Disaggregation of microwave remote sensing data for estimating near-surface soil moisture using a Neural Network

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Objective

Develop and test a Neural-Network based model for disaggregating low-resolution satellite microwave measurements to higher resolutions of land surface models, i.e. estimate the ‘correct’ high (model)-resolution soil moisture pattern using lower-resolution remote observations and ancillary data

Approach

How do we train and validate a disaggregation model?

What is ground truth?

• *In situ* ground truth soil moisture observations are very limited in spatial and temporal coverage, limiting our ability to train a neural network.

• Aircraft brightness temperature or emissivity measurements must be converted to soil moisture using an inverse model, adding uncertainty to the estimates. These data are also limited in space and time.

• The most viable approach seems to be to train a neural network using solely model soil moisture estimates, then test its performance using actual remotely-sensed data.

• In this approach, model-simulated data serve as a proxy for microwave measurements obtained from aircraft or satellite-borne sensors.

Assumptions

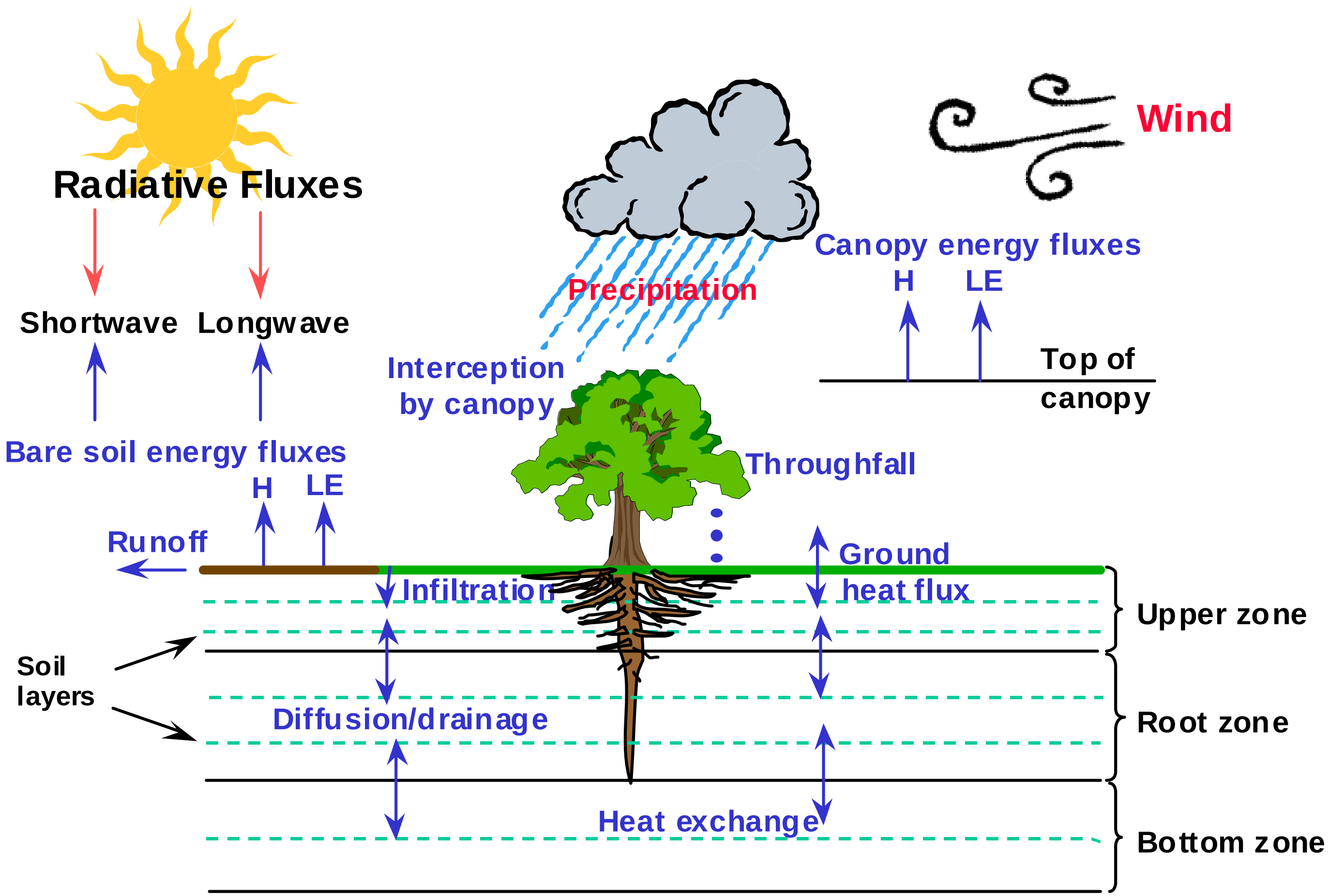
Our approach necessitates the following assumptions:

1. **The surface hydrology-radiative transfer model accurately simulates spatial patterns of soil moisture and brightness temperature within an actual or hypothetical satellite footprint, although the footprint mean may be biased with respect to the ground truth.**

2. **Low-resolution brightness temperature observations are unbiased with respect to the ground truth.**

3. **The functional relationship between brightness temperature and soil moisture ‘learned’ by the neural network is consistent with the relationship simulated by the radiative transfer model.**

SHEELS - Simulator for Hydrology and Energy Exchange at the Land Surface



- Accommodates any number of soil layers
- Explicit diffusion schemes for sub-surface moisture and heat fluxes
- Simulates overland runoff
- Linked to radiative transfer model to estimate microwave T_B and emissivity

Model study area and data sets

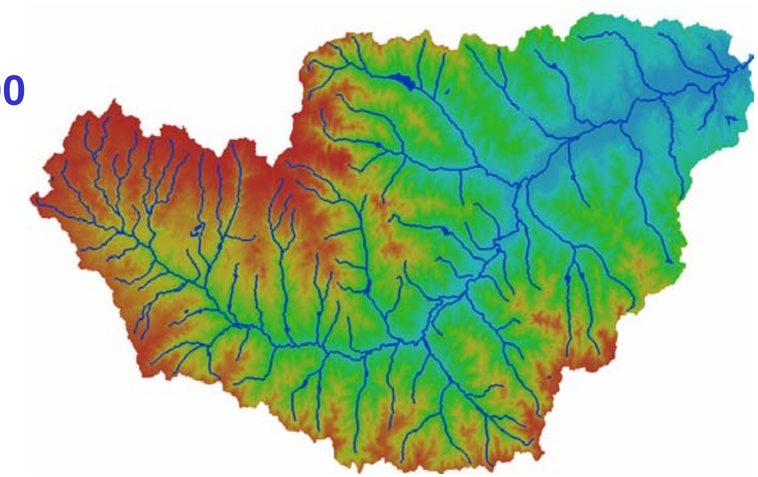
Model domain -- Little Washita River Basin, OK (600 km^2)

Model grid spacing -- 800 m

Terrain slope -- USDA/ARS 30 m DEM, aggregated to 800

Hydrography -- USGS DLG's

Vegetation parameters -- SGP'97 30 m Land Cover, aggregated to 800 m

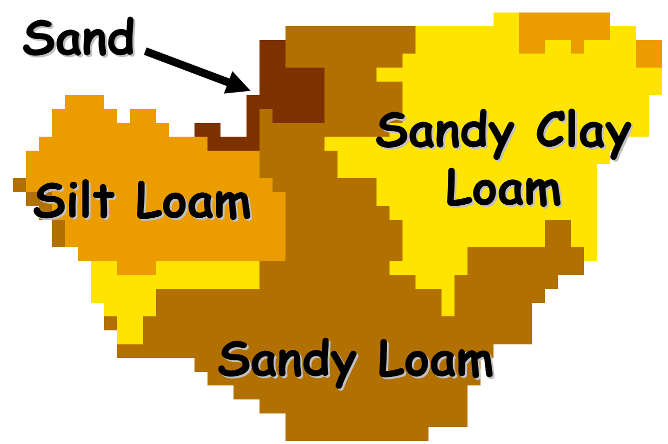


Soil properties -- CONUS 1 km multi-layer soil characteristics data set, resampled to 800 m

L band T_B -- SGP'97 ESTAR

- Surface roughness
- Soil moisture
- Soil bulk density
- Percent sand
- Percent clay
- Vegetation water content
- Vegetation b parameter

} ESTAR-associated data sets



Meteorological data -- Oklahoma Mesonet, USDA/ARS Micronet, SGP’97 soil profile stations

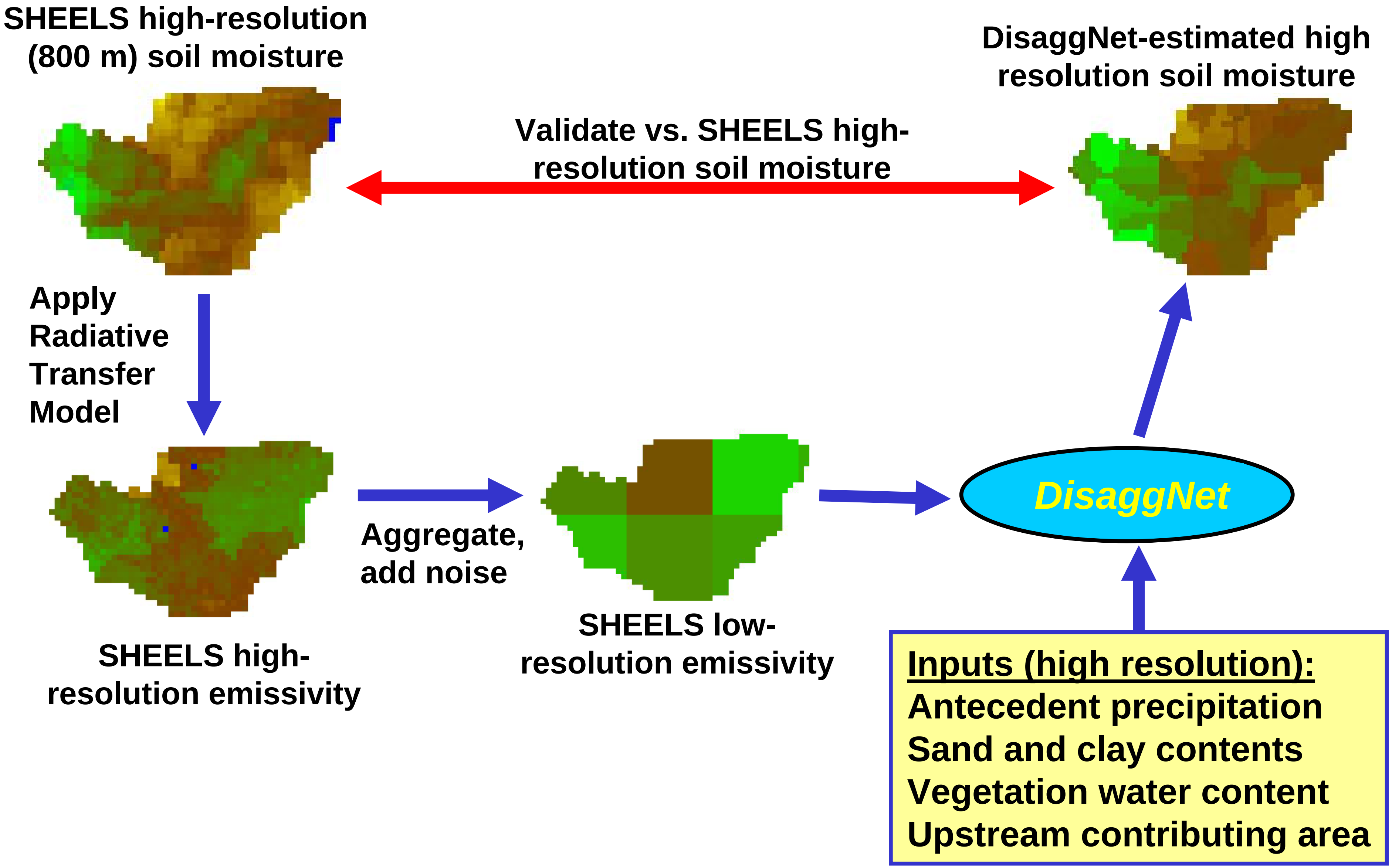
Precipitation-- USDA Micronet rain gage network, gridded at 800 m using Thiessen polygons

Disaggregation Neural Network (DisaggNet)

Design:
- Linear Artificial Neural Network
- Consists of a single neuron

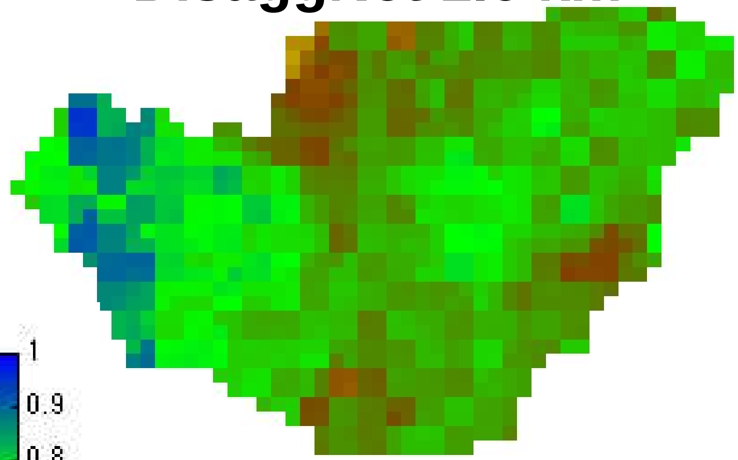
Training and applying using SHEELS-RTM output:
- Hourly data for 15 consecutive days used
- Wide range of soil moisture conditions
- Use model-estimated L-band emissivity, aggregated to various resolutions, as proxy for remotely-sensed data
- Neural network obtained through training applied to entire 33-day period with Gaussian noise added to emissivity inputs
- Noise has a standard error in emissivity of 0.02, equivalent to ~ 6 Kelvins in T_B or ~ 2% volumetric water content
- Validate with respect to SHEELS high-resolution soil moisture

Applying and testing DisaggNet using SHEELS data

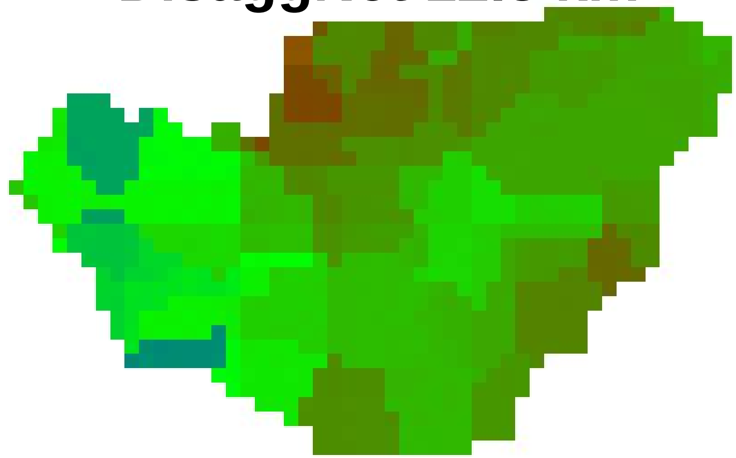


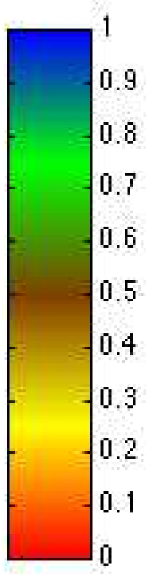
DisaggNet vs. SHEELS soil moisture estimates 1.6 km and 12.8 km emissivity inputs

DisaggNet 1.6 km

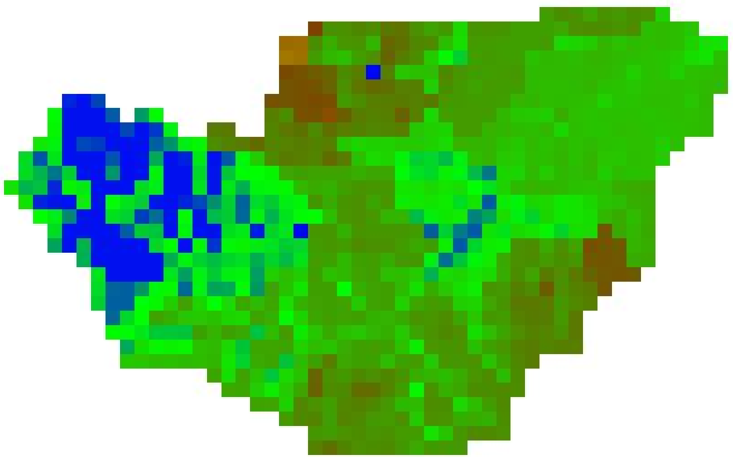


DisaggNet 12.8 km





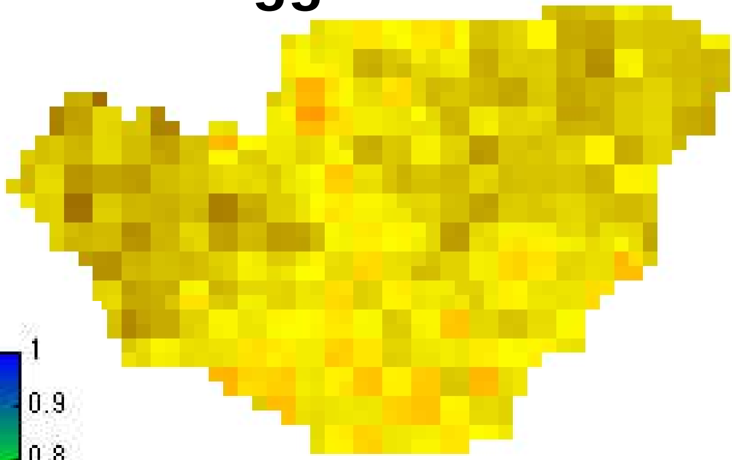
Day 192 - Wet



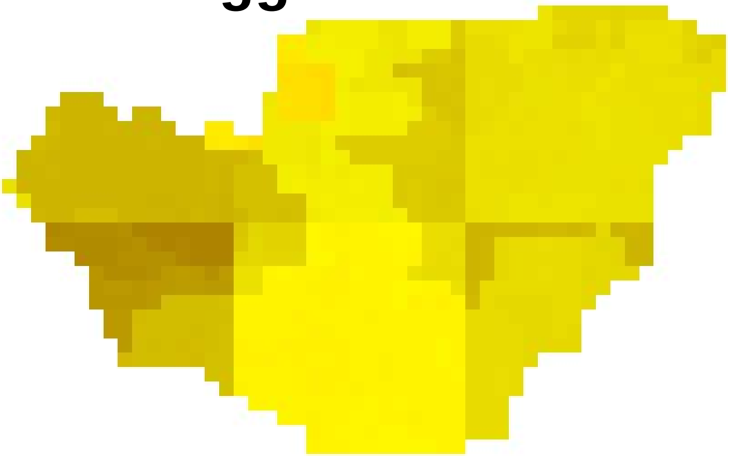
SHEELS 0-5 cm Fractional Water Content (Benchmark)

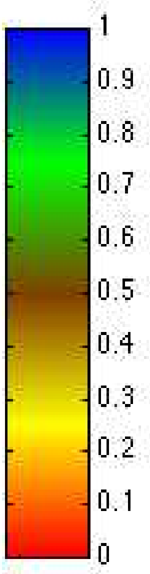
DisaggNet vs. SHEELS soil moisture estimates 1.6 km and 12.8 km emissivity inputs

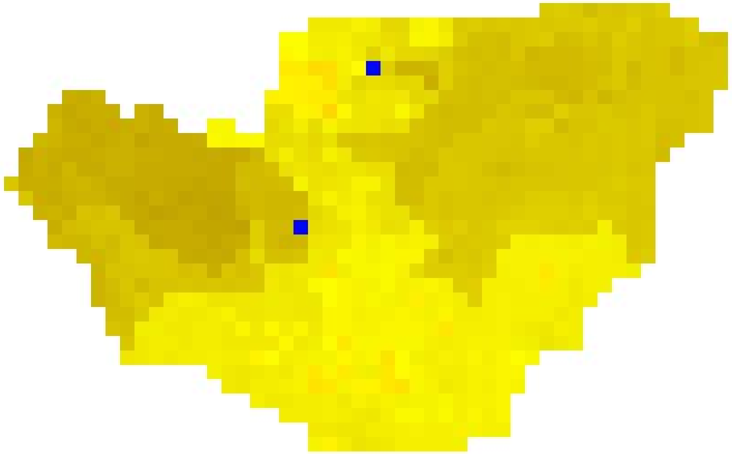
DisaggNet 1.6 km



DisaggNet 12.8 km



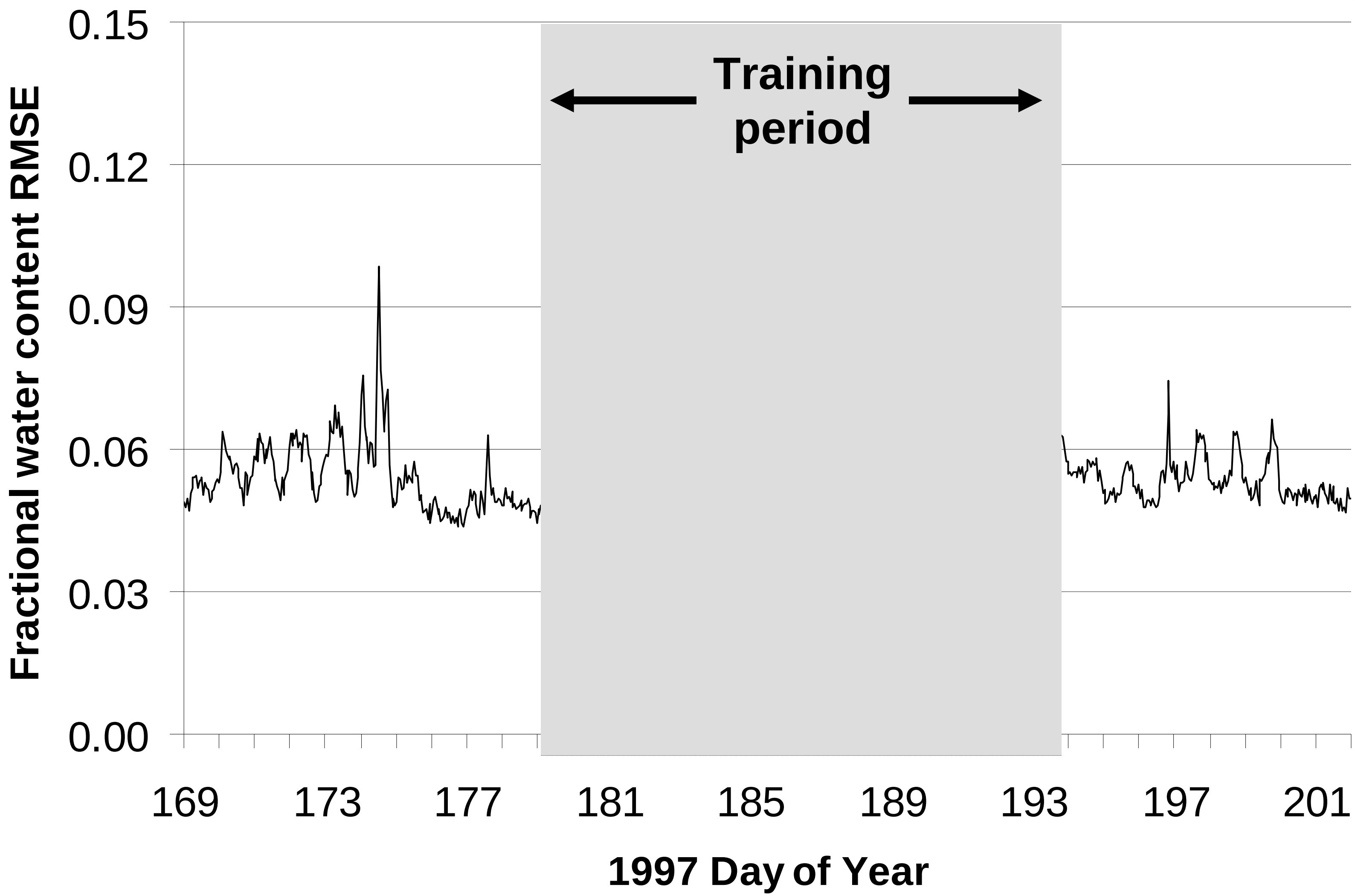




Day 184 - Dry

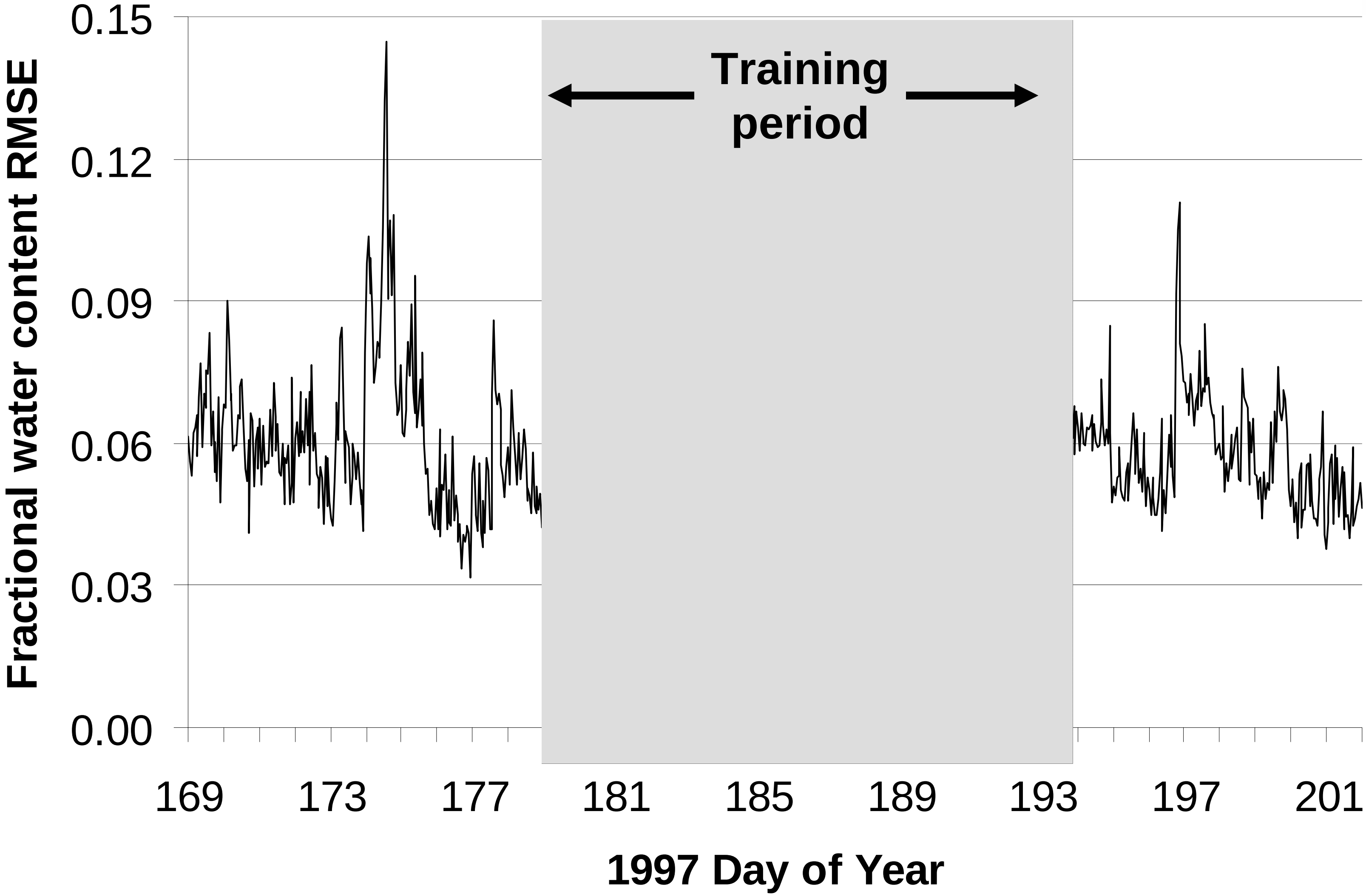
SHEELS 0-5 cm Fractional Water Content (Benchmark)

Root Mean Square Errors
DisaggNet vs. SHEELS soil moisture; 1.6 km input



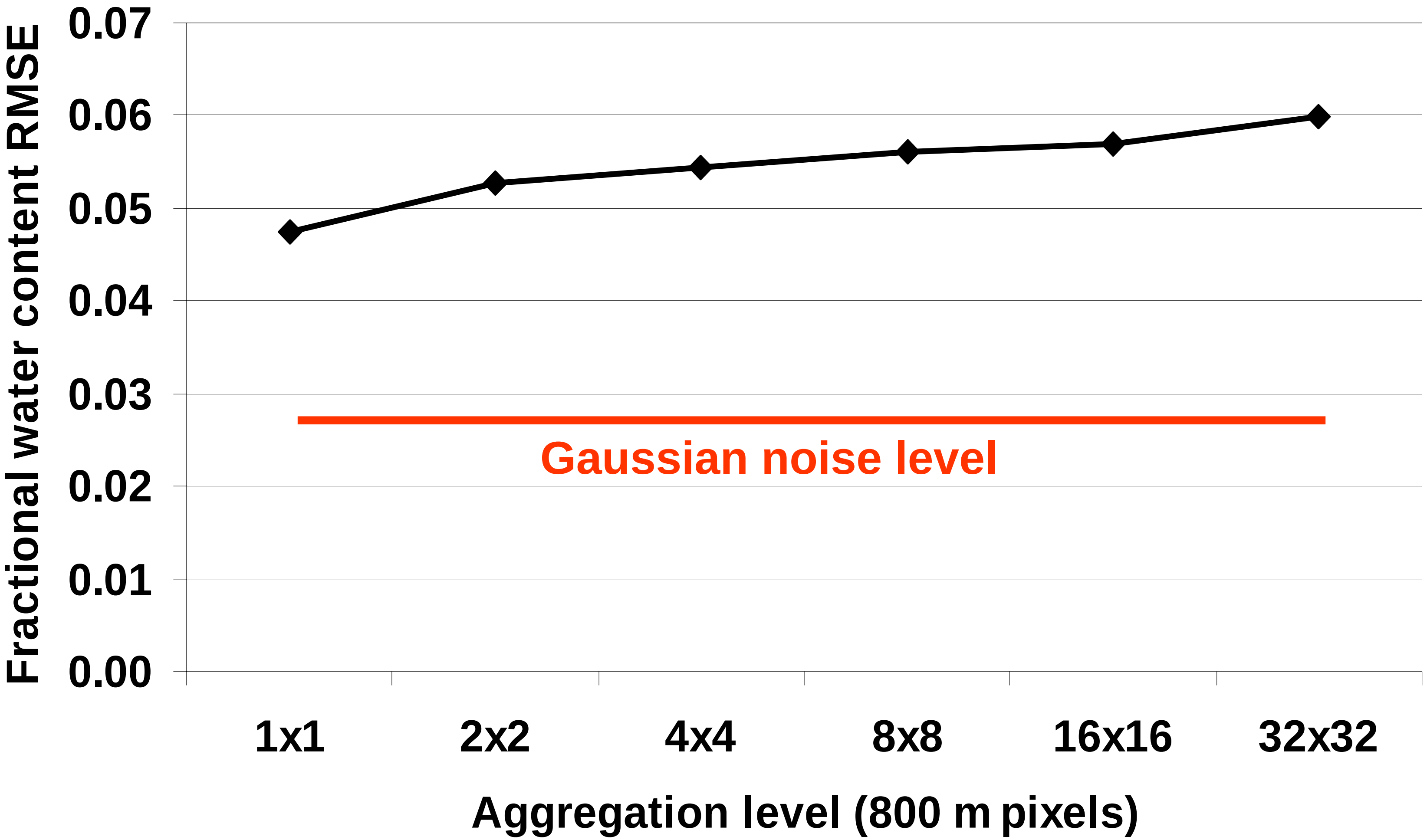
Note: fractional water content ≈ 2*volumetric water content.

Root Mean Square Errors
DisaggNet vs. SHEELS soil moisture; 12.8 km input



Note: fractional water content ≈ 2*volumetric water content.

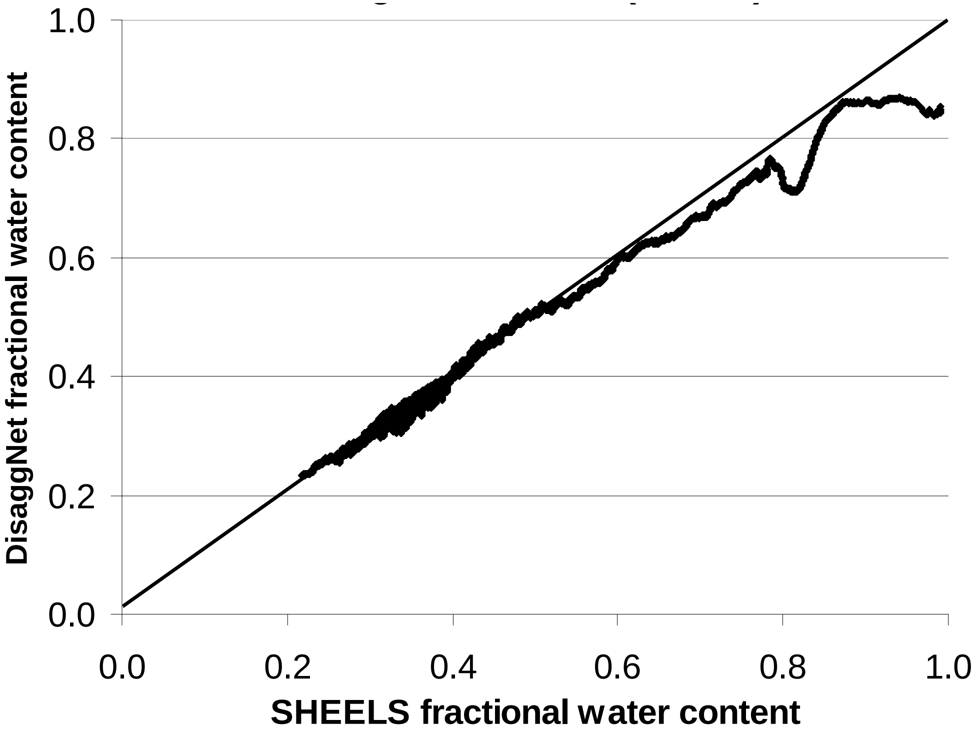
DisaggNet vs. SHEELS fractional water content



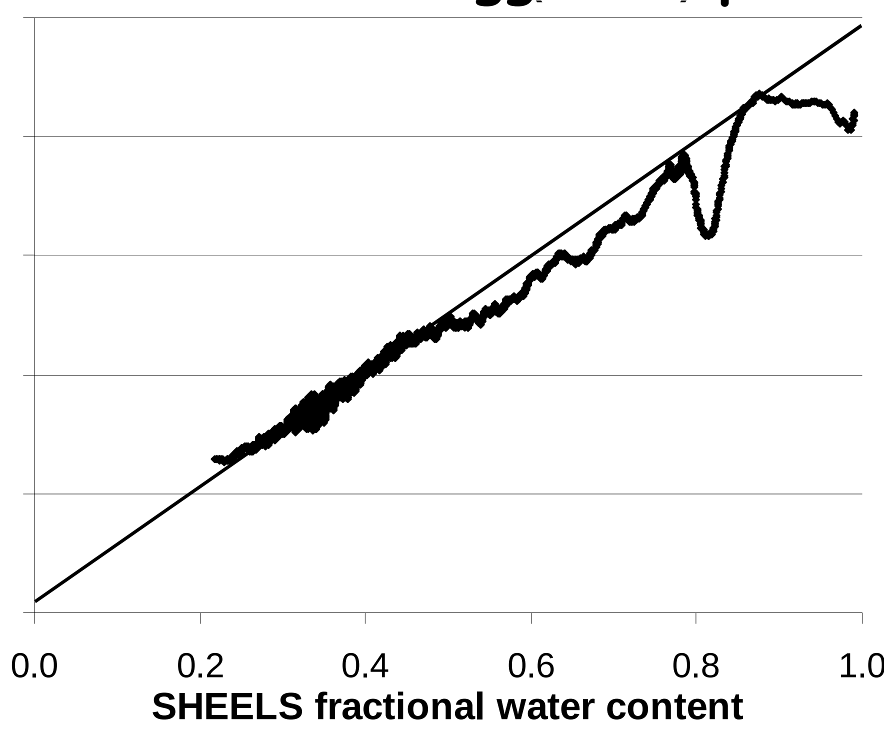
Time-averaged RMSE based on SHEELS-simulated emissivity inputs averaged over the indicated number of pixels with Gaussian noise added

DisaggNet vs. SHEELS fractional water content
Smoothed scatter plots

1.6 km DisaggNet input

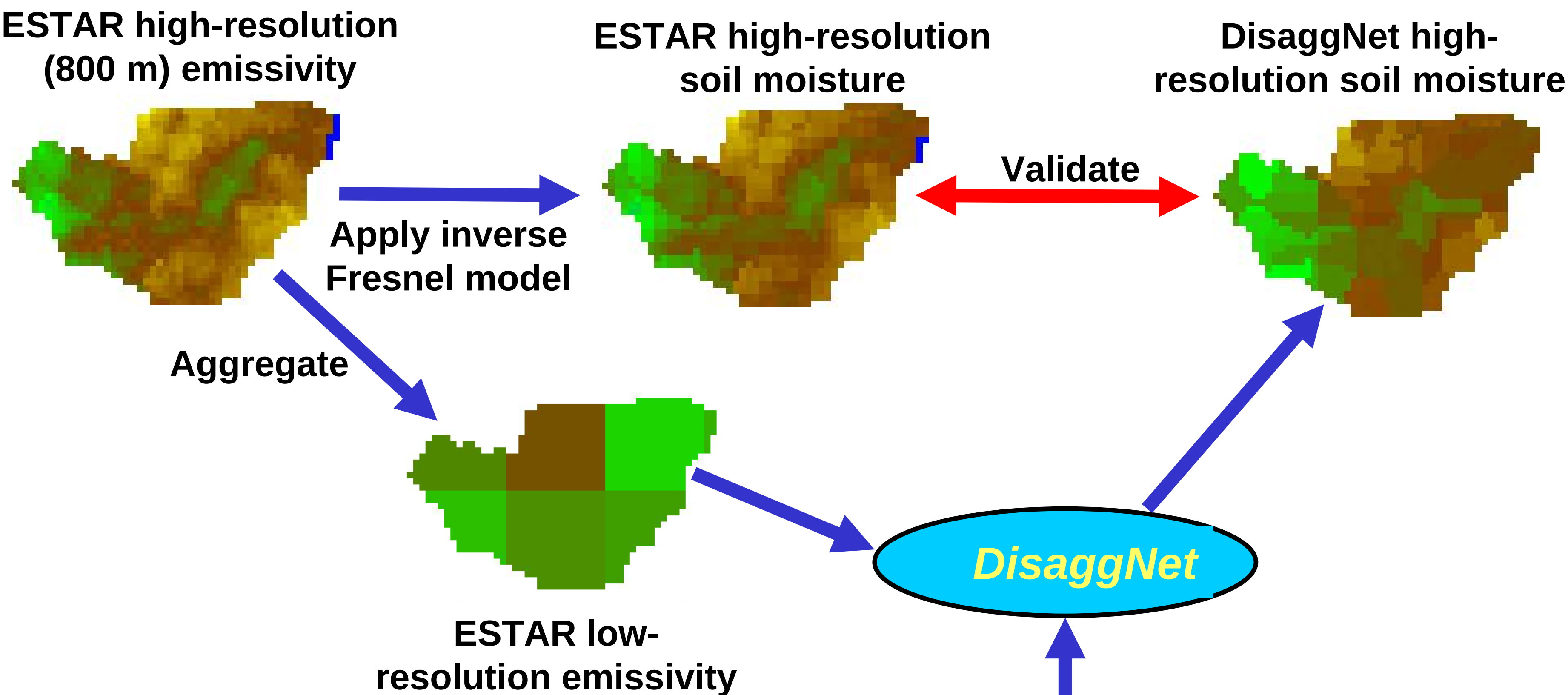


12.8 km DisaggNet input



Relationship between DisaggNet- and SHEELS-estimated FWC for high- and low-resolution inputs, for all grid cells and times. DisaggNet underestimates FWC under extremely wet conditions.

Applying and testing DisaggNet using ESTAR data

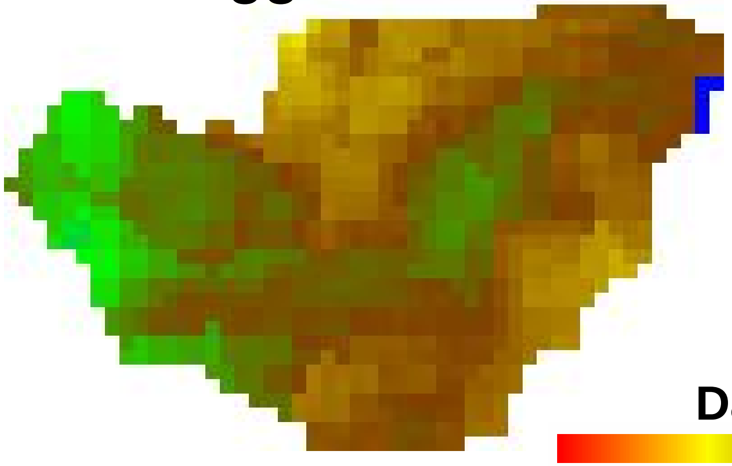


- No re-training performed
- One ESTAR overpass each day for 16 days

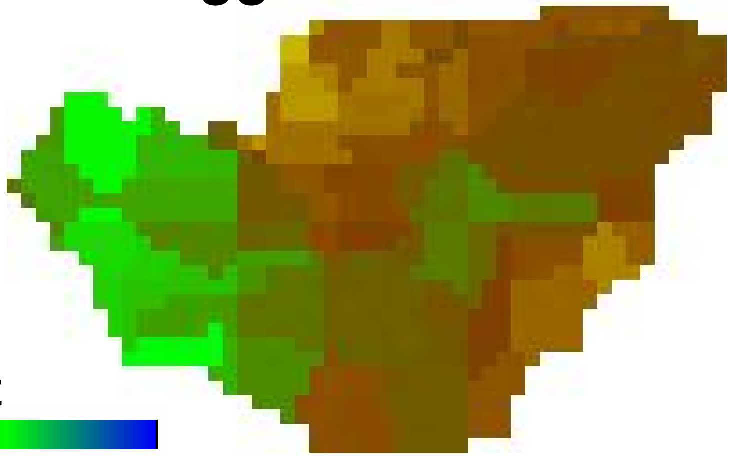
Inputs (high resolution):
Antecedent precipitation
Sand and clay contents
Vegetation water content
Upstream contributing area

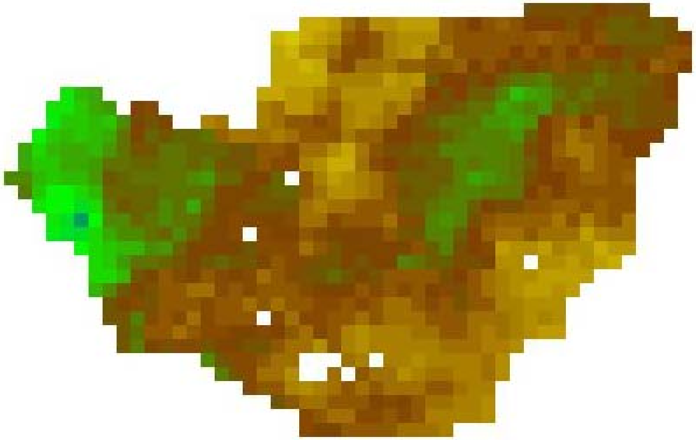
DisaggNet results using ESTAR emissivity

DisaggNet 1.6 km

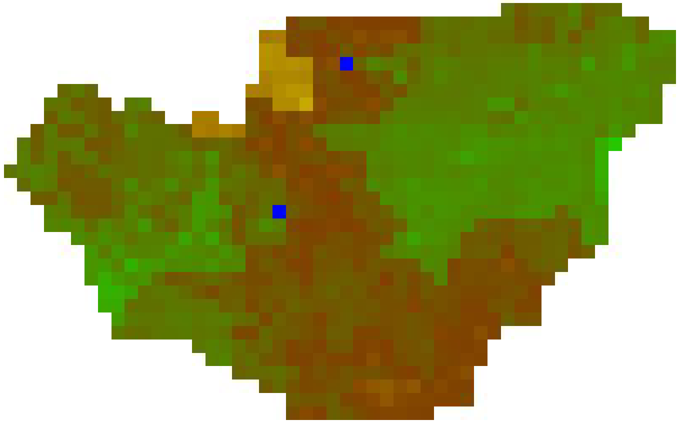


DisaggNet 12.8 km





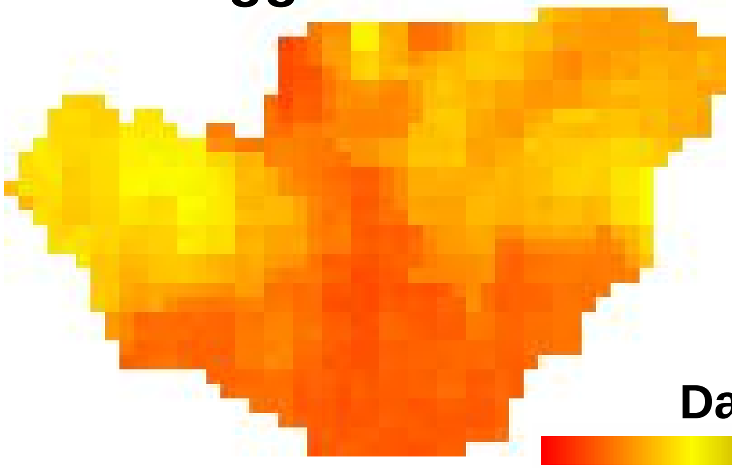
ESTAR 0.8 km
(Benchmark)



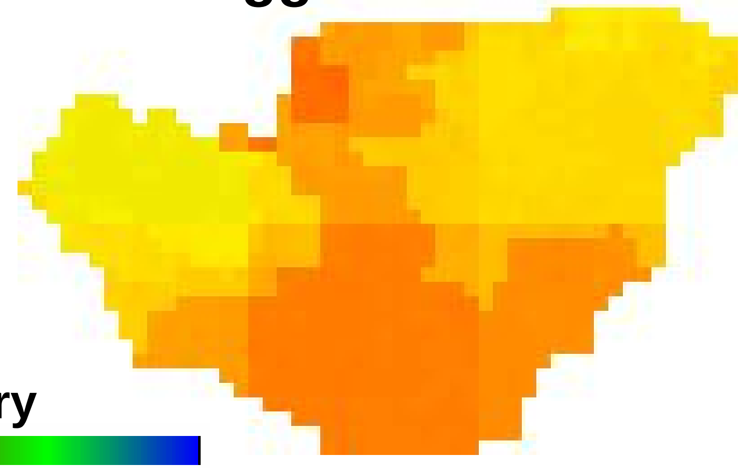
SHEELS 0.8 km

DisaggNet results using ESTAR emissivity

DisaggNet 1.6 km



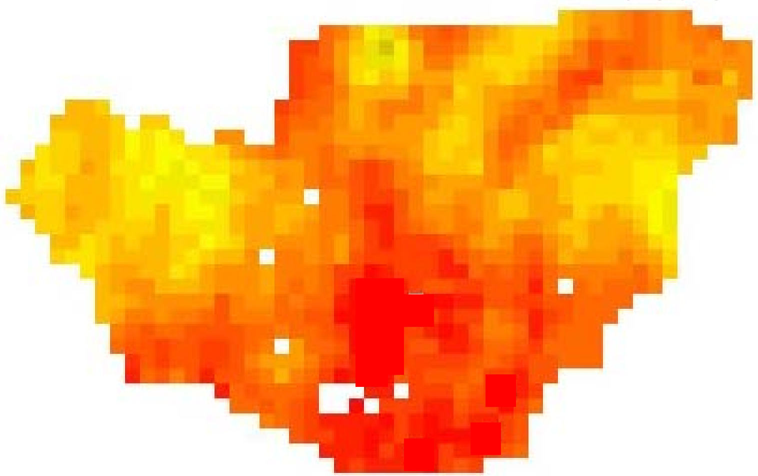
DisaggNet 12.8 km



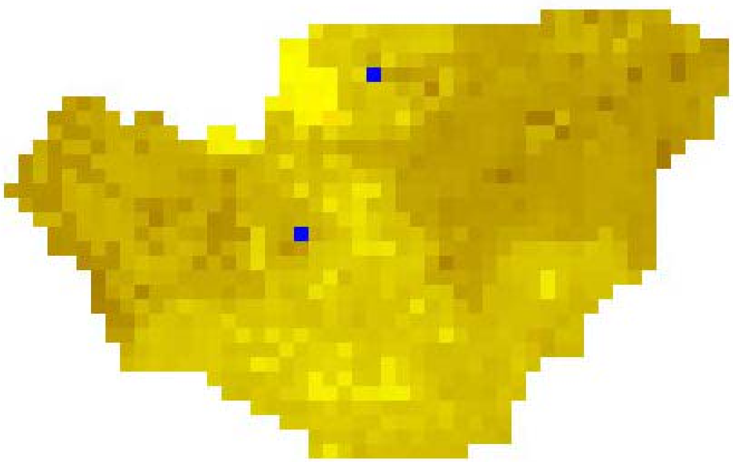
Day 184 - Dry

0.0 .25 .50 .75 1.0

Fractional water content

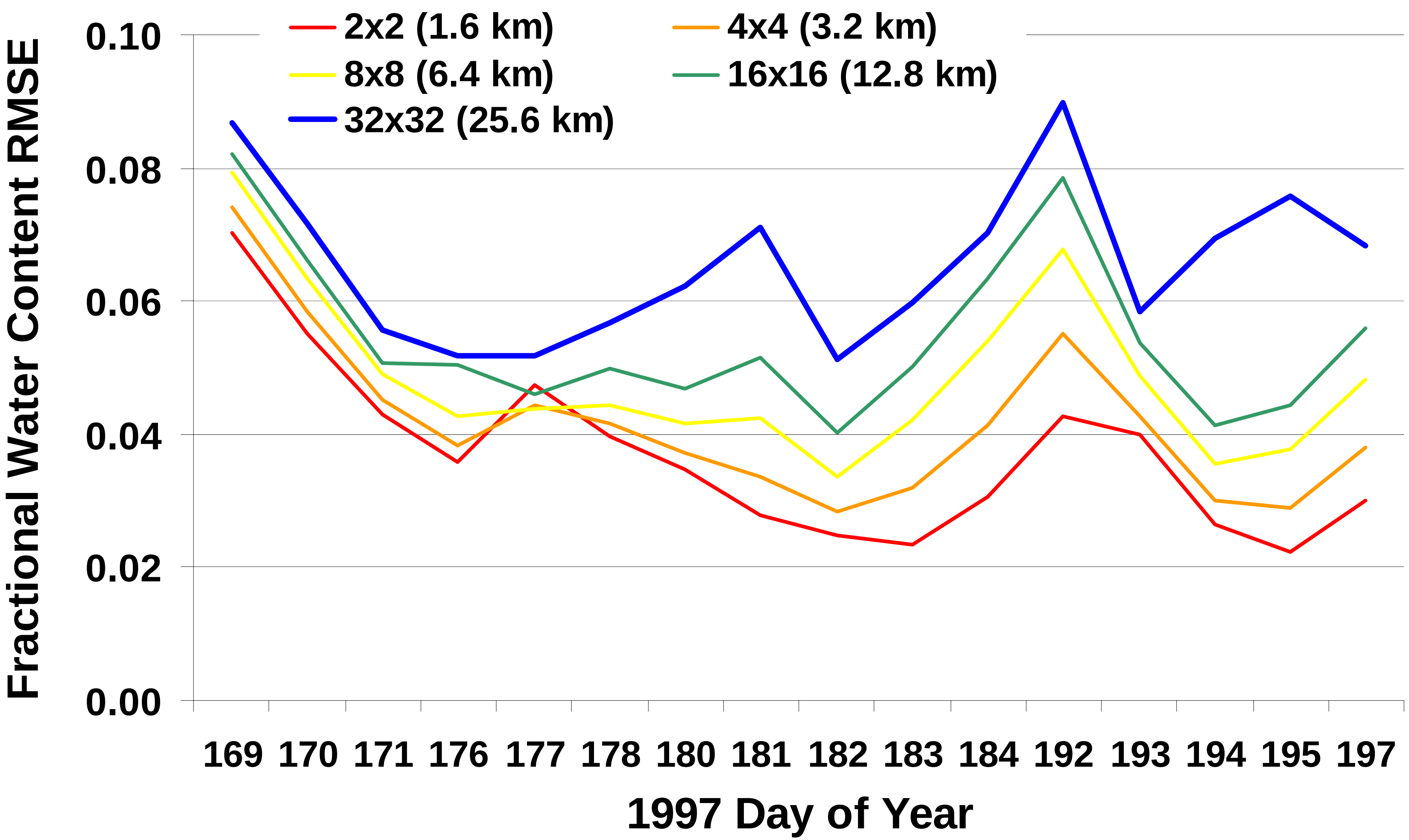


ESTAR 0.8 km
(Benchmark)



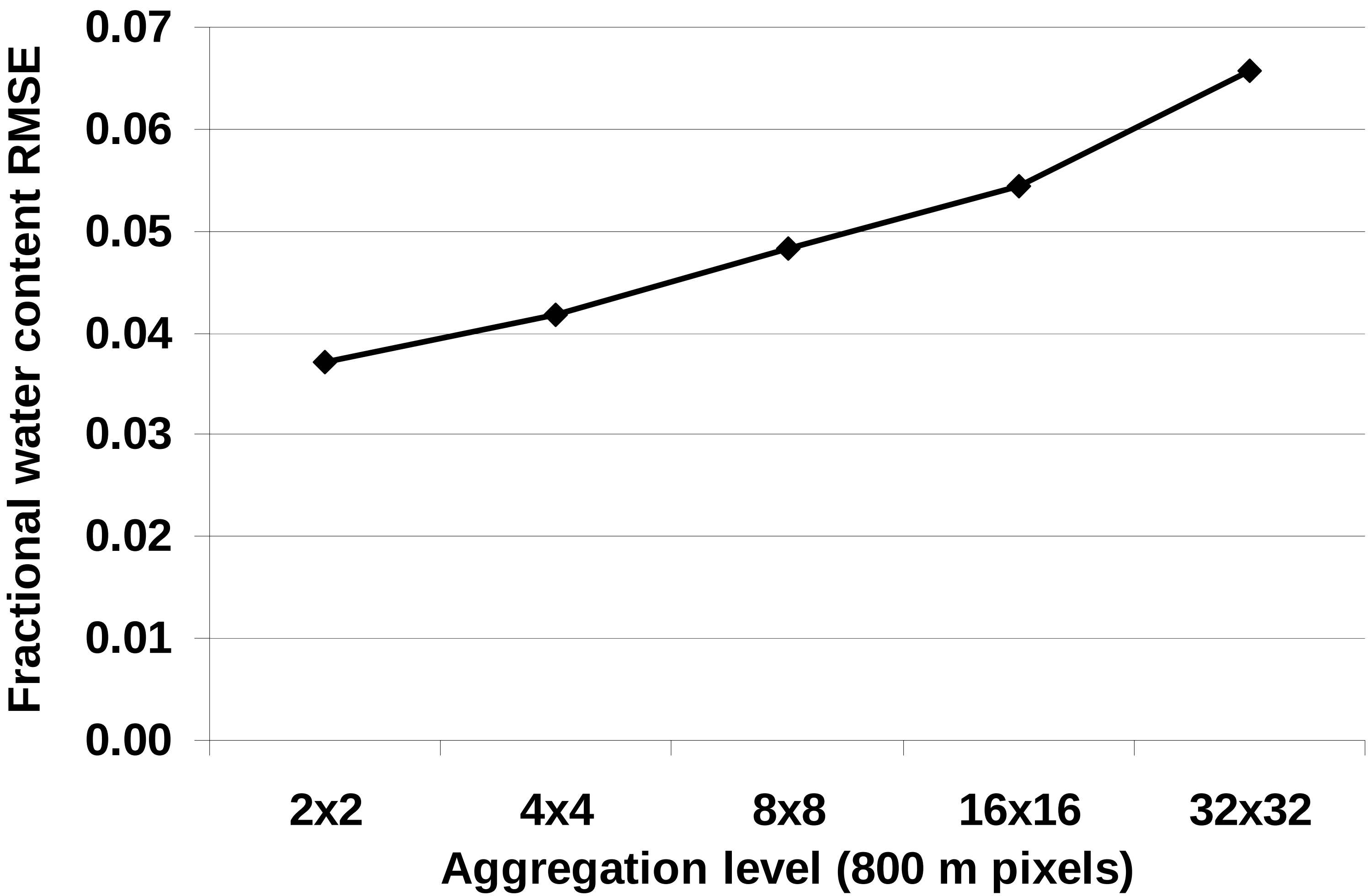
SHEELS 0.8 km

DisaggNet vs. ESTAR fractional water content



RMSE for each ESTAR overpass and for each resolution

DisaggNet vs. ESTAR fractional water content



Time-averaged RMSE based on ESTAR emissivity inputs averaged over the indicated number of pixels

Conclusions

- DisaggNet was trained using input data simulated by a surface hydrology-radiative transfer model.
- DisaggNet is capable of reproducing sub-pixel-scale soil moisture patterns from low-resolution remote sensing measurements, plus inputs of antecedent precipitation and vegetation, soil and topographic properties.
- Using model-simulated data, RMS errors in fractional water content were approximately 0.05, much of which is attributable to the noise added to the input emissivities.
- RMS errors increase only slightly as input resolution decreases.
- Once trained, DisaggNet was applied to L-band ESTAR emissivity measurements.
- RMS errors using ESTAR inputs are similar to errors obtained using model-simulated data.
- We plan to make the rainfall-soil moisture relationships non-linear, which may improve the performance under very wet conditions.