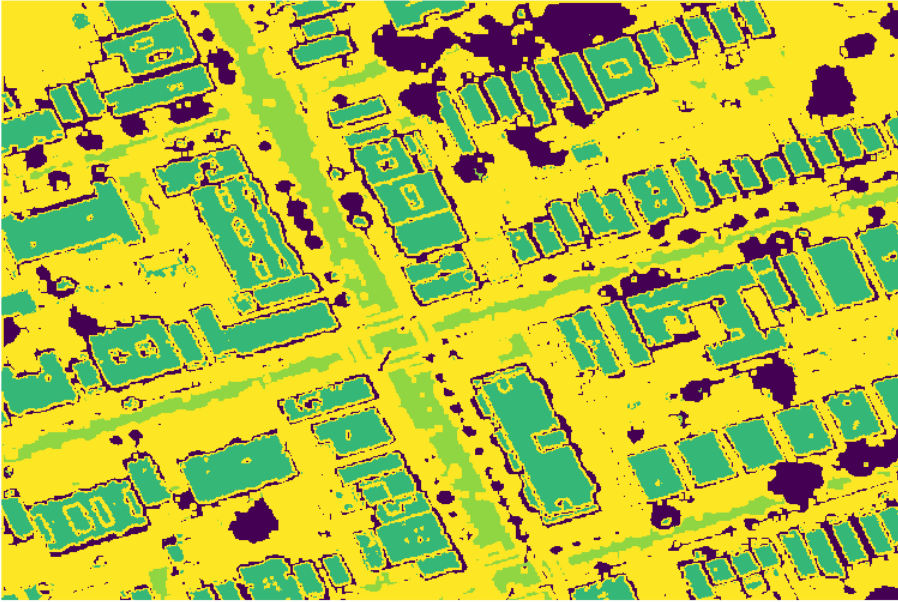
II.a Urban Forests (in NYC): From raw 3D LiDAR point cloud statistics ...

POINT CLOUD STATISTICS

| attribute | statistics | Fig. 2 index |
|-----------------|-------------------------------|--------------|
| reflectance r | minimum r_- | A |
| | maximum r_+ | B |
| | mean \bar{r} | C |
| | standard deviation r_Δ | D |
| count c | minimum c_- | E |
| | maximum c_+ | F |
| | mean \bar{c} | G |
| | standard deviation c_Δ | H |
| | sum Σ | I |
| elevation e | minimum e_- | J |
| | maximum e_+ | K |
| | mean \bar{e} | L |
| | standard deviation e_Δ | M |



II.a Urban Forests (in NYC): ... to tree identification ...



LABELING RULES FROM LIDAR STATISTICS

| class | pseudo (R,G,B) | binary classification rule |
|------------|-----------------------------|---|
| buildings | (e_-, e_Δ, e_+) | $e_- > \langle e_- \rangle \wedge e_\Delta < \langle e_\Delta \rangle \wedge e_+ > \langle e_+ \rangle$ |
| vegetation | $(c_+, e_\Delta, c_\Delta)$ | $c_+ > \langle c_+ \rangle \wedge e_\Delta > \langle e_\Delta \rangle \wedge c_\Delta > \langle c_\Delta \rangle$ |
| roads | (r_-, \bar{r}, e_-) | $r_- > .1r_{\max} \wedge \bar{r} < .6r_{\max} \wedge e_- < .1e_{\max}$ |

II.a Urban Forests: ... for long-term tree damage by Hurricane Sandy ...



(a) 2011: one year before storm



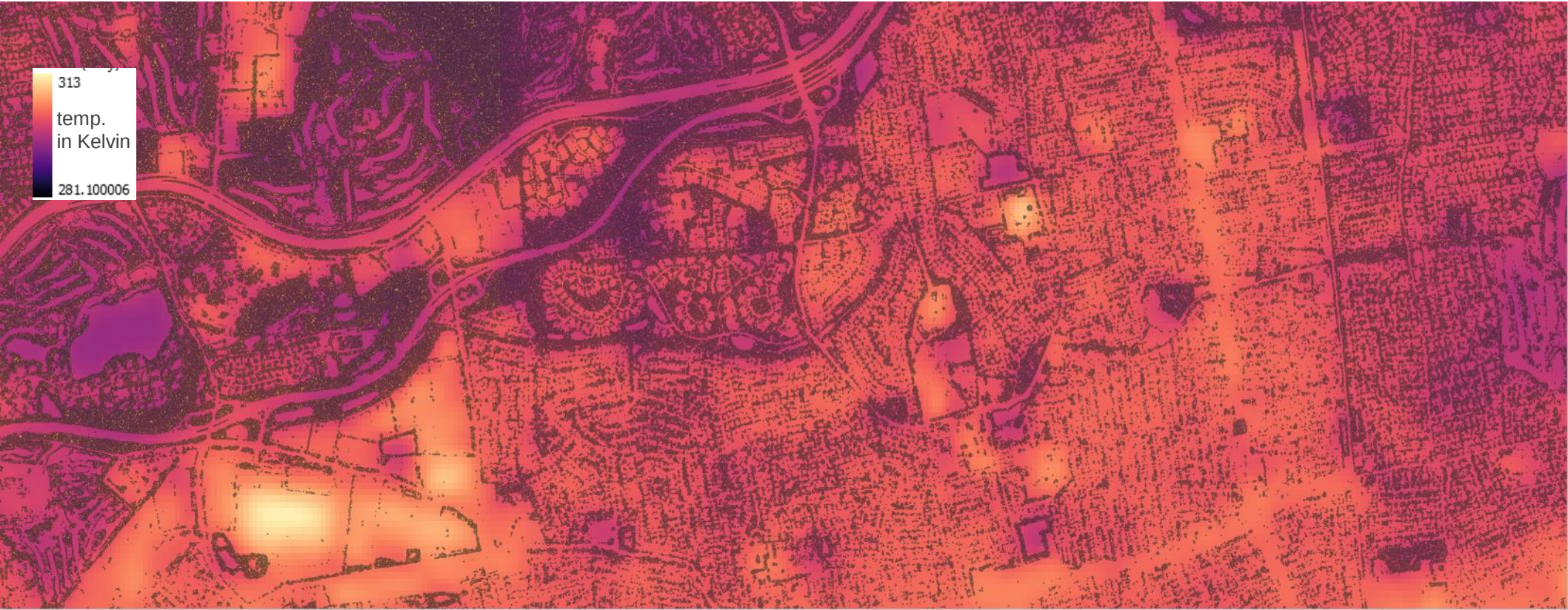
(b) 2013: one year after storm



(c) 2015: 3 years after storm

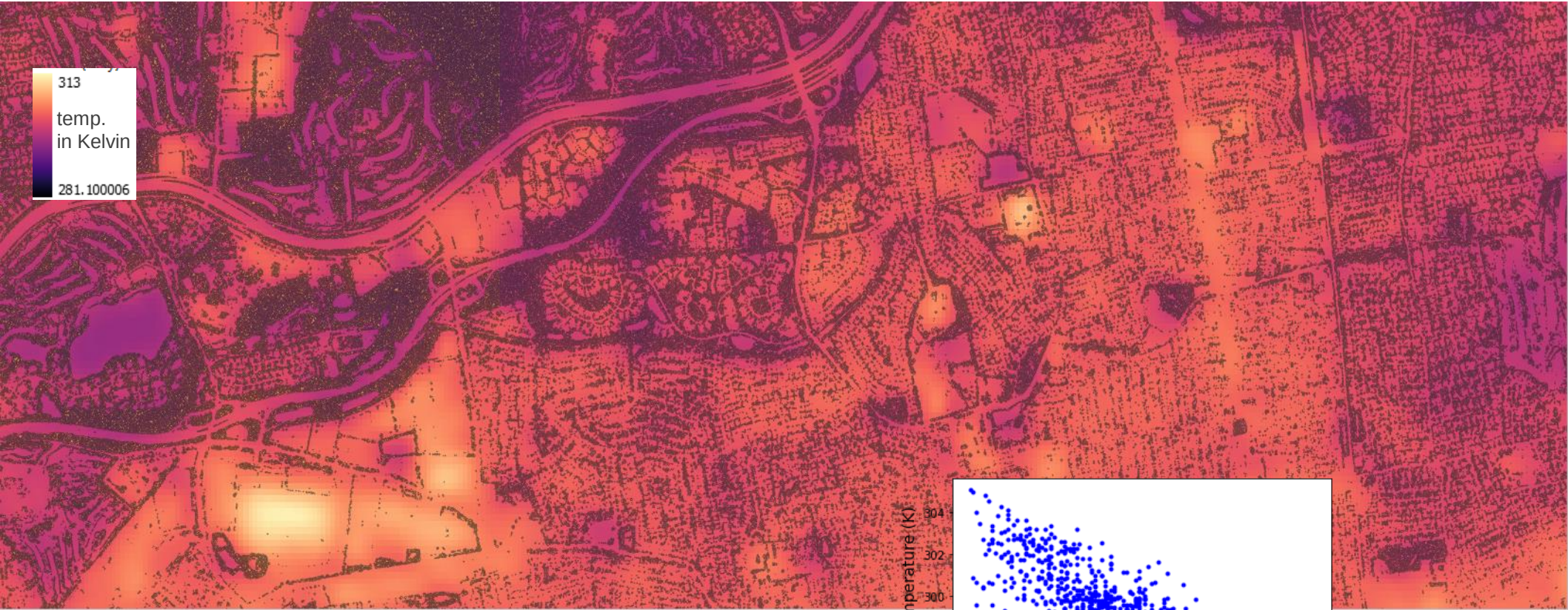
| scene definition | sample reference (<i>lat, lon</i>) | vegetation state description | relative change | |
|-------------------------|---|---------------------------------|-----------------|-------------|
| | | | 2011 → 2013 | 2013 → 2015 |
| suburban close to shore | (40.579, -73.947) | <i>damaged</i> | -14% | -5% |
| urban close to shore | (40.580, -73.958) | <i>little damage</i> | -3% | +4% |
| suburban inland | (40.599, -73.967) | <i>undamaged</i> | +5% | +3% |

II.a Urban Forests: ... or heat island identification & urban planning

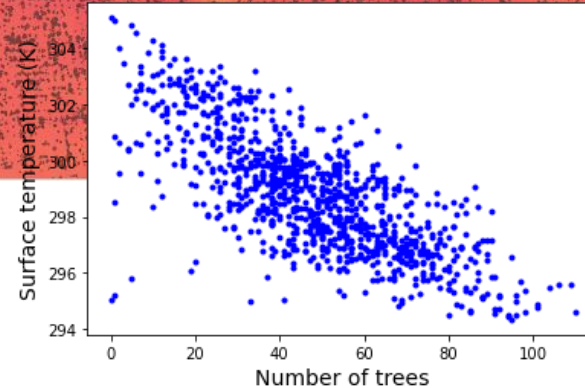


sensor fusion:
Landsat 8 satellite's thermo-**optical** sensor + vegetation identified by airborne **LiDAR** survey

II.a Urban Forests: ... or heat island identification & urban planning

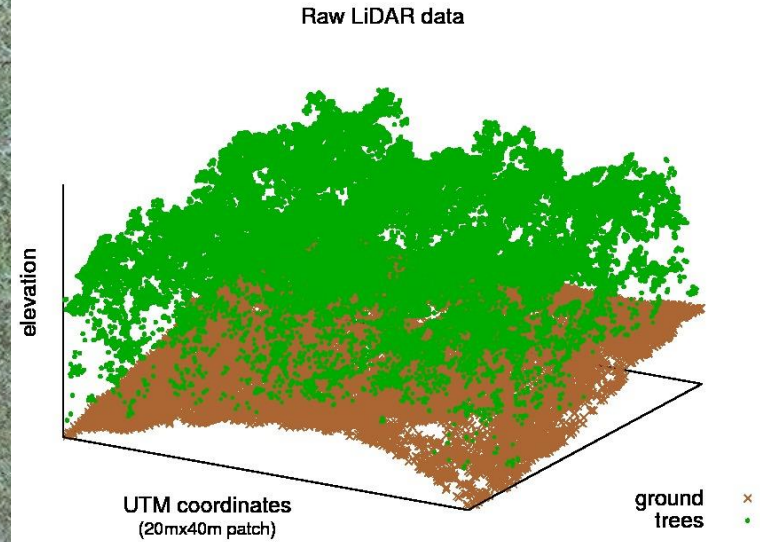


sensor fusion:
Landsat 8 satellite's thermo-**optical** sensor + vegetation identified by airborne **LiDAR** survey





II.b Archeology top-down: Digitally uncovering ancient urban infrastructure ...



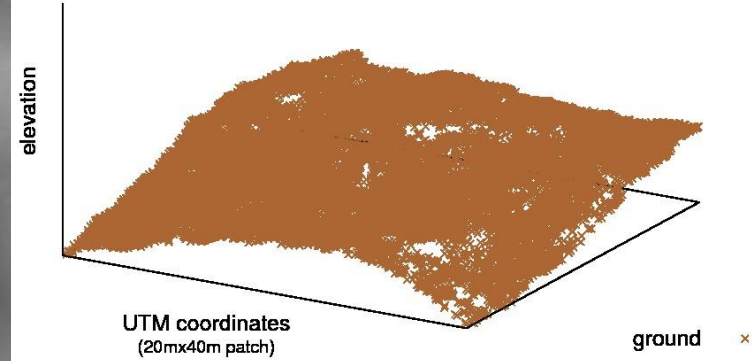
classify 3D LiDAR point cloud into
tree data vs. bare ground laser
reflections



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II.2 Archeology top-down: Digitally uncovering ancient urban infrastructure ...



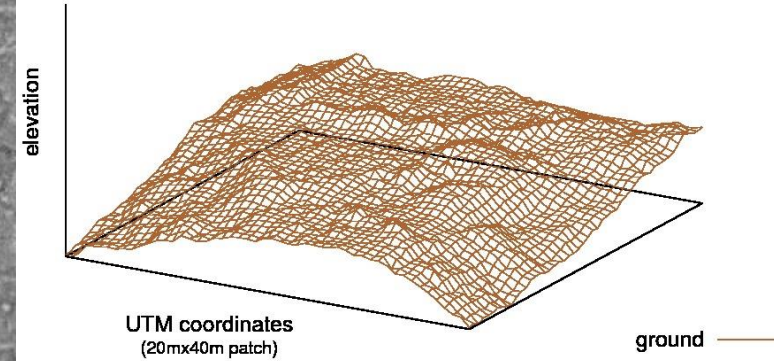
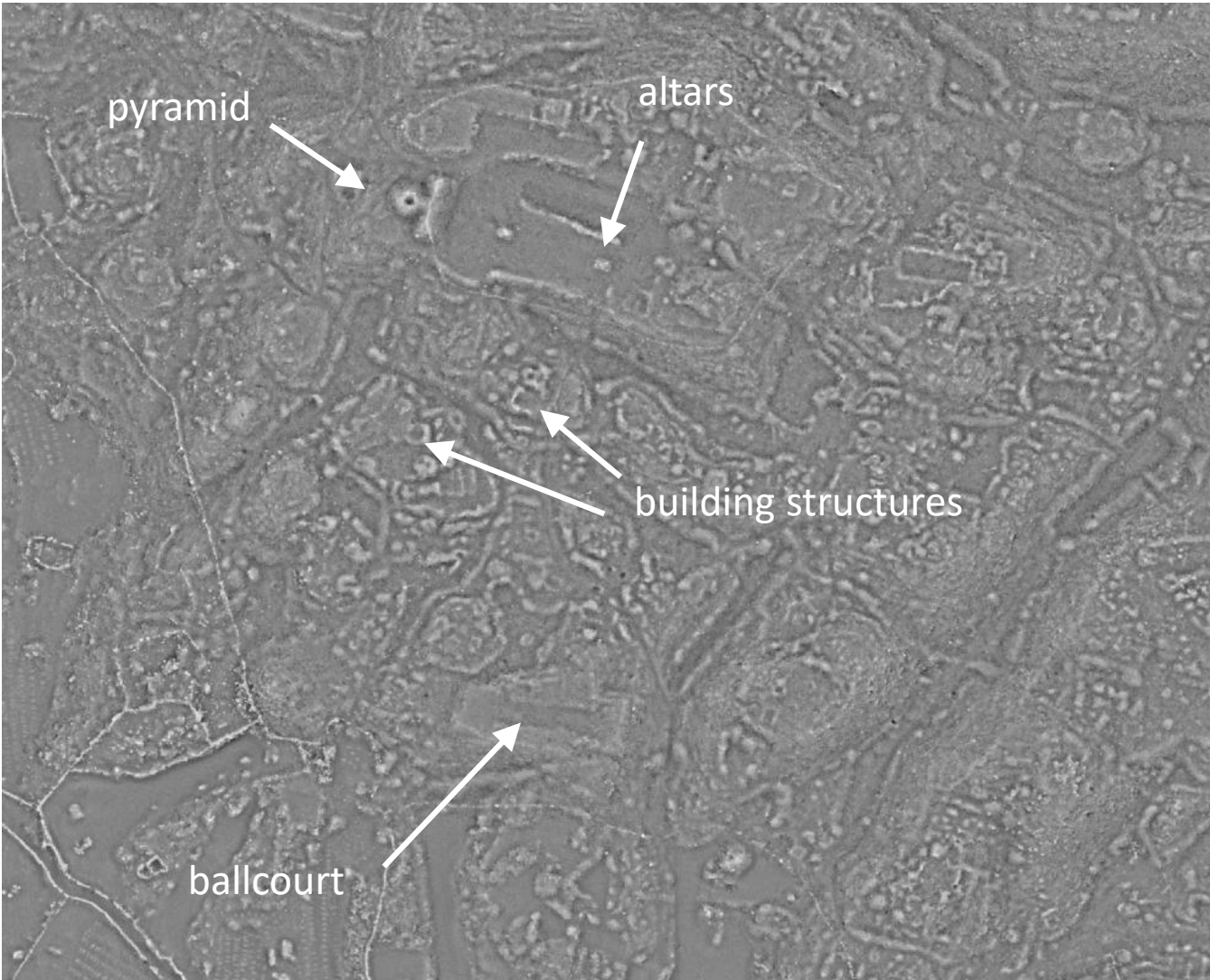
**virtually remove trees to obtain
rasterized digital elevation model**



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IBM
Research

II.b Archeology top-down: Digitally uncovering ancient urban infrastructure ...



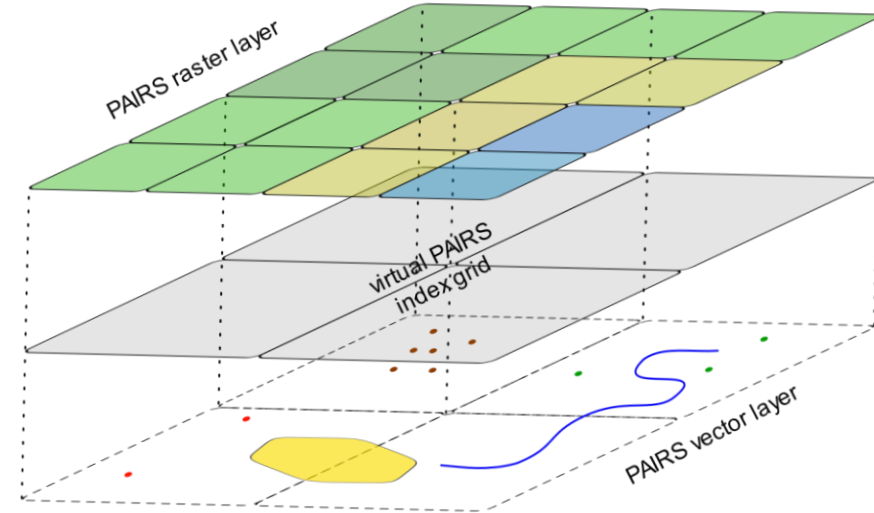
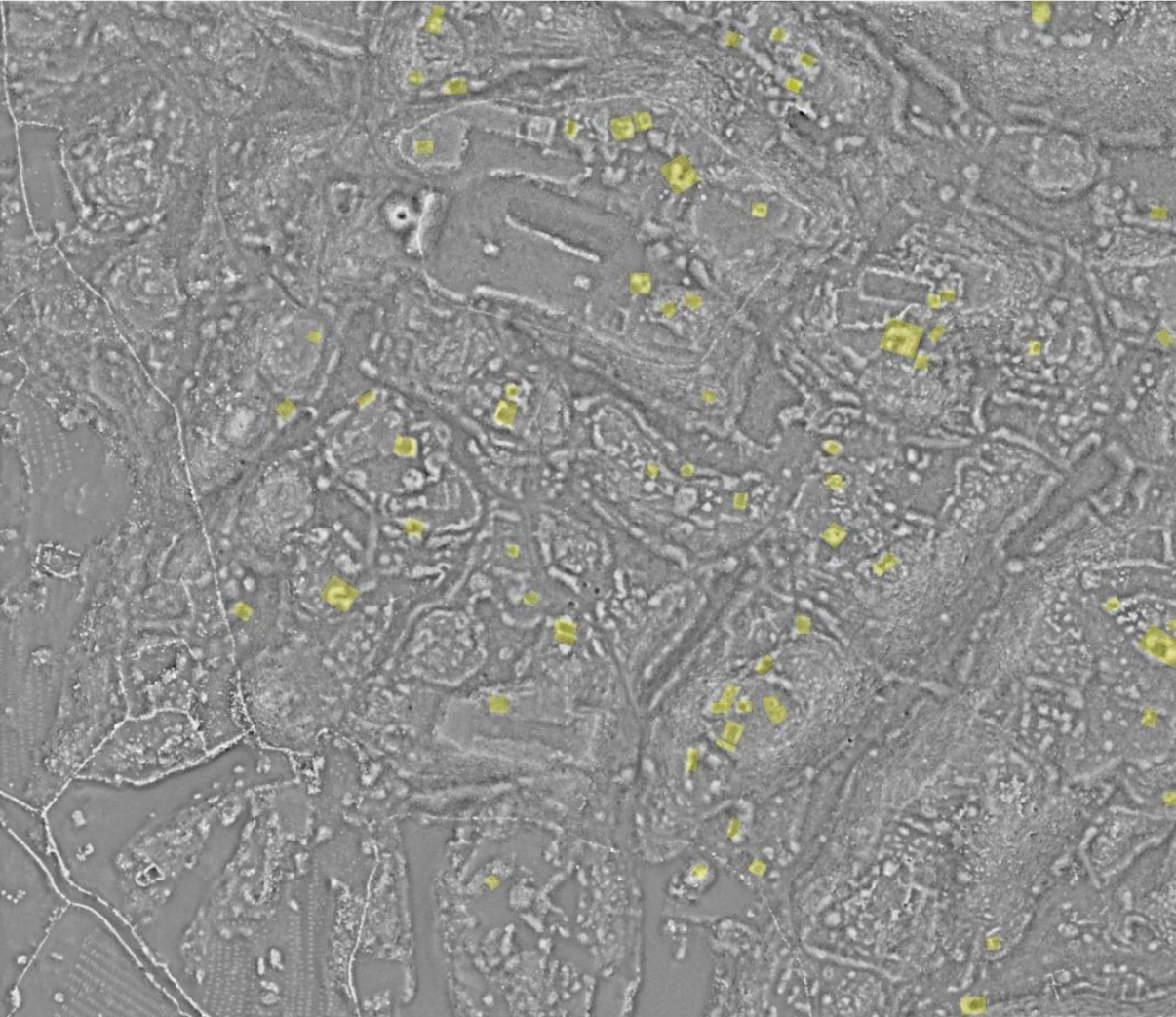
**(machine-learning aided)
identification of local terrain
structures in collaboration with
archeologists**



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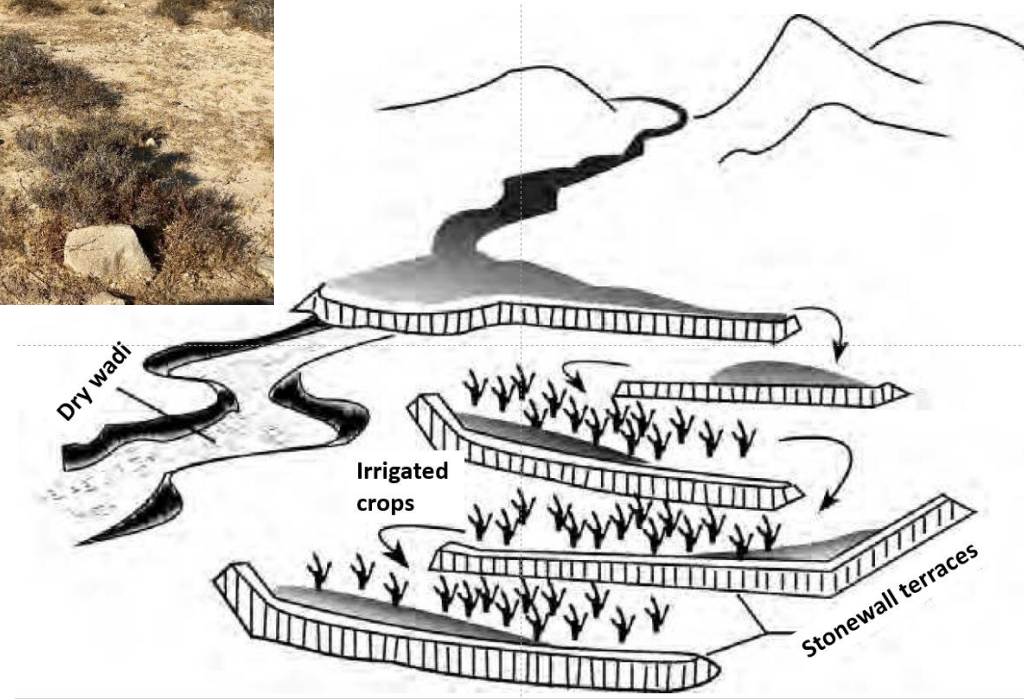
II.b Archeology top-down: ... and indexing it into a scalable geo-data platform



technical resources:

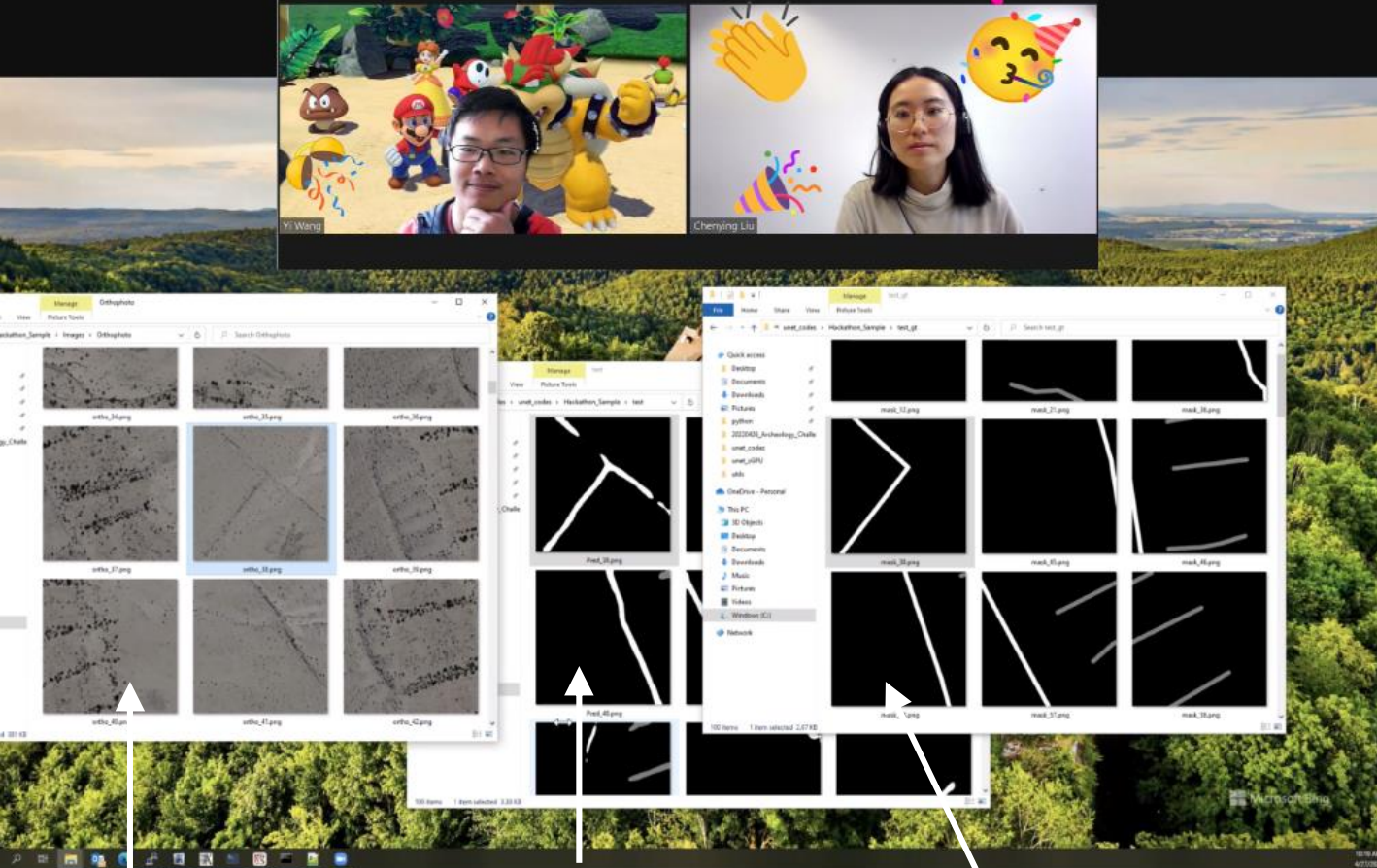
- <https://doi.org/10.1109/LAGIRS48042.2020.9165675>
- <https://eartharxiv.org/repository/view/1782>

II.b Archeology top-down: Ancient agriculture in Israeli's Negev desert ...



II.b Archeology top-down: ... unveiled by talented AI PhD students

... from fusion of multi-spectral (optical) drone imagery + LiDAR features



drone imagery

Artificial Neural
Network
results

ground truth image
segmentation masks



III Challenges & Perspectives: Towards a Digital Twin for Social, Economic & Environmental Good



by virtue of artificial intelligence applied to massive amounts of earth observation data ...

HELMHOLTZAI

:archeology

collect rainforest LiDAR, preserve & educate about our ancient heritage

:urbanization

improve local climate of urban spaces through unification with nature

:ecology

automatize geo-data analytics for environmental management
in harmony with human land use and agricultural needs

IV. plenum & discussion



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1.

How to leverage machine learning and remote sensing to improve the local climate in (mega)cities for the wellbeing of its urban population; and how to address ethical concerns?



DLR



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2. Does artificial intelligence in earth observation have the capacity to help preserve the Amazon rainforest (led by fair principles incorporating the "perspectives of all stakeholders" such as endangered species, local farmers, archeologists, and governments)?

3. What are the current limitations of these technologies vis-a-vis protection of human rights & ethics; and how to overcome such limitations?





source: https://upload.wikimedia.org/wikipedia/commons/f/f6/Shade_Cacao_Plantation%2C_Ixcacao_Mayan_Chocolate%2C_Belize.JPG

4.

How do we transparently implement AI-based environmental management inspired by the United Nation's Sustainable Development Goals?



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