## Implementing and Benchmarking an Agricultural Methane Emissions Model in E3SM

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**Focal Areas:** A major knowledge gap in our understanding of global carbon (C) cycling is the current and future role of croplands in both production and consumption of atmospheric methane (CH<sub>4</sub>). One of the most powerful tools available for assembling and testing our knowledge of CH<sub>4</sub> flux are Earth System Models such as E3SM. The current E3SM Land Model (ELM) does not consider any managed ecosystem CH<sub>4</sub> flux; therefore expanding ELM's capabilities, currently limited to wetlands, to include croplands will leverage emerging datasets from recent syntheses (Guo et al. 2023), eddy covariance networks (Delwiche et al. 2021), and top-down CH<sub>4</sub> flux estimates (Hannun et al. 2020) while building on the expertise already established in ELM.

**Science Challenge:** The challenge of this expansion is three-fold: 1) processes currently parameterized for wetland CH<sub>4</sub> flux will not directly translate to managed upland systems (Riley et al. 2011); 2) while data availability is improving rapidly, CH<sub>4</sub> flux and corresponding biotic and abiotic metadata from croplands are not as extensive as for wetland ecosystems; and 3) croplands are dynamically managed, requiring an understanding of the economic context that drives crop production and feeds back into CH<sub>4</sub> flux. We propose that machine learning (ML) approaches deployed in combination with domain expertise and additional DOE supported research products, can bridge these challenges and support the development and testing of a process-based, interpretable model.

Rationale: Most process-based ecosystem CH<sub>4</sub> emission models are oriented towards wetland ecosystems that are large natural producers of CH<sub>4</sub>. However, the global CH<sub>4</sub> emissions from croplands, primarily from rice cultivation are estimated to be 8% of the global anthropogenic CH<sub>4</sub> emissions (Saunois et al. 2020). Upland ecosystems can also be CH<sub>4</sub> sinks, and active management of croplands such as periodic drainage of rice paddies (Runkle et al. 2019) and no-till agriculture (Ussiri, Lal, and Jarecki 2009) have the potential to offset CH<sub>4</sub> release. Furthermore, global change is increasing both the magnitude of cropland sink potential and the frequency of intense rainfall events that could shift these systems to CH<sub>4</sub> sources. This combined with the dynamic potential of various agricultural management practices and the strong radiative forcing effect of CH<sub>4</sub> makes incorporating these agroecosystems in earth system models increasingly important. However, the spatiotemporal variability in CH<sub>4</sub> flux in cropland ecosystems, limitations of data availability on that flux, and the managed-lands aspect of these ecosystems all represent distinct challenges to this advancement.

**Narrative:** Our goal is to implement an Al-informed, process-based cropland CH<sub>4</sub> emission module within E3SM. The following steps outline our approach in broad strokes:

**Step 1.** Even with domain expertise, it is not immediately obvious what processes or parametrizations should be prioritized to update process-based models from wetland to cropland, particularly given the more limited data available for cropland. As a first step, we propose to utilize exploratory, unsupervised ML to identify reduced-form patterns explaining a meaningful proportion of variance in the spatiotemporal CH<sub>4</sub> datasets for different areas (see list). These datasets would include variables such as measured (or modeled) CH<sub>4</sub> concentration, meteorological data, temperature, humidity, and soil temperature. Self-Organizing Maps (SOMs) are a promising method to guide exploration of existing data sources to prioritize aspects for updating. By training SOMs on each of:

- observed wetland CH<sub>4</sub> data.
- simulated wetland CH<sub>4</sub> data,
- (albeit more limited) observed cropland CH<sub>4</sub> data,
- and cropland CH<sub>4</sub> data simulated with ELM's wetland CH<sub>4</sub> model,

a lower-dimensional representation (or generated map) of each will be produced (Nourani et al. 2013). Each generated map is an extraction of complex patterns characteristic to the training data, and the direct comparison of the resulting patterns will allow us to explore differences in cropland vs wetland CH<sub>4</sub> processes, thereby guiding development efforts in the next step.

More specifically, each generated map can treat the three non-training datasets as novel input data to be classified, essentially displaying the non-training dataset in the space of the training data's distribution in a visually digestible way. The resulting figures can be used to identify discrepancies among these datasets and guide approaches to adapt, update, and/or reparameterize the well-established wetland-CH<sub>4</sub> processes for cropland. Some essential additions are already known, for instance, ELM currently does not model rice, the dominant crop when considering agricultural CH<sub>4</sub> sources. However, interpreting these maps and their discrepancies fundamentally requires domain expertise because it is an exploratory exercise. This results in expertise-guided hypotheses of updates to the process-based wetland model for use in cropland that can be made and interpreted iteratively.

**Step 2.** After this exploratory phase, the revised cropland-CH<sub>4</sub> module will undergo quantitative assessment. This validation will come from comparing simulated ELM cropland CH<sub>4</sub> versus FLUXNET-CH<sub>4</sub> data. Here we will implement classical analysis of error between simulated and observed cropland CH<sub>4</sub> values as recommended by International Land Model Benchmarking (Collier et al. 2018). Additionally, we will use ML approaches to characterize multi-dimensional spatiotemporal error (Tebaldi et al. 2021) to highlight areas of improvement missed by classical multimetric approaches.

**Step 3.** As knowledge gaps are identified via Steps 1 and 2, literature review and synthesis using emerging data on upland CH<sub>4</sub> flux (e.g., (Guo et al. 2023) will be used to fill these gaps, when possible following statistically rigorous meta-analysis techniques (Morris et al. 2022). Additionally, on-going work as part of DOE's COMPASS project will provide valuable syntheses of upland CH<sub>4</sub> sink-to-source transition points.

**Step 4.** We hypothesize that land management practices are crucially important to capturing variability in cropland CH<sub>4</sub> flux. Therefore, the final component of this proposed research is to incorporate land management practices that can impact cropland CH<sub>4</sub> emissions and to use the updated model to quantify CH<sub>4</sub> mitigation that can be achieved in the future under various climate change scenarios. If our hypothesis is correct, expanding the current management options of ELM's cropland module to include soil drainage and aeration will be essential. One possibility that leverages additional expertise would be incorporation of the landuse and agricultural technology distributions from the Global Change Assessment Model (GCAM), which is now actively coupled into E3SM, opening exciting simulation possibilities in this area. GCAM is an integrated assessment model that takes into consideration the landenergy-human-climate system. Such models are the best tool available for assessing various global C management scenarios. An aspect of the cropland CH<sub>4</sub> module would then be the ability to reflect different (albeit estimated) adaptation rates of conservation agricultural practices under various policy scenarios.

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