Crop Residue Estimation Using SAR

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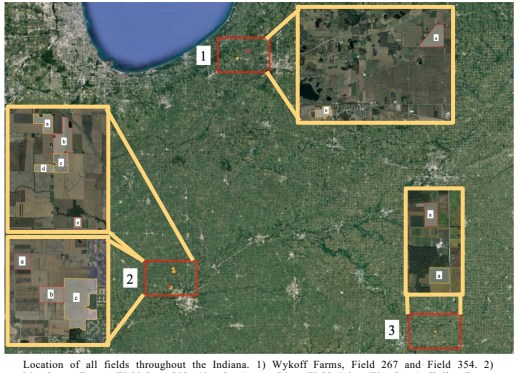
Abstract: The Purpose of this research is to develop a framework to estimate crop residue on a global scale for the upcoming NISAR mission. To this end, we collected UAS data over testbeds and developed a machine learning algorithm to estimate crop residue directly from the UASdata. We believe the UAS-derived crop residue estimates can be used as big training data for developing a global-scale crop residue estimation model.

Introduction

Crop Residue (CR) importance: 1) Protects soil from erosion 2) Helps soil to maintain its moisture during winter.
Tradition approach ⇨ **Line-transect method**
Advantages: One of the most accurate available approach.
Disadvantages: Labor and time consuming, error prone.

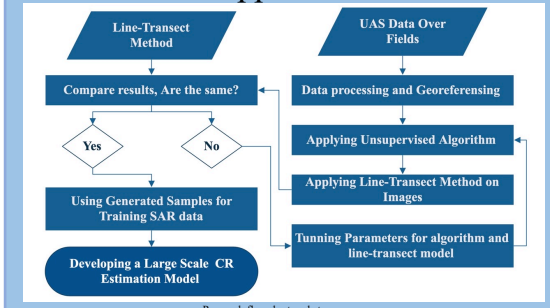
Data Acquisition

UAS data
- **UAS platform:** DJI M-300 with P
- **Testbeds**: 9 corn and 9 soybean fields (18 fields in total)
- **Data collection**: 2021 winter and 2022 spring
- **Spatial Resolution**: ~ 1cm



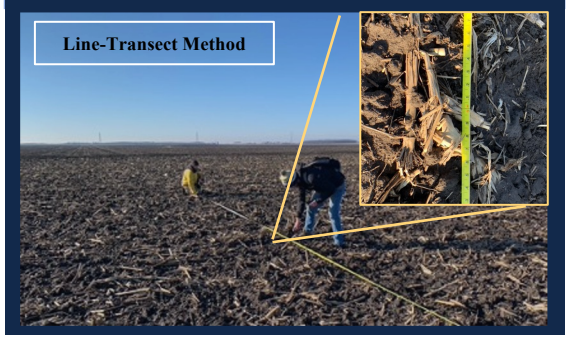
Location of all fields throughout the Indiana. 1) Wykoff Farms, Field 267 and Field 354. 2) Morehouse Farms (Field Don 209, Church, County Line, Field Griner-Wag-Russ), Kelley Farms (Field Chris 40), and ACRE (Field 69, Field 57, Mckinnis). 3) Field J and Field.

Approach

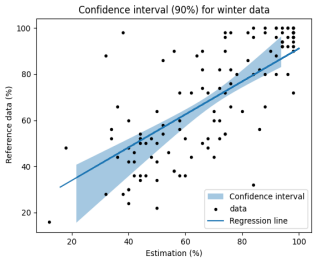


Research flowchart and steps

1) Data collection: measuring crop residue on the field using line-transect method as well as UAS data with GPS survey.
2) Estimating CR using UAS data:
   a. Processing and georeferencing UAS data
   b. Applying K-means algorithm with six clusters.
   c. Applying PCA algorithm and converting values to grayscale.
   d. Applying Otsu method to find a threshold between CR and non-CR.
   e. Comparing the CR estimates with the reference data
3) Estimating CR using NISAR data: generate the numerous training samples needed to train a model to detect crop residue from SAR data.

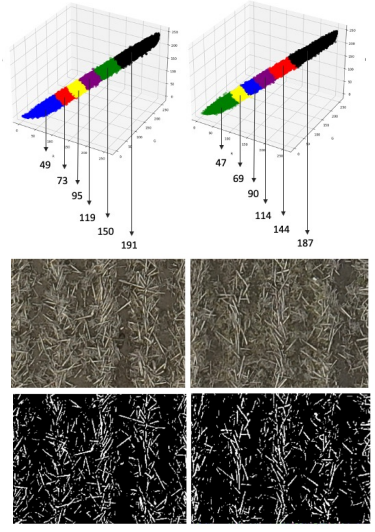


Result



Result of CR estimation using K-means machine learning algorithm and UAS data. As it is shown, the slope of the fitted regression line is close to the line 1:1.

Implementing a k-means algorithm and optimizing its parameters, the best result for estimating crop residue was achieved with a 6-cluster model, which yielded an R^2=0.77. However, using the automated process of PCA and thresholding method resulted in less accurate estimations and presented some challenges. These inaccuracies may be attributed to varying soil color within the field, changes in lighting throughout the day, and differing seasons. Future research will focus on addressing these issues to improve the accuracy of the estimation process.



Pixel values in RGB bands. RGB values of CR consistently fall within the higher range, regardless of the specific plot or field being analyzed.

Future Research

- Since the accuracy of CR estimation can be affected by the type of the field's soil, so considering spatial patterns of crop residue (object-oriented classification) may lead to better performance.
- Train NISAR data with the UAS-based CR estimates to generate a large-scale CR map using the state-of-the-art deep learning algorithms

References

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2. Miao Li, Shuying Zang, Bing Zhang, Shanshan Li & Changshan Wu (2014) A Review of Remote Sensing Image Classification Techniques: the Role of Spatio-contextual Information, European Journal of Remote Sensing, 47:1, 389-411, DOI: 10.5721/EuJRS20144723