

MEGAN3 emission factors, stress responses, and urban emissions

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MEGAN3 emission factors, stress responses, and urban emissions

1. MEGAN2.1 vs MEGAN3.2 (3.3 in preparation)

- Compounds
- Sources
- Landcover and environmental inputs
- Environmental models
- Emission response (nonstress)
- **Emission response (stress)**
- **Emission Factors**

2. Urban BVOC emissions

MEGAN Compounds

4 (GEIA, 1995) => 138 (MEGAN2.04, 2008) => 148 (MEGANv2.1, 2012) => 202 (MEGANv3, 2017)

MEGANv2.1 Emission Classes (20)

Isoprene }
232-MBO } Hemiterpenes
Myrcene }
Sabinene }
Limonene }
3-carene }
t-b-ocimene }
a-pinene }
b-pinene }
Other monoterpenes (34) }
b-caryophyllene }
a-farnesene }
Other sesquiterpenes (30) }
Methanol
Acetone
CO
Inorganic Nitrogen (3)
Stress VOC (15)
Other VOC (49)
C1-C2 oxyVOC (5)

MEGANv3.2 Emission Classes (19)

Isoprene (1 compound)
232-MBO (1 compound)
Monoterpene: α -pinene (1 compound)
Monoterpene: Ocimene-type (4)
Monoterpene: β -pinene-type (12)
Monoterpene: Limonene-type (7)
C10 arom/oxy: p-cymene/camphor (19)
Sesquiterpene:caryophyllene-type (25)
Sesquiterpene: longifolene-type (14)
Methanol (1 compound)
Acetone (1 compound)
CO (1 compound)
Inorganic Nitrogen (3 compounds)
Stress VOC (53 compounds)
Other VOC (26 compounds)
Ethanol and acetaldehyde (2 comp.)
Organic acids: e.g., formic acid (3)
C2-C4 hydrocarbons (9 compounds)
C8-C13 oxygenated (11 compounds)
Oxidation products (2 compounds)

MEGAN Emission Sources

MEGANv2

Whole ecosystem
net flux to above
canopy atmosphere



MEGANv3

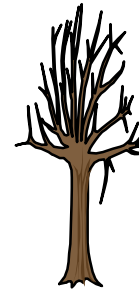
Ecosystem
component
emission



Foliage,
phyllosphere
microbes



Soil, Soil
microbes, roots



Other: Floral, fruits,
trunk/stems, stumps, etc

MEGAN Inputs, Ecosystem modeling, non-stress response

MEGANv2.1  MEGANv3.2

Canopy environment model

- Modified leaf temperature model
- transparency
- emission capacity vary by depth

Soil moisture model

- User can provide

Landcover inputs

- Higher resolution satellite data

Modified controlling processes

- Past Temperature and sunlight, CO₂, bidirectional fluxes

Variable plant traits

- Light dependence Factor

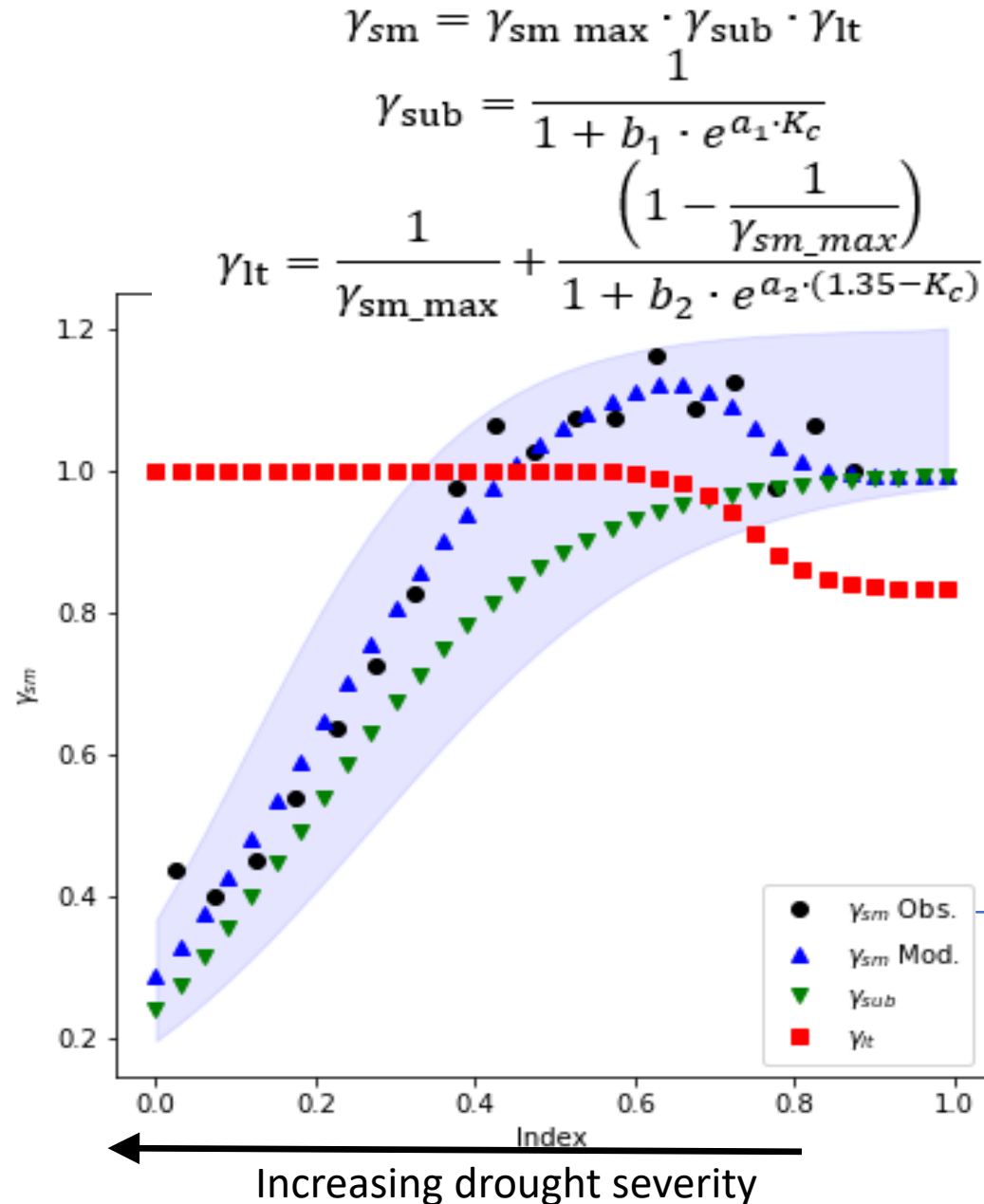
Stress: Isoprene drought response algorithms

MEGANv2.1

Used soil moisture threshold (slightly above wilting point) to shut down isoprene emission
Guenther et al. 2012

MEGANv3

Jiang et al. 2018
Used output from CLM land model to determine when to shut down isoprene emission



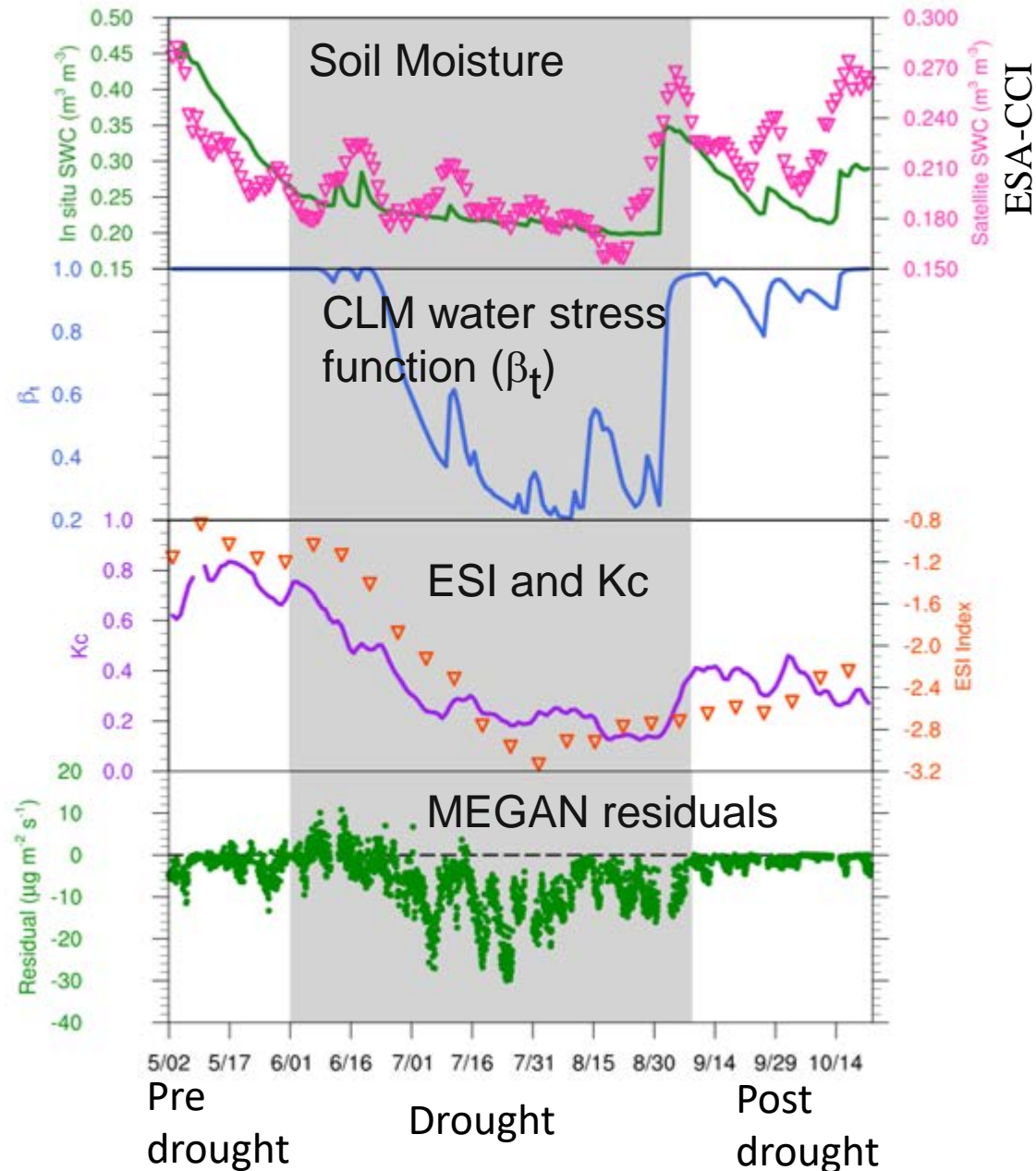
MEGANv3.3

Wang et al. submitted 2022

MOFLUX canopy flux data
New algorithm
Substrate inhibition
Leaf temperature stimulation

Drought indicator examples

MOFLUX site in 2012



Soil Moisture

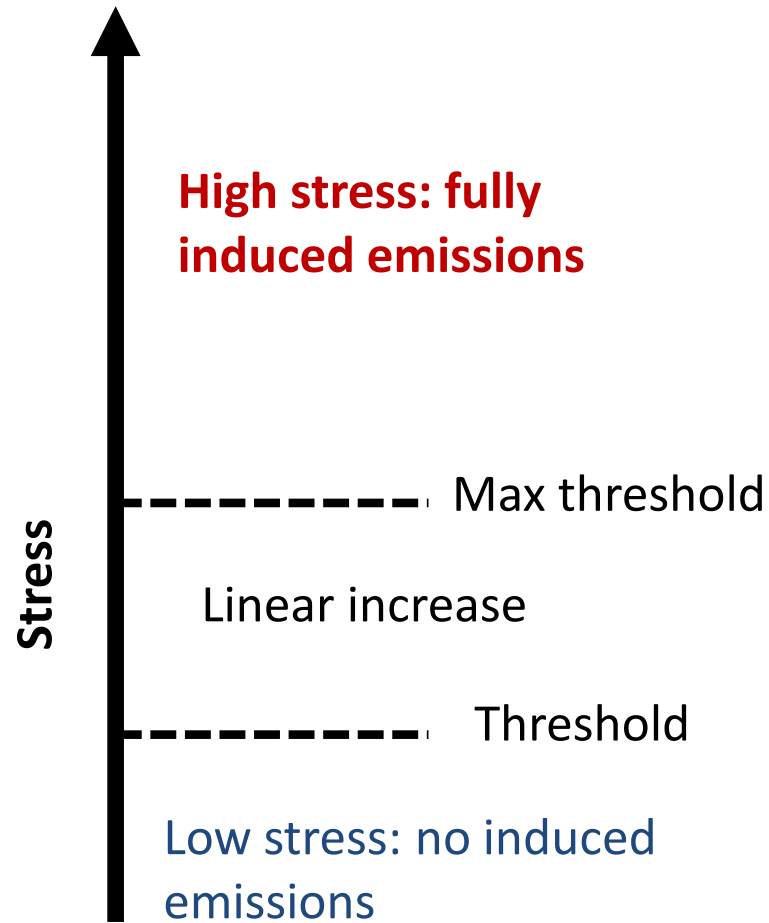
- Uncertain threshold
- Inconsistent soil and climate datasets
- Ignores atmos. vapor pressure deficit

Evaporative Stress Index (ESI) describes temporal anomalies in evapotranspiration (ET)

Kc is the ratio of actual evapotranspiration to potential evapotranspiration

Wang et al. submitted 2022

MEGANv3.2 initial attempt to simulate other stresses (simple threshold function)



Four new stress types all induce emissions:

1) Temperature extremes: High

2) Temperature extremes: Low

Canopy scale data: e.g., Karl et al. 2008, Emmerson et al. 2016

3) Extreme storm (high wind speed).

Canopy scale: e.g., Kaser et al. 2013

4) Air pollution (ozone W126, biologically based air quality index).

Enclosures: e.g., Heiden et al. 1999, Ghirardo et al. 2016, Karl et al. 2005, Jud et al. 2016

- Initial effects are simple and conservative
- Empirical, not mechanistic
- Useful for understanding sensitivity and where to focus research

MEGAN Emission Factors

MEGAN 2.1

Landscape average values based on expert judgement with little explanation or references.

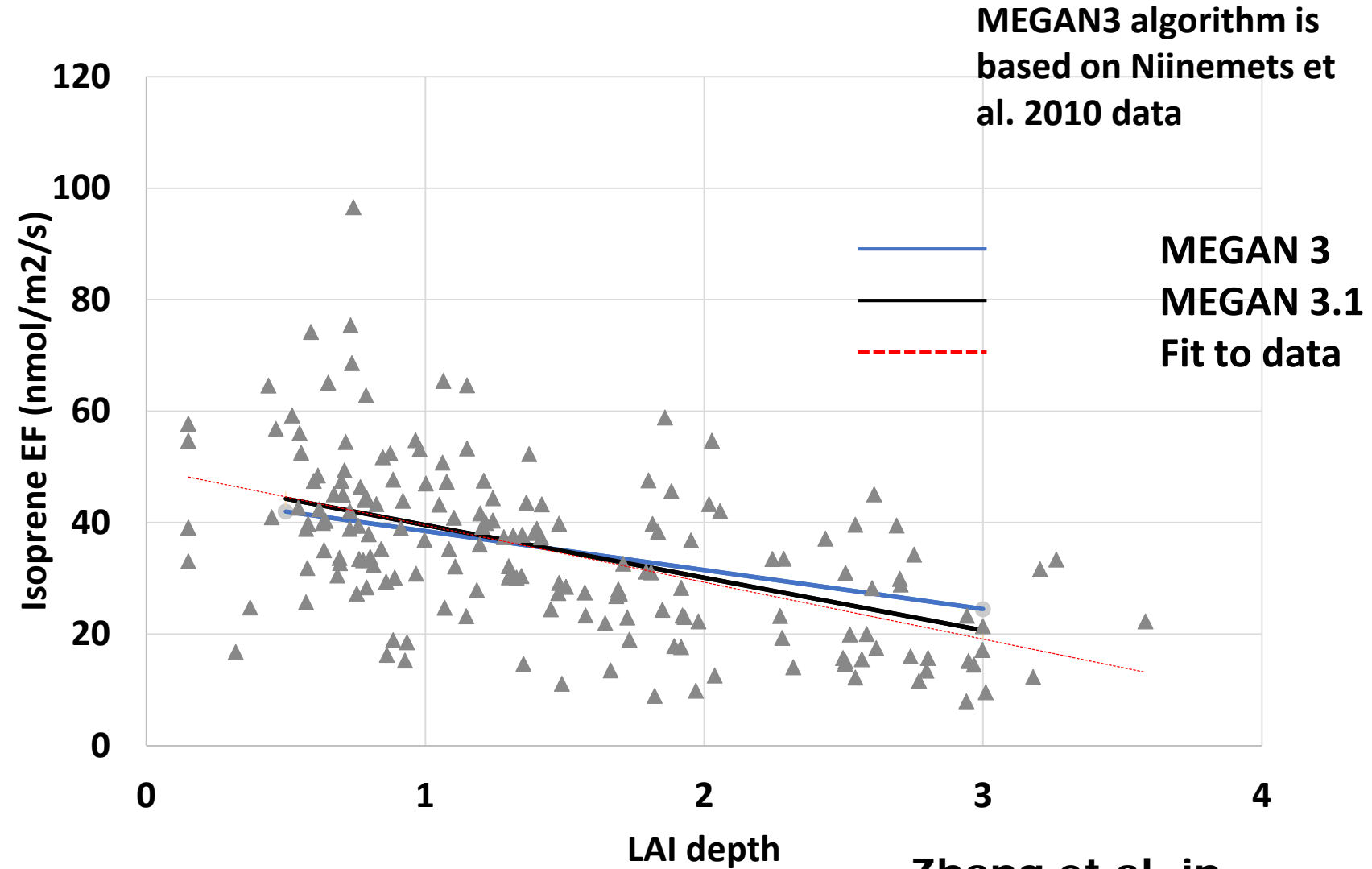
MEGAN 3.0/3.1

More transparent approach, Emission Factor Processor (MEGAN-EFP Python/SQLite program), to integrate all reported emissions data while considering data quality.

MEGAN 3.2 and beyond

Simplified MEGAN-EFP Python/SQLite program with emission factors described in planned series of manuscripts summarizing emission factors for individual plant families. Also working on an alternative approach based on plant traits

Isoprene emission factors



Zhang et al. in
prep 2022

Reconciling isoprene emission factors

Texas 2019 field campaign (328 leaves measured)
(Canopy average and standard error)

Species	$\text{nmol m}^{-2} \text{ s}^{-1}$	$\mu\text{g g}^{-1} \text{ h}^{-1}$
Post Oak	24±3.1	53
Shumard Oak	27±5.3	89
Sweetgum	30±4.2	84
Southern Live Oak	33±1.4	55
Swamp Chestnut Oak	35±1.9	81
Water Oak	45±2.6	86

USEPA BEIS3 (all broadleaf trees) 24 79

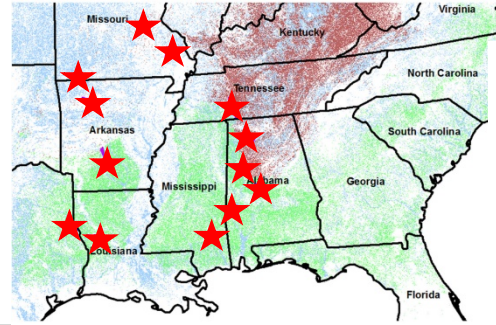
Literature values of isoprene EF ($\text{nmol m}^{-2} \text{ s}^{-1}$)

	Branch Enclosures	Leaf Enclosure
Post Oak	21 to 39	29 to 50
Sweetgum	5 to 22	25 to 44
Southern Live Oak		40
Water Oak		46

Zhang et al. in
prep 2022

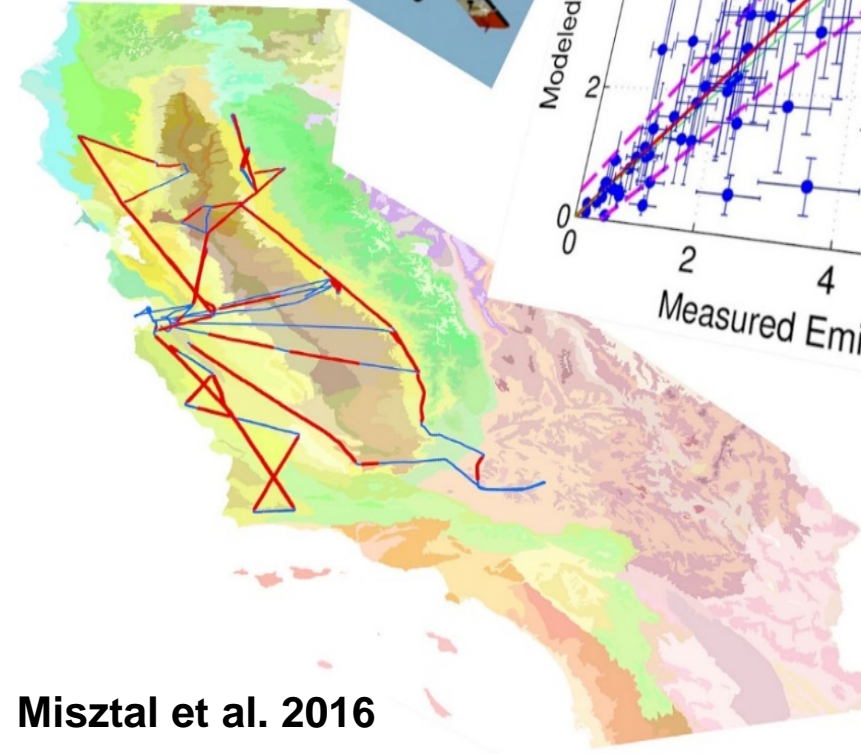
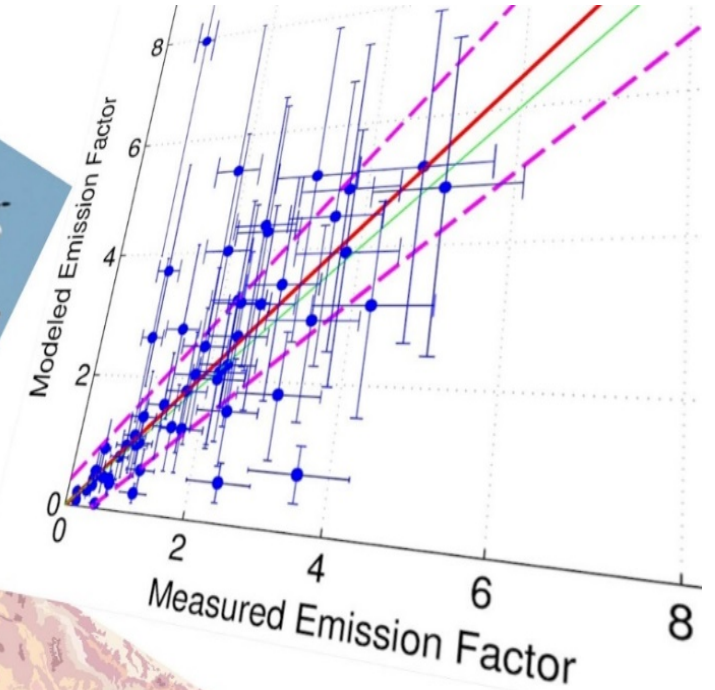
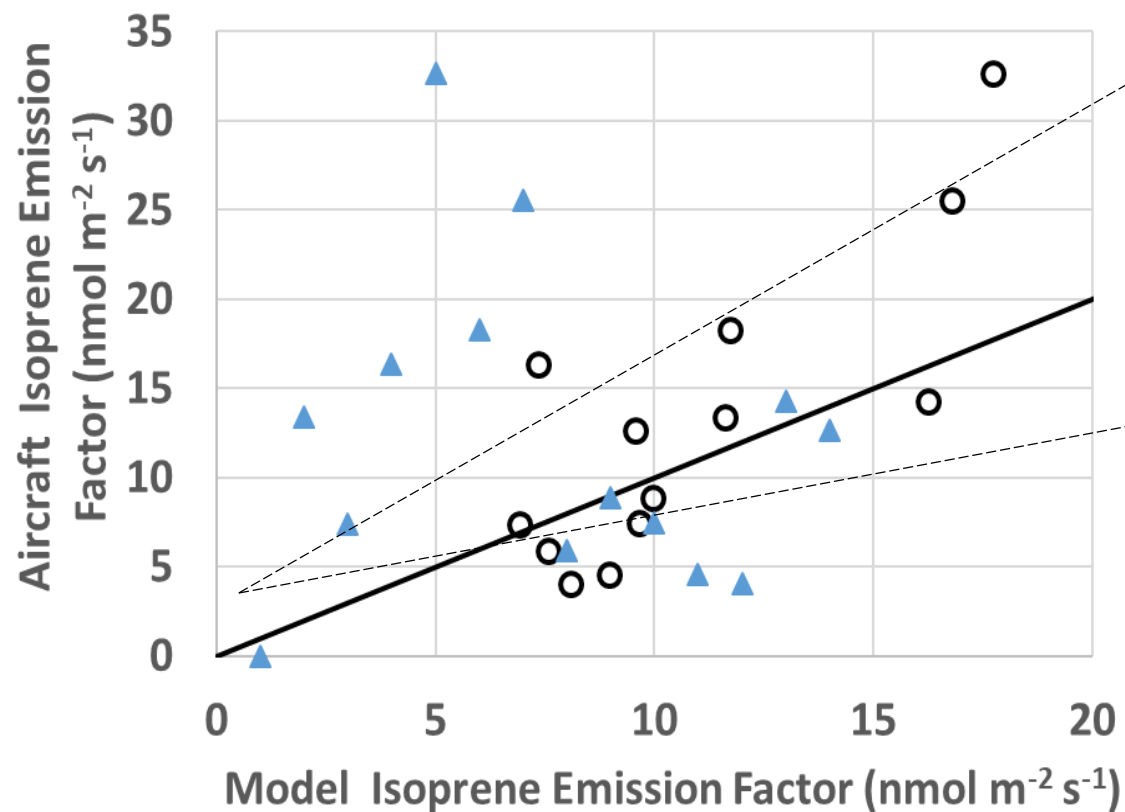
MEGAN evaluation with airborne direct (eddy covariance) isoprene flux measurements

SAS 2013



MEGAN v3.0
MEGAN v3.1

Yu et al. 2018



Misztal et al. 2016

Ratio of BEI S3/Observed Monoterpene (MT) and Sesquiterpene (SQT) emission factors



1. Detected more compounds and have lower losses than in some previous studies
2. Heat stress probably impacted previous branch enclosure measurements

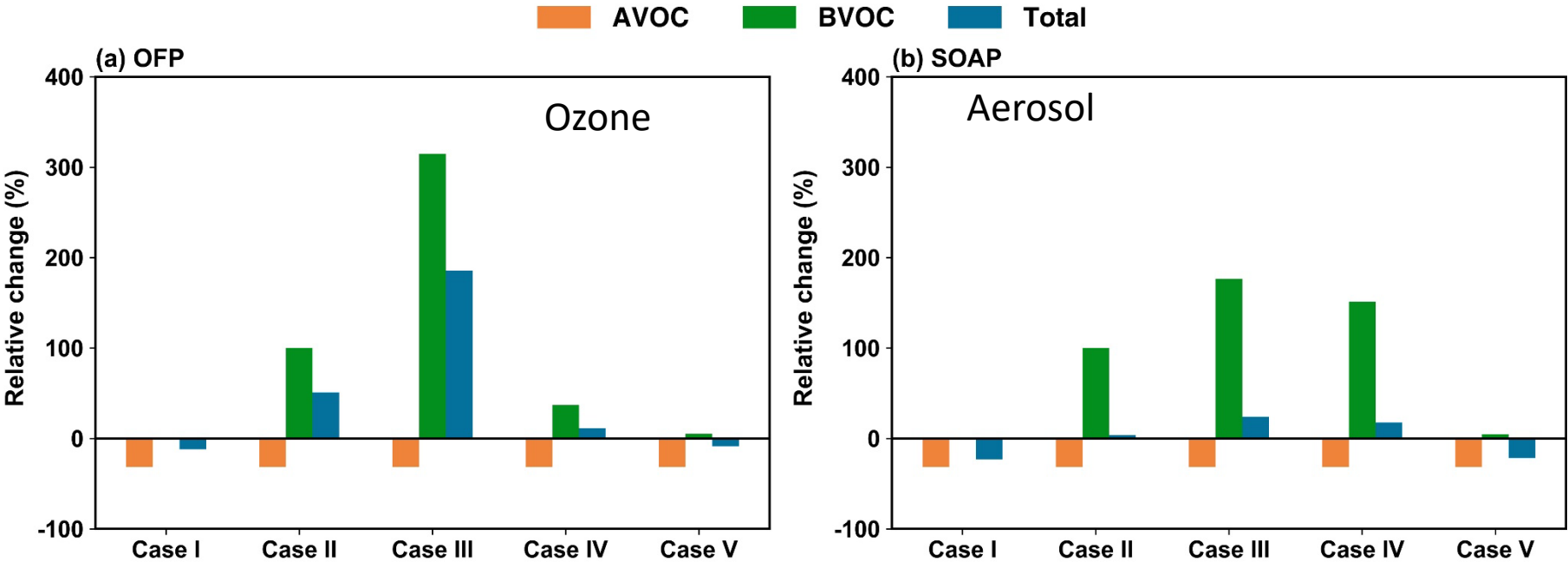
Tree Species	MT	SQT
Pecan	0.13	1.38
Hackberry	3.6	60
Ashe juniper	0.58	7.5
Redcedar	1.03	3
Sweetgum	6.1	25
Magnolia	0.44	18
Shortleaf pine	0.91	0.13
Longleaf pine	8.8	0.63
Loblolly pine	1.8	0.32
Honey mesquite	0.38	90
Plateau live oak	2.4	2.8
Water oak	0.59	3.6
Willow oak	1.62	2.1
Post oak	0.45	0.084
South. live oak	0.11	0.33
Baldcypress	0.042	0.02
Cedar elm	0.022	8.2

Monoterpenes or sesquiterpenes (or both) differed by a factor of 2 or more for 17 other species.

No BEIS values for 3 tree species

Nagalingam et al. in prep 2022

Biogenic and Anthropogenic BVOC emission for Los Angeles County USA
Population: 10 million. Density: 930/km² (56th of 3143 US Counties)



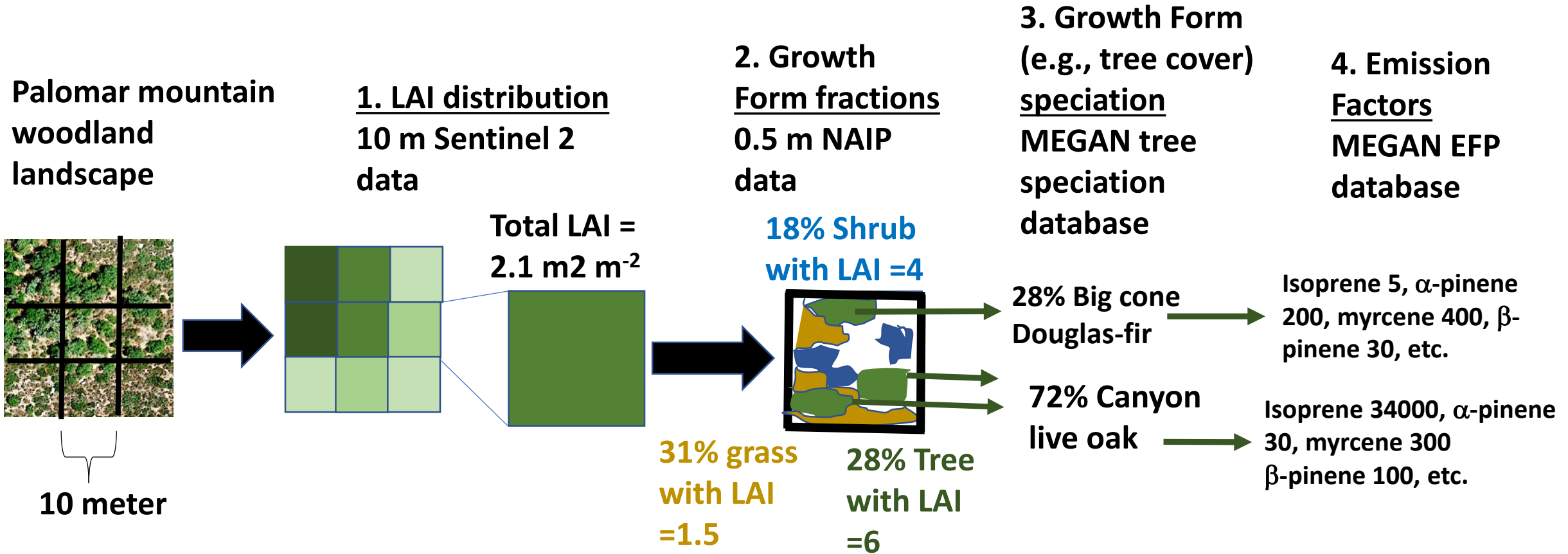
Current
(1000 Tons per year)

Category	Emission	OFP	SOAP
Total BVOC	81.1	552	2.78
Total AVOC	115	329	7.58

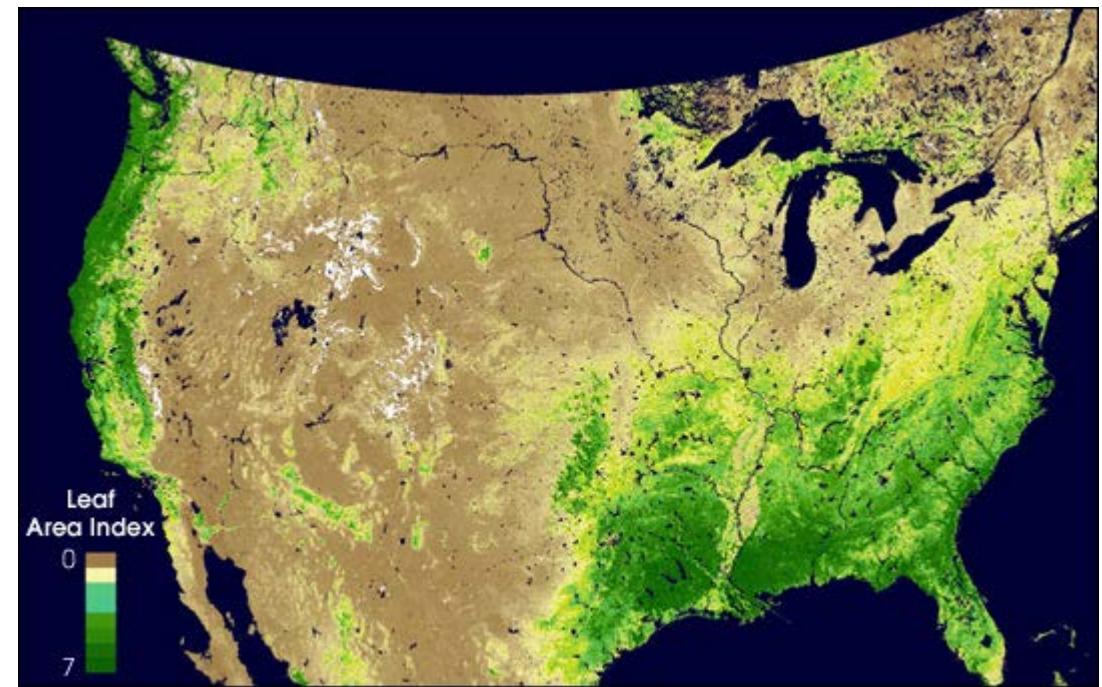
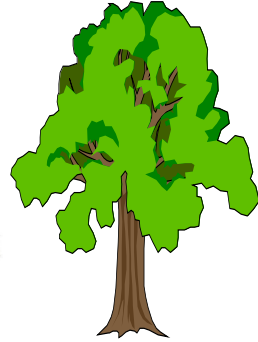
Gu et al., Environ.
Sci. Tech. 2021

BVOC: Biogenic Volatile Organic Compounds
AVOC: Anthropogenic Volatile Organic Compounds
OFP: Ozone Formation Potential
SOAP: Secondary Organic Aerosol Production

How can we quantify fine scale (10 m) BVOC emission heterogeneity?



#1: Quantify total Leaf Area Index

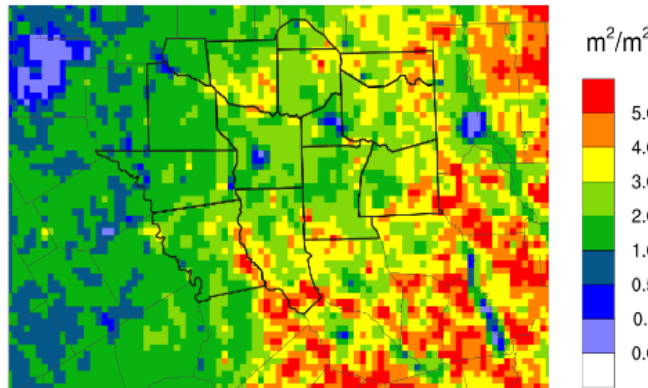


LAI data: Sentinel 2 is available globally at 10-meter resolution

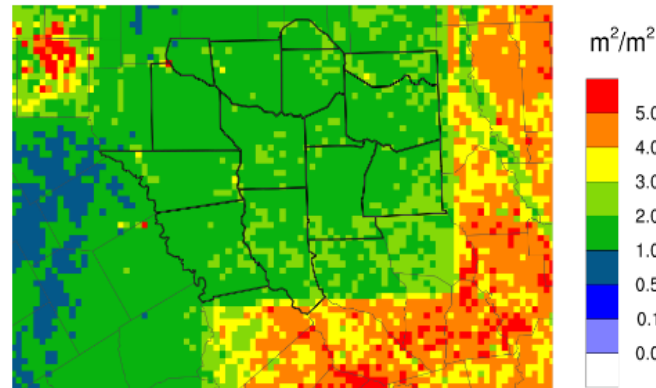
<https://earthobservatory.nasa.gov/>

But... we need ground-based LAI calibration (estimates differ by more than a factor of 2)

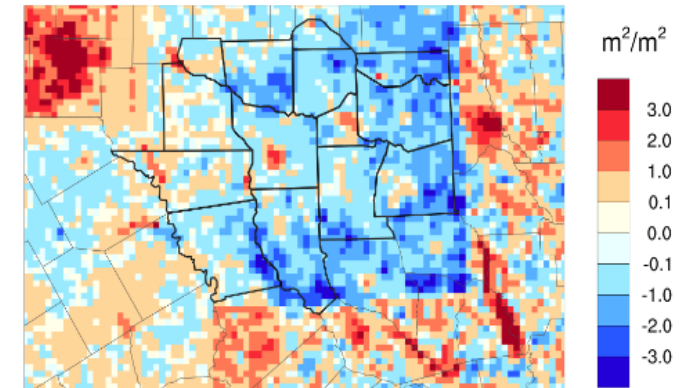
NASA MODIS LAI



ESA Sentinel 2 and PROBA-V

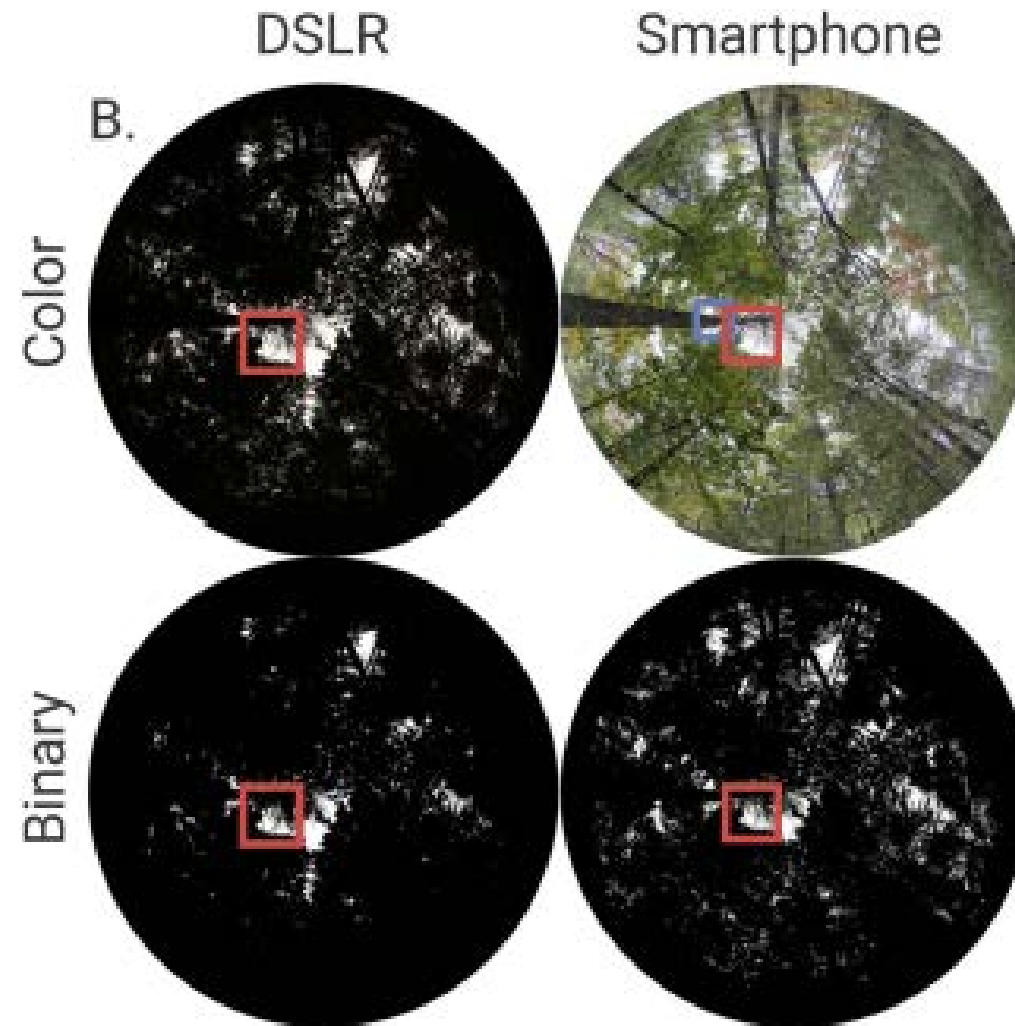


LAI Difference



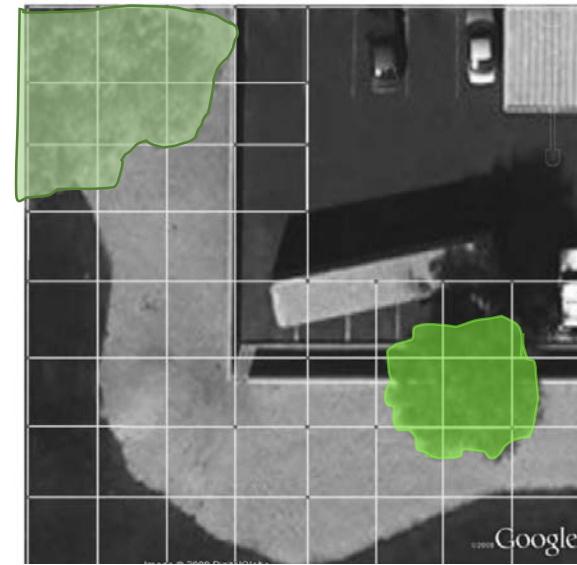
Shah et al. 2021

Spherical panoramic hemispherical photography (Google street view, smartphones)



Arietta et al. 2021

#2: Quantify amount of each growth form (tree, shrub, grass, crops).



Estimate relative contribution of each growth form (tree, shrub, grass, crops) using aerial/satellite imagery.

Global data available as discrete values at 10 m (need to “calibrate”), continuous fields at 30 m (NLCD) for US and 300m global (but are low in urban areas and woodlands).

Tree and other ground cover distribution at the Lions Municipal Golf Course in Austin Texas.

New urban tree cover is often >50% higher than previous estimates (MODIS, NLCD)



NAIP natural color image:
50 cm spatial resolution



Segmentation (object-based) and **machine learning** classified cover: tree (green shades), grass (yellow), bare soil (brown), built (grey, red, white)

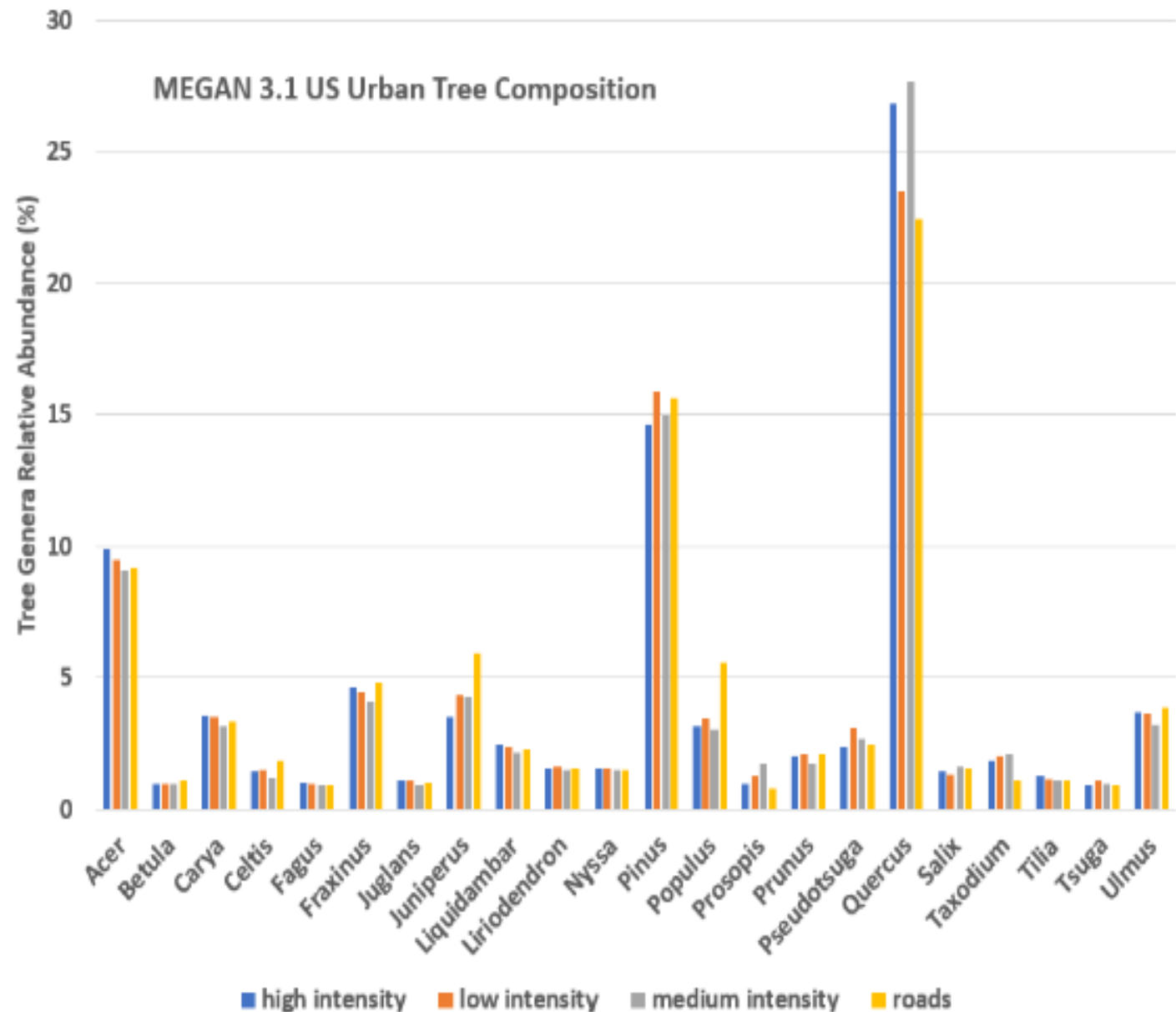
Can iterate with iTree cover assessments to get accuracy better than 20%

#3: Quantify BVOC emission types.



Rural areas: use forest inventory data (e.g., USDA FIA based on ground surveys at randomly selected plots) to assign tree speciation to individual forest types.

Urban areas: Default approach has been to use average US tree speciation data.



The Virtual Urban Tree Survey (VUTS) approach for estimating urban tree species composition

Step 1: Use i-Tree to randomly locate 300+ trees in urban area (could be >1000 points)



Step 2: Acquire multi-season Google Map aerial view and (if available) multi-season Google Street view images for each tree

March



May

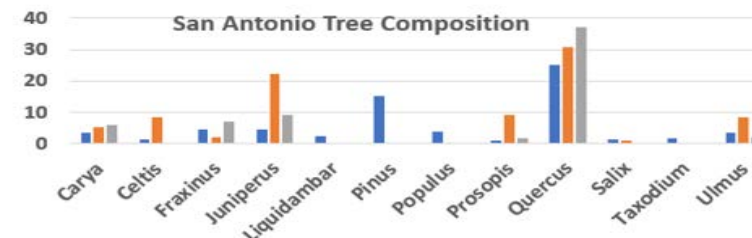


Step 3: Identify tree using tree key developed for specific urban area

Street View Key for Texas Trees

- 1 leaves are narrow (< 3mm); needles or scale like.....Pine
- 2 leaves are needles.....Juniper
- 2 leaves are scale like.....Palm
- 1 leaves are wider (> 5 mm)
- 3 leaves are very large and fan shaped.....Group 1
- 3 leaves not as above
- 4 leaves are compound (with leaflets).....Sweetgum
- 4 leaves are simple
- 5 large leaves (> 10 cm wide) that are lobed; almost as wide as long.....Sycamore
- 6 leaves star shaped, with deep lobes; bark grey to brown.....Deciduous Oak
- 6 leaves with 3 to 5 shallow lobes; bark pale white.....Willow
- 5 leaves not as wide as above and/or longer than wide
- 7 leaves have lobes.....
- 7 leaves are entire or toothed but do not have lobes
- 8 leaves are linear, length is > than 3 times the width
- 9 leaf edge finely toothed; upright branching habit.....

Step 4: Assign average tree species composition to urban area(s)



Virtual Urban Tree Survey species composition estimates

Random sampling points and identification using a taxonomic key (scheme) based on multi-temporal Google Earth and Google street view imagery.

Shah et al. 2021

Percent isoprene emitters

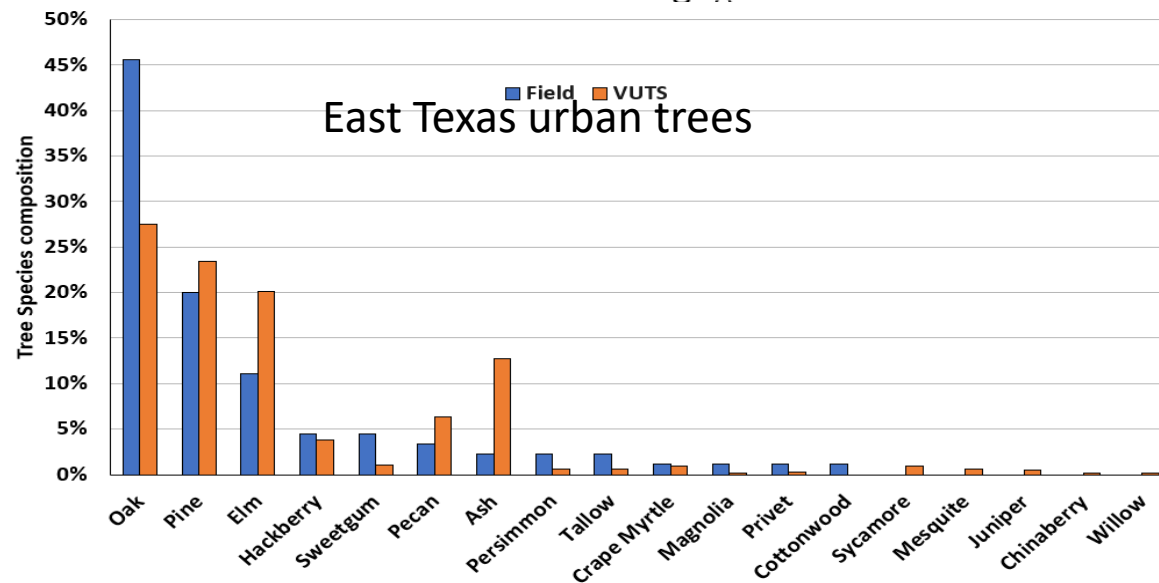
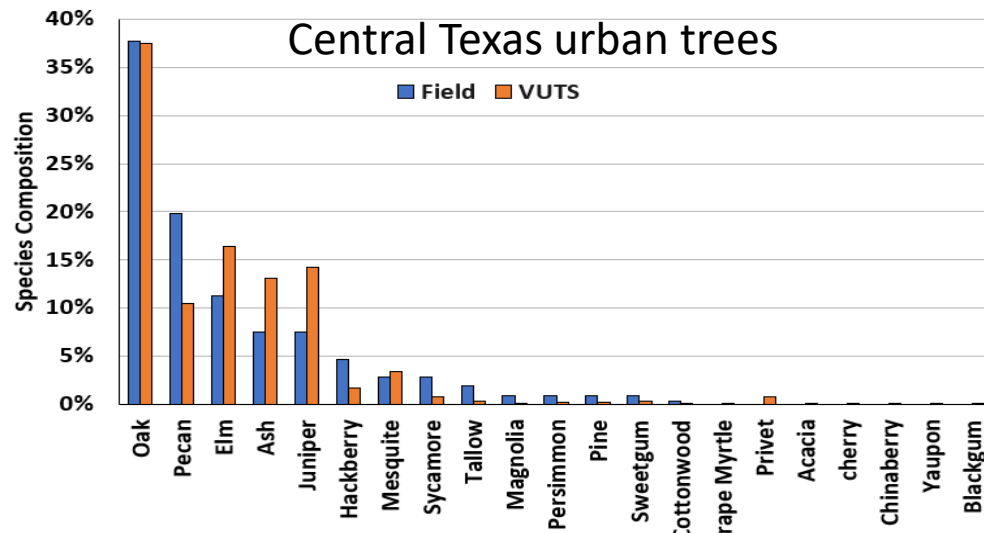
- MEGAN US default: 33.7%
- VUTS: 41.9%
- Field: 40.6%

20% higher than default value

Percent isoprene emitters

- MEGAN US default: 33.7%
- VUTS (initial key based on Central Texas): 29.7%
- Field 51.1%
- VUTS (key developed for East Texas): 46.5%

50% higher than default value



Key points

- **Emission factors: Isoprene emission factors reconciled for dominant US trees but larger uncertainties for plants in some regions (e.g., urban, sparse veg). Monoterpene and sesquiterpenes (and other BVOC) are more uncertain.**
- **We need to simulate stress response to accurately characterize at least some extreme events (e.g., drought).**
- **Urban BVOC is important but currently is poorly characterized. Approaches are available for accurately characterizing fine scale BVOC emissions in urban landscapes.**