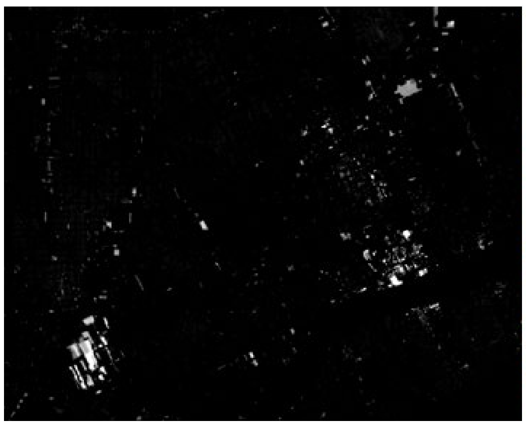
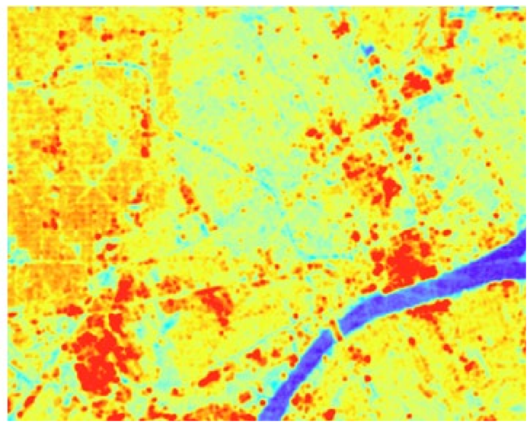
International Meeting on
Land Cover/Land Use Change (LCLUC)
in South/Southeast Asia and Synthesis

Quantifying Urban Built-up Volume with Lidar and Radar





Adam Mathews

Department of Geography

Binghamton University (State University of New York), USA

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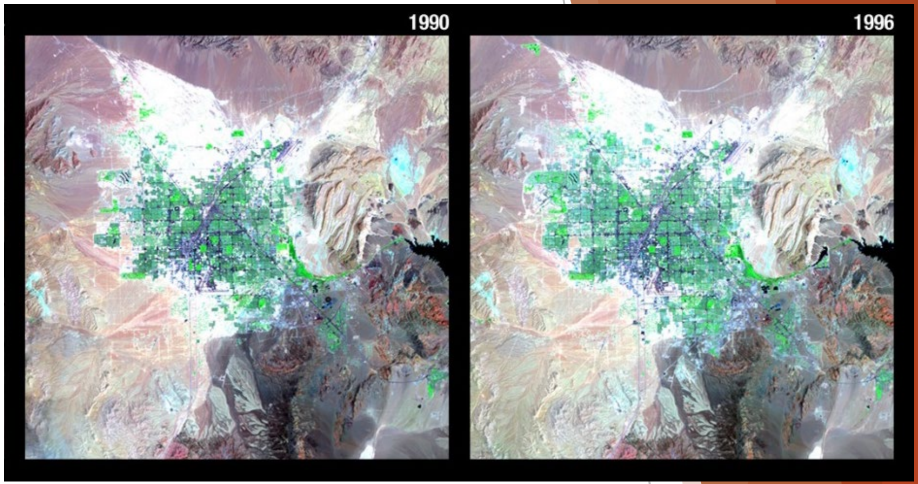
Introduction



- Global trend of urban growth
  - Population growth
  - Rural-to-urban migration

    (Grimm et al., 2008)

- Impacts and significance
  - Biodiversity and ecosystems processes (Tian et al., 2004)
  - Pollution (Jerrett et al., 2005)
  - Urban heat island effect (Imhoff et al., 2010)
  - Green space access (Lovasi et al., 2008; Flocks et al., 2011)

- Utility of remote sensing (Jensen and Cowen, 1999; Yang, 2002)

Introduction

LCLUC
Land-Cover / Land-Use Change Program

- NASA Land-Cover/Land-Use Change (LCLUC)
  - Emerged to document change

    (Gutman et al., 2004; Justice et al., 2015)
  - Reliance on optical, 2D satellite-based measurements

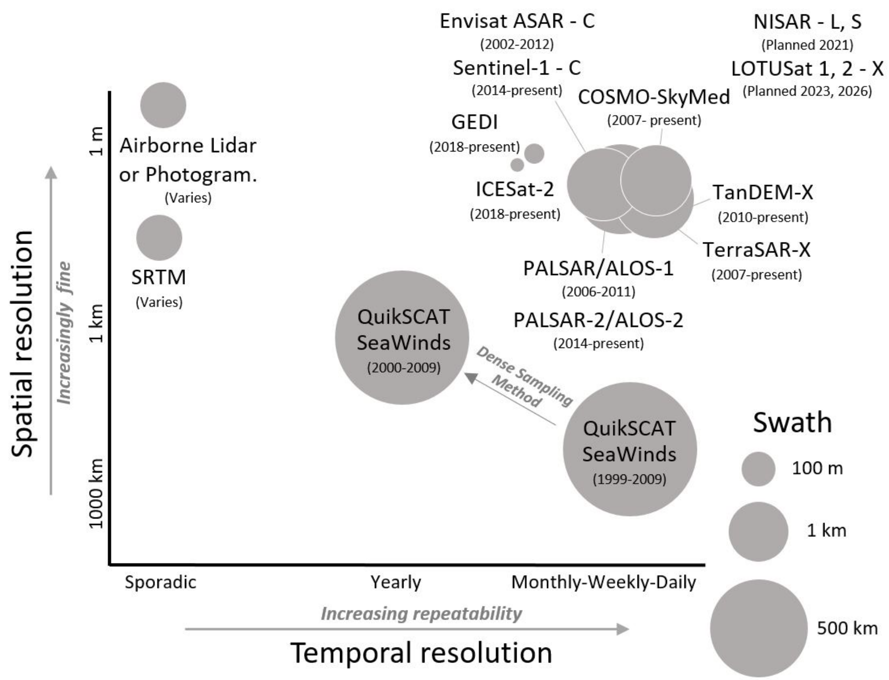
    (Yang, 2002; Gutman et al., 2004; LCLUC, 2016)
  - Need for comprehensive assessment
    - Three-dimensionality overlooked (Singh et al., 2012)
      - Most urban studies focus on 2D building footprint extraction

        (Cheuk and Yuan, 2009; Yu et al., 2010)
    - Need to observe growth <u>and decline</u>
      - Remote population estimation

        (Frazier et al., 2013; Frazier and Bagchi-Sen, 2015)

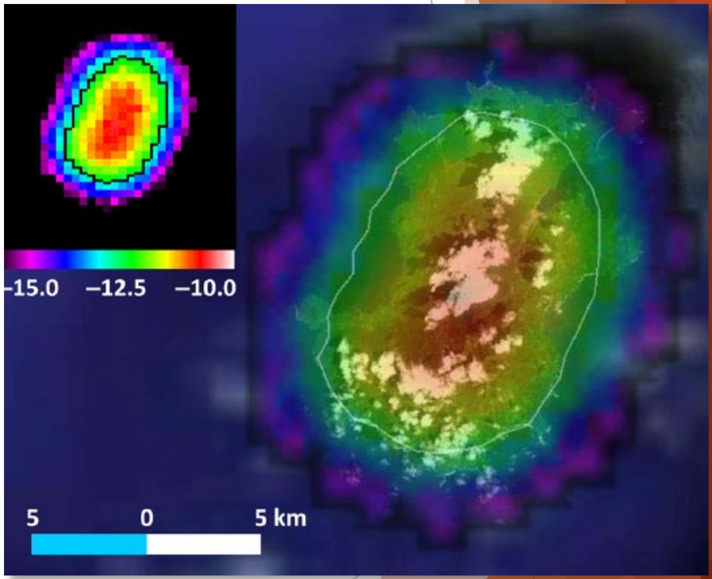
Introduction

- Light detection and ranging (lidar) provides an ideal means by which to accurately examine urban build-up, but…
  - Lidar is expensive, repeat acquisitions not common
  - So, alternatives are needed
    - Radar offers the best option albeit usually with coarser spatial resolution



QuikSCAT for urban analyses

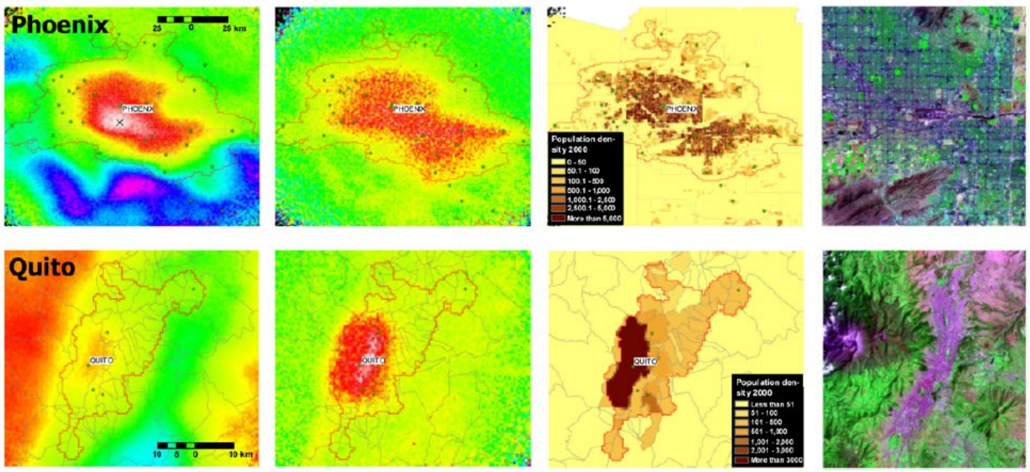
- Dense Sampling Method (Nghiem et al., 2009)
  - Developed and patented by California Institute of Technology/JPL
  - SeaWinds scatterometer data
  - 10 year lifespan → ~10 TB of data
  - 25 x 37 km footprint
    - Temporal resolution reduced to yearly scale
    - 1 km spatial resolution
  - Tested on Príncipe Island
    - Area, shape accurately represented

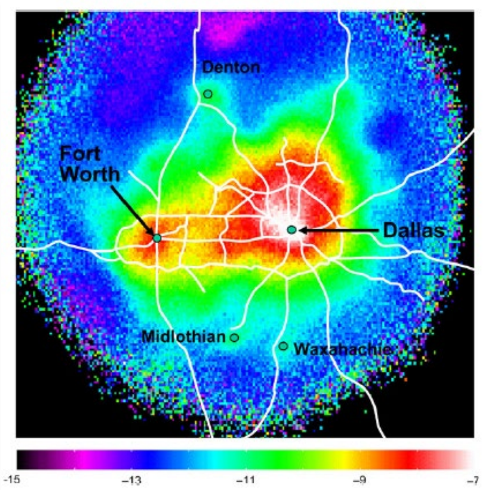


urban.jpl.nasa.gov

QuikSCAT for urban analyses

- Dense Sampling Method (Nghiem et al., 2009)
  - Dallas-Fort Worth → high backscatter from largest structures
  - Correlative with population density, urban extent, areas of change, other urban variables
    (Nghiem et al., 2014; Jacobson et al., 2015)
  - Cannot estimate volume without calibration
    - Applicability of airborne lidar (Butkiewicz et al., 2008)





Objective

- ***Validate the use of spaceborne radar data for deriving urban building volume (as validated with airborne lidar data)***
  - QuikSCAT Ku-band scatterometer
  - Sentinel-1 C-band SAR

- Significance
  - Urban (and other) remote sensing analyses often limited to two-dimensions
  - Vertical component critical to comprehensive study of urban areas

Data and Methods

Radar scatterometer data

- SeaWinds scatterometer on QuikSCAT satellite (2000-2009)
- Processed using Dense Sampling Method (DSM)
  - Increase spatial resolution by aggregating year of data

$$\overline{\sigma}_0 = \frac{1}{N\Gamma_A}\sum_{i=1}^{N}\iint_A dx\,dy\,G(\phi_i,x,y)\,\overline{\sigma}_0(x,y) + \frac{1}{N\Gamma_A}\sum_{i=1}^{N}\iint_A dx\,dy\,G(\phi_i,x,y)\,\varepsilon(\phi_i,t_i,x,y)$$

- 1km spatial resolution (backscatter units of dB)

Data and Methods

Lidar data

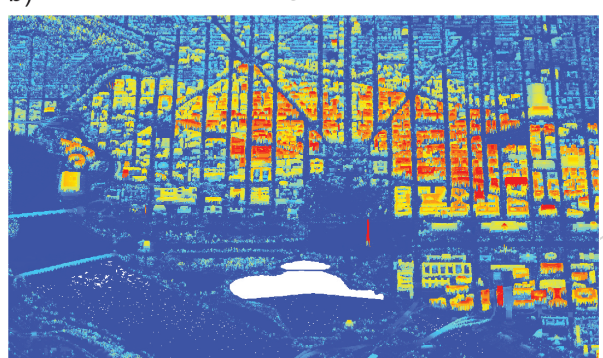
- Provided by U.S. Army Geospatial Center
- Lidar-derived last-return DHMs (1m)
    - DHM = Surface – Terrain [relative heights]
- Building footprints, aggregate to 1km
- Analysis extents determined by lidar

Table A. Study cities and lidar data coverage.

City	Year	Analysis extent (km^2)	Population (2010)
Atlanta, GA	2003	79	420,003
Austin, TX	2006	390	720,390
Buffalo, NY	2004	342	261,310
Detroit, MI	2004	347	713,777
Los Angeles, CA	2007	64	3,792,621
New Orleans, LA	2008	346	343,829
San Antonio, TX	2003	640	1,327,407
Tulsa, OK	2008	1,329	391,906
Washington, DC	2008	8,297	601,723

a) Austin, TX

b) Washington, DC



Data and Methods

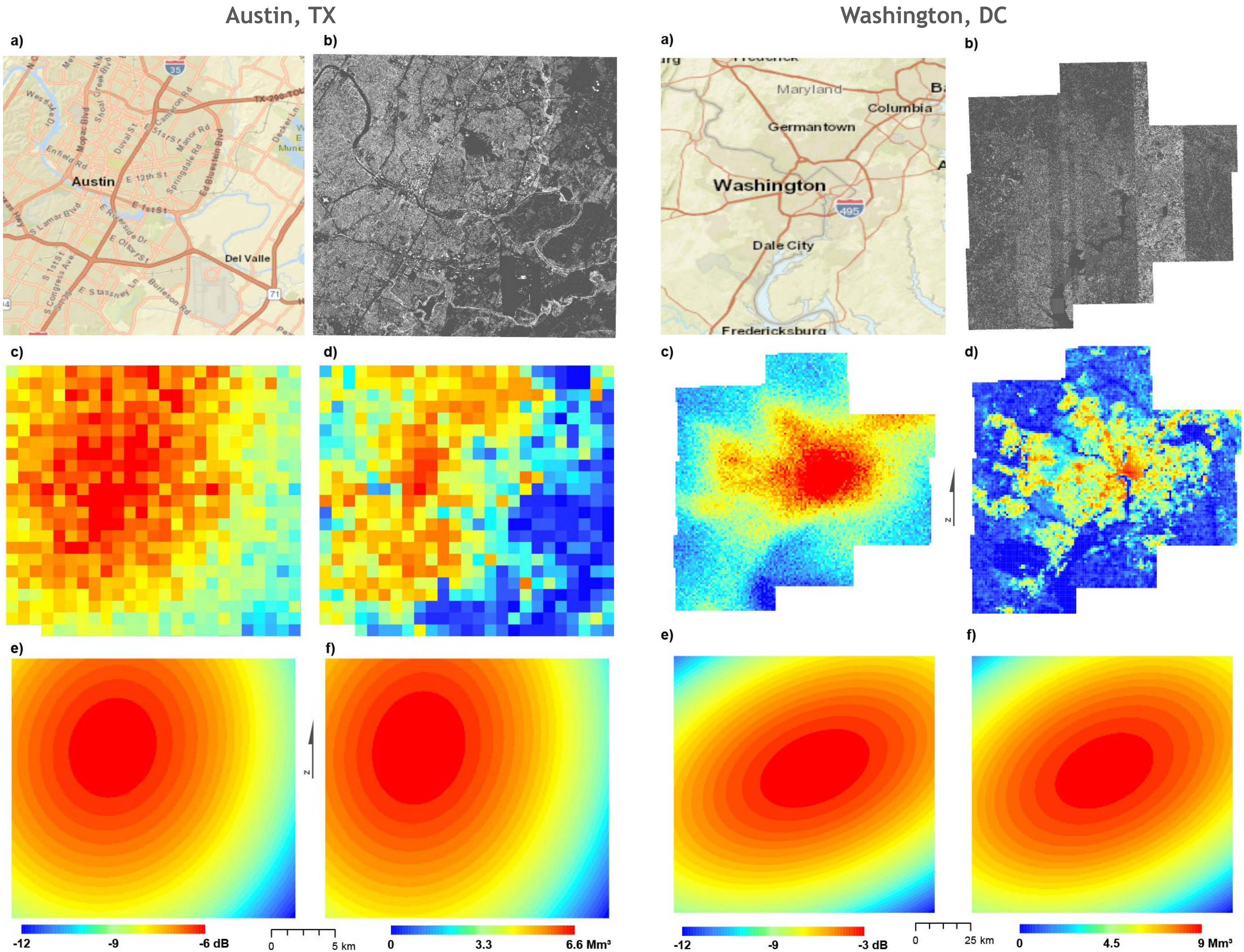
Analytical comparisons

- Direct comparison problematic due to data types
  - Gradient of built-up volume more appropriate
  - Transformation to comparable second-order polynomial regression format (i.e. spatial trend)
- Correlative statistical analyses (r^2, r, ρ, and τ)
  - Raw DSM radar vs. raw lidar
  - Trended DSM radar vs. trended lidar
  - Raw DSM radar vs. trended lidar

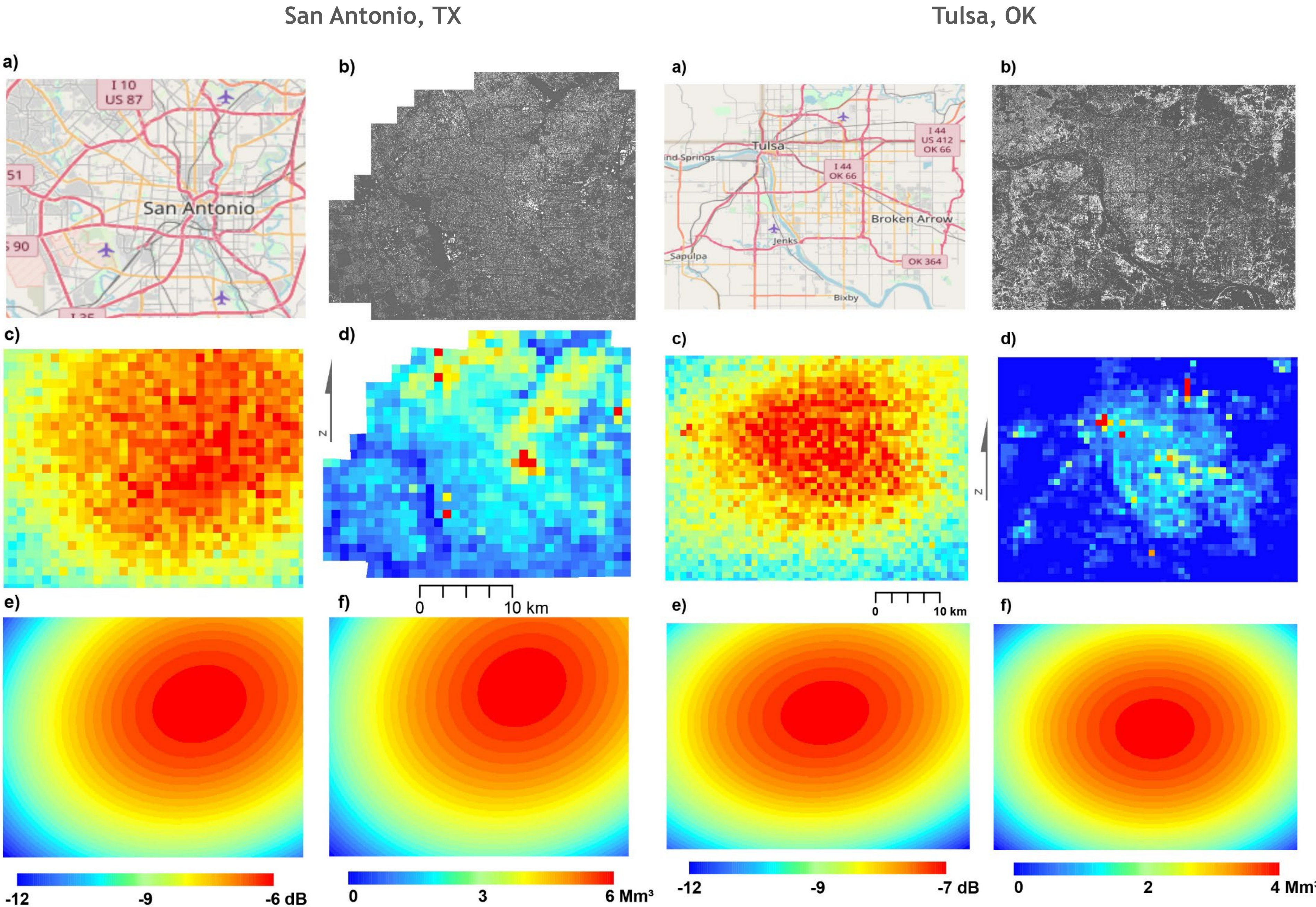
Same approach taken with Sentinel-1 SAR C-band data (using DSM method to increase spatial resolution to 40m)

Results

- Spatial distributions of are similar
  - Spatial trend required
- Correlations weak between raw radar and lidar
  - e.g., $r^2 = 0.20$ for San Antonio
- Strongest correlations between trended radar and trended lidar
  - e.g., $r^2 = 0.97$ for San Antonio
- Strong correlations between raw radar and trended lidar
  - e.g., $r^2 = 0.75$ for San Antonio



Austin, TX
Washington, DC
a)
b)
Austin
Del Valle
E 12th St
E 1st St
Springdale Rd
Ed Bluestein Blvd
Manor Rd
Mopac Blvd
Duval St
Shoal Creek Blvd
Enfield Rd
S Lamar Blvd
E Riverside Dr
Burleson Rd
E Stassney Ln
S Congress Ave
S 1st St
TX-290-TOLL
35
71
Maryland
Columbia
Germantown
Washington
495
Dale City
Fredericksburg
c)
d)
e)
f)
N
-12
-9
-6 dB
0
5 km
3.3
6.6 Mm³
-3 dB
25 km
4.5
9 Mm³



San Antonio, TX
Tulsa, OK
a)
I 10
US 87
51
San Antonio
90
b)
c)
d)
N
0
10 km
e)
f)
-12
-9
-6 dB
0
3
6 Mm^3
a)
Tulsa
nd Springs
I 44
US 412
OK 66
I 44
OK 66
Broken Arrow
Jenks
Sapulpa
OK 364
Bixby
b)
c)
d)
N
0
10 km
e)
f)
-12
-9
-7 dB
0
2
4 Mm^3

Table B. Correlations between raw DSM radar data and raw lidar data.

City	r^2	r	ρ	τ
Atlanta, GA	0.13	0.36	0.54	0.38
Austin, TX	0.21	0.45	0.64	0.50
Buffalo, NY	0.14	0.38	0.51	0.35
Detroit, MI	0.10	0.32	0.43	0.30
Los Angeles, CA	0.04*	0.20*	0.44	0.30
New Orleans, LA	0.04	0.19	0.20	0.13
San Antonio, TX	0.20	0.45	0.57	0.40
Tulsa, OK	0.26	0.51	0.59	0.40
Washington, DC	0.32	0.56	0.67	0.48

Table C. Correlations between trended DSM radar data and trended lidar data.

City	r^2	r	ρ	τ
Atlanta, GA	0.77	0.88	0.90	0.73
Austin, TX	0.98	0.99	0.99	0.91
Buffalo, NY	0.69	0.83	0.86	0.67
Detroit, MI	0.81	0.90	0.93	0.78
Los Angeles, CA	0.64	0.80	0.73	0.55
New Orleans, LA	0.33	0.57	0.61	0.44
San Antonio, TX	0.97	0.98	0.97	0.87
Tulsa, OK	0.84	0.92	0.93	0.77
Washington, DC	0.98	0.99	0.99	0.91

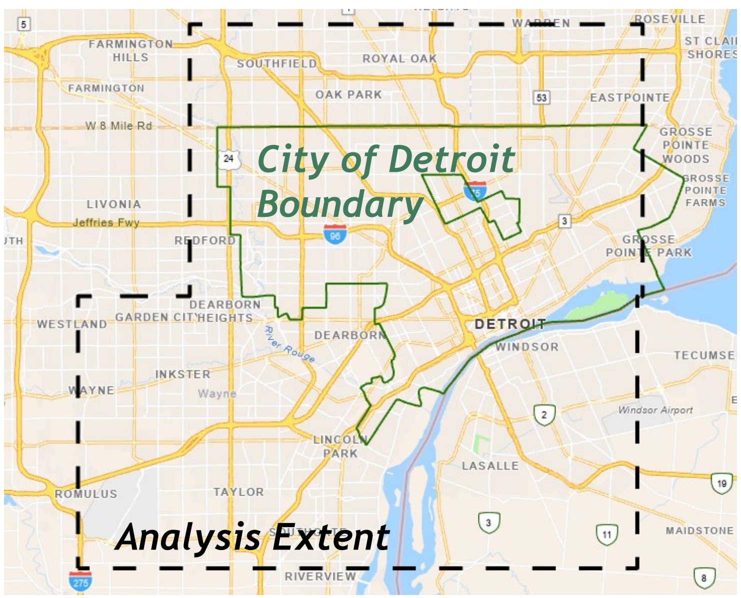
Table D. Correlations between raw DSM radar data and trended lidar data.

City	r^2	r	ρ	τ
Atlanta, GA	0.33	0.57	0.58	0.42
Austin, TX	0.72	0.85	0.86	0.67
Buffalo, NY	0.38	0.61	0.64	0.45
Detroit, MI	0.52	0.72	0.74	0.54
Los Angeles, CA	0.26	0.51	0.50	0.35
New Orleans, LA	0.21	0.46	0.47	0.32
San Antonio, TX	0.75	0.87	0.83	0.64
Tulsa, OK	0.63	0.80	0.82	0.61
Washington, DC	0.66	0.81	0.86	0.66

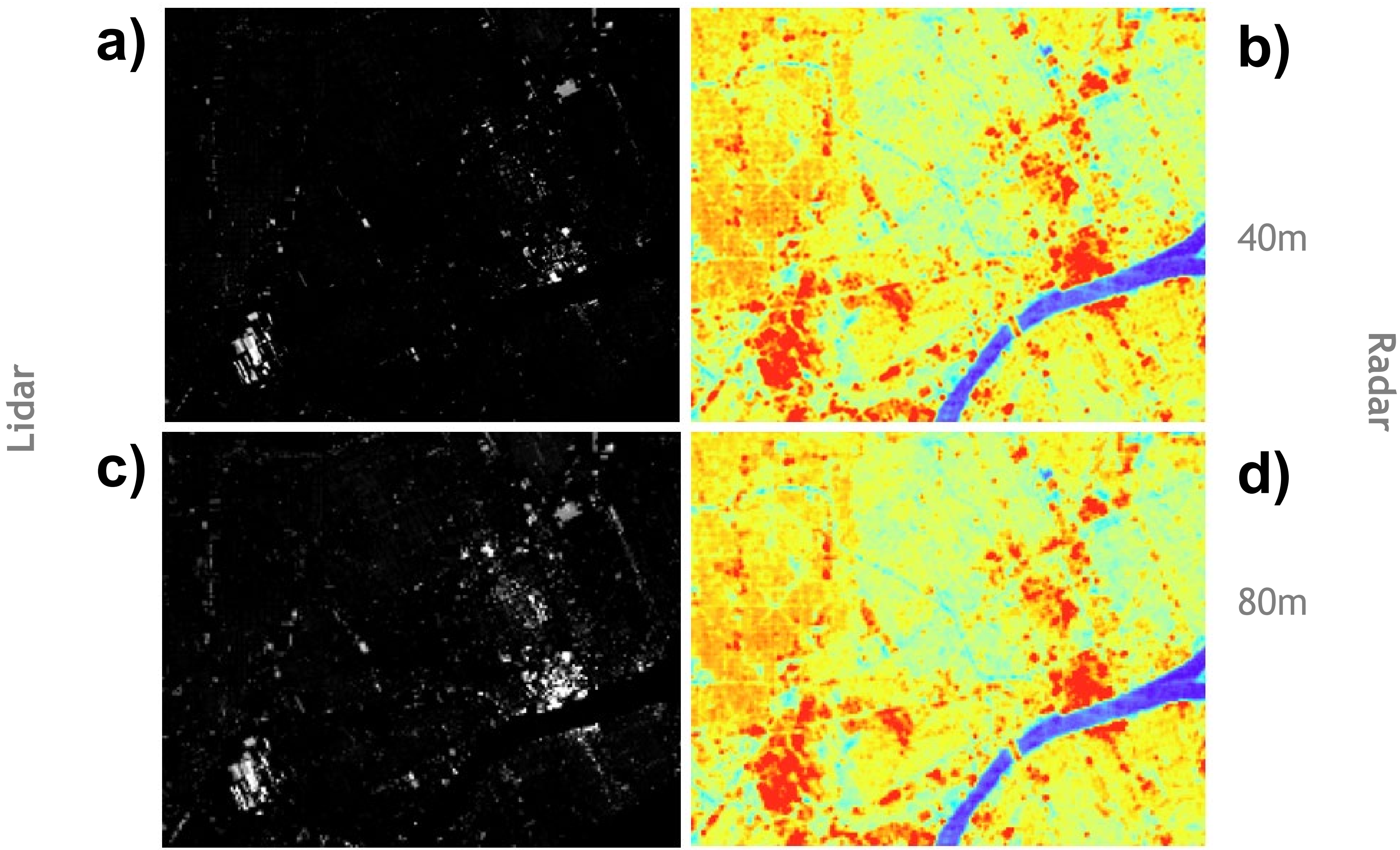
r^2: coefficient of determination in linear model;
r: Pearson correlation coefficient;
ρ: Spearman rank correlation coefficient;
τ: Kendall rank correlation coefficient.
All correlations significant with p-values < 0.01 unless otherwise noted (< 0.05*).

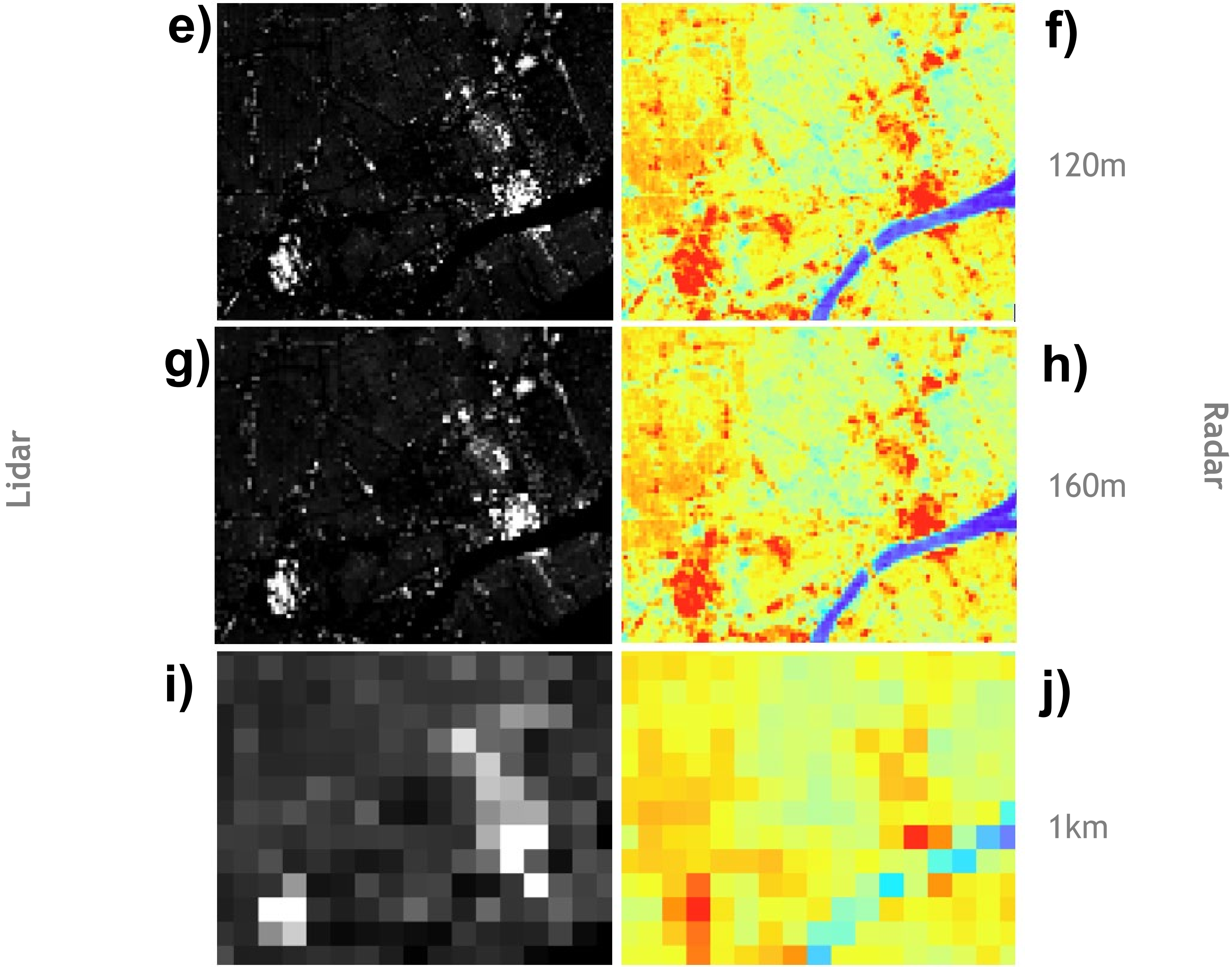
Results

- Sentinel-1 C-band SAR
  - Focused on the greater Detroit area for a single year
  - Direct comparisons not possible due to scale mismatch
    - HH (horizontal transmit and horizontal receive) and HV (horizontal transmit and vertical receive) analyzed
    - Analysis conducted at multiple aggregated spatial resolutions: 40m, 80m, 120m, 160m, 1km

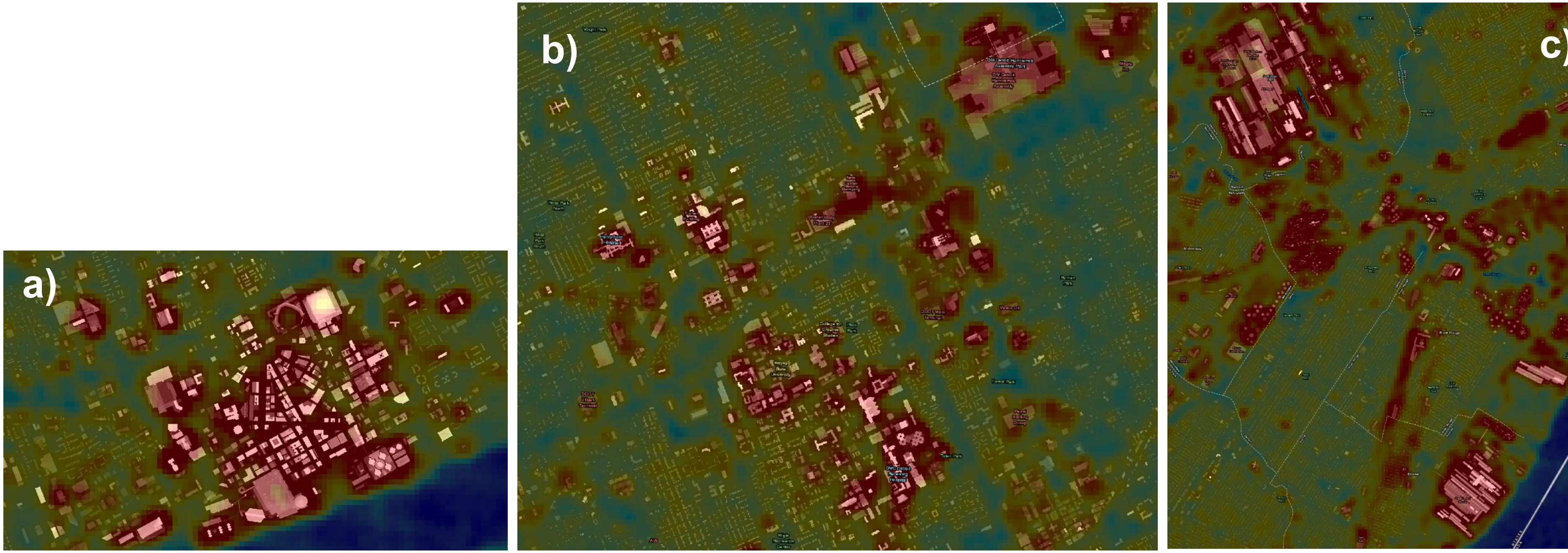


		r^2	r	ρ	τ
40m	HH	0.14	0.38	-	-
	HV	0.13	0.37	-	-
80m	HH	0.19	0.44	0.58	0.43
	HV	0.22	0.43	0.48	0.36
120m	HH	0.22	0.47	0.61	0.46
	HV	0.20	0.45	0.50	0.37
160m	HH	0.23	0.48	0.62	0.46
	HV	0.22	0.67	0.50	0.37
1km	HH	0.24	0.49	0.52	0.39
	HV	0.13	0.35	0.35	0.25


a)
b)
c)
d)
Lidar
Radar
40m
80m



e)
f)
120m
g)
h)
Lidar
160m
Radar
i)
j)
1km



Interactive map

Discussion

- LCLUC analyses require 3D data to comprehensively evaluate urban dynamics
- Radar as substitute to difficult to obtain lidar data
  - Other: ICESat-2, GEDI—still lack historic data
- Linear relationship significance
  - Equally able to estimate areas with low and high built-up volume
- Spatial trend approach limitation
  - Second-order methodology may not work for cities with multiple urban cores
- Temporal and spatial resolution differences (lidar vs. radar)
- Future work
  - Further testing needed on additional cities (i.e. non-U.S. urban areas, smaller footprint cities for sensitivity analysis), other radar data (TanDEM-X, COSMO-SkyMed), higher spatial resolution

Conclusions

- Analysis of many U.S. cities with differing urban characteristics showed that:
  - Both DSM-processed scatterometer data and C-band SAR data effectively spatially correlate with airborne lidar data
    - DSM results showed higher correlation values but were coarser in spatial resolution
  - Strong linear correlations indicate that DSM method is accurate for estimating urban volume
    - Provides generalized alternative to lidar with higher temporal frequency and greater areal coverage

Acknowledgments

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  - Son Nghiem and colleagues, NASA JPL/CalTech
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Publications

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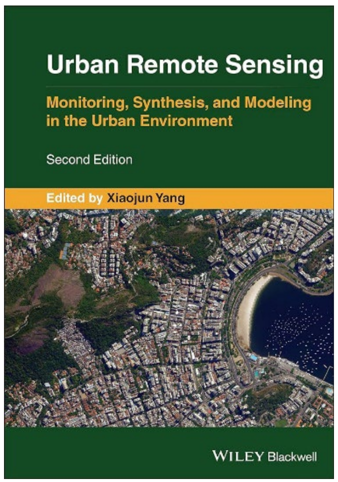
Satellite scatterometer estimation of urban built-up volume: Validation with airborne lidar data

Adam J. Mathews[a,*], Amy E. Frazier[b], Son V. Nghiem[c], Gregory Neumann[c], Yun Zhao[d]



CHAPTER 2

Examining Urban Built-up Volume: Three-Dimensional Analyses with Lidar and Radar Data

Adam J. Mathews[1] and Son V. Nghiem[2]

[1]*Department of Geography, Environment, and Tourism, Western Michigan University, Kalamazoo, MI, USA*

[2]*NASA Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA*

Computers, Environment and Urban Systems 73 (2019) 85–94

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Object-based delineation of urban tree canopy: assessing change in Oklahoma City, 2006–2013

Emily A. Ellis[a], Adam J. Mathews[b,*]

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Questions?

Thanks for your time!

Adam Mathews

Department of Geography

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