Extracting Information from High Resolution Remote Sensing Data

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Acknowledgement

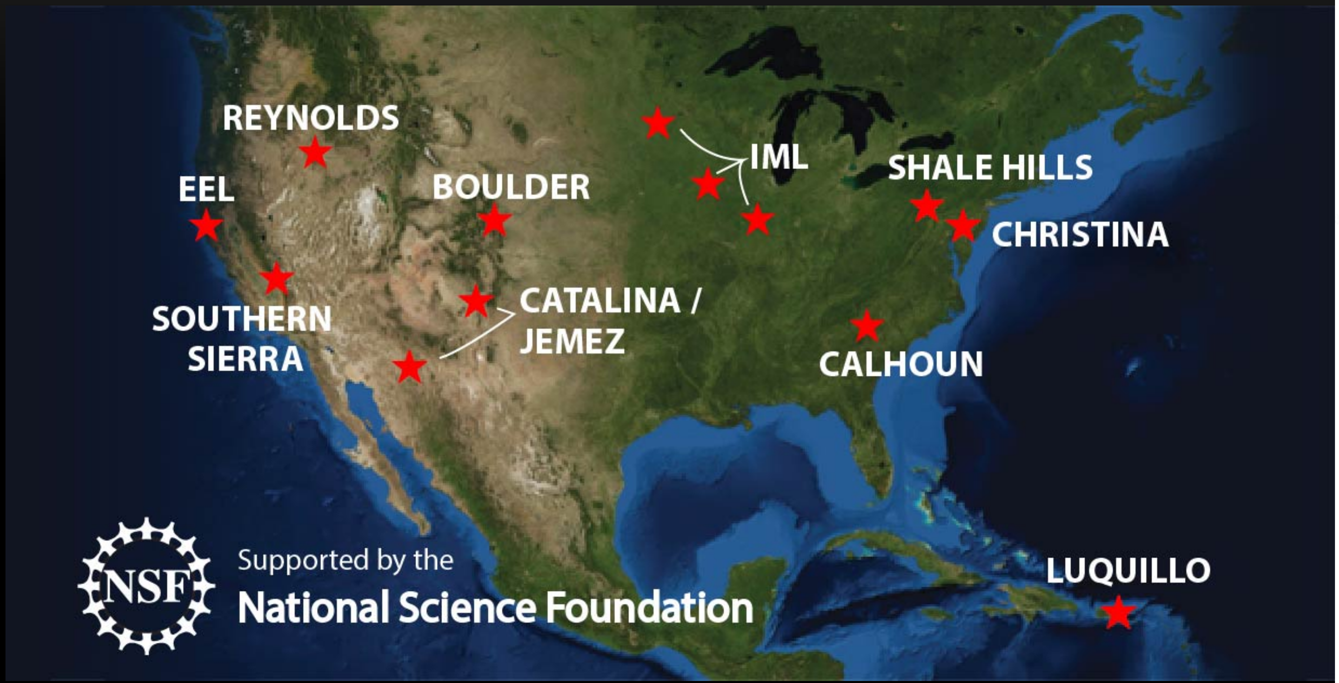
Debsunder Dutta, Kunxuan Wang, Qina Yan, Esther Lee

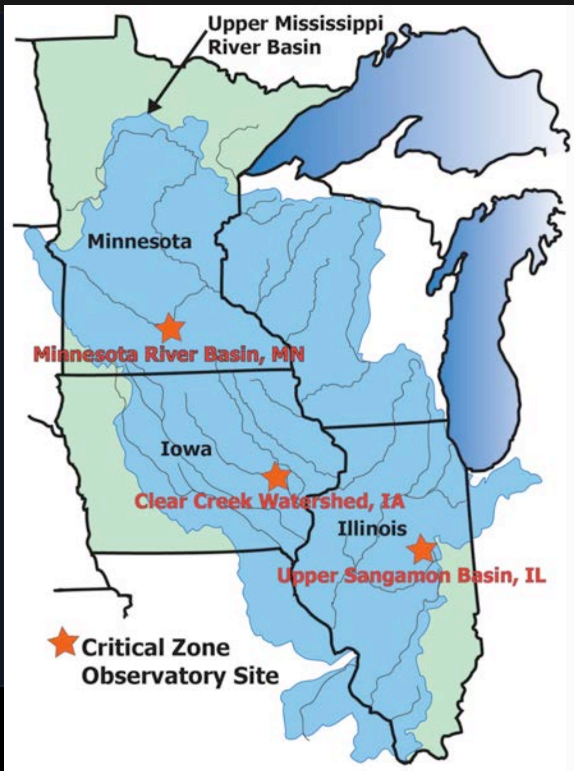
Theme: High Resolution Data & Model Integration

- Quite revolution in high resolution multi-disciplinary data for Earth science: remote sensing, in situ, geophysics, …
- ➔ address new inter-disciplinary questions across space and time scales
  - Theoretical formulations
  - Machine learning
  - Hybrid (CPU+GPU) computing

- Methodological and phenomenological outcomes
  - Human impact, and natural setting

Critical Zone Observatories Network

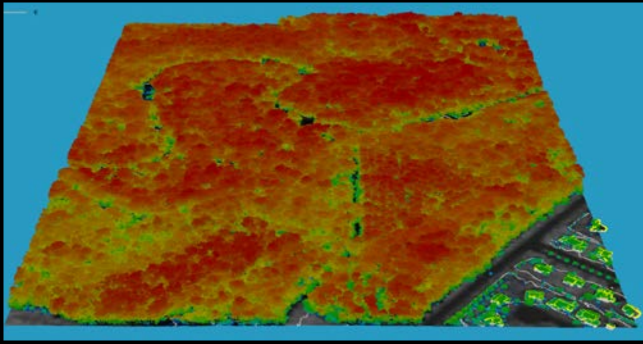


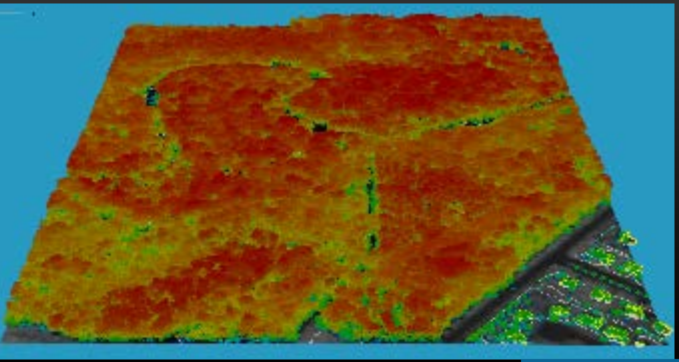


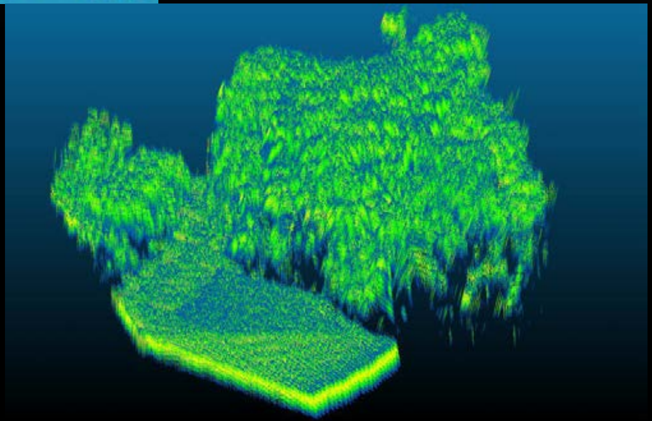
IMLCZO uses remote sensing & in-situ observations

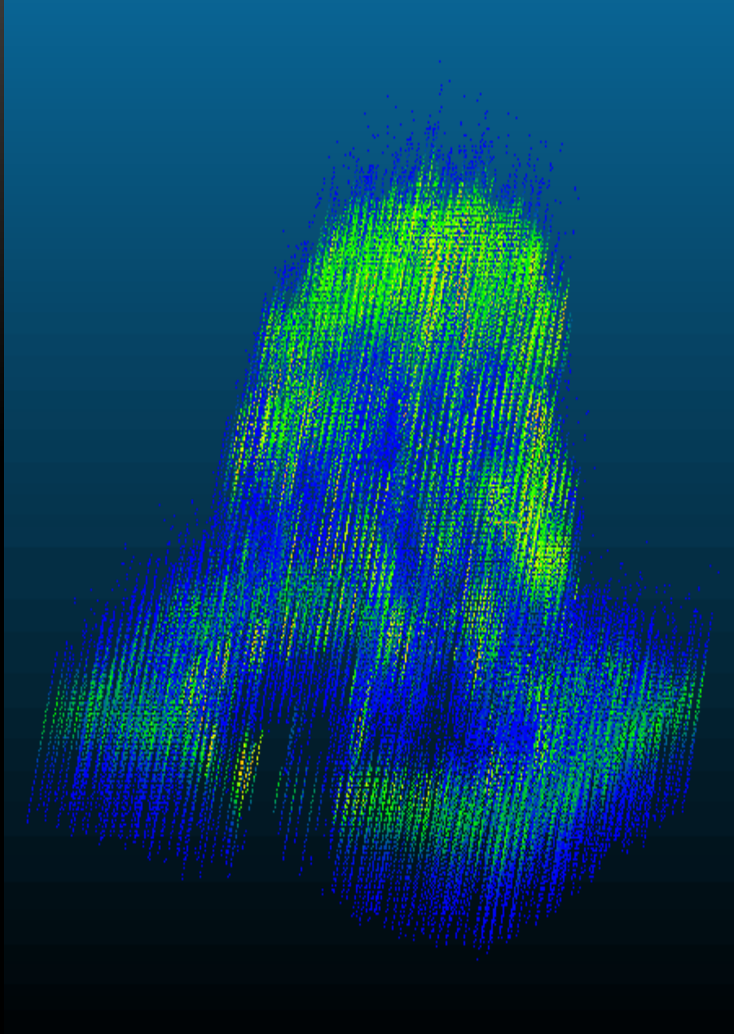






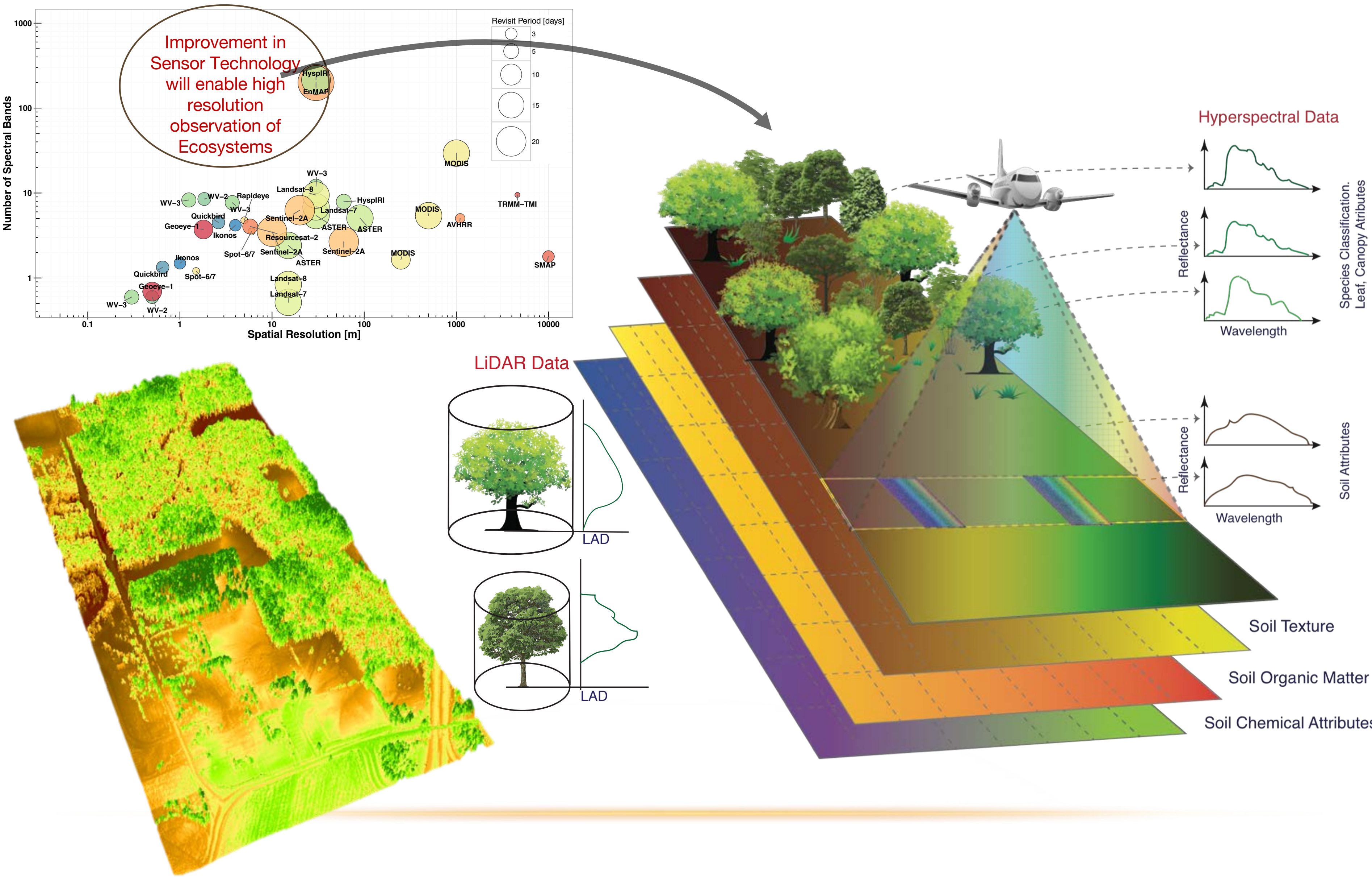




USING EMERGING HIGH RESOLUTION DATA

Dutta et al., IEEE TGRS, 2015
Dutta et al., IEEE TGRS, 2017
Dutta et al. IEEE JSTARS, 2017
Dutta & Kumar, IEEE TGRS, 2018

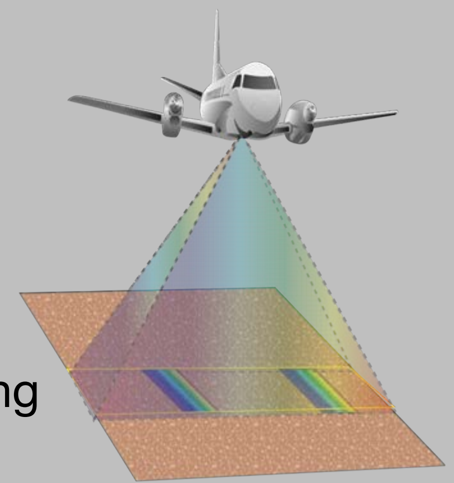
Airborne Remote Sensing Data

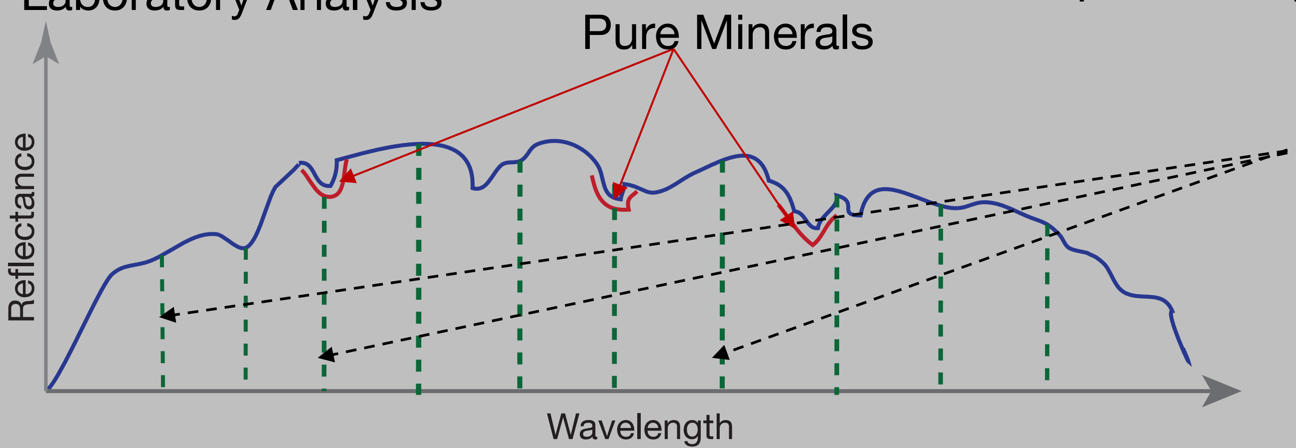


Soil Characterization

Laboratory Analysis

Airborne Imaging Spectroscopy





1. Can we predict soil properties?
2. Which spectral bands are important and further how important?
3. To what extent can we predict?
4. What does the model tell us?

Characterizing Fine Resolution Soil Constituent

Characterizing Soil Constituents as an Inverse Problem

$$X = \mathcal{F}(Y) + v$$

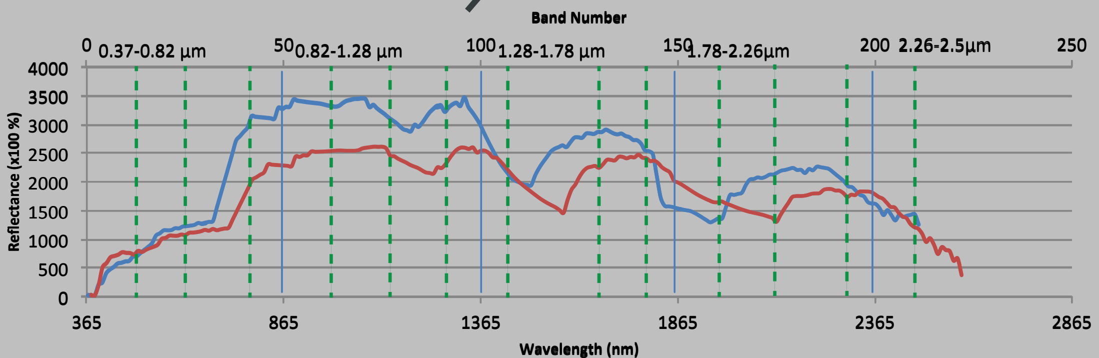
$$X = \{x_1, x_2, x_3, \ldots, x_{n_r}\}^T$$

band1, band2, band 3,…, band n

$$Y = \{y_1, y_2, y_3, \ldots, y_{n_p}\}^T$$

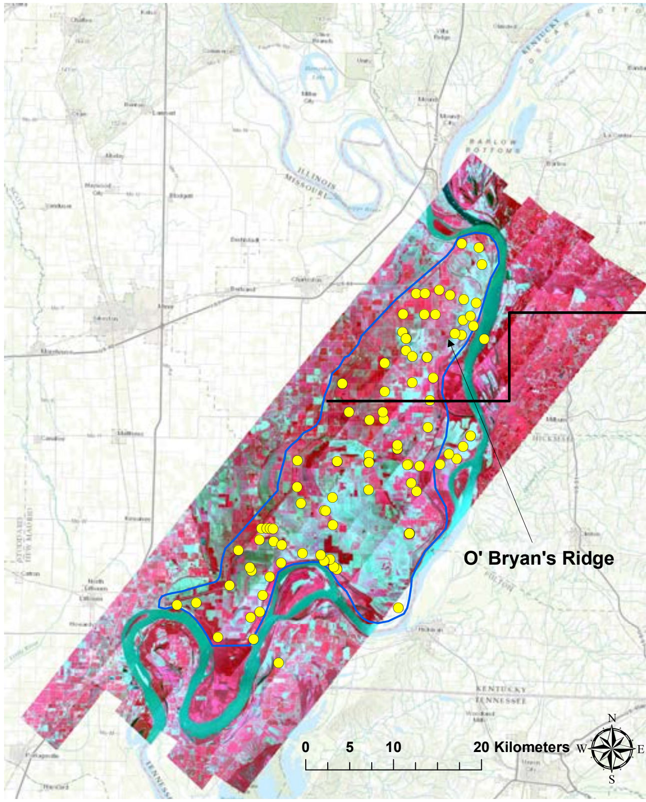
sand, silt, clay, SOM, Ca, Mg,…

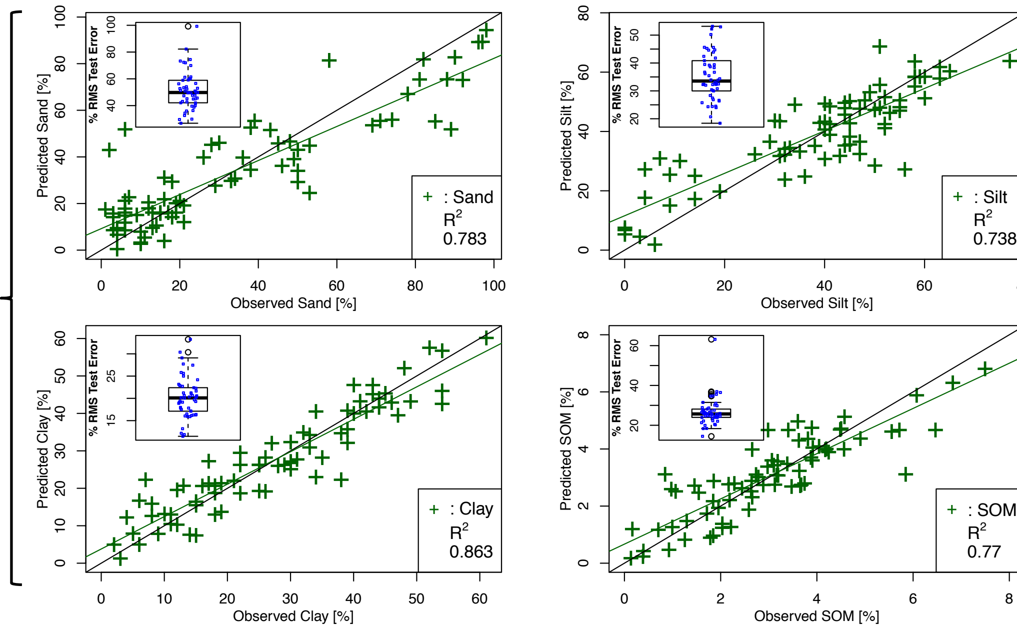
$$Y = CX + e$$

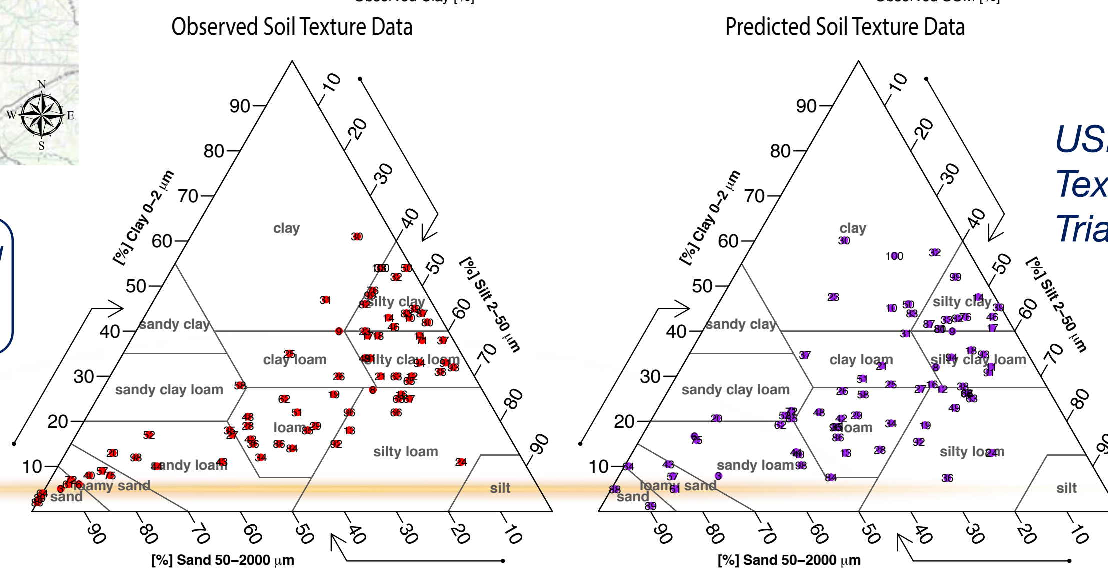


- *Extract the relationship from the data*
- *Represent the entire spectral range in the models*
- *Develop a robust model with limited data sets*

Machine Learning: Soil Texture from Hyperspectral Data







USDA Soil Texture Triangle

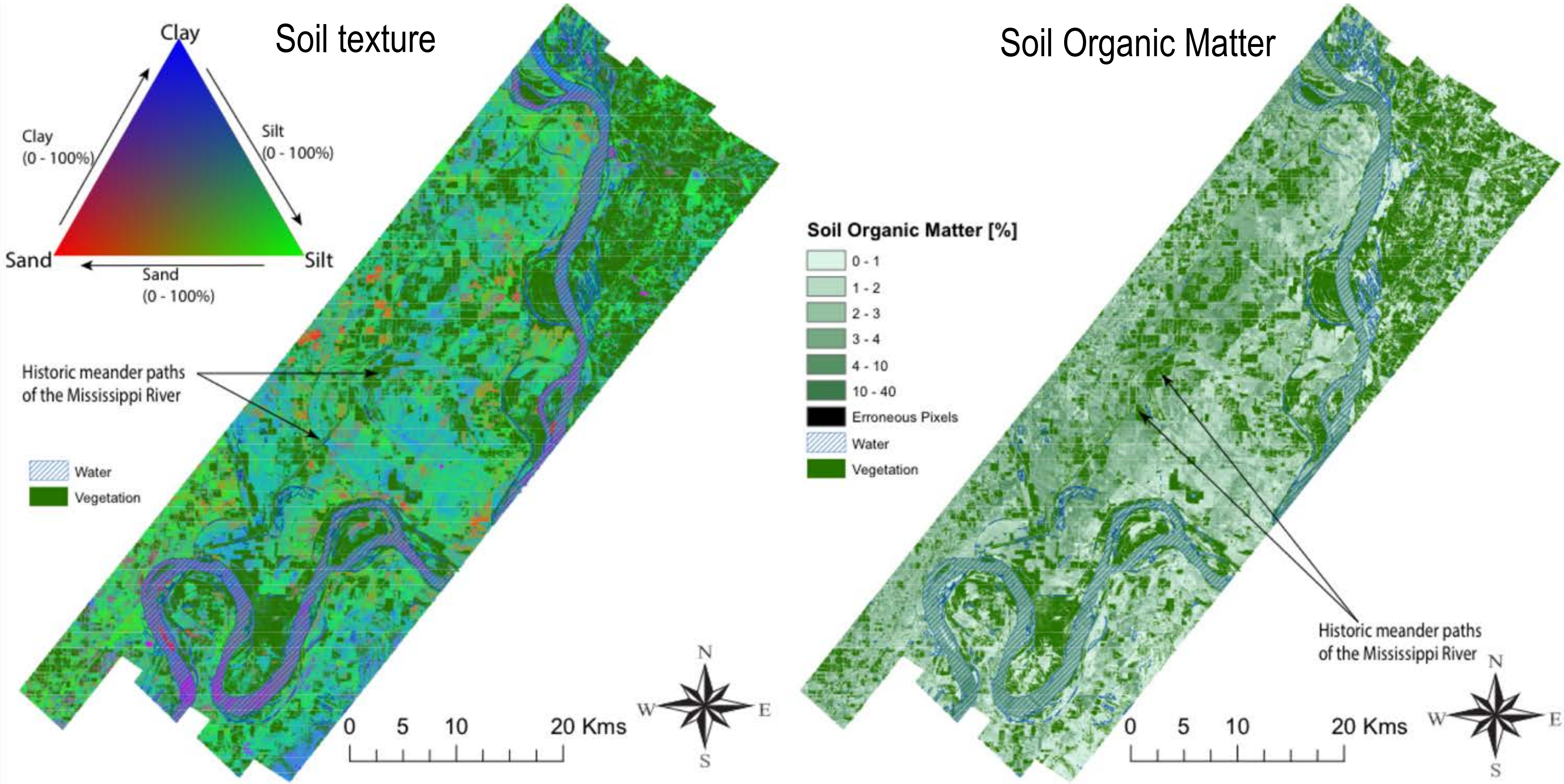
Results obtained from models developed using AVIRIS spectra and field sample locations in yellow

$$\Delta_{sand\%} = |\Delta_{sand\%}^{observed} - \Delta_{sand\%}^{predicted}|$$

$$\Delta_{clay\%} = |\Delta_{clay\%}^{observed} - \Delta_{clay\%}^{predicted}|$$

$$\Delta_{total\%} = \Delta_{sand\%} + \Delta_{clay\%}$$

Spatial Prediction



Results obtained by application of prediction models across the entire landscape about 700km^2 in area at 7.5 m resolution

Tree Species Classification Using Hyperspectral Data

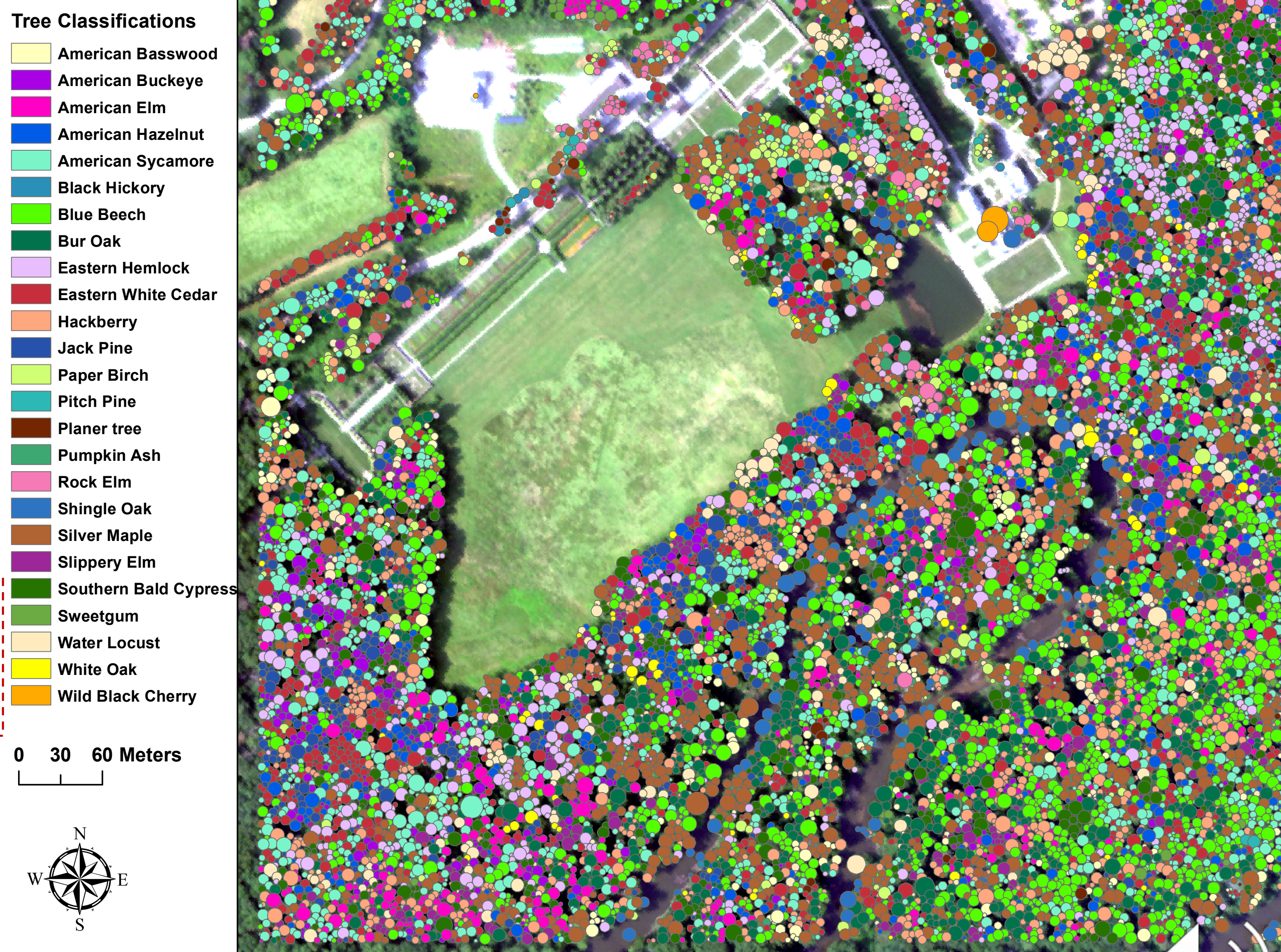
Canopy Height Model (CHM) Generation
- Digital Surface Model (DSM)
- Digital Terrain Model (DTM)

↓

Tree Crown Segmentation
- Inverted Watersheds
- Filtering

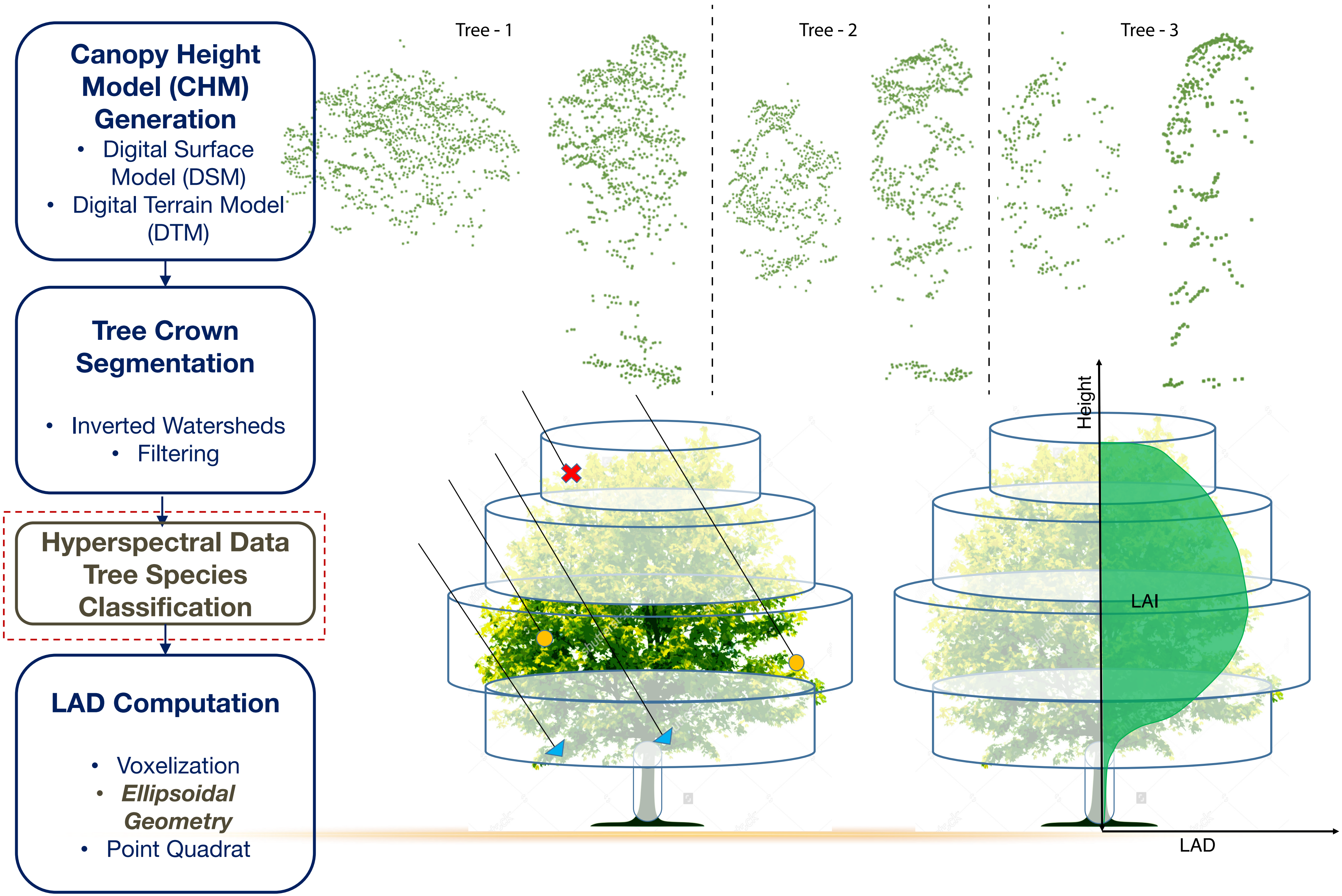
↓

Hyperspectral Data Tree Species Classification

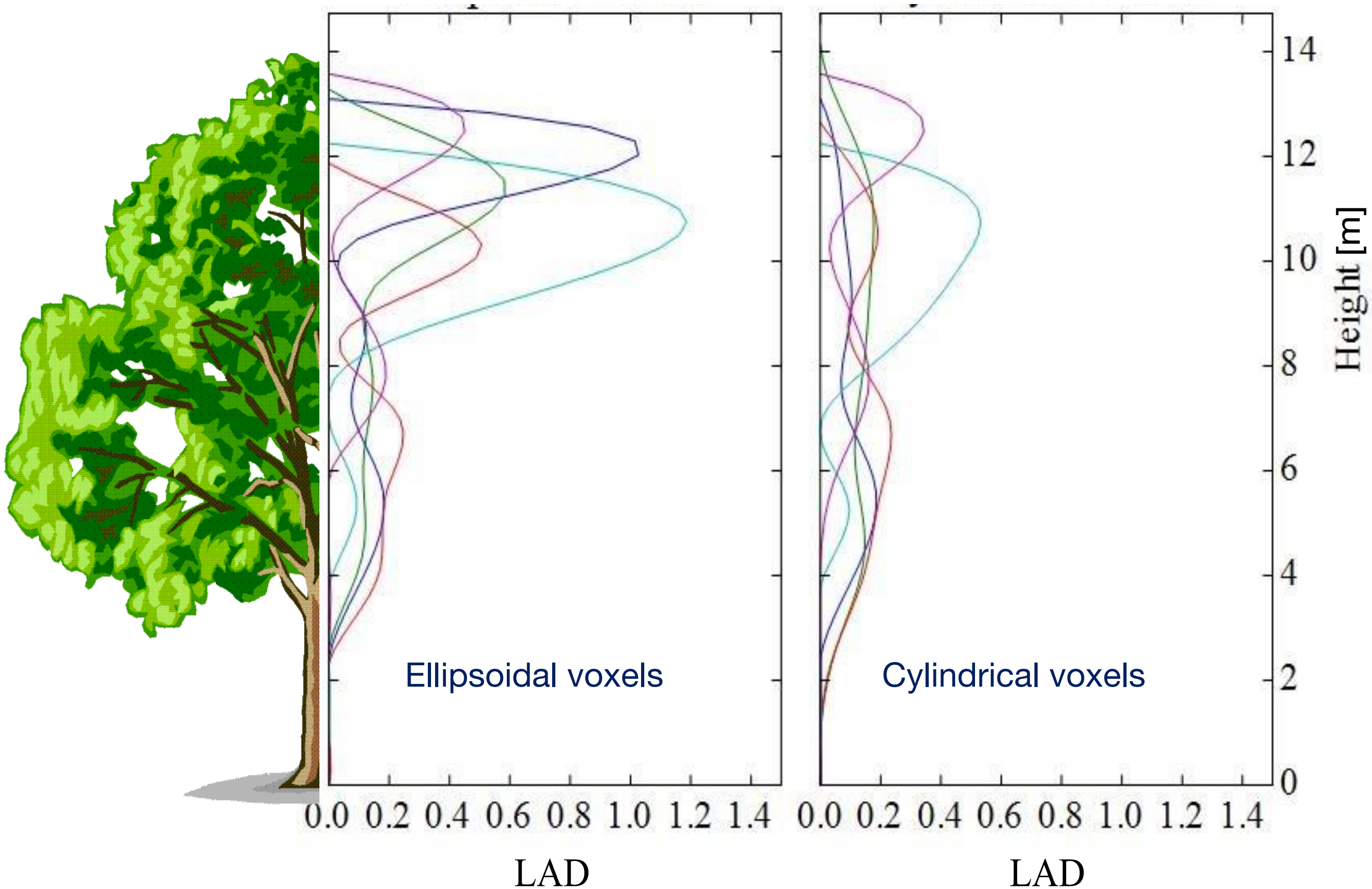


Study Site: Allerton Park

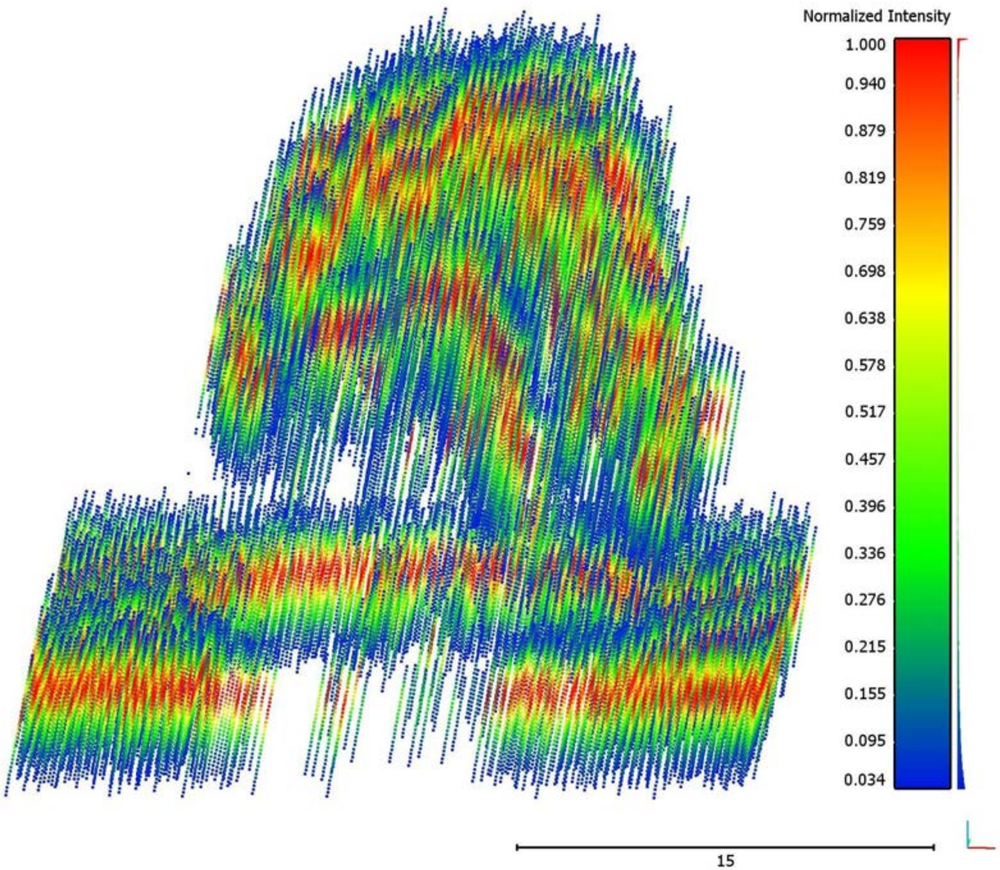
Estimation of Leaf Area Density (LAD)

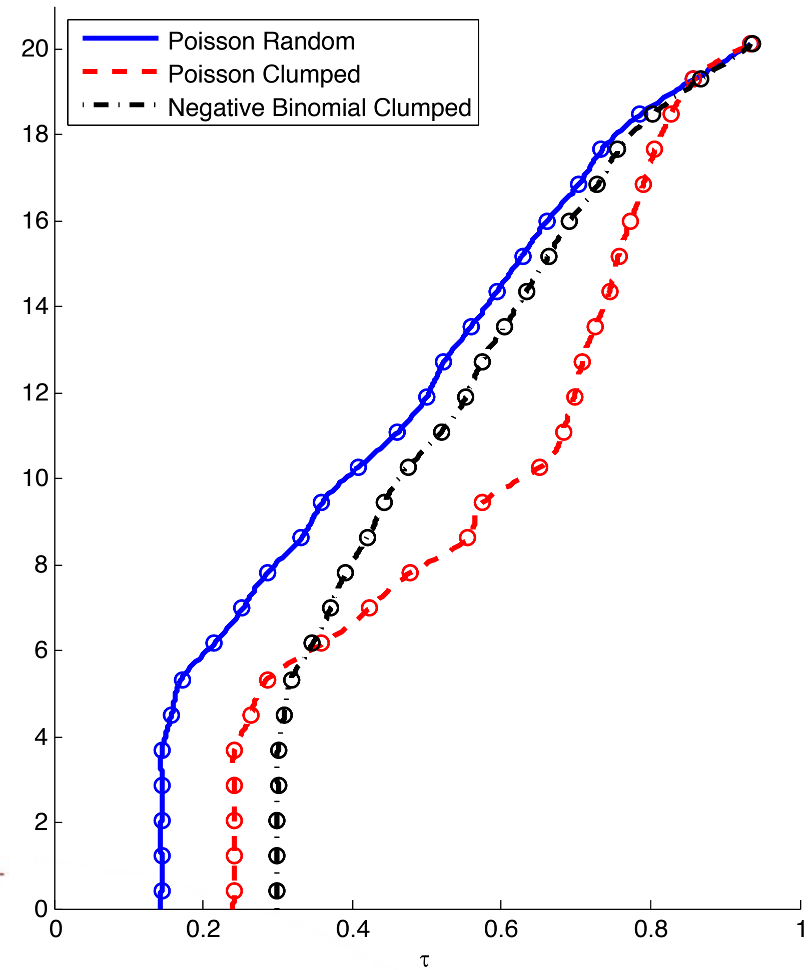


LAD Profiles for Several Trees



Light Penetration and Canopy C & H_2O Modeling

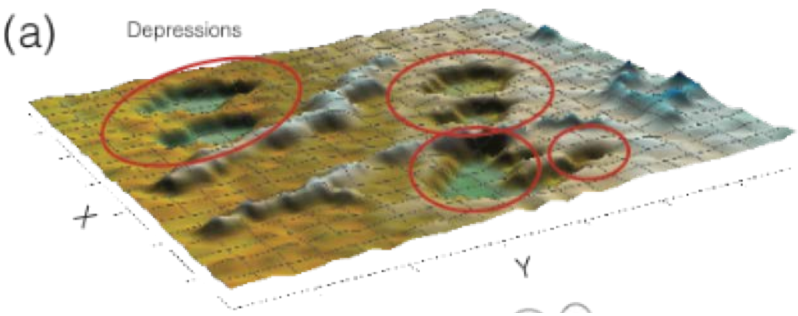


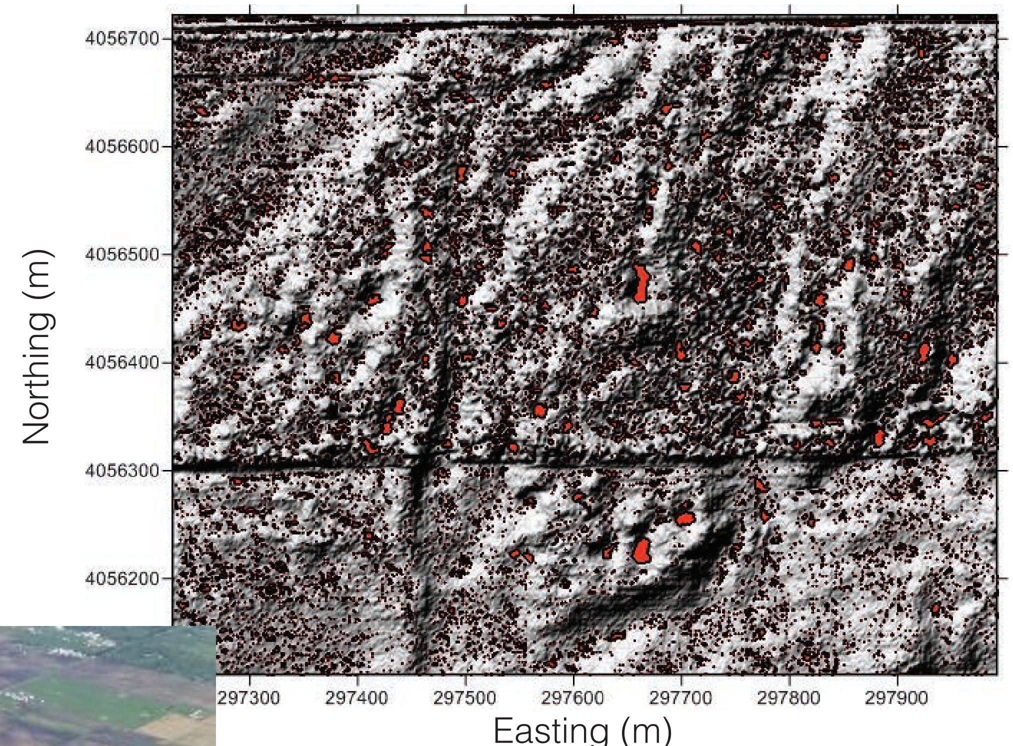


ECOHYDROLOGIC DYNAMICS

Drewry et al., JGR-BGS, 2010a,b
Quijano et al, WRR, 2012, 2013
Le & Kumar, GRL, 2015
Le et al., Env. Mod. & Soft., 2015
Le & Kumar, WRR, 2017
Woo & Kumar, WRR, 2017

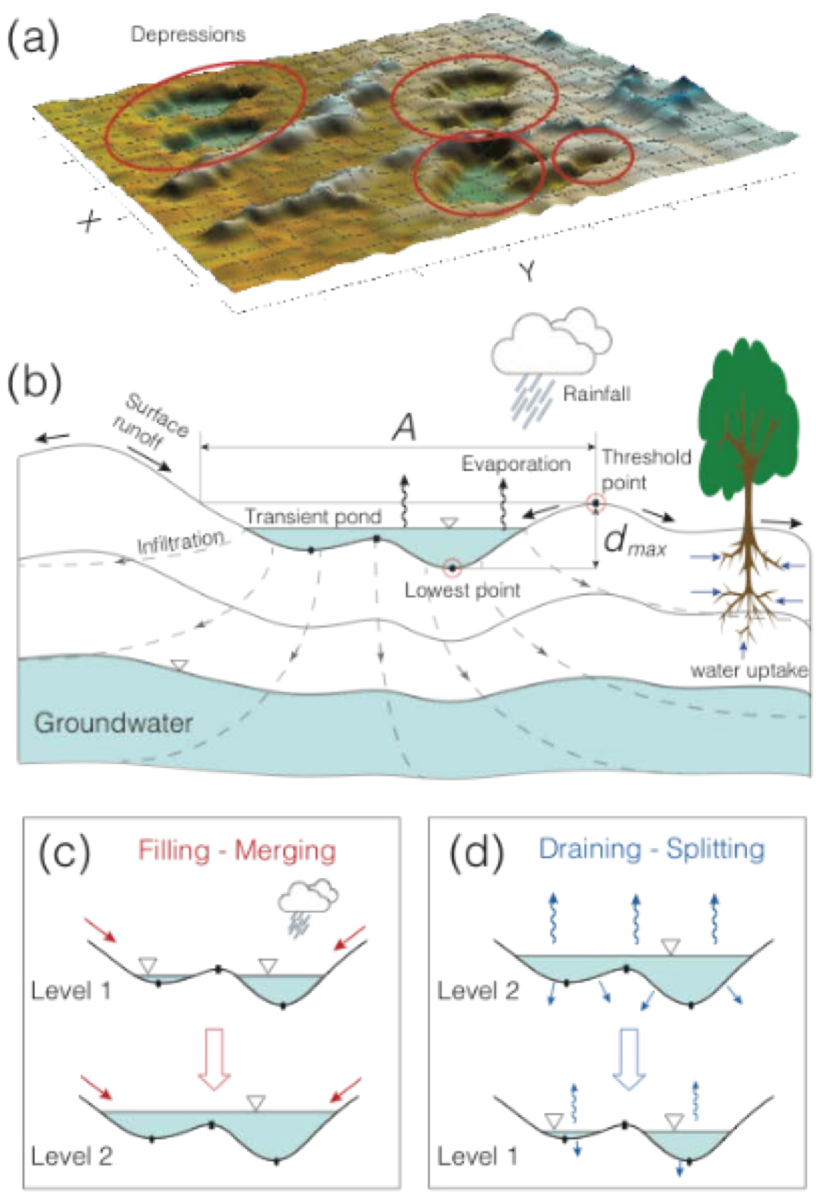
Micro-topographic controls

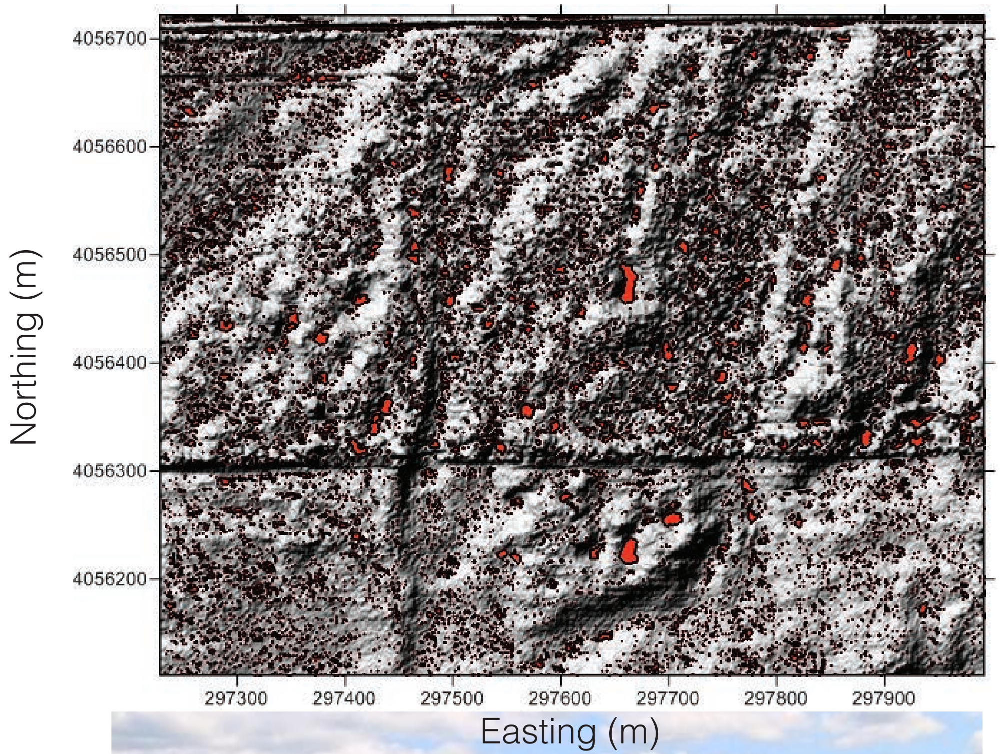


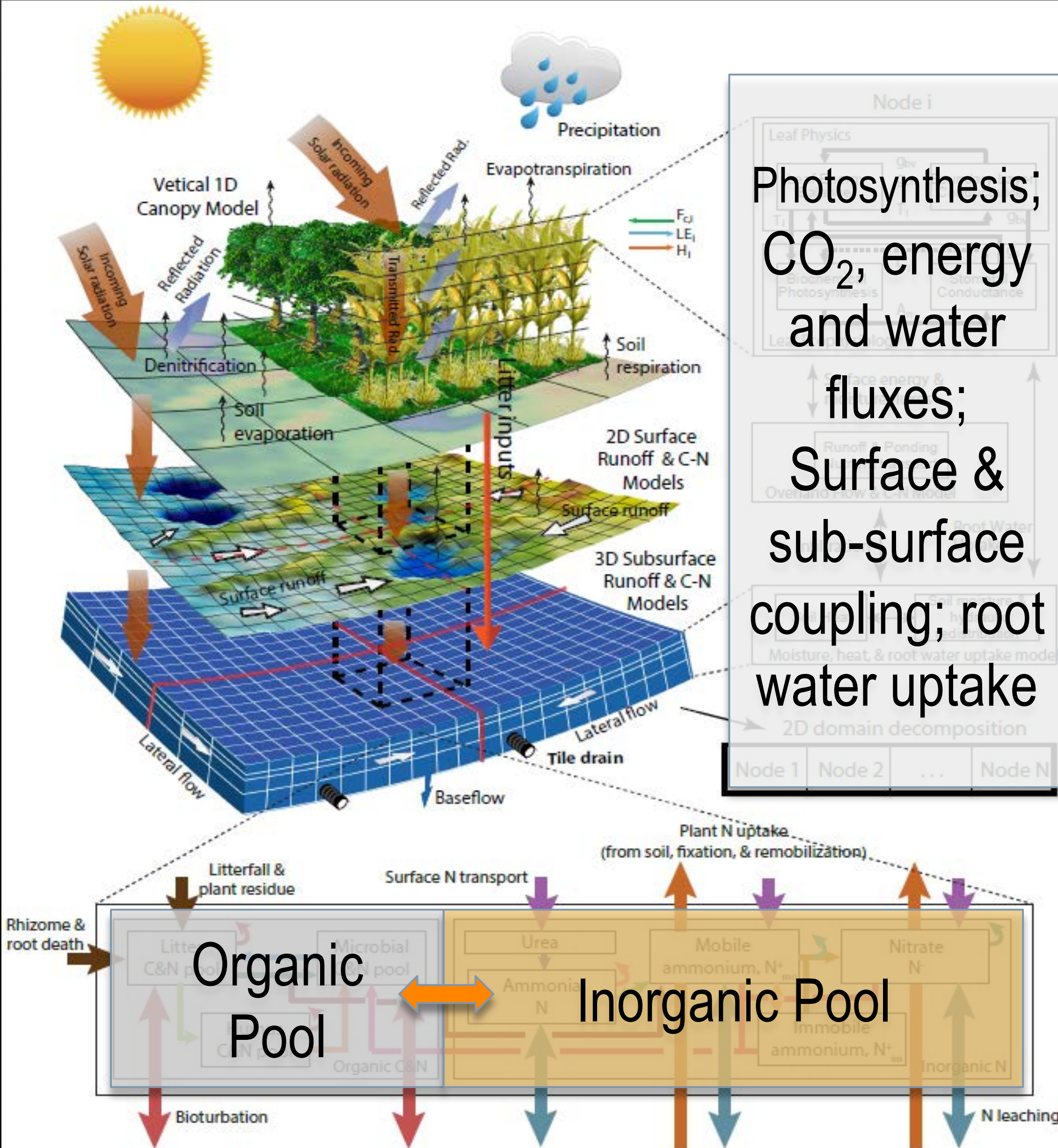


Le & Kumar, GRL 2014
doi: 10.1002/2013GL059114

Micro-topographic controls



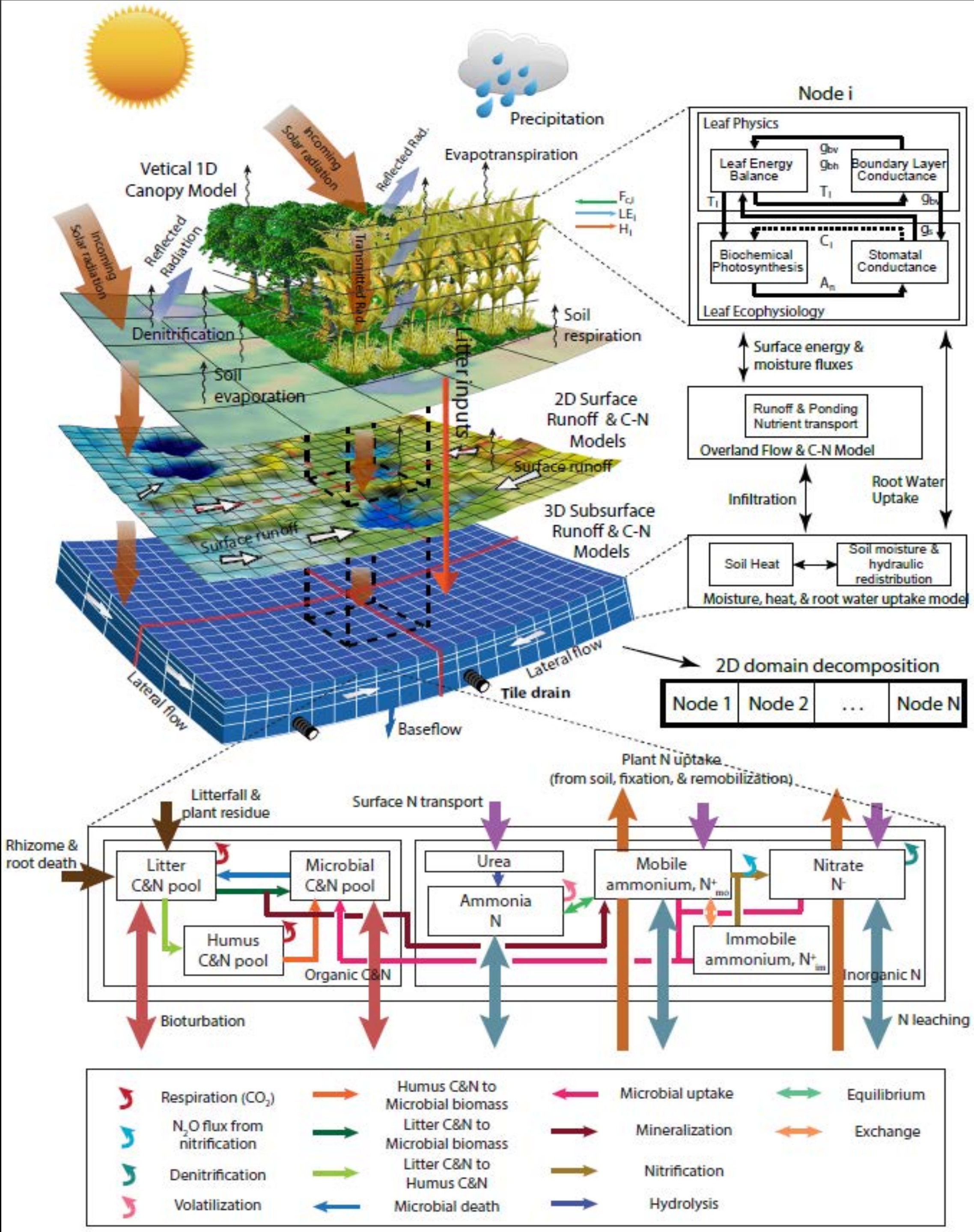




Dhara Model

High Resolution (~m) explicit 3-D transport + Multi-layer vegetation model

Dhara (sanskrit): earth, flow



Dhara Model

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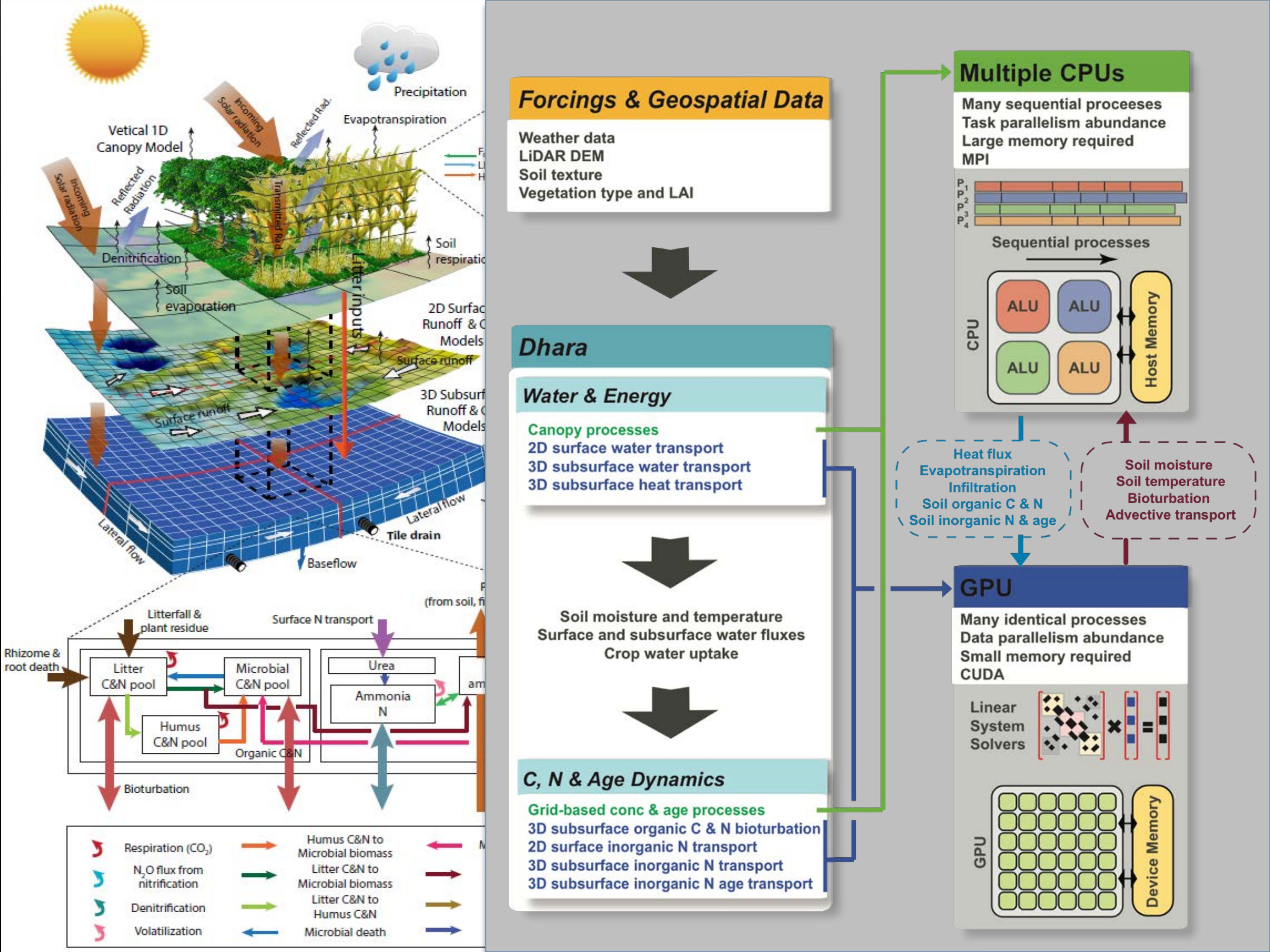
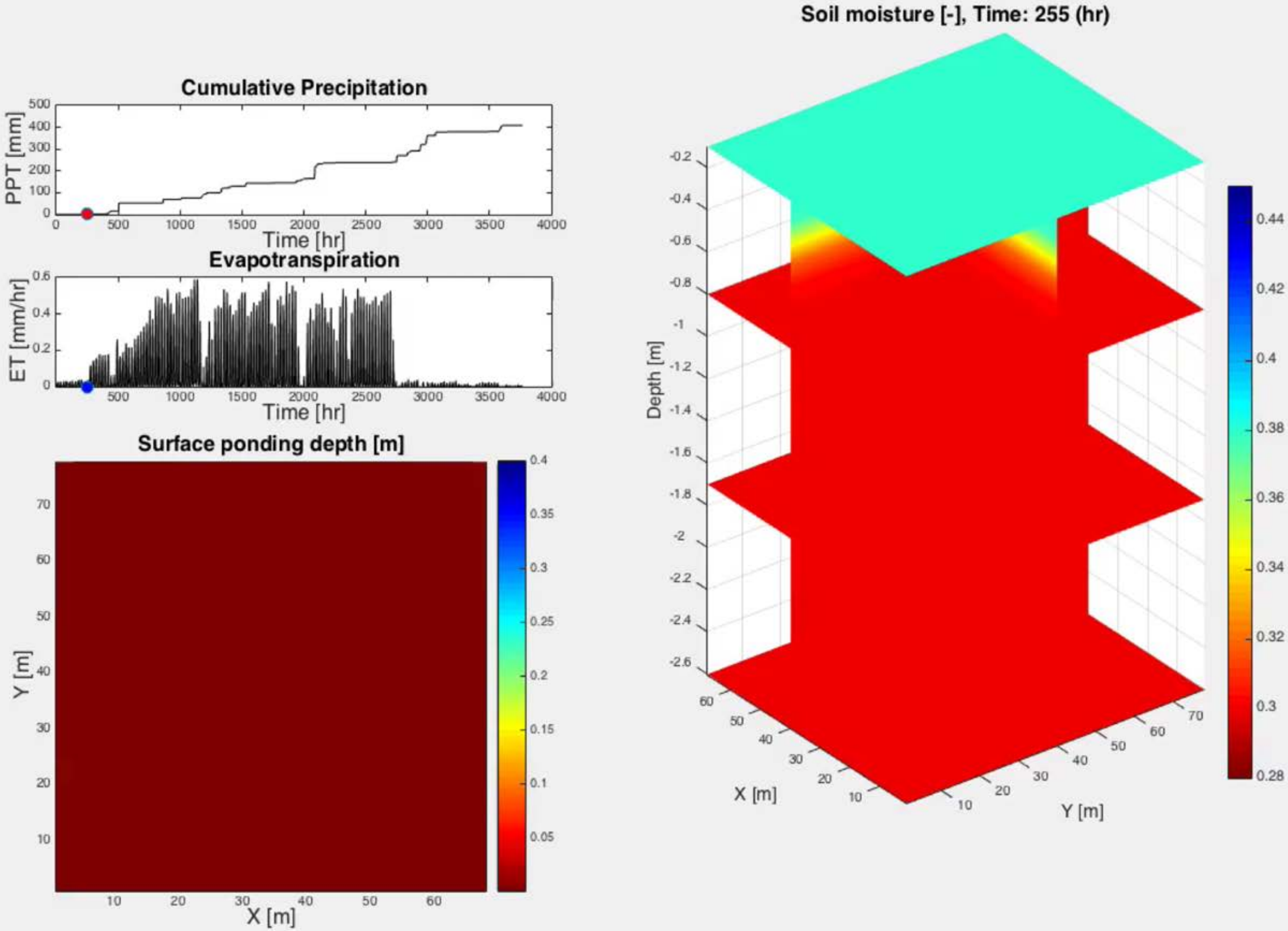

Precipitation
Vetical 1D
Canopy Model
Incoming
Solar radiation
Reflected Rad.
Evapotranspiration
Reflected
Radiation
Transmitted Rad.
Denitrification
Soil
evaporation
Soil
Litter inputs
Surface runoff
Models
Lateral flow
Tile drain
Baseflow
Litterfall &
plant residue
Surface N transport
Rhizome &
root death
Litter
C&N pool
Microbial
C&N pool
Humus
C&N pool
Organic C&N
Urea
Ammonia
N
Bioturbation
Respiration (CO_2)
N_2O flux from
nitrification
Denitrification
Volatilization
Humus C&N to
Microbial biomass
Litter C&N to
Microbial biomass
Litter C&N to
Humus C&N
Microbial death
Forcings & Geospatial Data
Weather data
LiDAR DEM
Soil texture
Vegetation type and LAI
Dhara
Water & Energy
Canopy processes
2D surface water transport
3D subsurface water transport
3D subsurface heat transport
Soil moisture and temperature
Surface and subsurface water fluxes
Crop water uptake
C, N & Age Dynamics
Grid-based conc & age processes
3D subsurface organic C & N bioturbation
2D surface inorganic N transport
3D subsurface inorganic N transport
3D subsurface inorganic N age transport
Multiple CPUs
Many sequential proceses
Task parallelism abundance
Large memory required
MPI
P_1
P_2
P_3
P_4
Sequential processes
CPU
ALU
ALU
ALU
ALU
Host Memory
Heat flux
Evapotranspiration
Infiltration
Soil organic C & N
Soil inorganic N & age
Soil moisture
Soil temperature
Bioturbation
Advective transport
GPU
Many identical processes
Data parallelism abundance
Small memory required
CUDA
Linear
System
Solvers
GPU
Device Memory

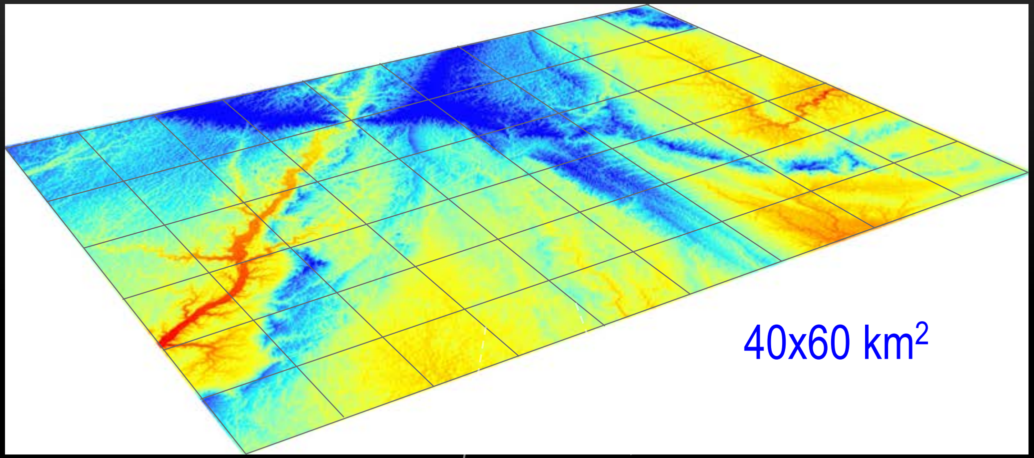
MOISTURE DYNAMICS

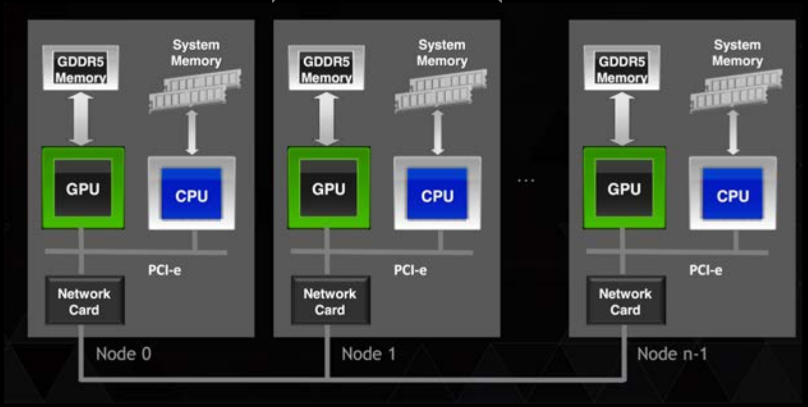
Le & Kumar, GRL, 2015
Le et al., Env. Mod. & Soft., 2015
Le & Kumar, WRR, 2017

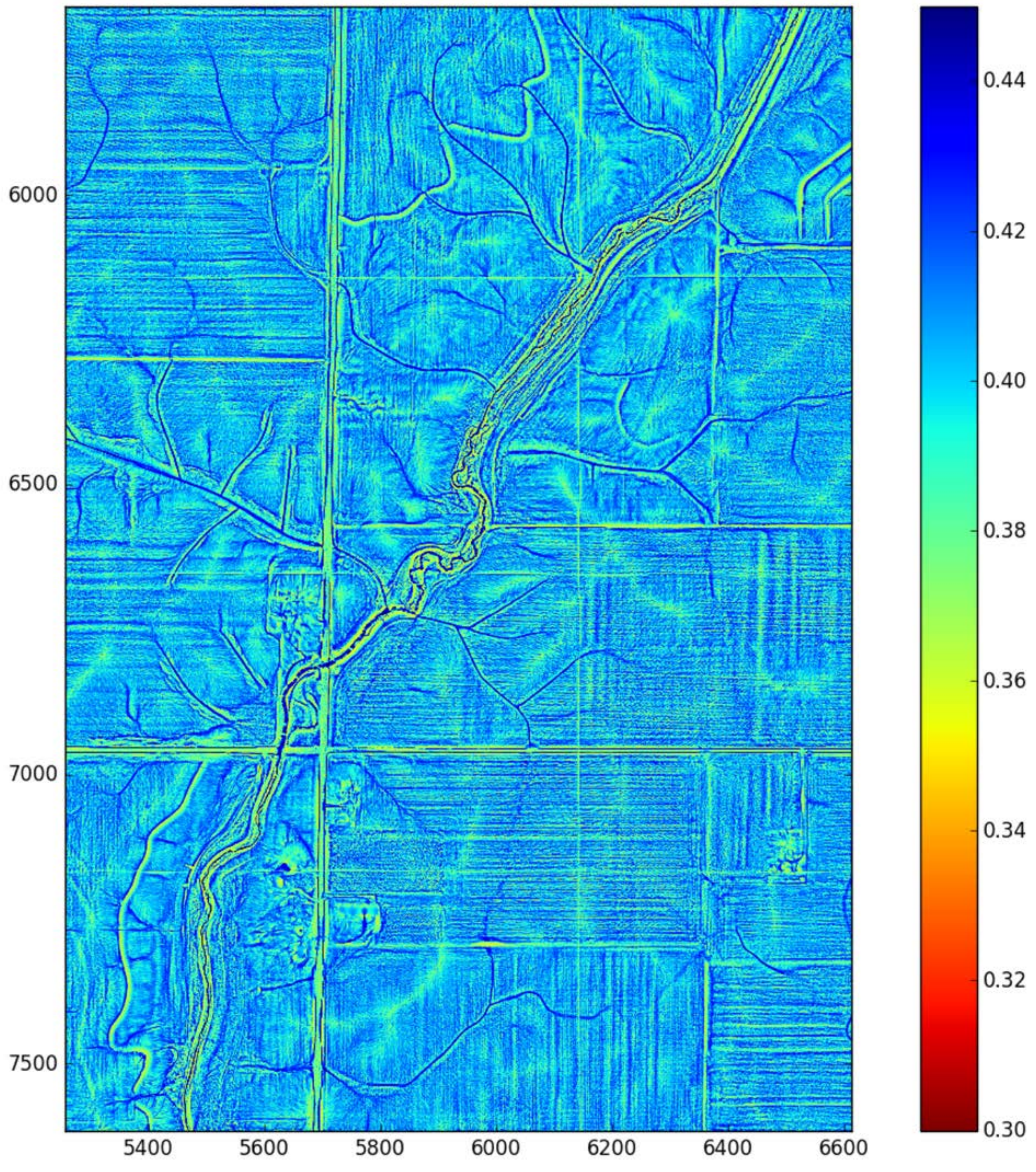

Cumulative Precipitation
PPT [mm]
0 100 200 300 400 500
0 500 1000 1500 2000 2500 3000 3500 4000
Time [hr]
Evapotranspiration
ET [mm/hr]
0 0.2 0.4 0.6
500 1000 1500 2000 2500 3000 3500 4000
Time [hr]
Surface ponding depth [m]
Y [m]
10 20 30 40 50 60 70
X [m]
10 20 30 40 50 60
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4
Soil moisture [-], Time: 255 (hr)
Depth [m]
-0.2 -0.4 -0.6 -0.8 -1 -1.2 -1.4 -1.6 -1.8 -2 -2.2 -2.4 -2.6
X [m]
10 20 30 40 50 60
Y [m]
10 20 30 40 50 60 70
0.28 0.3 0.32 0.34 0.36 0.38 0.4 0.42 0.44

Scaling up computation for large basin

- Computation:
  - 10s – 100s billion unknowns
  - Mix task and data parallelisms
- Domain decompositions and communications
- Blue Waters supercomputer (peta-scale):
  - Cray X7 nodes
  - Kepler GPUs
  - CUDA-Aware (Direct communication GPU to GPU)







6000
6500
7000
7500
5400
5600
5800
6000
6200
6400
6600
0.44
0.42
0.40
0.38
0.36
0.34
0.32
0.30

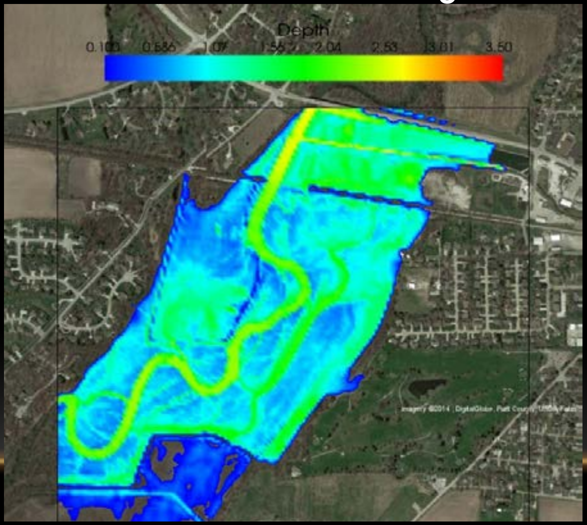
Flooding Simulation Results

iRIC Project
Changing River Science

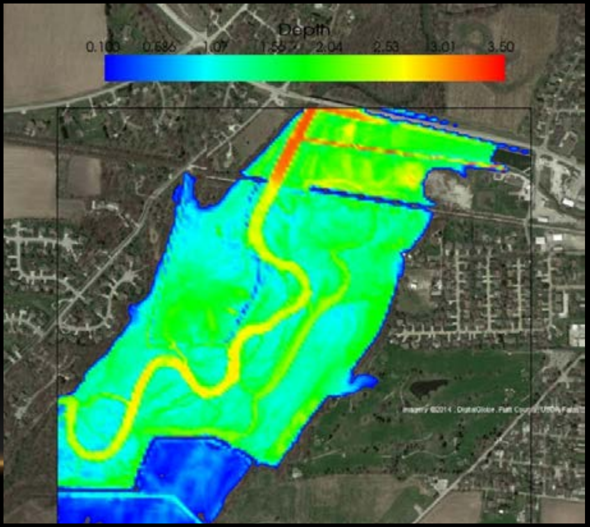
- Input data
  - LiDAR DEM (raster), 2 m resolution
- Inflow starts from the upstream river
- Free outflow in the downstream
- Discharge, run untill steady state
- Output
  - Water Surface elevation
  - Flow direction

Bankfull Discharge

10-Year Flood Discharge



100-Year Flood Discharge



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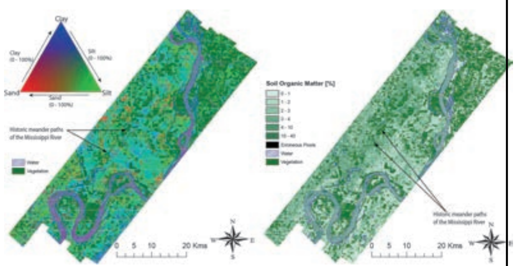
SEPTEMBER 2015 VOLUME 53 NUMBER 9 IGRSD2 (ISSN 0196-2892)



High-resolution spatial prediction map of soil texture shown as tricolor RGB composite for percentages of sand, silt, and clay (left) and soil organic matter content (right) for Bird's Point New Madrid Floodway. Large-scale legacy landscape features of the Mississippi River are clearly observable.

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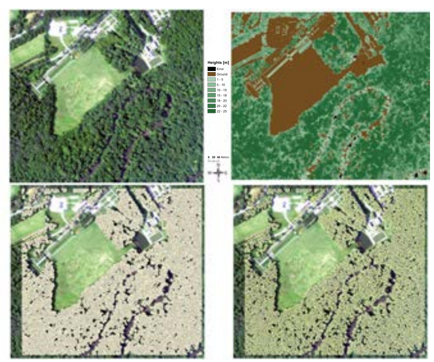

(Top left) True color composite of CASI hyperspectral imagery. (Top right) "Pit-free" CHM generated using the program LAStools. (Bottom left) Polygons generated using the watershed delineation algorithm for tree crown detection. (Bottom right) Irregular-shaped polygon converted into simple circular geometry representing the tree canopy tops.

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Water Resources Research

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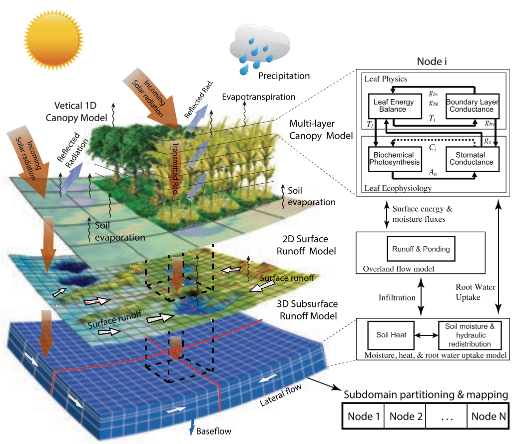

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Thank you
(Collaborations welcome!)