

# Cooperative Demonstration of Technology

## Next-Generation NATO Reference Mobility Model

# Methods for Data Collection and Remote Sensing

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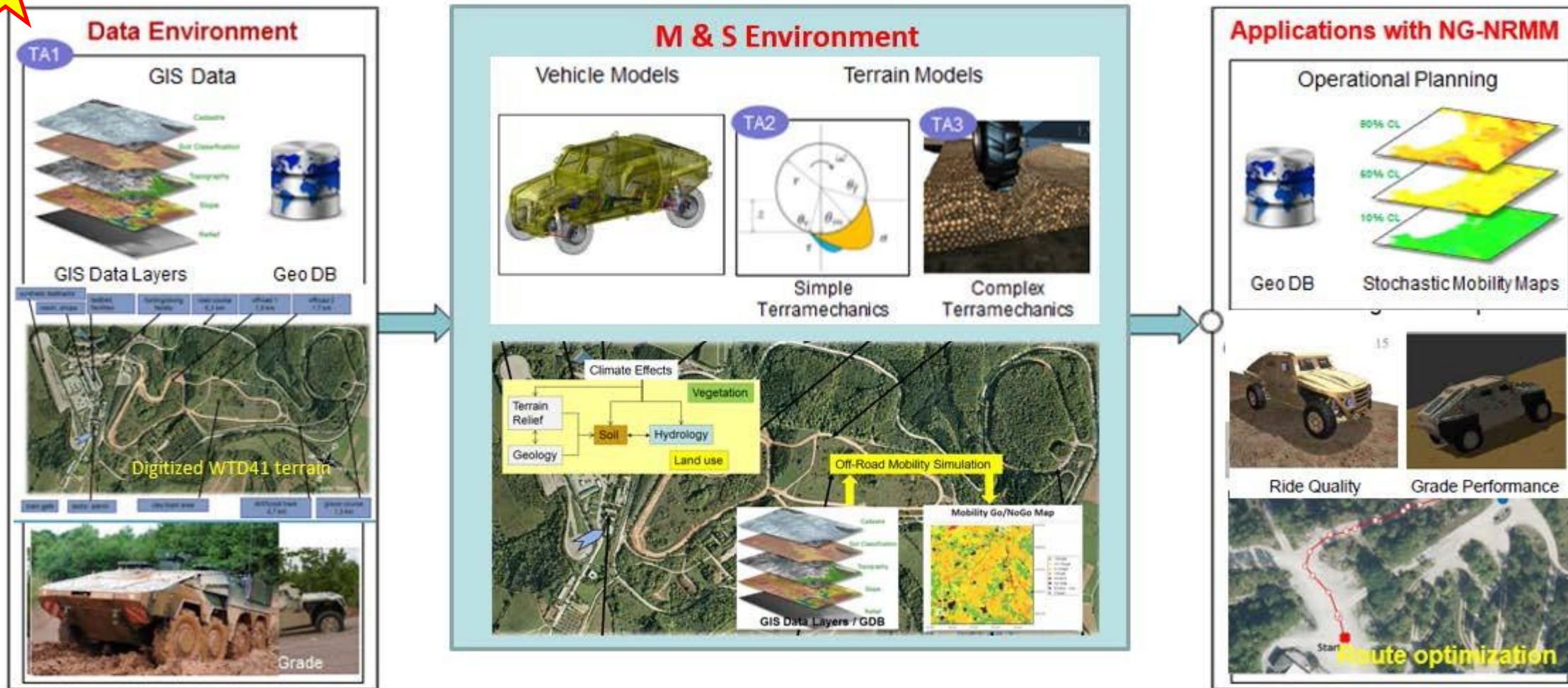


Michigan  
Technological  
University

# Agenda

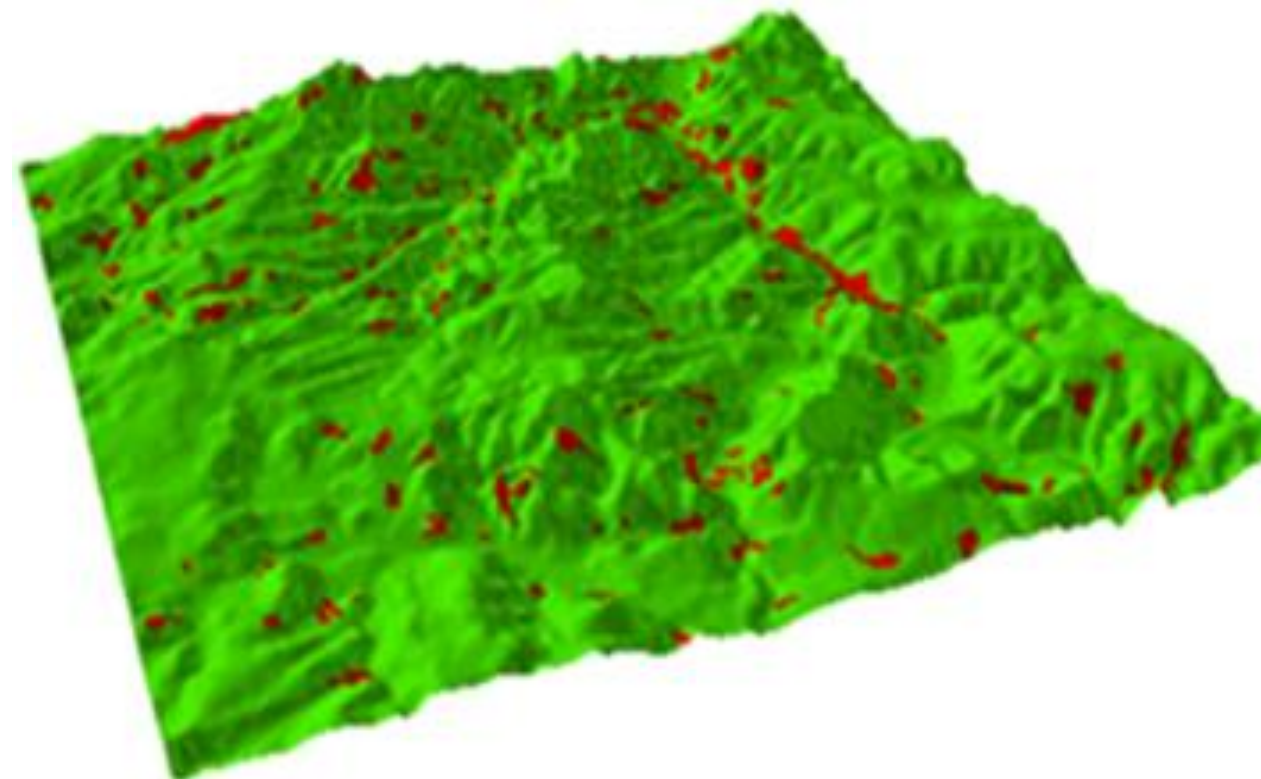
- NG-NRMM
- Background
- Trier Data Collection
- Machine Learning & Interpolation Methods
- Prediction Maps
- Concluding Remarks

## CDT-2 Structure



## Relevance

- **Mobility maps are critical for mission planning**
  - They provide the best route options for which ground forces should maneuver through a terrain
  - Ultimately to avoid unwanted traps, attacks, or having the vehicles get stuck due to path conditions
- **Mobility maps created for NG-NRMM have multiple parameters that go into developing them**



# NG-NRMM Go/No Go Map Development

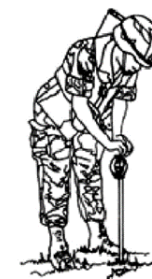
Scenario data	Terrain Data	Vehicle Input
Snow depth and density	Surface conditions, e.g. normal, slippery	General dimensions
Freeze and/or thaw depth	USCS soil type classification	Axles, bogies or track assemblies
Driver: maximum braking acceleration, braking reaction time, safety factor, recognition distance	Land use	For each powered or braked axle
Plowing Depth	Wetness index	Pushbar height and force
Seasonal visibility	Soil strength: 0-6", 6-12", data for four 'seasons'	Driver's position, eyes and seat
Obstacles: height, width, length, angle, spacing	Depth to bedrock	Center of gravity
AASHO curvature safety factor	Slope	Suspension: spring and damper rates
Slope stability & traction	Surface roughness	Wheelbase and axle positions
Throttle setting	Area	Tires: section height/width, type, deflection/pressure
On & off road visibility	Obstacles: random or linear	Tracks: road wheels, sprockets/idlers, track
Surface: dry, wet, icy	Obstacles: height, width, length, angle, spacing	Drivetrain: engine, all gearboxes, torque converter
Tire deflection: highway, cross-country with/without sand/snow	Vegetation: tree stem size and spacing	Dual tires
	Visibility	Snow Chains

# Current Methodology

- **In Situ Measurements:**
  - Cone Penetrometer, Bevameter, or Drawbar Pull tests
- **Limitations:**
  - Costly, sometimes impossible to collect
  - Point measurement and therefore limited spatial coverage
  - Relies heavily on in-situ measurements
    - In-situ terrain data collection can put the soldiers in harms way
- **Goal**
  - Develop remote terrain strength characterization to support off-road mobility in unknown territories



Bevameter



Using the cone penetrometer in the upright position.



Using the sampler to obtain a soil sample for a remolding test.



Applying drop hammer blows with the remolding equipment.



Measuring cone index in the remolding cylinder before and after hammer blows.

# Background: Remote Sensing

- **Electromagnetic Spectrum**

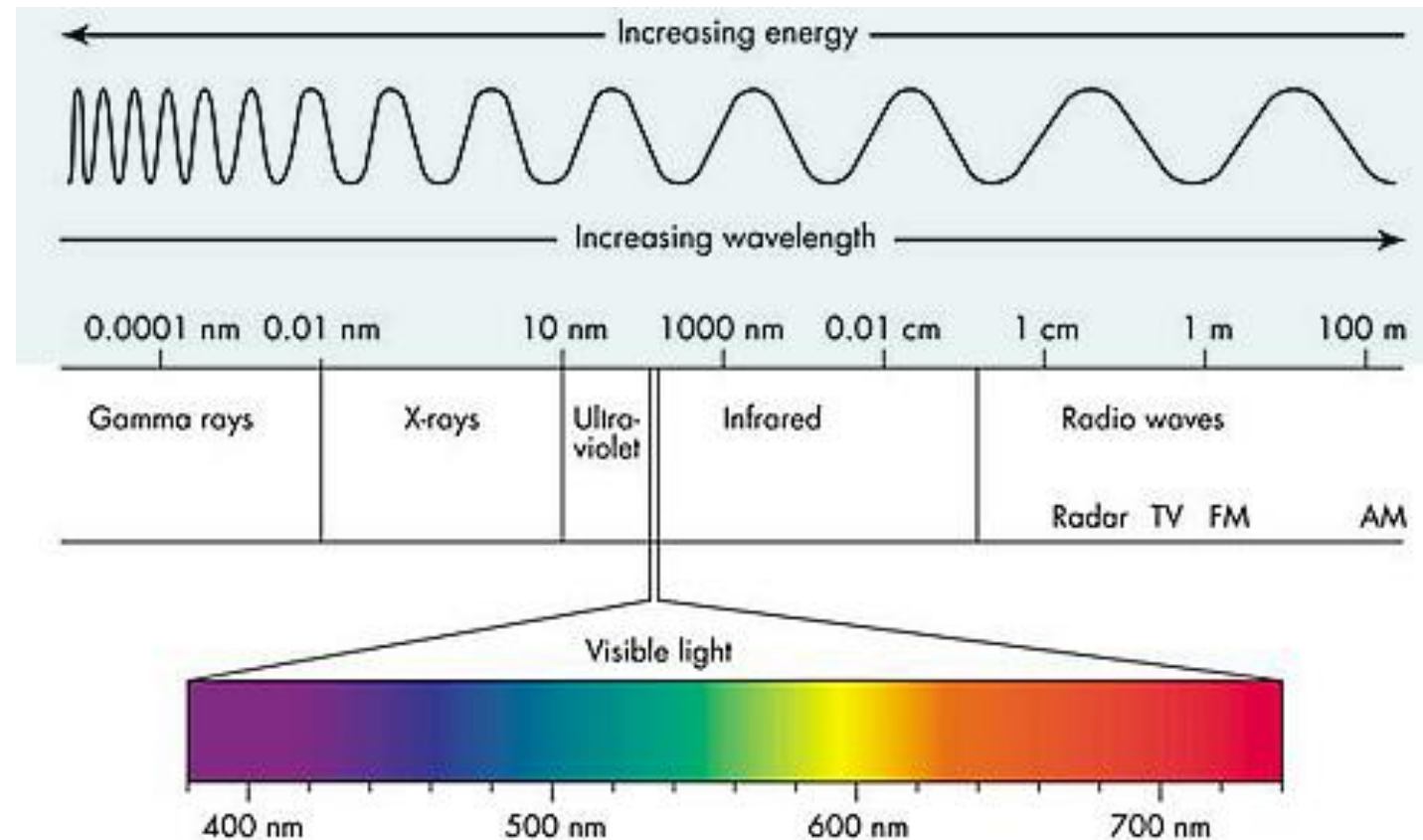
- Light energy is either reflected, transmitted, or absorbed when interacting with a material

- **Thermal: 7.5 – 13.5  $\mu\text{m}$**

- Soil absorbs the energy and is then radiated back out. Provides subsurface data about the material.

- **Hyperspectral: 400-1000 nm**

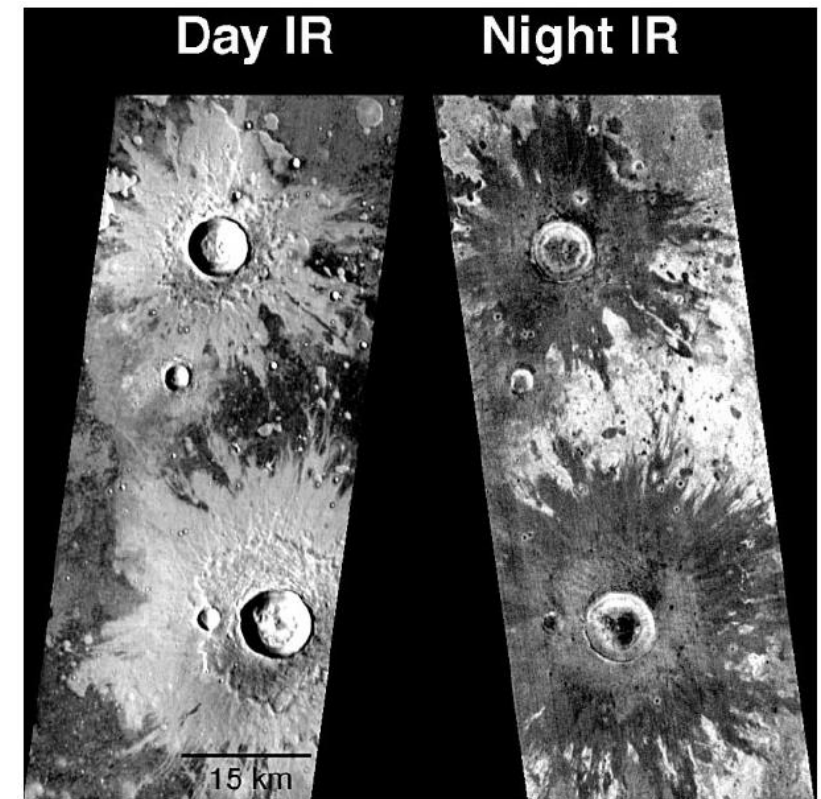
- Light reflected on the surface gives only surface data to allow for classification of the soils.



<https://www.cyberphysics.co.uk/topics/light/emspect.htm>

# Background: Thermal Inertia & Apparent Thermal Inertia

- **Thermal Inertia:**  $TI = (k\rho c)^{1/2}$ 
  - The potential of a material to absorb and store heat (measures a material's resistance to change in temperature)
  - Function of material composition / type
  - $k$  = thermal conductivity,  $\rho$  = bulk density of the surface material,  $c$  = specific heat
- **Apparent Thermal Inertia (ATI): close approximation of Thermal Inertia**
  - $ATI = (1 - \alpha) / \Delta T$ 
    - $\alpha$  = albedo,  $\Delta T$  = change in temp.



*Thermal images of Mars from day and nighttime. By day, brighter areas mean warmer and dustier terrain while darker indicates more rocks. The pattern reverses at night, as rocks stand out by their warmth (Christensen et al. 2003)*

# Data Collect: Trier Site

- **Areas**
  - Pit 1: Purple
  - Pit 2: Blue
  - Pit 3: Green
- **Remote Sensors**
  - RGB Camera, FLIR Vue Pro R, BaySpec (Hyperspectral) Sensor
- **In Situ Devices (Ground Truth)**
  - Moisture Probe, Cone Penetrometer



# Data Collect: Sensors & Drone

- Remote: BaySpec Sensor (Hyperspectral, 400 – 1000 nm, ~ 5-7 nm FWHM), FLIR Vue Pro R (Thermal, 7.5 - 13.5  $\mu\text{m}$  )
- In Situ: Cone Penetrometer, Moisture Probe
- Drone: Hexacopter



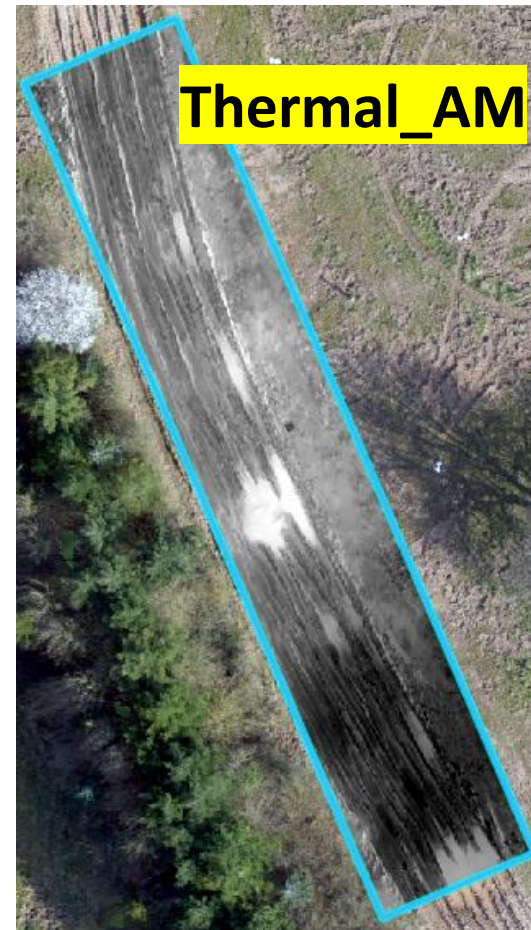
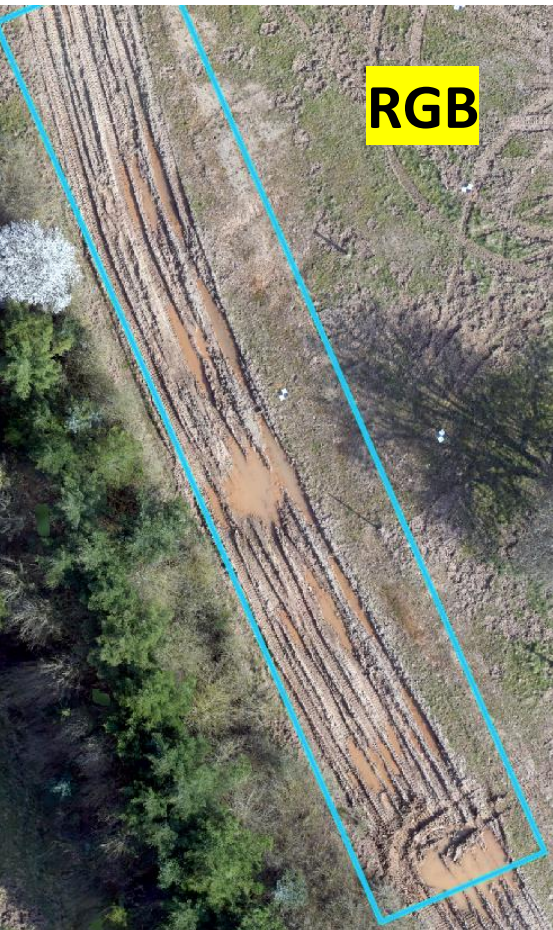
# Data Collect: Pit 1

- Dimensions: 10 m (wide) x 59 m (long)



## Data Collect: Pit 2

- Dimensions: 12 m (wide) x 64 m (long)



## Data Collect: Pit 3

- Dimensions: 12 m (wide) x 80 m (long)

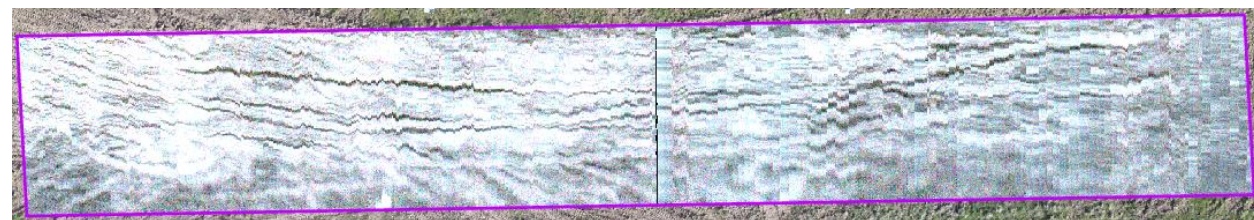
RGB



Thermal\_AM



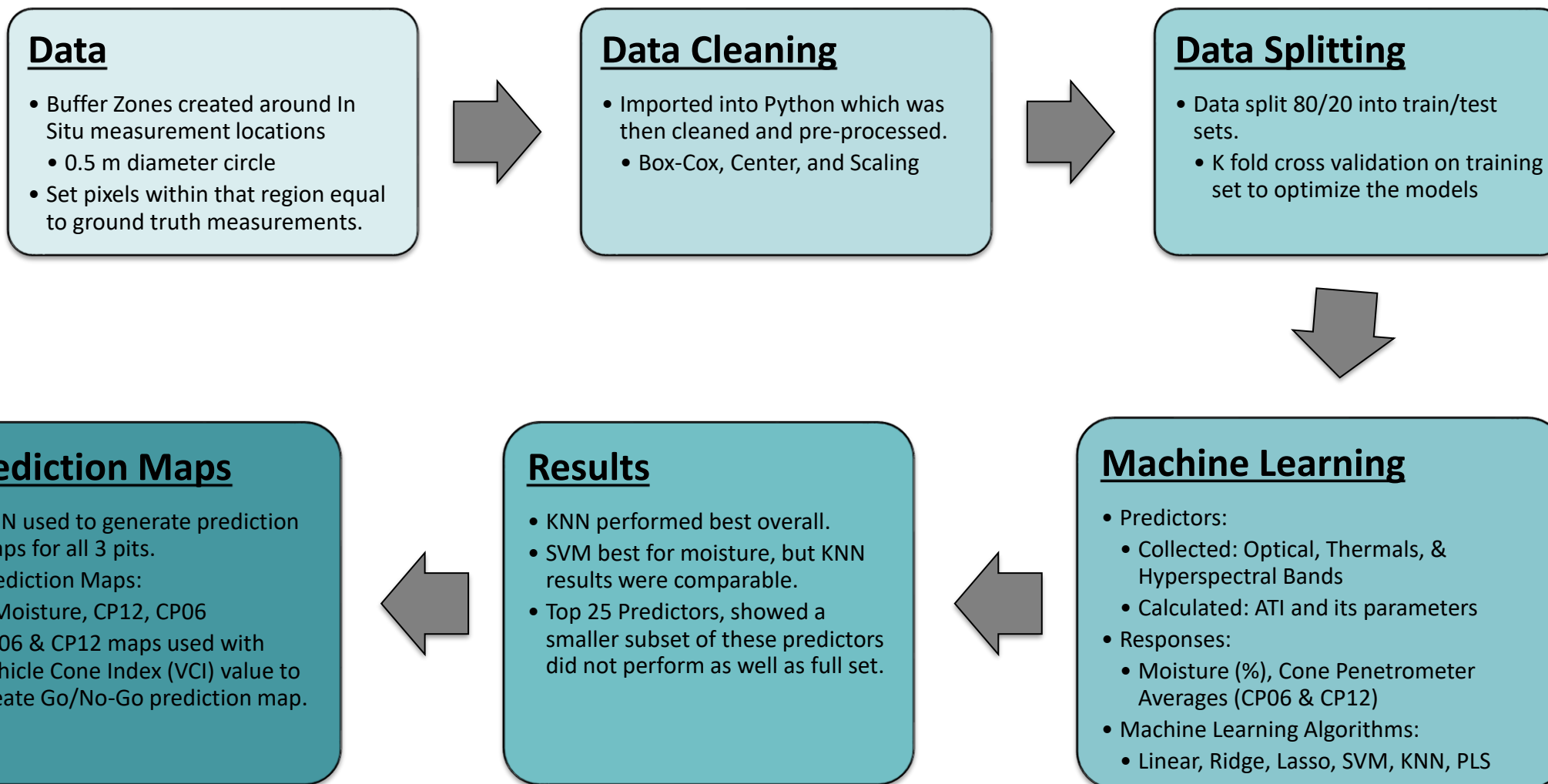
Hyperspectral



Thermal\_PM



# Processing: Flowchart

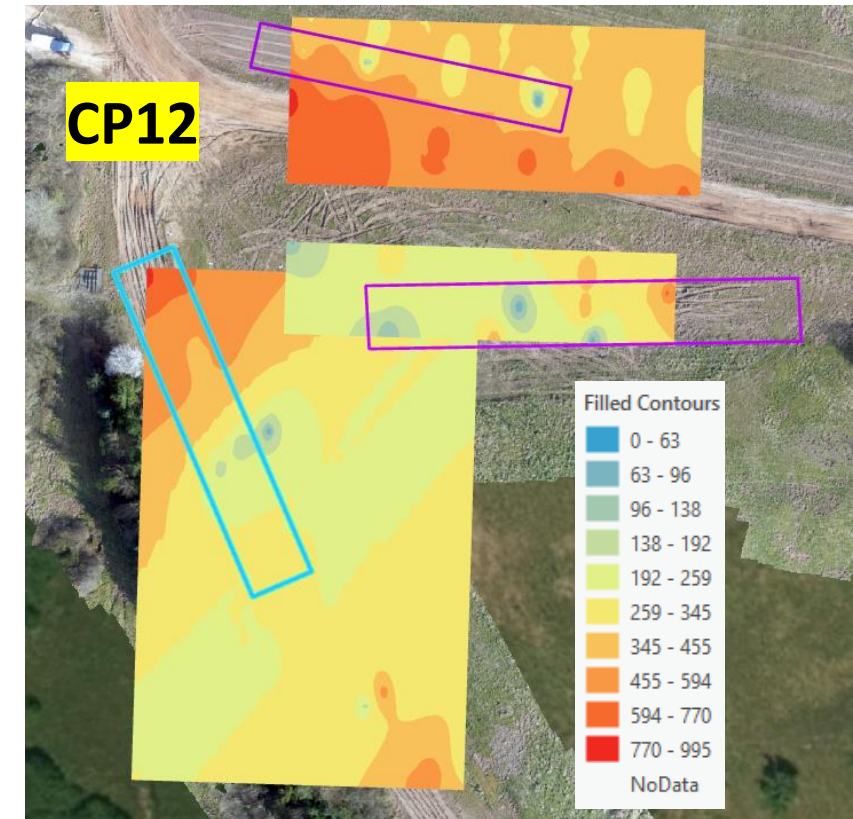
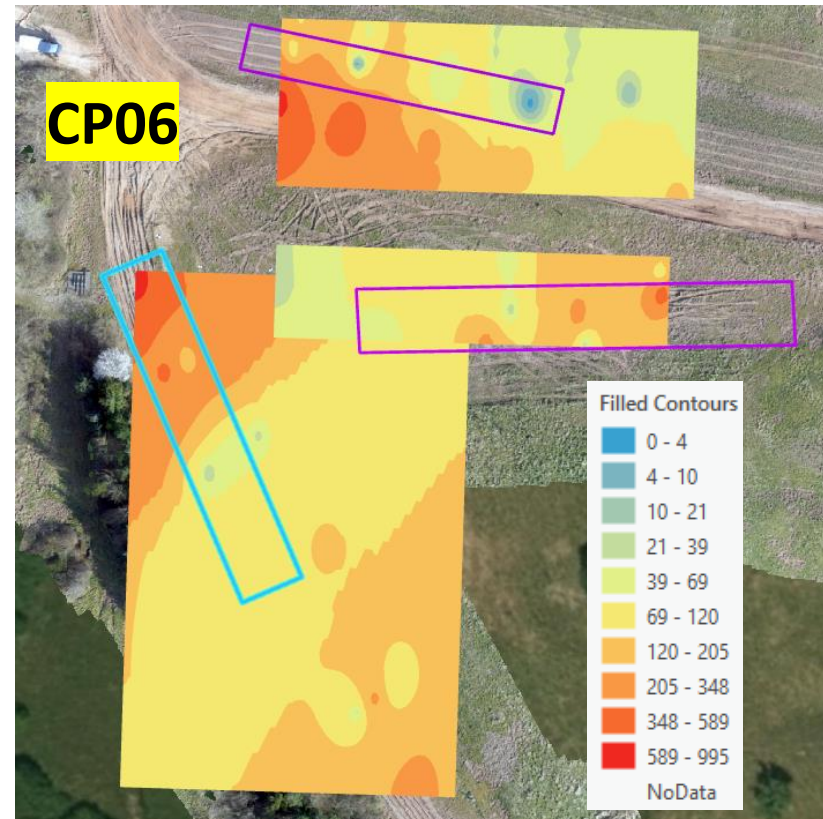
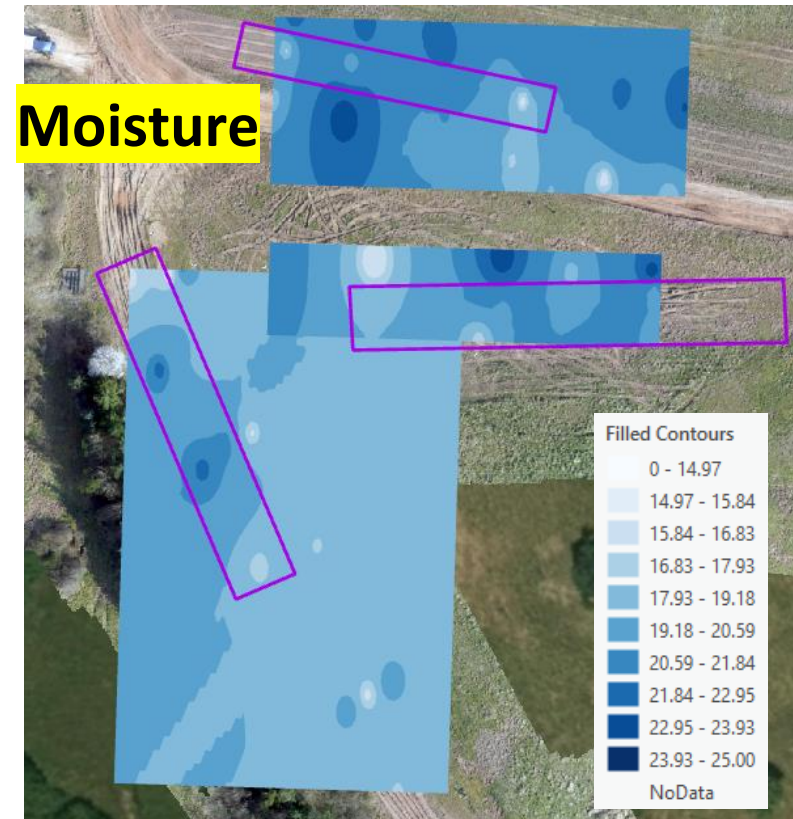


# Data Processing: Machine Learning Results

	CP12 [psi]		CP12 (Top 25) [psi]		CP06 [psi]		Moisture [%]	
Algorithms	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE
Linear	0.360	243.30	0.225	267.70	0.490	193.87	0.595	2.29
Ridge	0.368	241.66	0.226	267.58	0.493	193.39	0.596	2.29
Lasso	0.369	241.66	0.231	266.83	0.496	192.87	0.597	2.28
SVM	0.438	227.91	0.398	235.94	0.492	193.61	0.944	0.85
KNN	0.922	85.099	0.590	194.80	0.958	55.71	0.903	1.12
PLS	0.360	243.29	0.228	267.22	0.490	193.94	0.595	2.29

# IDW Prediction Maps: Individual Pits

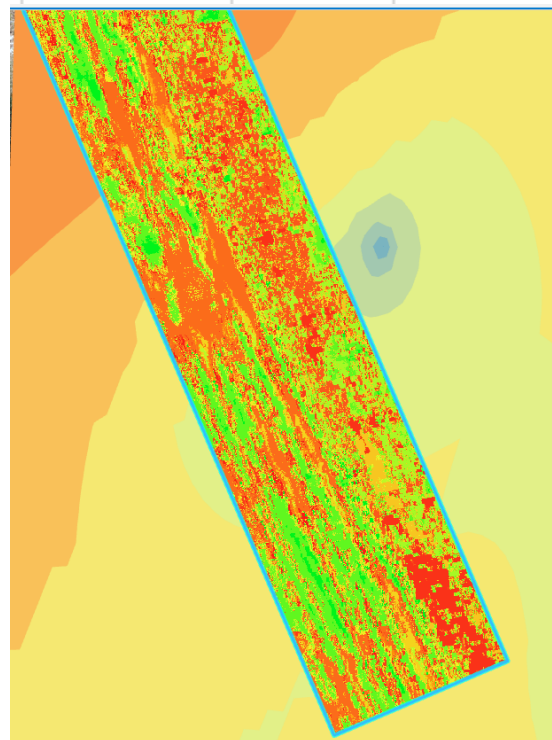
- Colored boxes are Pit Extents for KNN models
- Color range is similar for each of the pits, legend for pit 2 predictions displayed below.



# IDW Prediction Maps: Accuracies

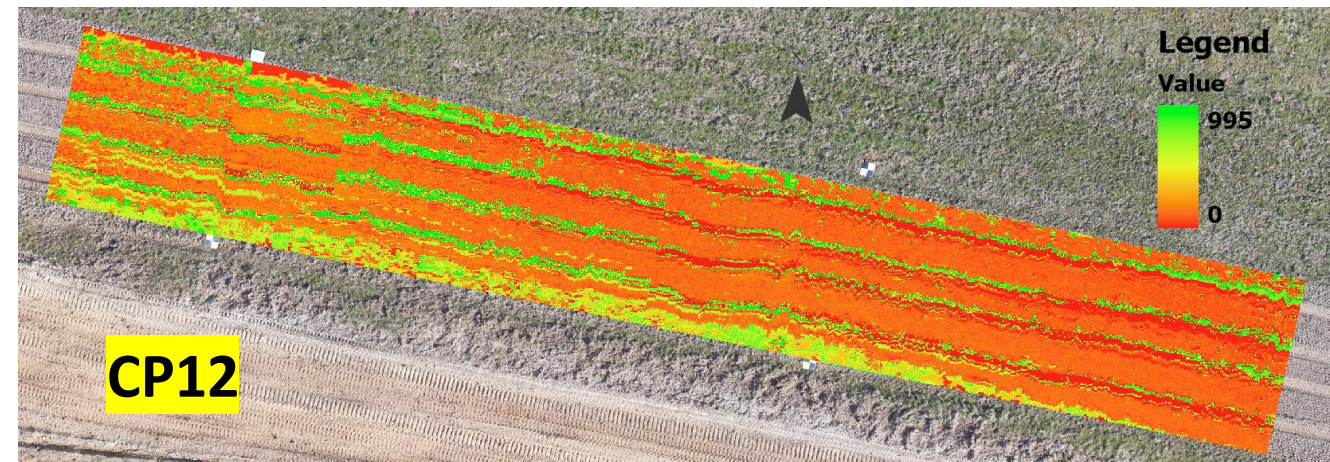
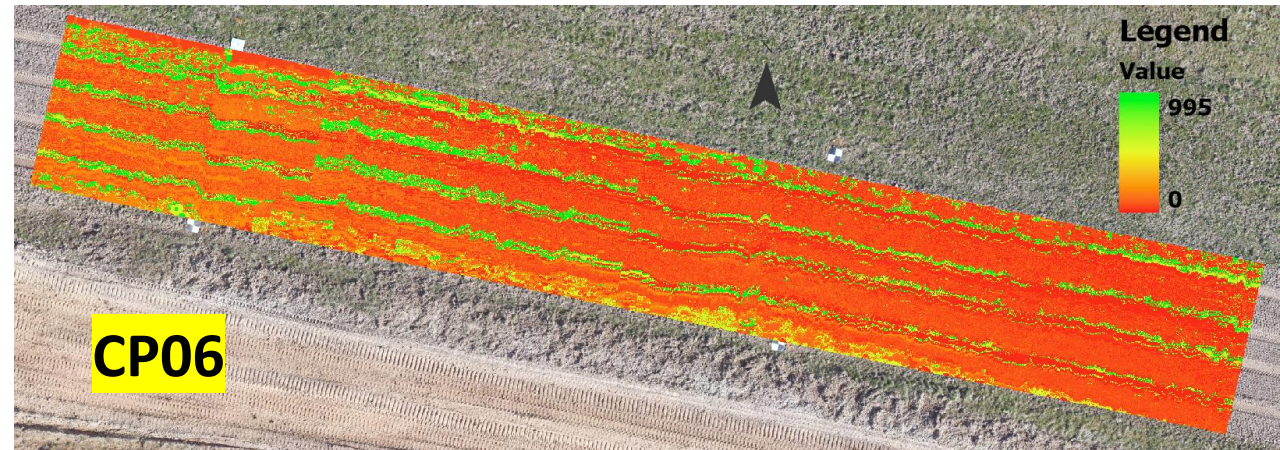
- **Inverted Distance Weighted geospatial interpolation resulted in poor accuracies for predicting these areas.**
  - KNN performed better (for all three pits) than IDW on individual ones.
- **Level of detail is displayed in image showing the higher resolution prediction map (CP12) generated by KNN compared to that of IDW for a section of Pit 2.**

KNN Results	All 3 Pits	
RESPONSE	k value	RMSE
Moisture	3	1.121189
CP06	2	55.71332
CP12	2	85.09914

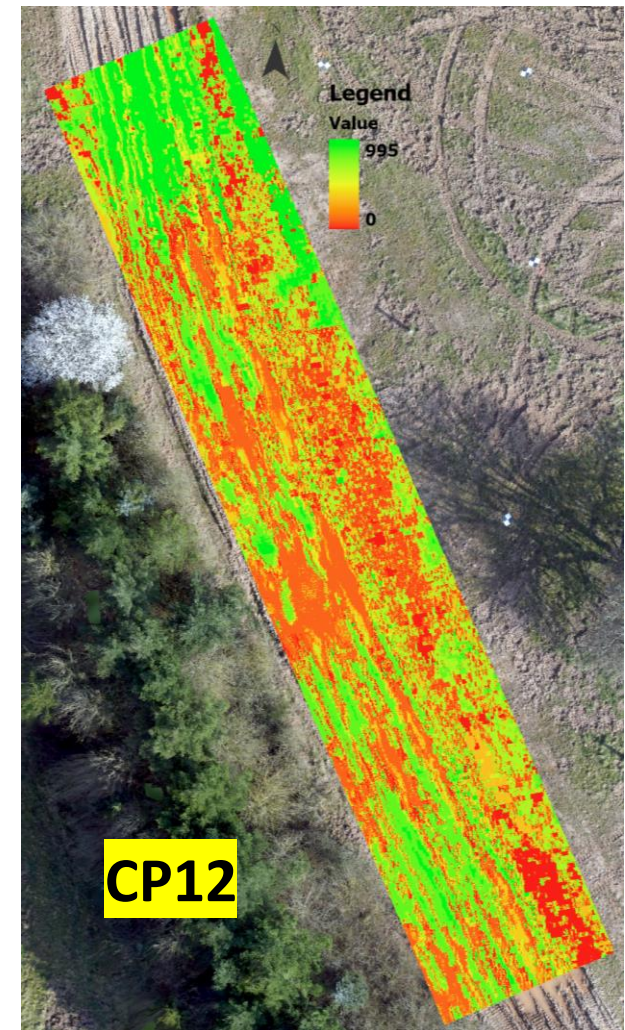
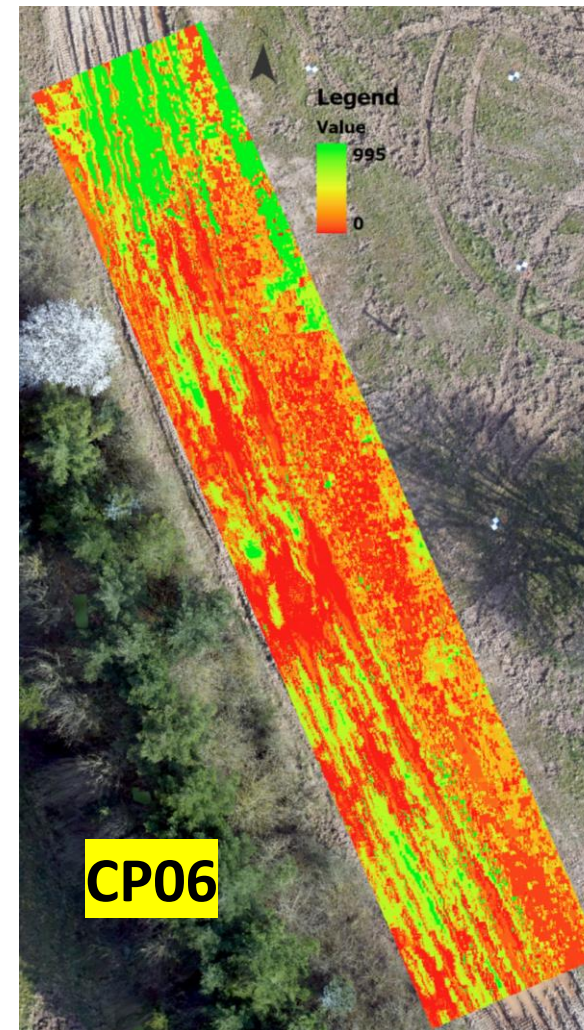


Pit 1	IDW	
RESPONSE	Power	RMSE
Moisture	1	7.783639
CP06	1	262.934
CP12	1	306.7982
Pit 2	IDW	
RESPONSE	Power	RMSE
Moisture	1	3.681677
CP06	1.127836	232.7844
CP12	1	278.8619
Pit 3	IDW	
RESPONSE	Power	RMSE
Moisture	1	3.228583
CP06	1	246.6307
CP12	1	310.2781

# Prediction Maps: Pit 1

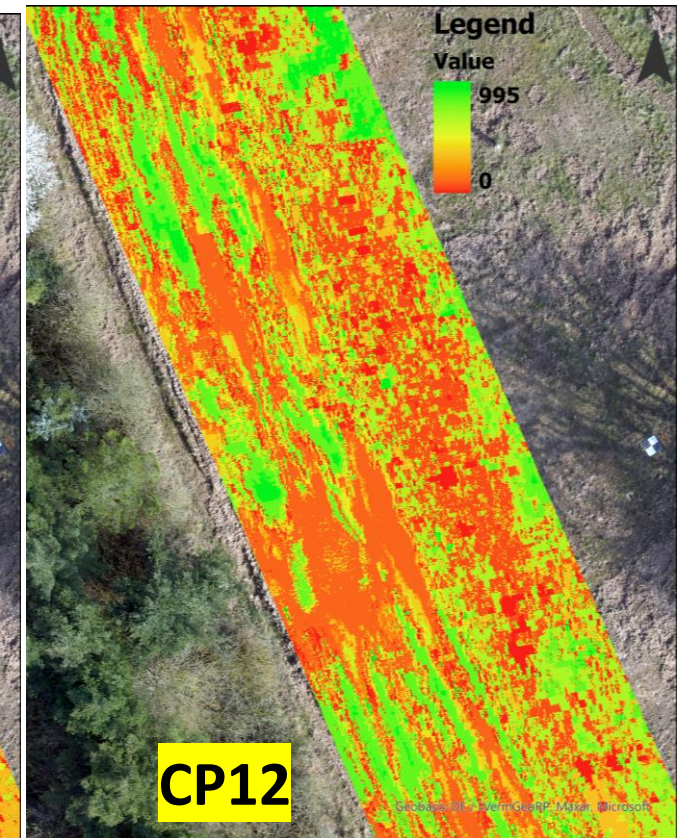
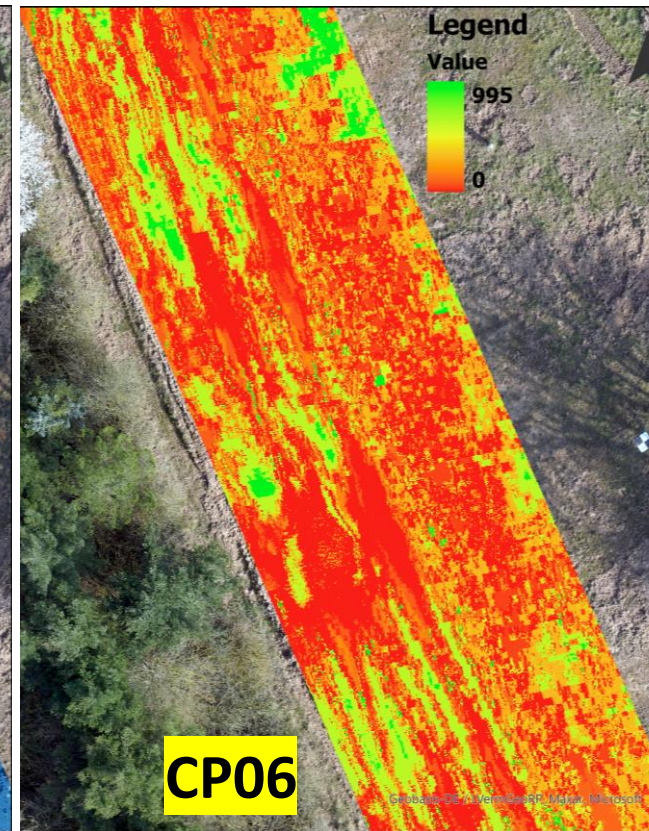


# Prediction Maps: Pit 2



# Prediction Maps: Pit 2 (Zoomed In)

- Pit 2 portion with puddles, where tanks were bottoming out

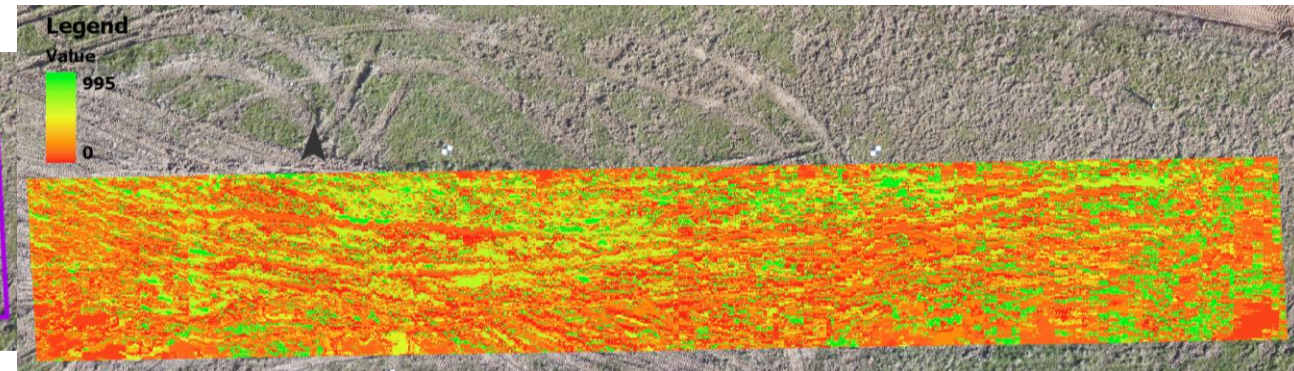


# Prediction Maps: Pit 3

RGB



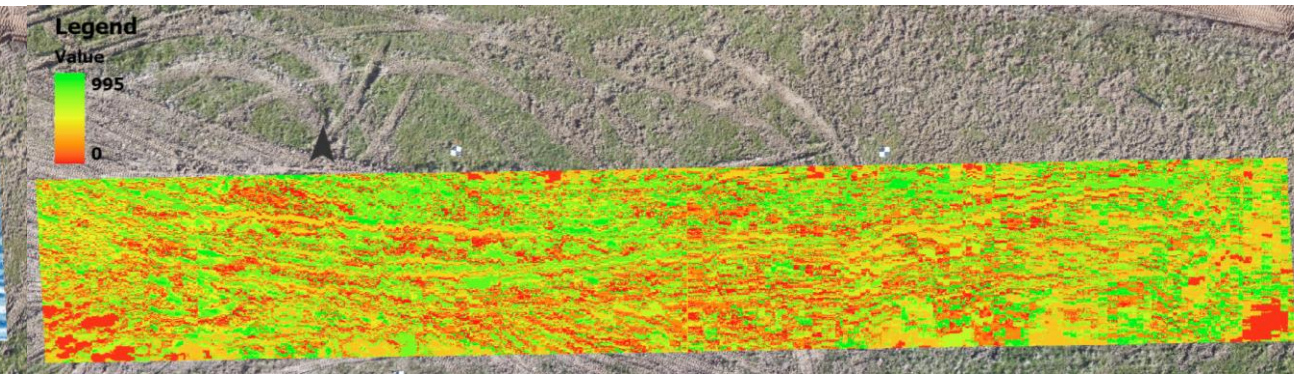
CP06



Moisture

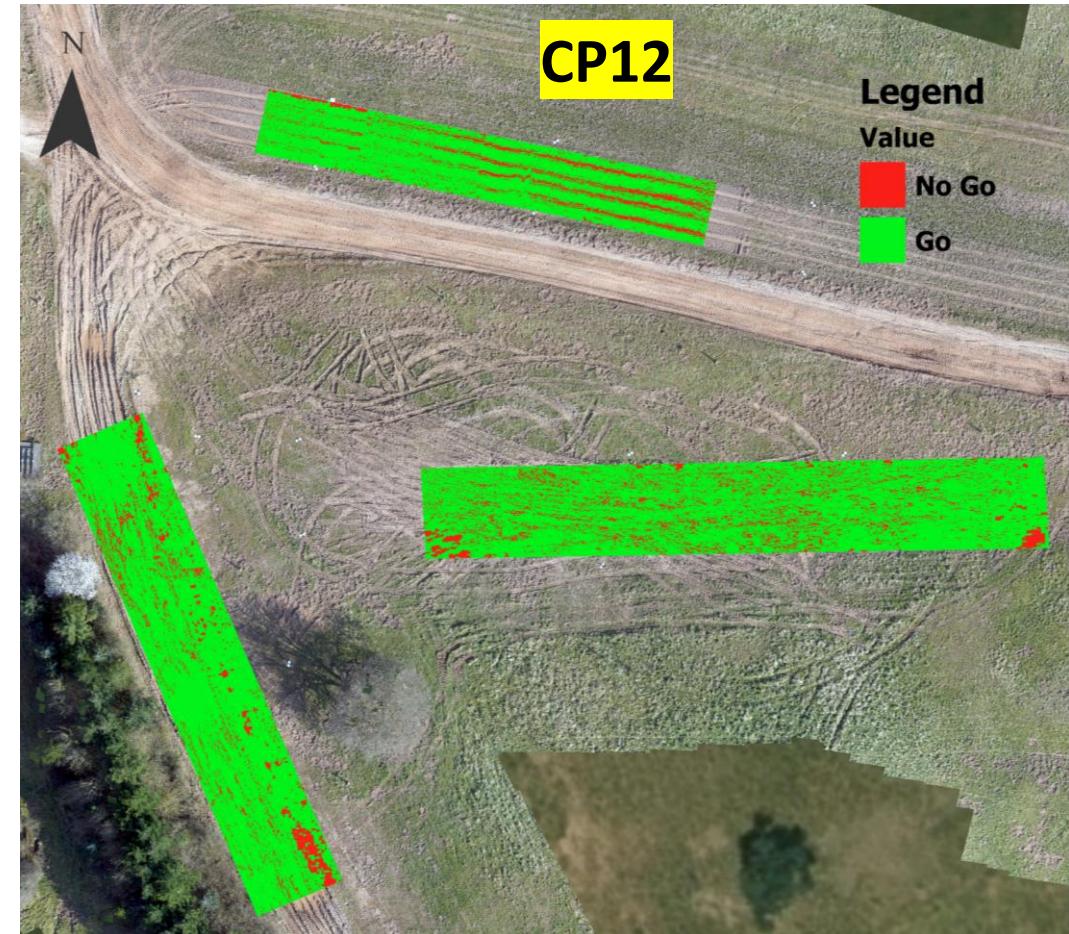
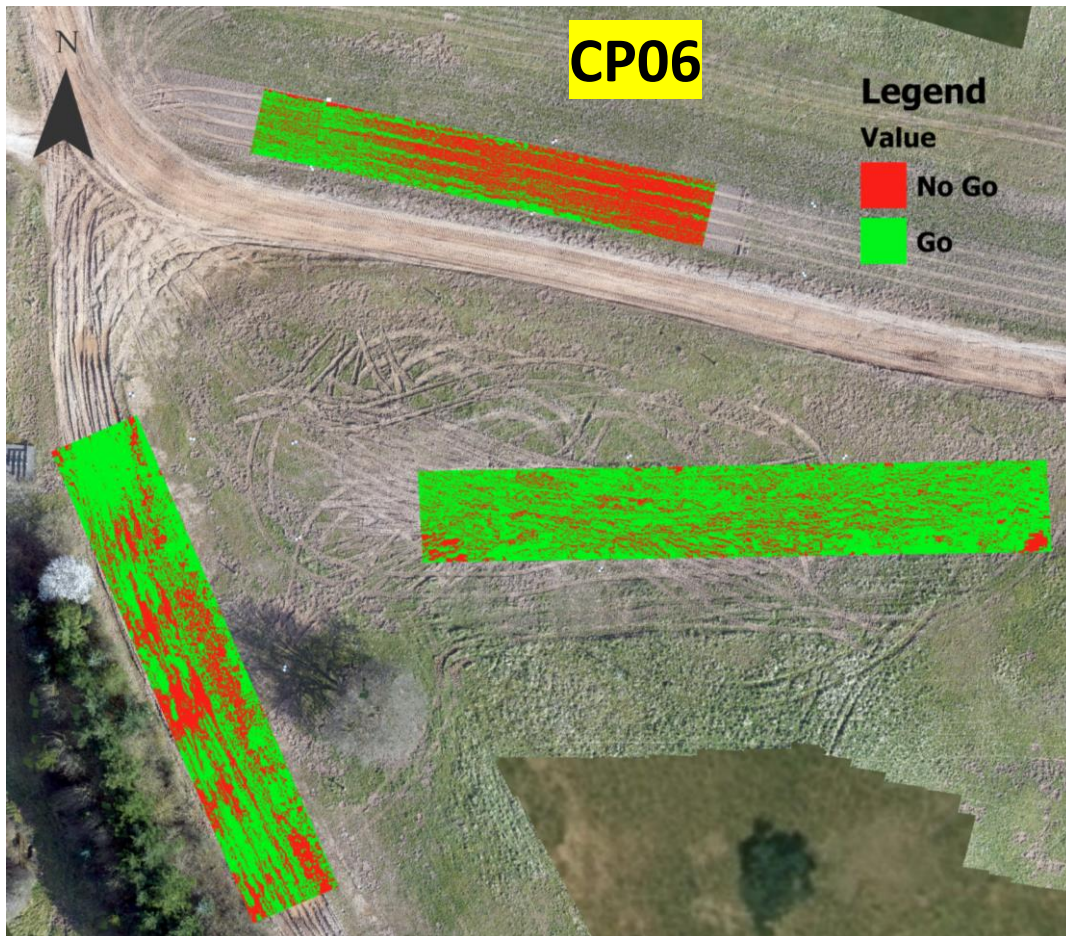


CP12



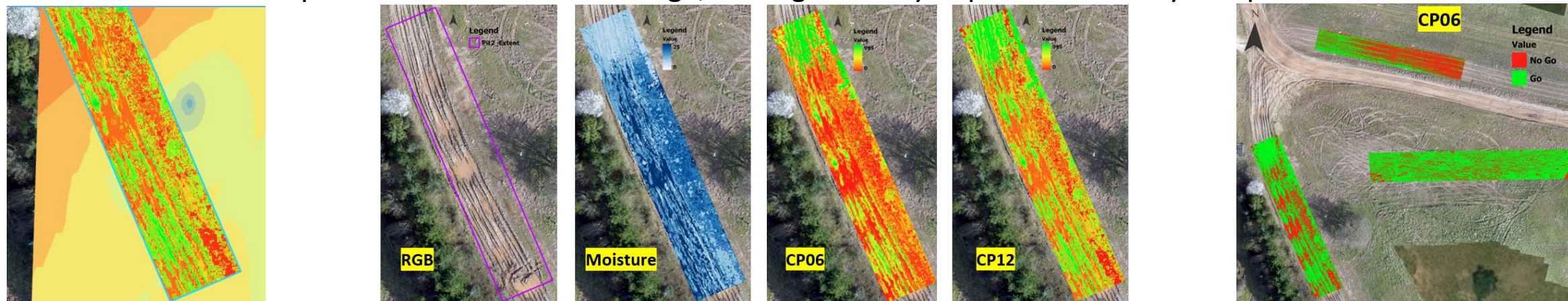
# Go / No-Go Maps: CP06 & CP12 (KNN) vs. VCI\_50

- Using a VCI\_50 value (64) as the Go / No Go threshold



# Conclusions

- Remote sensing methods provided good prediction maps.
  - Moisture Content, Cone Penetrometer 0" – 6" and 0" – 12" average strength
  - Strength maps used to create Go / No Go maps using different VCI values
- Remotely sensed data-based KNN models outperformed in-situ measurement-based geospatial interpolation (IDW) method
  - Yielding both a higher accuracy and higher resolution output.
- This methodology can be used in the NG-NRMM as an input of soil conditions and building global Go / No Go maps for the area of interest
  - Provides better spatial resolution and coverage, and significantly improved accuracy compared to in situ methods.



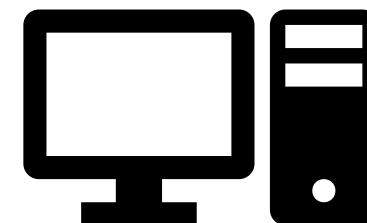
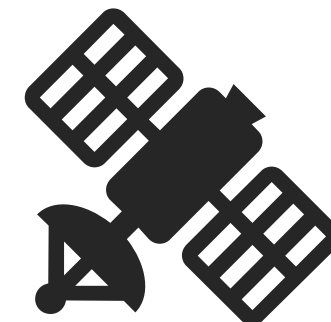
# Final Remarks

- **Limitations:**

- Collection size in this study was limited by flight time of the drone.
- Models were run on this site with multiple moisture / strength conditions but is only one soil type present.
- Need to be tested with varying soil type and vegetation influences
- Requires two flights (AM & PM), making this more suitable for offline and not online mobility

- **Future Work**

- Hope to test how this method scales up to higher platforms such as that of satellite imagery.
- We hope to expand the database by collecting more diversity in soil types and develop a large soil database for the machine learning and advanced deep learning models.





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