Knowledge-based artificial intelligence for agroecosystem carbon budget and crop yield estimation

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1. Introduction

- Accurate estimation of carbon budgets is vital to assessing the climate change mitigation potentials of terrestrial ecosystems. Cropland carbon budgets play an important role in regional carbon budgets over cropland dominates the landscape such as the U.S. Midwest.
- However, there is still no reliable product on cropland carbon budget with high spatial and temporal resolutions over the U.S. Midwest.
- Empirical studies use flux tower observations to quantify different components of cropland carbon budget at local scale, such as net ecosystem exchange (NEE), but it is difficult to scale local observations up to regional scales.
- Process-based models can simulate individual components of cropland carbon budget, but are lacking effective constraints from observations.
- Although there is an increasing interest in leveraging recent advances in machine learning, capturing this opportunity requires going beyond the ML limitations, including limited generalizability to out-of-sample scenarios, demand for massive training data, and low interpretability due to the "black-box" use of ML
- To fill this gap, we used the knowledge-based artificial intelligence to integrated the advanced ecosystem model, *ecosys*, with a new remotely-sensed daily ecosystem gross primary production (GPP) observations to estimate the crop yield, ecosystem respiration (Reco), and NEE at field scale in the U.S. Midwestern cropland.

2. Method and Data

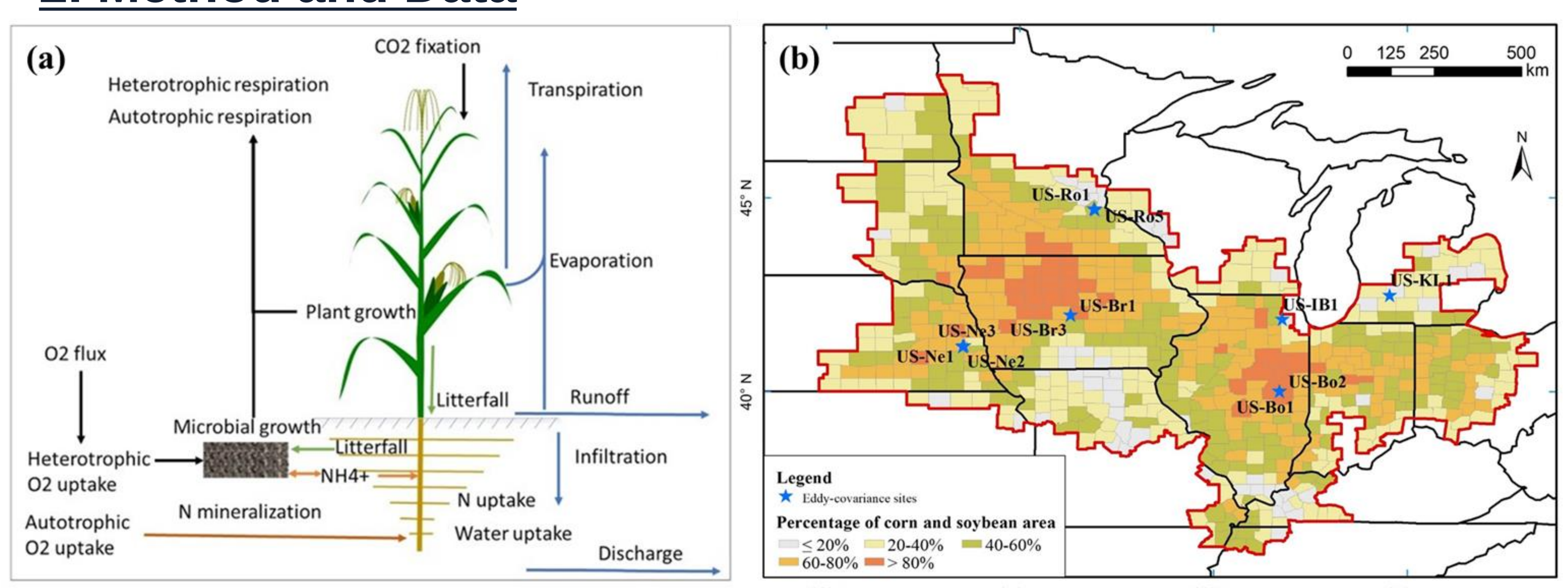

Fig. 1. (a) Major processes represented in the *ecosys* model (revised from (Grant, 2004; Zhou, 2021)), and (b) locations of the flux towers and the counties selected in this study.

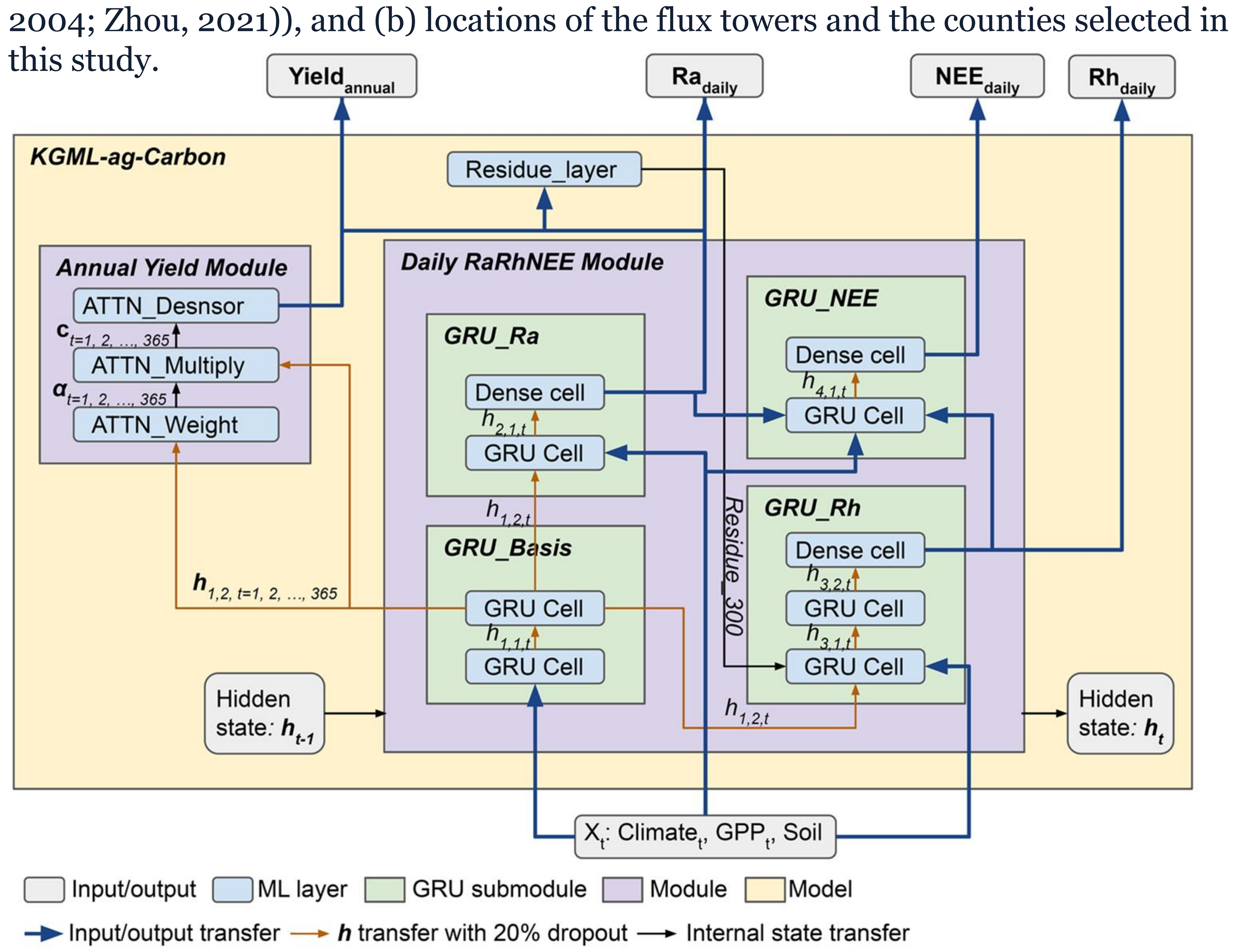

Fig. 2. The structural of knowledge-based machine learning for agricultural carbon budget estimation (KGML-ag-Carbon) developed in this study. KGML-ag-Carbon model would be carefully trained by including knowledge constraints before regional extrapolation.

3. Performance of KGML-ag-Carbon in crop yield estimation

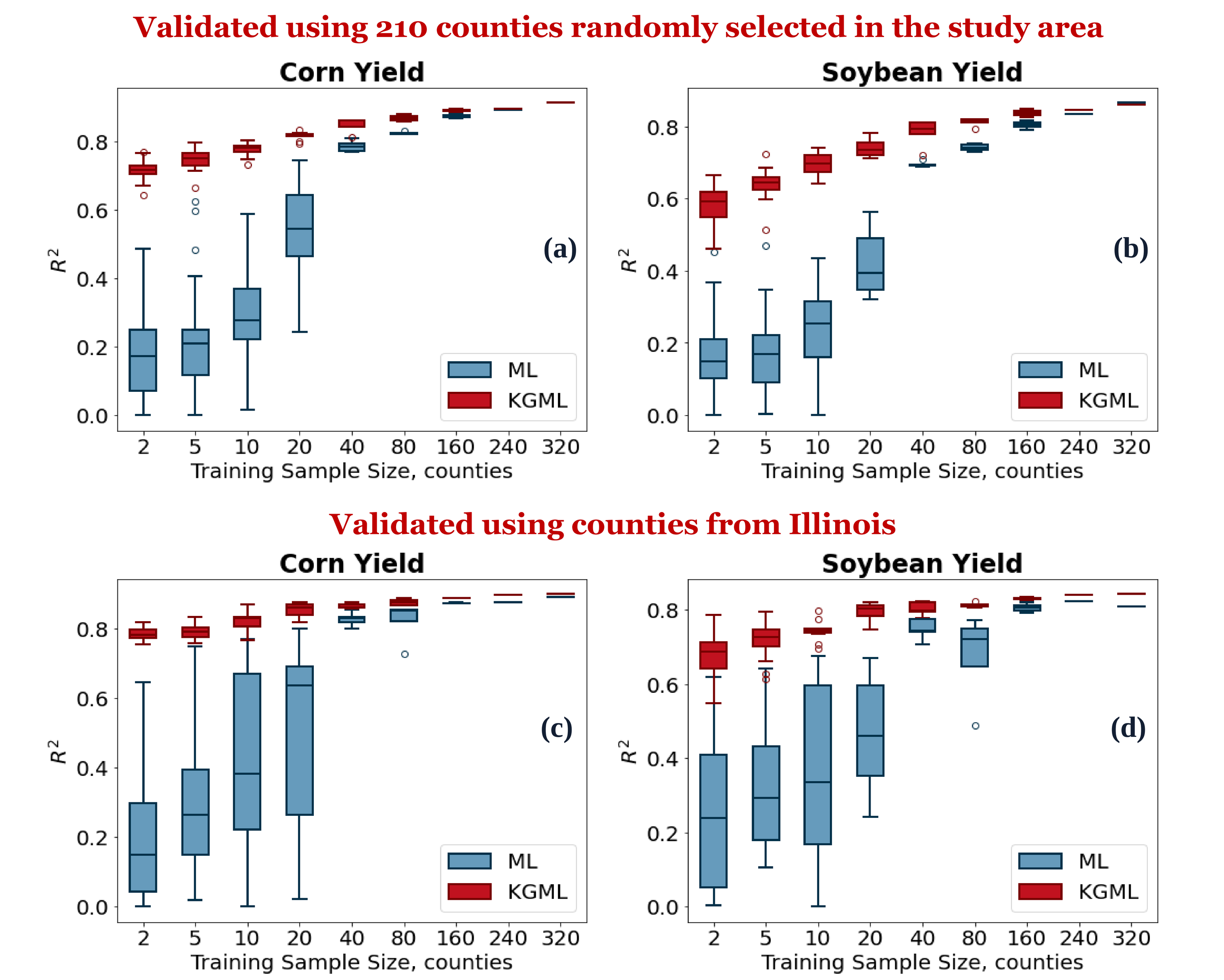

Fig. 3. The performance of KGML-ag-Carbon and pure machine learning (ML) in crop yield estimation. (a) and (b) were the model performance validated using 210 counties randomly selected in the study area for corn and soybean, respectively, and (c) and (d) were the model performance validated using the counties from Illinois for corn and soybean, respectively.

4. Carbon fluxes estimation over the U.S. Midwestern cropland

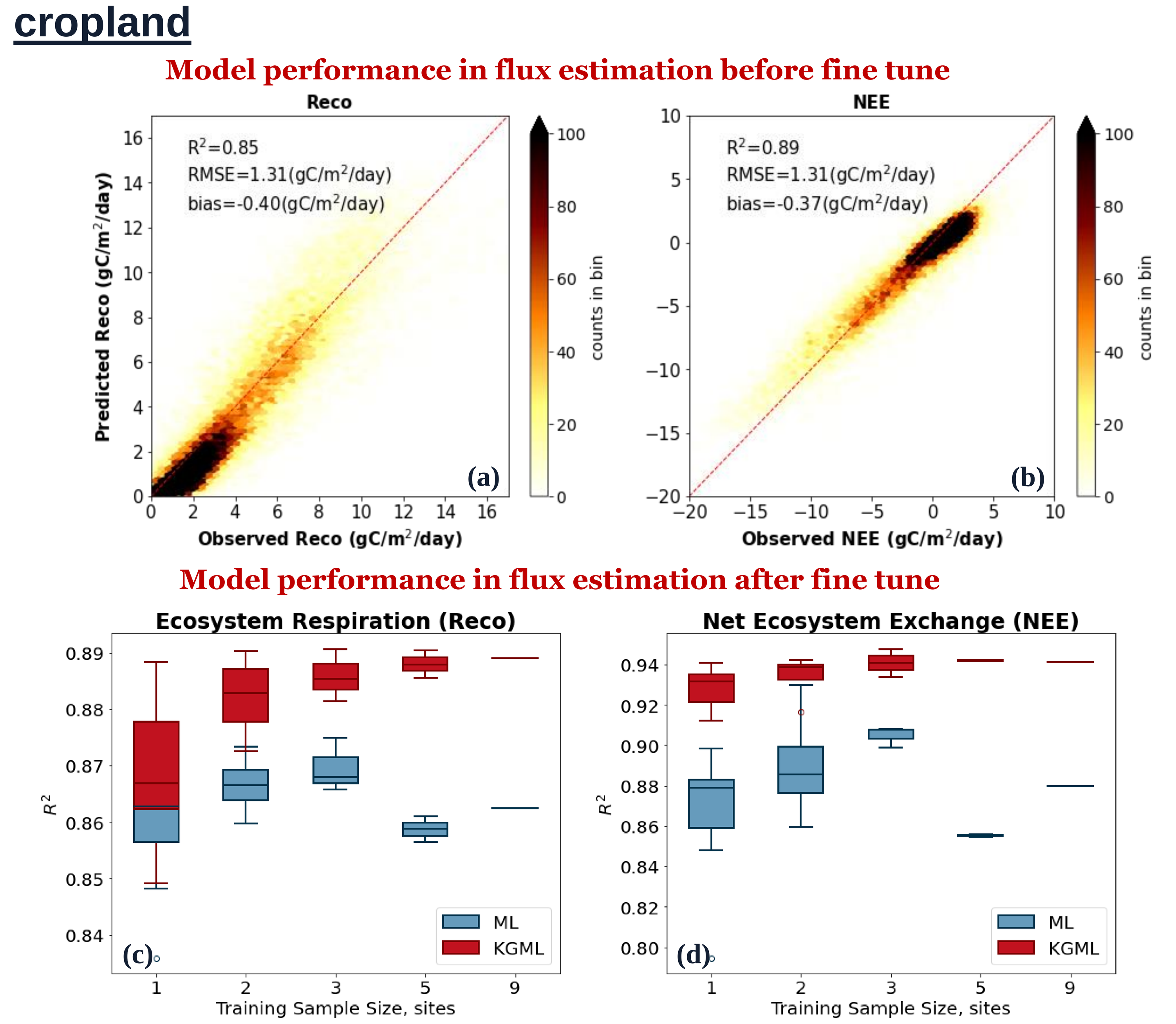

Fig. 4. The performance of KGML-ag-Carbon and pure machine learning (ML) in carbon fluxes (Reco and NEE) estimations. (a) and (b) were the KGML-ag-Carbon performance at 11 fluxtower sites before fine tuning, and (c) and (d) were the model performance for KGML and ML at US-Br1 and US-Br3 with different number of sites for fine tuning (or training), respectively.

4. Carbon fluxes estimation over the U.S. Midwestern cropland

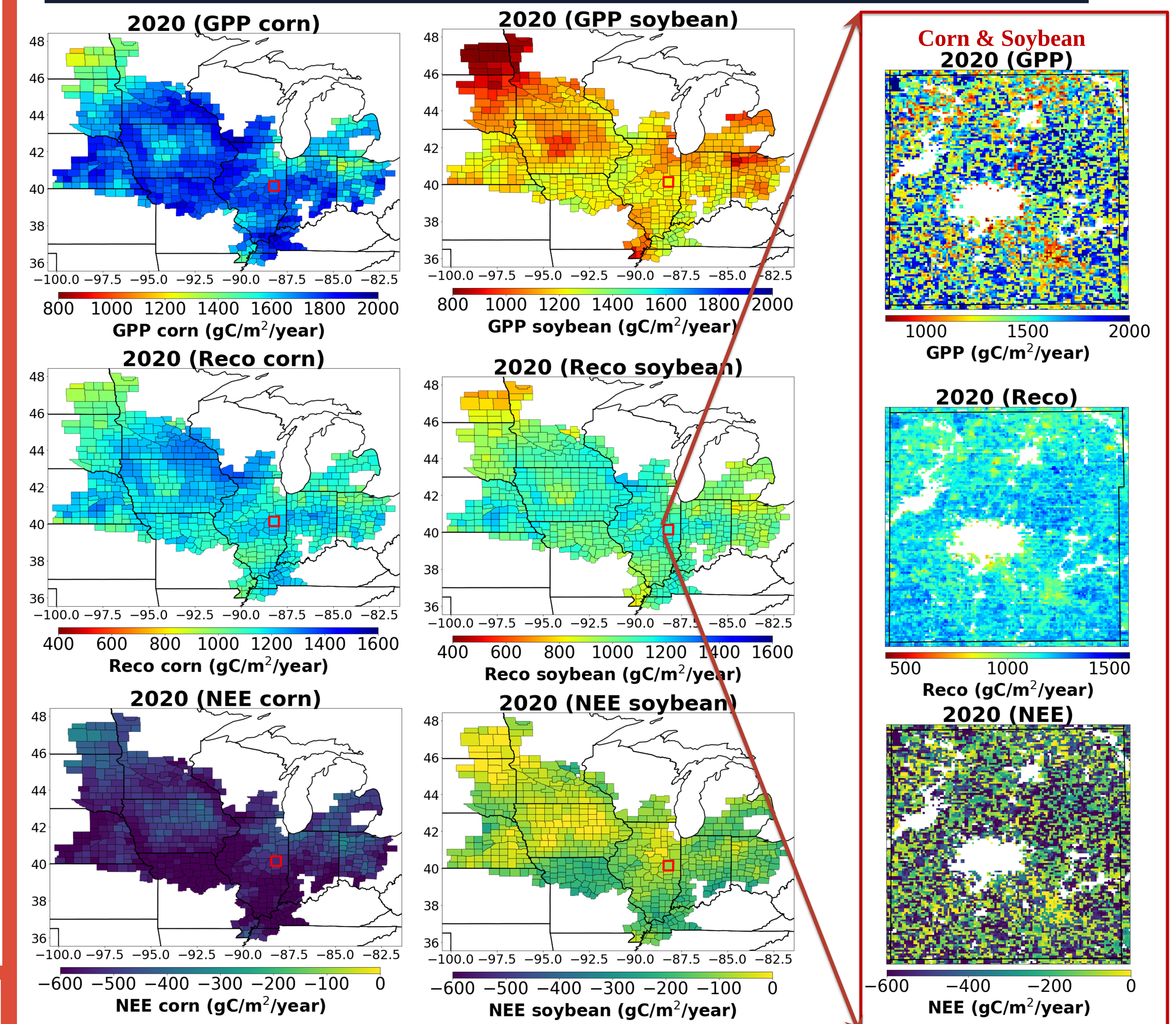

Fig. 5. An example of NIRv-based GPP and KGML-ag-Carbon estimated carbon fluxes (Reco and NEE) in 2020.

5. Conclusion

- Built an AI-based field scale carbon budget (Yield, Reco, NEE) estimation framework (KGML-ag-Carbon) by integrating knowledge-based artificial intelligence, advanced ecosystem model, and remotely-sensed GPP observations.
- Validated the performance of KGML-ag-Carbon in corn and soybean yield and carbon fluxes estimations using the crop yield from USDA NASS at county scale, and Reco and NEE at 11 cropland eddy-covariance sites in the U.S. Midwest.
- An efficient and reliable tool to estimate crop carbon and detailed components in high spatial and temporal resolution
- It has potential to evaluate soil, climate and management influences on carbon credit in field level and therefore guide farmers and policy makers to make right decisions
- The final product can feedback to process-based model for calibration and testing

6. References and Acknowledgements

[1] Grant (2004). Modeling topographic effects on net ecosystem productivity of boreal black spruce forests. *Tree Physiology,* 24, 1-18.

[2] Jiang, et al. (2021). A daily, 250 m and real-time gross primary productivity product (2000–present) covering the contiguous United States. *Earth System Science Data,* 13, 281–298.

[3] Liu, et al. (2021). KGML-ag: A Modeling Framework of Knowledge-Guided Machine Learning to Simulate Agroecosystems: A Case Study of Estimating N2O Emission using Data from Mesocosm Experiments. *Geoscientific Model Development Discussions*.

[4] Zhou, et al. (2021). Quantifying carbon fluxes, crop yields, and their responses to environmental variability using the *ecosys* model for U.S. Midwestern agroecosystems. *Agricultural and Forest Meteorology*, 307, 108521.

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