

Biogenic Emission Inventory Improvement Using High-resolution Satellite Products

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Overview

- Background
- Purpose
- Vegetation cover improvements
- Sensitivity of biogenic emissions to vegetation cover change
- Conclusion



Emission Inputs for Chemical Transport Models

- Point
- Area
- Mobile
 - On-road
 - Off-road
- Biogenic
- Fire



Biogenic VOC have an important role in atmospheric chemistry due to their large emission fraction of the total VOC at the global scale and higher chemical reactivity compared to many anthropogenic VOC



Biogenic emission models

Two widely used biogenic emission models

- Model of Emissions of Gases and Aerosols from Nature (MEGAN3.2)

 <u>https://bai.ess.uci.edu/megan/data-and-code</u>
- Biogenic Emission Inventory System (BEIS4.0): embedded in the SMOKE/CMAQ model

 <u>https://www.cmascenter.org/smoke/</u>
- Emission estimates from BEIS and MEGAN differ because they use different data and contain different algorithms which reflects the complexity of estimating biogenic emissions



Purpose



- Biogenic emissions are important for urban air quality because they contribute to the formation of pollutants like groundlevel ozone and fine particulate matter
- Accurate land cover data is a fundamental input for biogenic emission models like MEGAN (Model of Emissions of Gases and Aerosols from Nature).
- High-resolution data can capture finescale variations in land cover. This is especially important in urban areas where land use can change rapidly over short distances.



Where is ozone sensitive to VOC emission estimates?



Figure 11. Formaldehyde – NO₂ – Ratio (FNR) in Texas averaged across April through September 2019 using the

i (left) operational TROPOMI products (center left) operational TROPOMI HCHO product and TROPOMI NO₂ product with new AMFs and (right) CAMx column amounts. Only CAMx data coincident with the overpass time and valid TROPOMI pixels are included.

Goldberg et al. ACP 2022

Red: NOx sensitive ozone White/Blue: VOC sensitive ozone



Improved Land Cover Data for Urban Areas

- Challenging to estimate biogenic emissions for urban areas because of vegetation heterogeneity and lack of locally specific data
- New generation of high-resolution remote sensing products make it possible to improve landcover characterization for urban areas
- The goal is to improve land cover data for several urban areas in Texas and Utah by combining virtual tree surveys with aerial/satellite imagery and using machine learning





Overview of MEGAN3.2

- MEGAN3.2 uses "ecotypes", "growth forms" and LAI input data typically based on satellite imagery and ground surveys to characterize the vegetation types
- New WRFCAMx support and a more transparent approach for assigning BVOC emission factors (EFs)
- New Berkeley/Dalhousie Soil NOx emission algorithm
- Improved representation of canopy processes
 - o leaf temperature model
 - o transparency
 - emission capacity varies by depth
- Treatments for previously unrepresented processes including stress-induced emissions



Actual canopy area is less and some leaves are shaded which reduces isoprene emissions.



MEGAN Landcover Inputs

- Illustration of three types of landcover data inputs required for MEGAN.
 - LAI is the total amount of BVOC emission source in a 10 m x 10 m area
 - Growth form fractions divide the LAI into four categories that can be mapped at 10-m spatial resolution
 - Growth form speciation quantifies the plant species composition to assign species-specific emission factors





Improve Leaf Area Index (LAI) distributions

- Acquire Sentinel-2 highresolution (10 m) data for the area of interest.
- Process the Sentinel-2 Level 2A radiance data into LAI using European Space Agency's (ESA) Sentinel Application Platform (SNAP) toolbox (46 8-day periods for each location).
- Calibrate or validate LAI estimates using ground-based measurements.



An example of Sentinel-2 based LAI estimates at 10 m resolution (red=0, yellow = low, green = high) for Austin TX and surrounding region (left) with zoomed in results for the U. Texas J.J. Pickle campus in Austin



Improve growth form fraction

Three key components:

- sub meter resolution (individual trees),
- segmentation for object-based classification,
- machine learning (random tree)

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



NAIP natural color image: 60 cm spatial resolution



Segmentation (object-based) and machine learning classified cover: tree (green shades), grass (yellow), bare soil (bro¹¹/_wn), built (grey, red, white)

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Improve tree species composition

The Virtual Urban Tree Survey (VUTS) approach was developed to estimate 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

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

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





Мау

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Street View Key for Texas Trees

1 leaves are narrow (< 3mm); needles or scale like	
2 leaves are needles	Pine
2 leaves are scale like	Juniper
1 leaves are <u>wider(></u> 5 mm)	
3 leaves are very large and fan shaped	Palm
3 leaves not as above	
4 leaves are compound (with leaflets)	<u>Group</u> 1
4 leaves are simple	
5 large leaves (> 10 cm wide) that are lobed; almost as wide as long	
6 leaves star shaped, with deep lobes; bark grey to brown	Sweetgum
6 leave with 3 to 5 shallow lobes; bark pale white	Sycamore
5 leaves not as wide as above and/or longer than wide	
7 leaves have lobesDe	ciduous Oak
7 leave 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	Willow





Comparing MEGAN v3.2, v3.1 and BEIS v3.7: Soil NO emissions

TCEQ 12 km domain Summer 2019 total emission MEGANv3.2: 4,157 tons/day MEGANv3.1: -29% BEISv3.7: -66%



Comparing MEGAN v3.2, v3.1 and BEIS v3.7: Isoprene emissions

TCEQ 12 km domain Summer 2019 total emission MEGANv3.2: 30,673 tons/day MEGANv3.1: -12% BEISv3.7: -45%





Comparing MEGAN v3.2, v3.1 and BEIS v3.7: Monoterpene emissions

TCEQ 12 km domain Summer 2019 total emission MEGANv3.2: 8,915 tons/day MEGANv3.1: -14% BEISv3.7: -36%

TERP(MEGANv32_mcip-BEIS)







Impact of landcover inputs on urban isoprene and terpene emission estimates

ISOP(MEGANv32_mcip-MEGANv31)

5.0 4.0 3.0 2.0 1.0 0.0 -1.0 -2.0 -3.0 -4.0 -5.0

> 2.0 1.5 1.0 0.5 0.0 -0.5 -1.0

-1.5

-2.0

ISOP(MEGANv32_mcip-BEIS)



TERP(MEGANv32_mcip-BEIS) TERP(MEGANv32_mcip-MEGANv31) tons/day



Key Takeaways

- The 10 m LAI data includes the contribution of isolated vegetation cover on scales of 100 m2 or less that is missed by lower spatial resolution products. High-resolution imagery can more accurately quantify LAI.
- Sub-meter imagery and object-based machine learning classification can accurately quantify tree cover for MEGAN input.
- Virtual urban tree survey (VUTS) is a cost-effective approach for quantifying urban tree species composition and urban isoprene emitter fraction can be accurately characterized using the VUTS approach.
- For TCEQ's 12 km domain, MEGAN3.2 soil NO emissions are 40% higher than MEGAN3.1 and 200% higher than BEIS3.7. These findings are for a specific region/year - other regions may differ.



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