Combining Remote Sensing and Eddy Covariance to Improve Dairy Greenhouse Gas Budgets

Susanne Wiesner^{1,2}, Ankur R. Desai², Alison J. Duff³, Stefan Metzger^{4,2}, and Paul C. Stoy^{1,2}

¹ University of Wisconsin, Department of Biological Systems Engineering, Madison WI, ² University of Wisconsin, Department of Atmospheric and Oceanic Sciences, Madison WI, ³ U.S. Dairy Forage Research Center, USDA Agricultural Research Service, Madison, WI, ⁴ Battelle, National Ecological Observatory Network, 1685 38th Street, Boulder, CO 80301, USA





Rational

Challenge:

Atmospheric CO₂ concentrations are still steadily increasing [1]. In livestock agriculture "nature based" strategies can mitigate on-farm greenhouse gas emissions (GHG), by imitating natural processes that store CO₂ from the atmosphere, which include cover crops [2,3,4], and conversions of annual croplands to continuous green cover such as pastures [5]. Agricultural GHG balances often ignore the role that landscape productivity plays in whole-farm emission mitigation [6,7]. Measurements of sources and sinks are time consuming and expensive, and rarely within the realms of possibilities for a dairy producer [8].

Solution:

A broader suite of tools to implement natural climate solutions that boost carbon sequestration and mitigate GHG emissions in agricultural systems. Remote sensing data have been applied to predict aboveground biomass with relatively low uncertainty in agricultural systems [9,10]. But their implementation into full farm GHG budgets is still limited [11]. Eddy covariance can help improve crop specific parameters on a continuous basis, but these systems are expensive, time-intensive, and require technical skills, and are often constrained to one vegetation type [12,13].

Testbed:

We use eddy covariance measurements and the environmental response function approach [14] to improve crop parameters inputs of remote sensing models to improve a whole farm greenhouse gas budget for the Dairy Forage Research Center (DFRC) farm (890 ha, Fig. 1) in Sauk County, Wisconsin for 2019.

Objectives

- 1. Can we use eddy covariance to monitor vegetation productivity from spatially complex agroecosystems?
- 2. Can we use eddy covariance results to improve remote sensing models to upscale vegetation productivity across larger spatial scales?

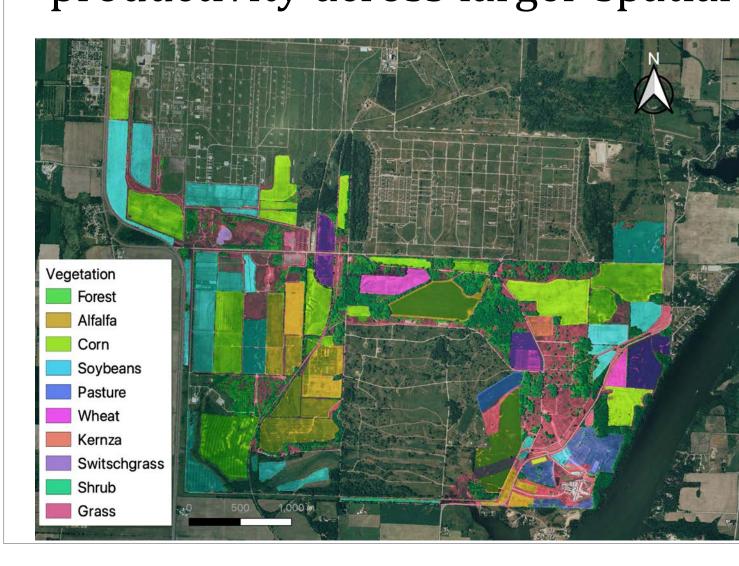


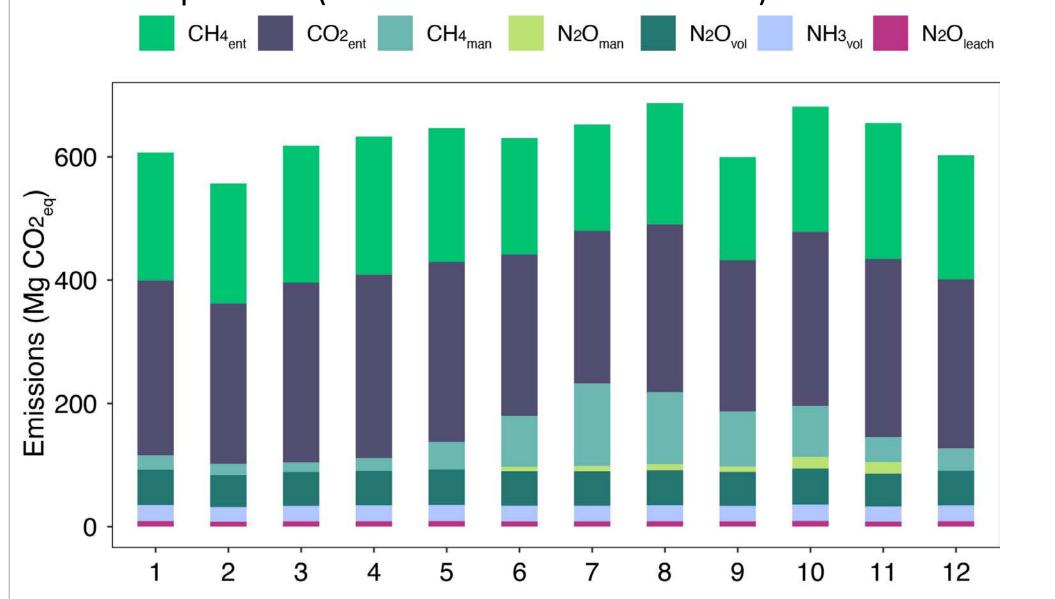
Figure 1: Crop and natural vegetation distribution at the Dairy Forage Research Center farm, Wisconsin, USA during 2019

NEP

Monthly Farm Emissions

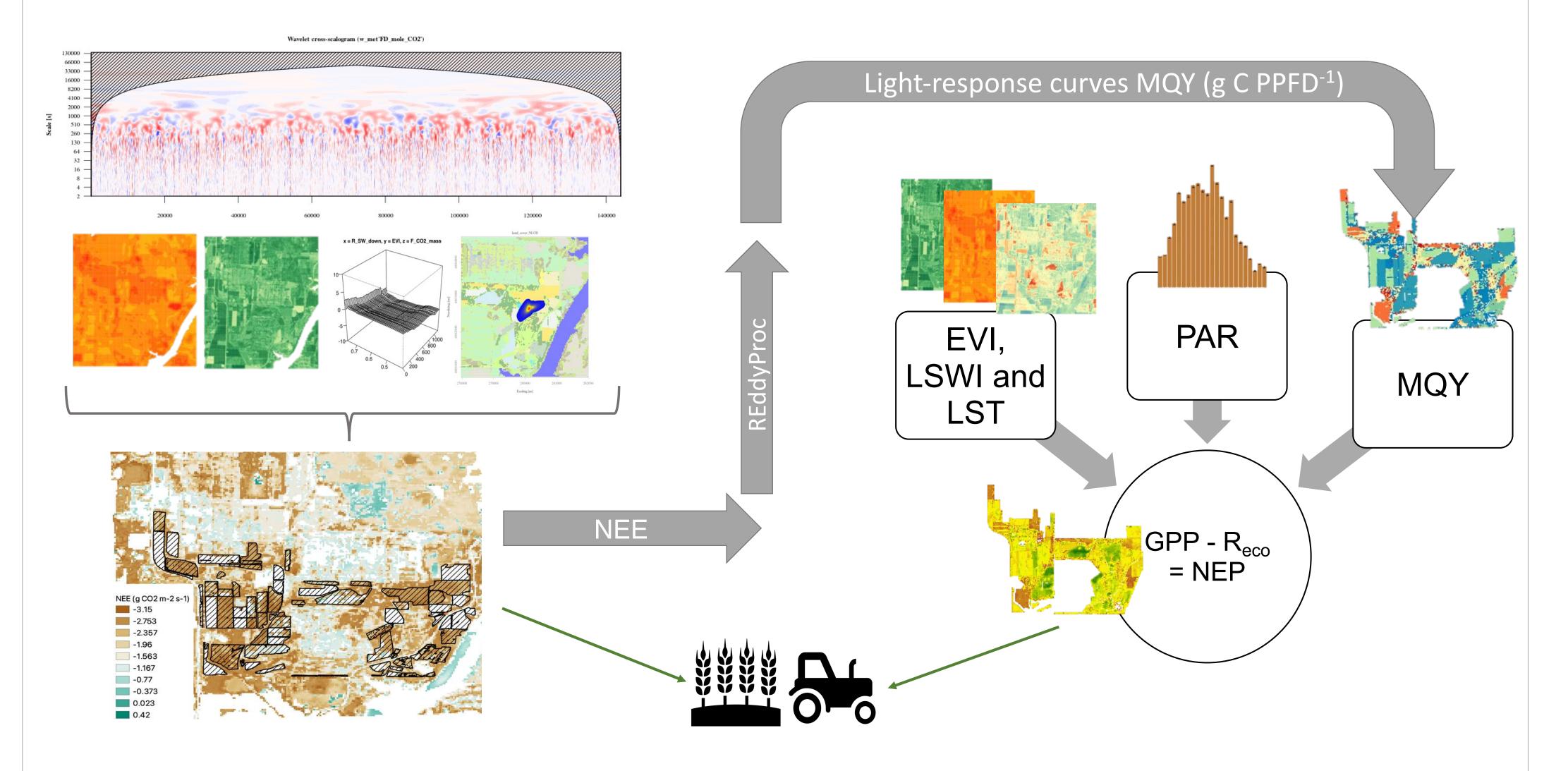
Daily enteric, manure and field GHG emissions were estimated from diet nutritive values following IPCC guidelines [15]

Figure 2: Barn and field emissions by month converted to CO2eq for direct comparisons (for abbreviations see table 1)

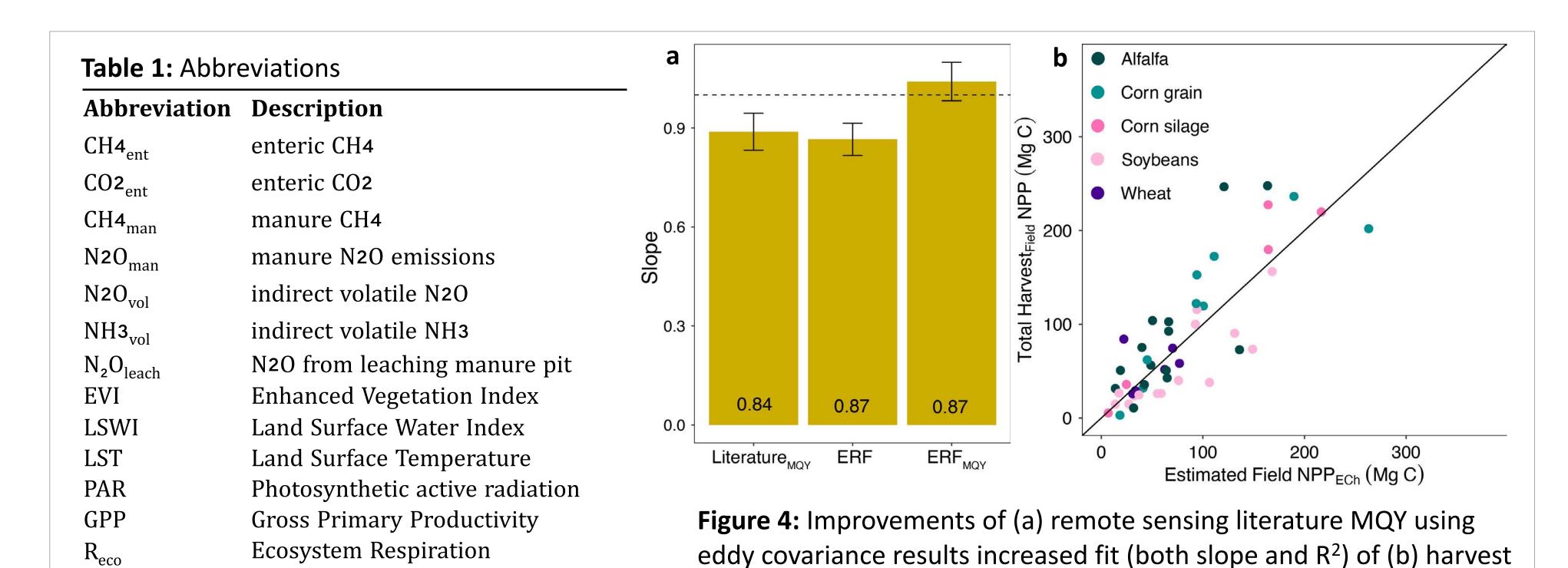


Improving Remote Sensing Crop Parameters using Eddy Covariance

Figure 3: Workflow improving remote sensing vegetation productivity models via eddy covariance environmental response function (ERF) approach



Greenhouse Gas Budget for the Dairy Forage Research Center Farm



Net Ecosystem Productivity Net Ecosystem Exchange of CO2

NEP and remote sensing NEP for each field and crop type at the DFRC

Maximum Quantum Yield

- Manure emission increased during summer due to reduced field applications (Fig. 2)
- Updating Remote sensing models using eddy covariance improved model predictions of annual harvest NEP (Fig. 4a)
- Annual field NEP predictions correlated well with harvest annual NEP estimates (Fig. 4b)

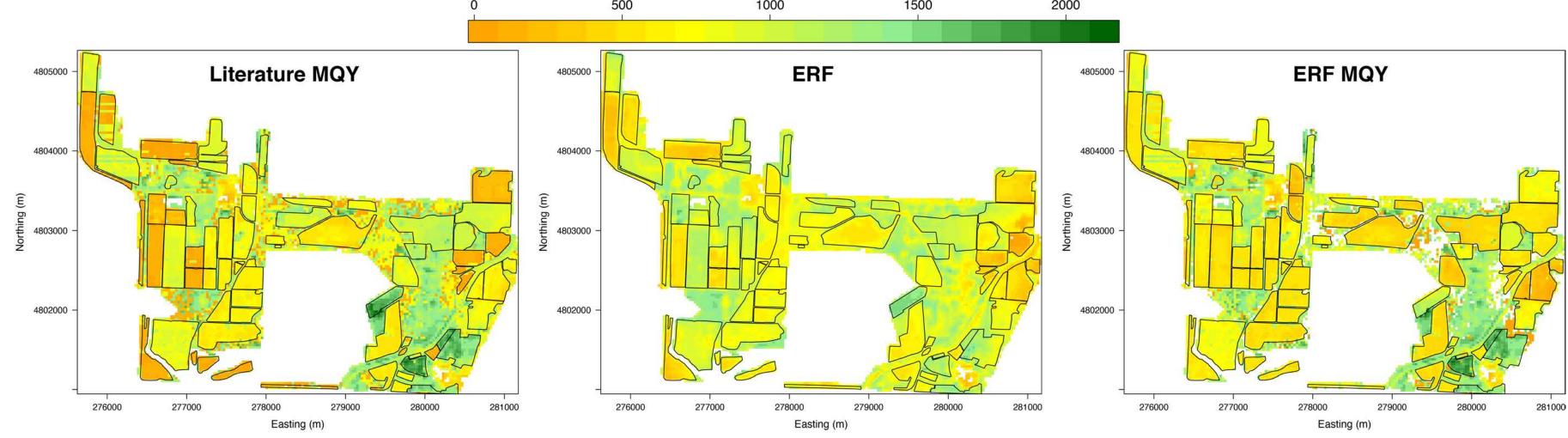


Figure 5: Crop and natural vegetation distribution at the Dairy Forage Research Center farm, Wisconsin, USA during 2019

- Eddy covariance can be used to monitor agroecosystem productivity while accounting for the spatial complexity of landscapes
- Eddy covariance can improve remote sensing models to upscale vegetation biomass productivity and vegetation health
- Eddy covariance ERF spatial NEE allows for monitoring of ecosystems at night
- The DFRC dairy farm had a net zero carbon budget for the year 2019 mitigating all on-farm emissions

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SW and PS acknowledge funding from the Dairy Innovation Hub at the University of Wisconsin-Madison. The National Ecological Observatory Network is a program sponsored by the National Science Foundation (NSF) and operated under cooperative agreement by Battelle. This material is based in part upon work supported by NSF through the NEON Program. All authors would like to thank Jonathan Thom for help during instrumentation and data upkeep. All authors would like to thank the USDFRC farm crew and field technicians, namely Kristine Niemann and Malachi Persche. The authors would like to acknowledge and honor that both the University of Wisconsin-Madison, as well as the USDFRC farm, where this research took place, occupy ancestral Ho-Chunk land, which the Ho-Chunk Nation was forced to cede in 1832. As researchers we value and respect the sovereignty of the Ho-Chunk Nation, along with the eleven other First Nations of Wisconsin. We are deeply grateful for the Nation's continued land stewardship.