Capturing Uncertainty in GHG Biogeochemical Process Modes: A Path Forward for Ag Offset Protocols

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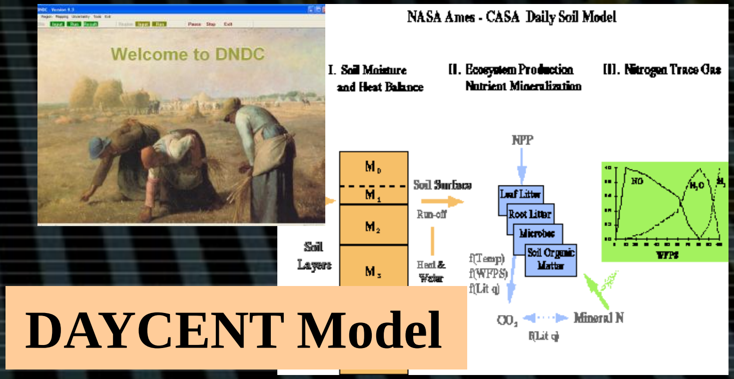
Quick Outline

- Background
- Objectives of the White Paper
- Process model overview
- Quantifying model structural uncertainty
- Assessing model uncertainty due to uncertainty in model inputs
- Accounting for uncertainty in Ag GHG offset projects

How do we estimate GHG emissions from agriculture?

- Measurements
  - ✓ Micrometerological methods: area sources
  - ✓ Flux chambers: site specific
- **Emission Factors**
  - ✓ Use activity data * EF (e.g. N2O emissions = 1% of Nitrogen applied to crops)
- Models
  - ✓ Simple empirical models
  - ✓ Mechanistic (also known as process models)

E = A x EF x (1-ER/100)
where:
E = emissions;
A = activity rate;
EF = emission factor, and
ER =overall emission reduction efficiency, %



DAYCENT Model

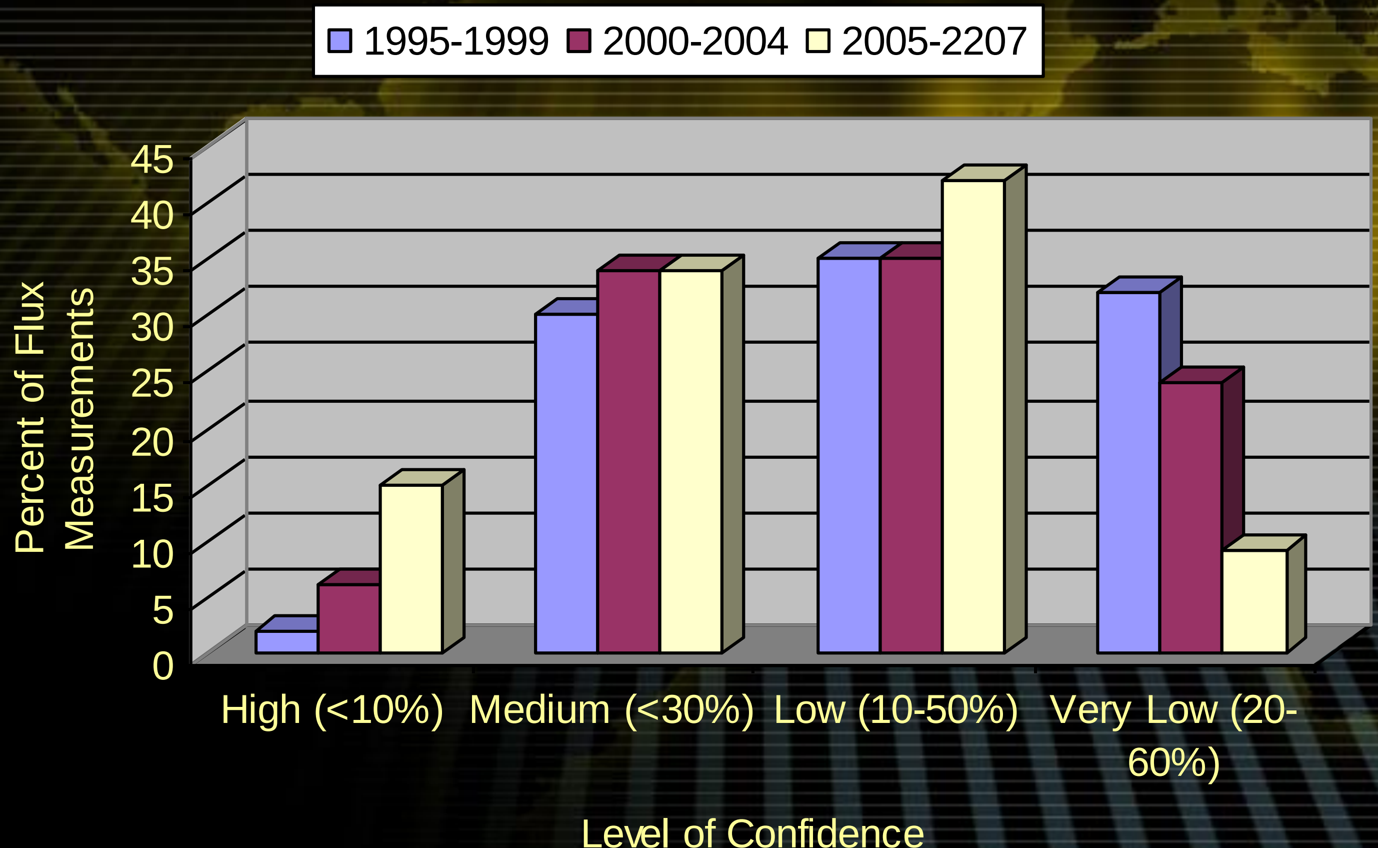
Field Measurements of N2O and CH4

- Measurement approaches:
  - ✓ Flux chambers: site specific – useful for model validation if all model inputs are known
  - ✓ Micrometerological methods: area sources – useful for evaluating regional model simulations (scaling from site to region)

- Accuracy/uncertainty of measurements?

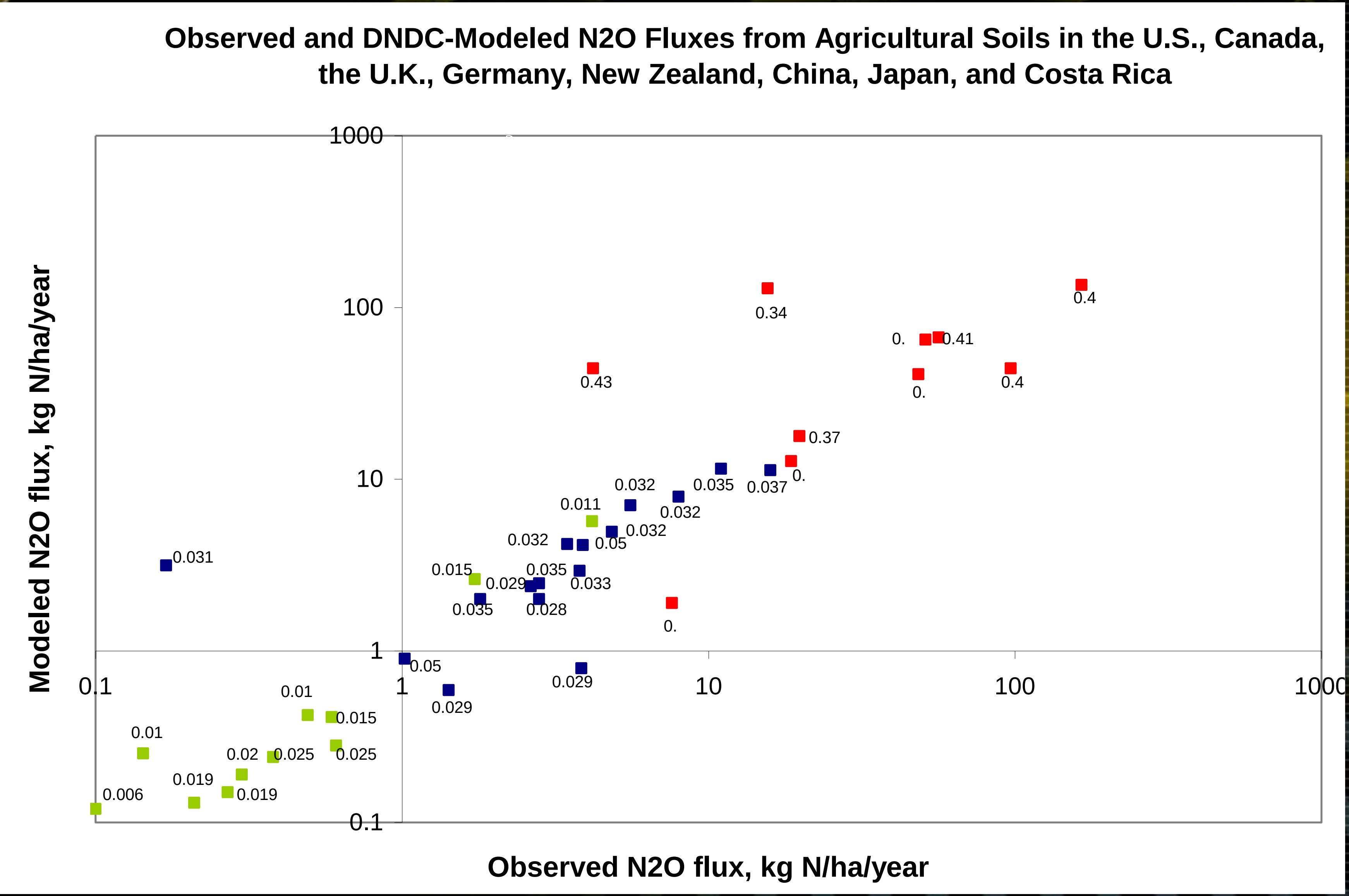
Field Measurements & Uncertainty

- Uncertainty of field measurements due to methods is quite variable.



Source: Rochette and Eriksen-Hamel, SSSAJ:72(2) March-April 2008

Nitrous Oxide Validation



Model Evaluation

Coefficient of determination, *R*^{2}
Provides a measure of how well future outcomes are likely to be predicted by the model (0-1)

$$R^2 \equiv 1 - \frac{SS_{\rm err}}{SS_{\rm tot}}.$$

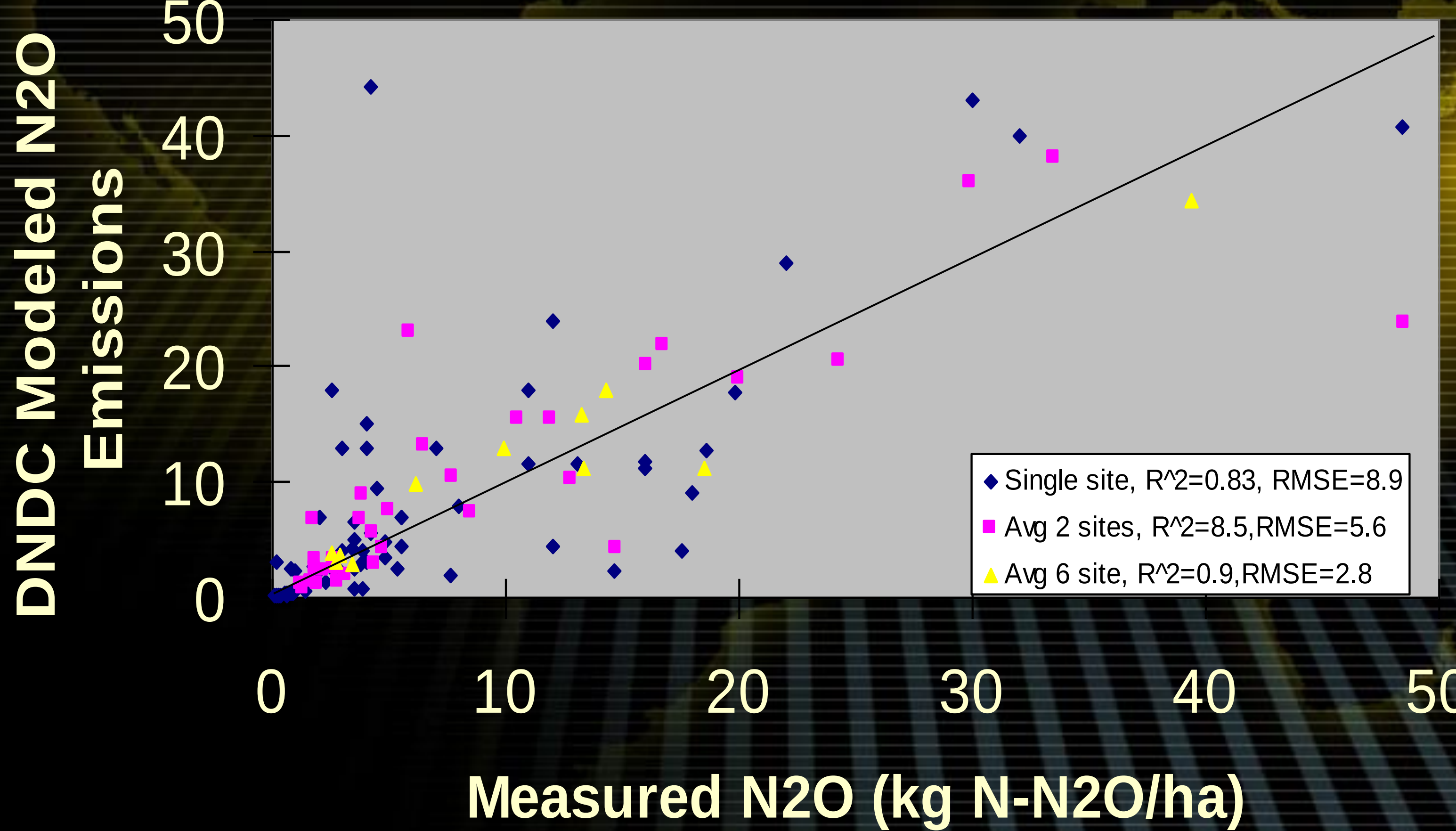
$$SS_{\rm tot} = \sum_i (y_i - \bar{y})^2,$$

$$SS_{\rm err} = \sum_i (y_i - f_i)^2$$

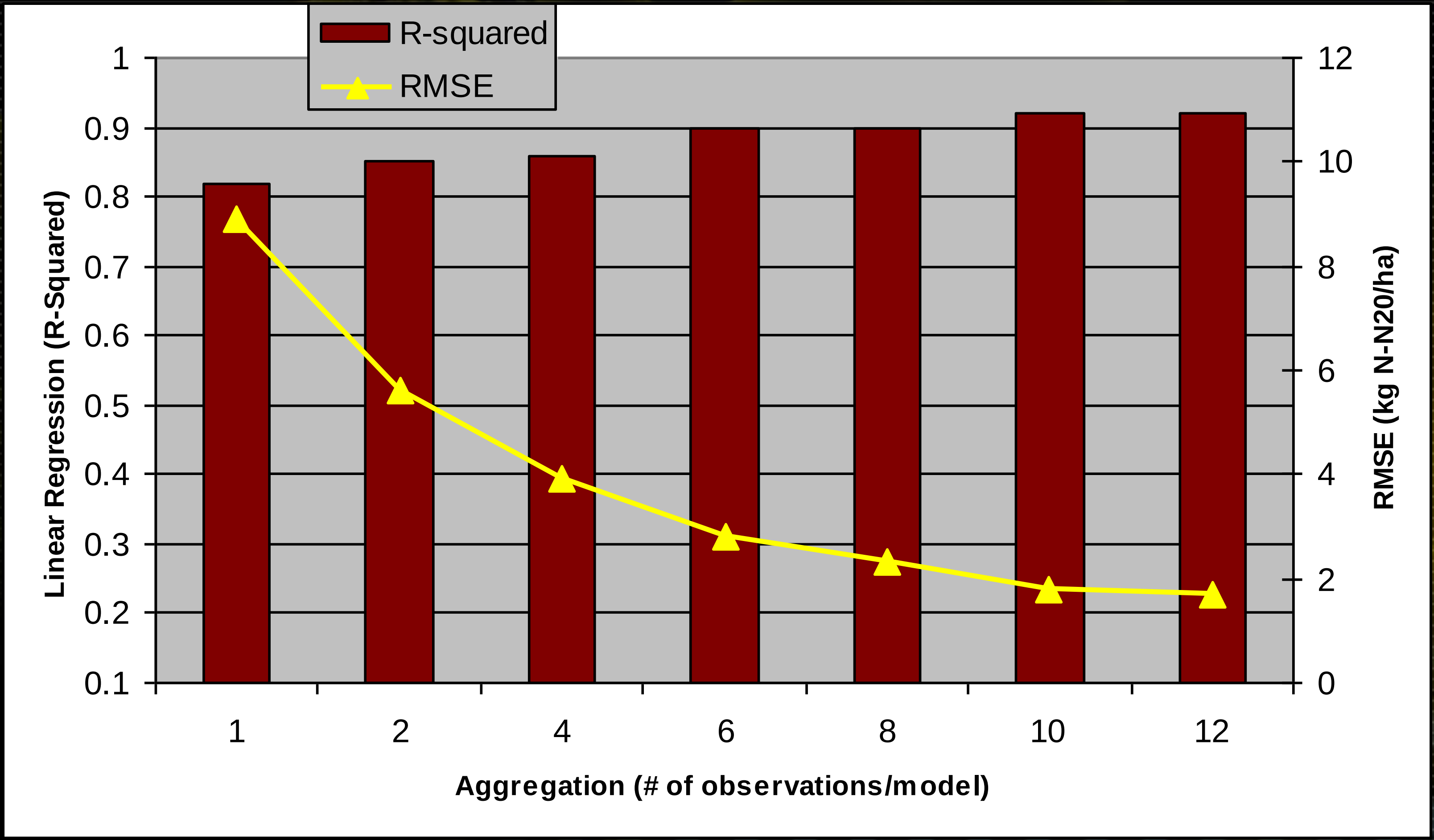
Root mean square error (RMSE)
A measure of the precision of the model in comparison with the field measurements. Units are the same as the model units.

$$\sqrt{\frac{\sum_{i=1}^{n}(x_{1,i} - x_{2,i})^2}{n}}$$

Impact of Scale: Does the model perform better when we aggregate?



Performance improves with aggregation



…implications for use in protocols and for emission inventories.

Objectives of White Paper

- Initiate discussion on how to assess uncertainty in application of biogeochemical process models for agricultural GHG offset projects.
- Identify sources of model uncertainty
- Present some statistical approaches for model evaluation – no single right criterion
- Create a “living document”
- Very rough version 0, more questions than answers

What are Process-based Models?

- Process-based, or mechanistic, modeling refers to biochemical and geochemical reactions or processes
- **Biogeochemical processes**… like decomposition, hydrolysis, nitrification, denitrification, etc…
- True process-based models **do not rely on constant emission factors**.
- They simulate and track the impact on emissions of varying conditions within soil and crop environment

Advantage of Process-based Models

- Capture impact of soils on C and N cycling and GHG emissions
- Capture variability of weather/climate on C and N cycling
- Capture impact of management practices on crop yields and GHG emissions
- Can be used to assess a wide range of ecosystems services (climate, food/fiber, air quality, water quality)
- Not limited to sites/regions where they were develop (empirical models are limited)

Disadvantage of Process-based Models

- Requires numerous datasets for calibration and validation
- Build statistics for quantitative uncertainty for GHG offsets.
- Can be difficult to use
  - ✓ Numerous inputs
  - ✓ Impact of using default input parameter

Role of process models?

Science: Interpret, integrate and extrapolate field observations – feedback between field research and modeling science

Link with spatial GIS databases for regional emissions estimates and inventories

Decision Support:

- Assess mitigation opportunities
- Quantification tools for offset protocols

Motivation for Validation and Assessing Uncertainty has Changed

- New role for models ---- moving from basic research to regional assessments/inventories and decision support and policy tools (offset protocols)
- New questions
  - ✓ Structural uncertainty versus sensitivity to inputs? Uncertainty propagation in scaling up.
  - ✓ Calibration trade-offs: ease of use versus precision/accuracy
  - ✓ Uncertainty in model estimates for changes in management: relative changes?
  - ✓ Impact of aggregation on model performance – implications for offset protocols

Quantifying Model Structural Uncertainty

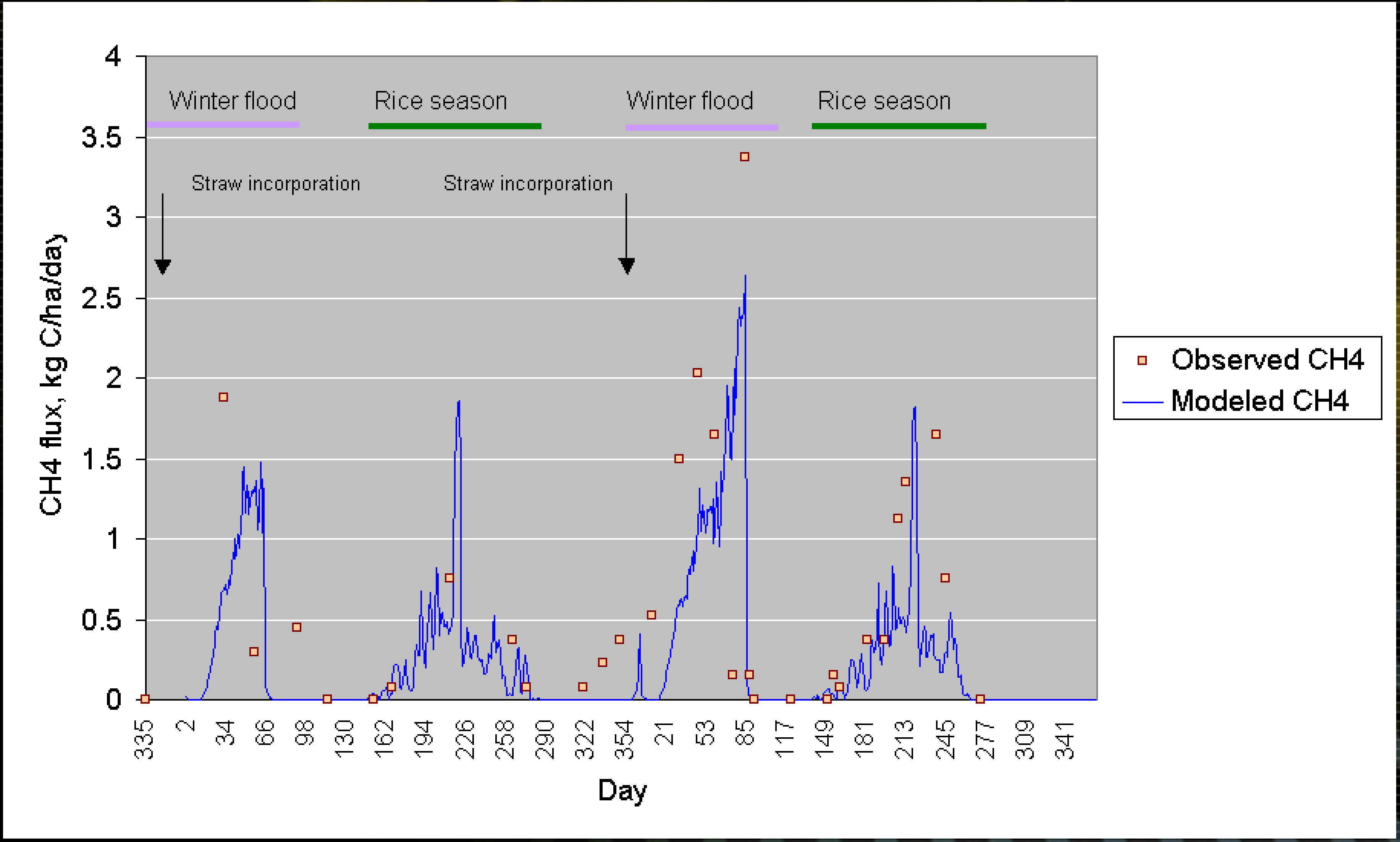
Model Structural Uncertainty

- Approach:
  - use independent validation data,
  - perform statistical analysis of modeled versus measured residuals,
  - assess heteroskedasticity, assess distribution of the residuals, etc. Note: there are non-parametric (no distribution assumed) and parametric approaches (distribution must be assumed)
- Assessing uncertainty for absolute emissions or emission reductions? Or both?
- How to define confidence intervals?

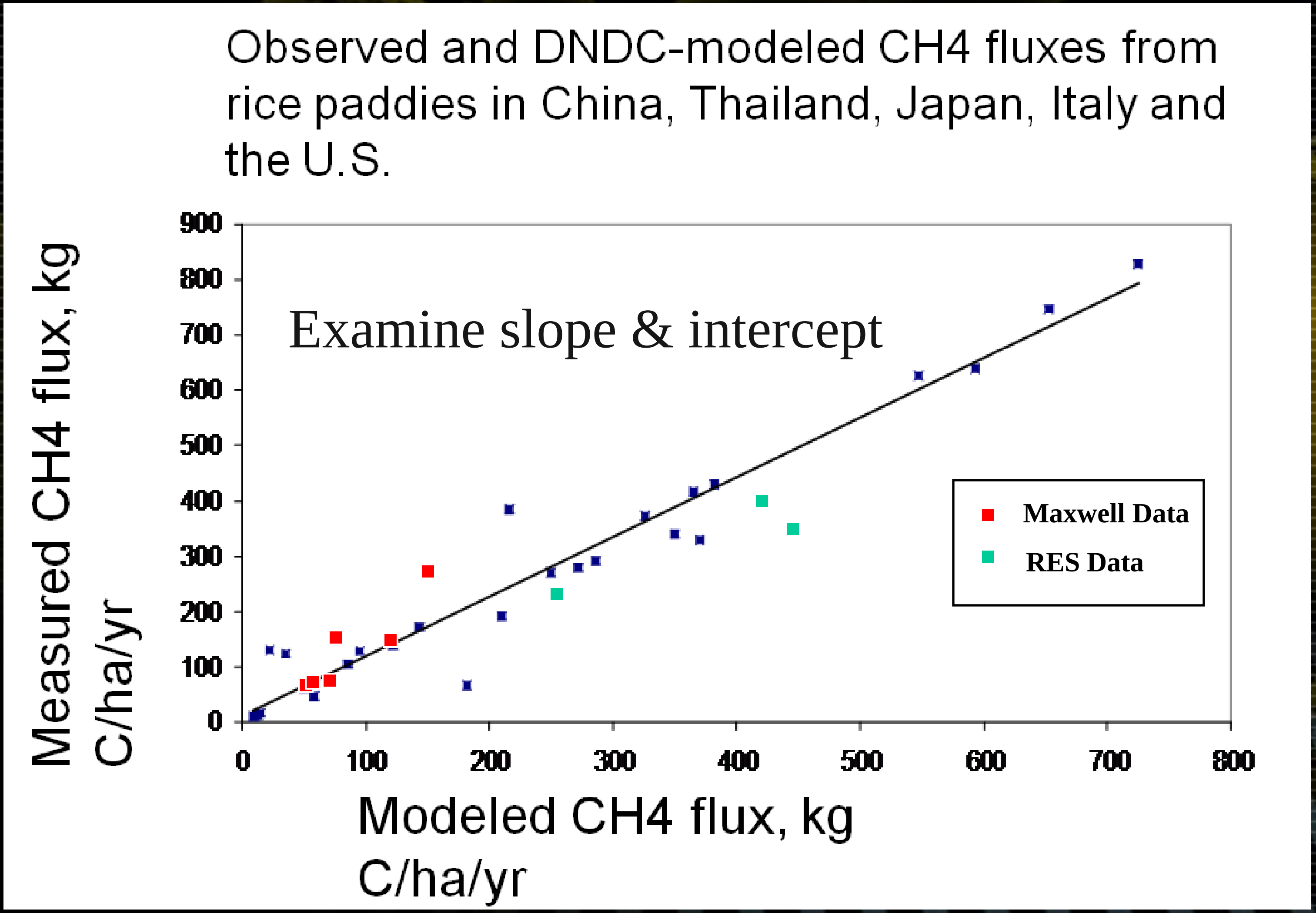
Rice Example

- Compiled validation data set for DNDC rice methane emissions
  - 99 data points (extracted from peer reviewed papers)
  - Data from Asia, Europe and U.S.
  - Range of water and crop residue management
  - Range of biophysical (soils and climate) conditions
- NB: validation data from several versions of DNDC: working on redoing the validation with a single version…

Step 1: Compile Annual Flux (modeled vs measured) at individual sites/fields



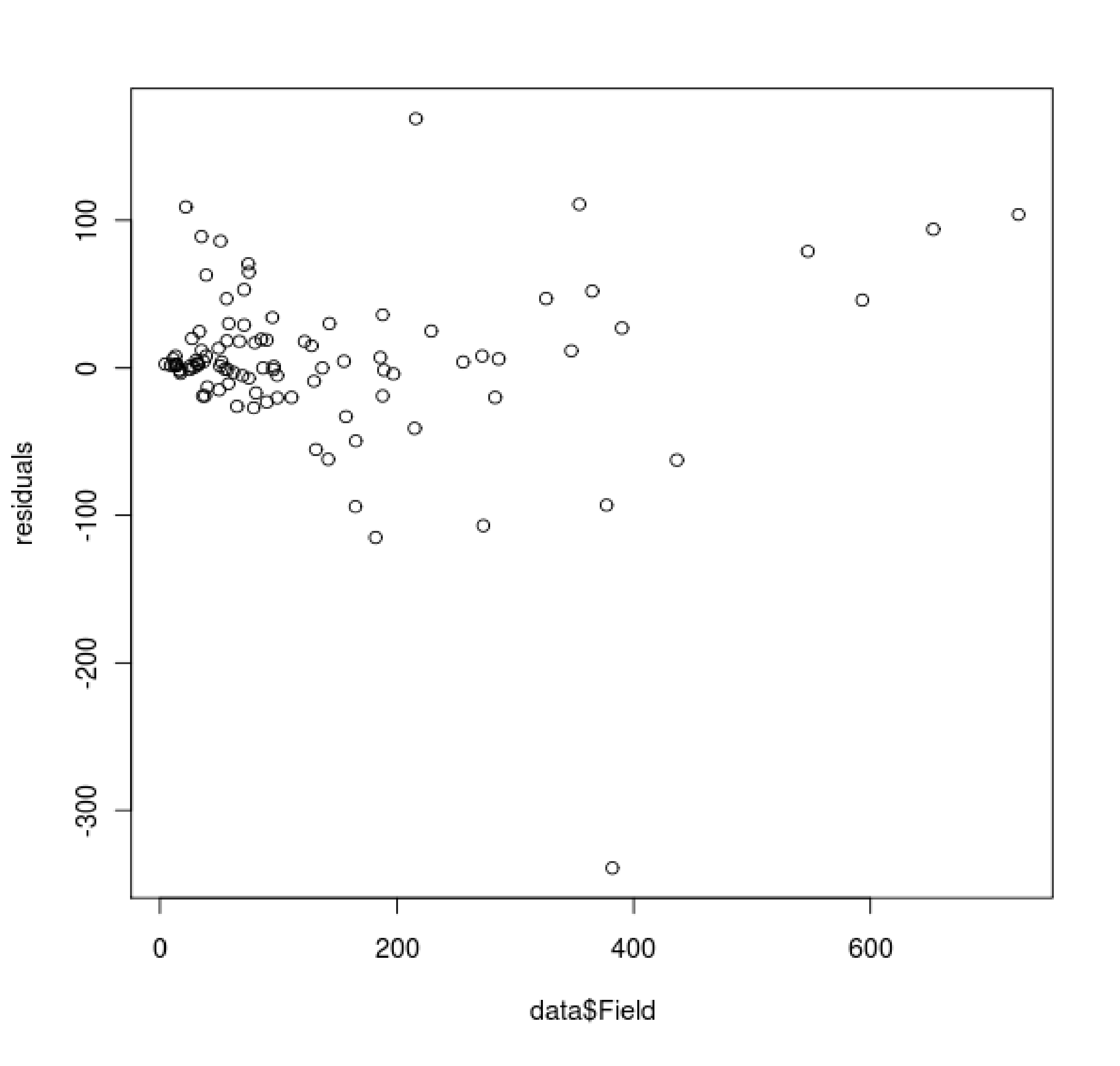
Step 2: Compile Site Validation Data



Model Structural Uncertainty: DNDC Rice CH4 Example

- The average of the modeled is 139.6 kg CH_4/ha and the average of the observed is 135.1 kg CH_4/ha.
- The median residual is 2.5 kg CH_4/ha .
- The median of the absolute value of the residuals is 18 kg CH_4/ha (i.e. 50% of the residuals are more than 18 or less than -18).
- The standard deviation of the residuals is 55.9 and the RMSE is 55.8 kg CH_4/ha .

Rice Validation Example: Residuals



Residuals do show limited heteroskedasticity. The error around observations less 100 seem to have a different distribution than the observations greater than 100 kg CH4/ha/year

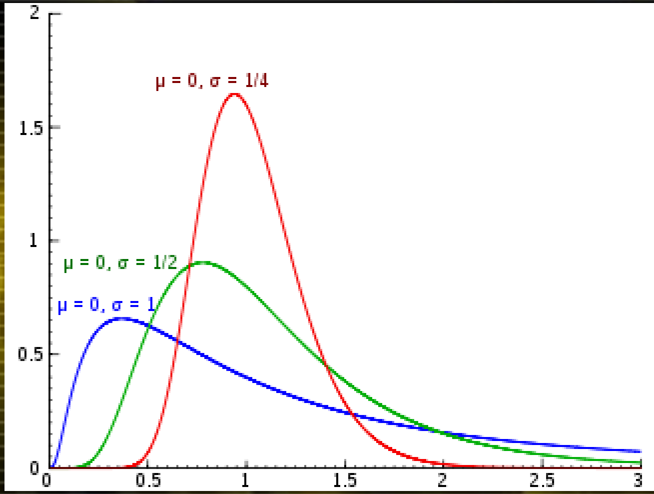
Assessing model uncertainty due to uncertainty in model inputs

Impact of Input Uncertinaties

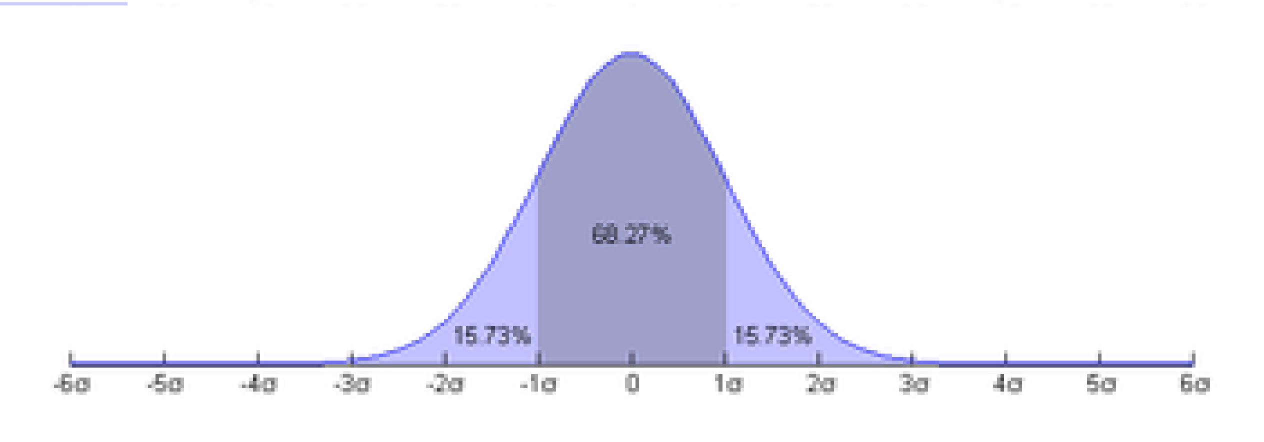
- Sources of uncertainty in input data for process models: soils, crop parameters
- How do the input uncertainties propagate through the model (sensitivity)?
- Approach: Apply Monte Carlo algorithm (perform 1000s of model runs, compile statistics on model results)
  - ✓ How to estimate parameter probability density functions (pdf)?
  - ✓ Account for covariates?

Estimating Soil Parameter PDFs

Parameter	PDF	Uncertainty
Bulk density	**Log-normal**	**0.1 g/cm^3**
Clay content	**Log-normal**	**+/- 10%**
SOC	**Log-normal**	**+/- 20%**
pH	**Normal**	**+/- 1 pH unit**



Source selected from http://www.abdn.ac.uk/modelling/cost627/Questionnaire.htm



Should we account for covariates in inputs?

- Soil parameters are correlated (e.g. texture and bulk density)
- Compiled correlation matrix based on SSURGO data for CA rice

	Clay fraction	OM fraction	Bulk Density	pH
Clay fraction	1	-	-	-
OM fraction	0.139	1	-	-
Bulk Density	-0.526	-0.685	1	-
pH	0.263	0.098	-0.126	1

Impact of input uncertainty…

- Ran Monte Carlo with DNDC for rice baseline (winter flooding) and project (no winter flooding)
- Assessed impact of accounting for covariates

	Assuming no correlation in soil input parameters		Accounting for correlation of input soil parameters	
	CH4 GWP (90% CI / Mean)	Global Warming Potential (90% CI / Mean)	CH4 GWP (90% CI / Mean)	Global Warming Potential (90% CI / Mean)
Baseline	14.7%	14.4%	14.0%	13.7%
Project	18.5%	20.0%	17.5%	19.1%
Baseline-Project	**1.0%**	**2.2%**	**0.2%**	**1.4%**

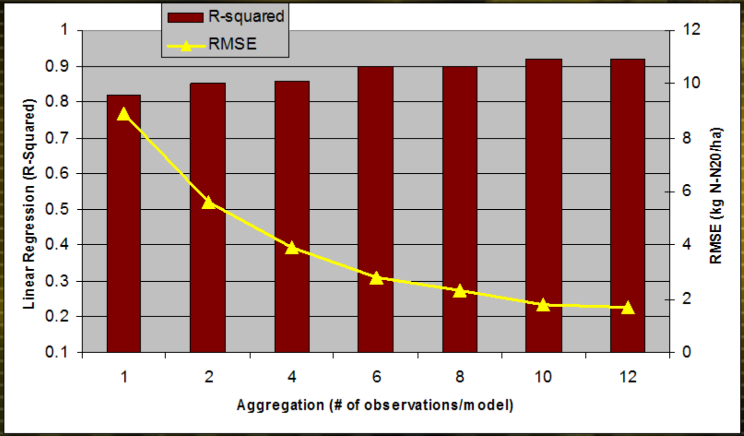
Accounting for Uncertainty in Ag GHG offset projects

Discounting Modeled Reductions

1. Ensure consistency across projects and across project types: one must standardize calculations according to the certainty of the calculations.
2. Use a confidence interval and calculate the minimum amount of credits that is generated with a certain confidence.
3. By using a deduction based on uncertainty, one does not only achieve consistency across projects, but also incentivizes better monitoring and provides flexibility for projects with a small field monitoring budget.

Role of aggregation in reducing model structural uncertainties

- Models perform better as we aggregate to multiple fields

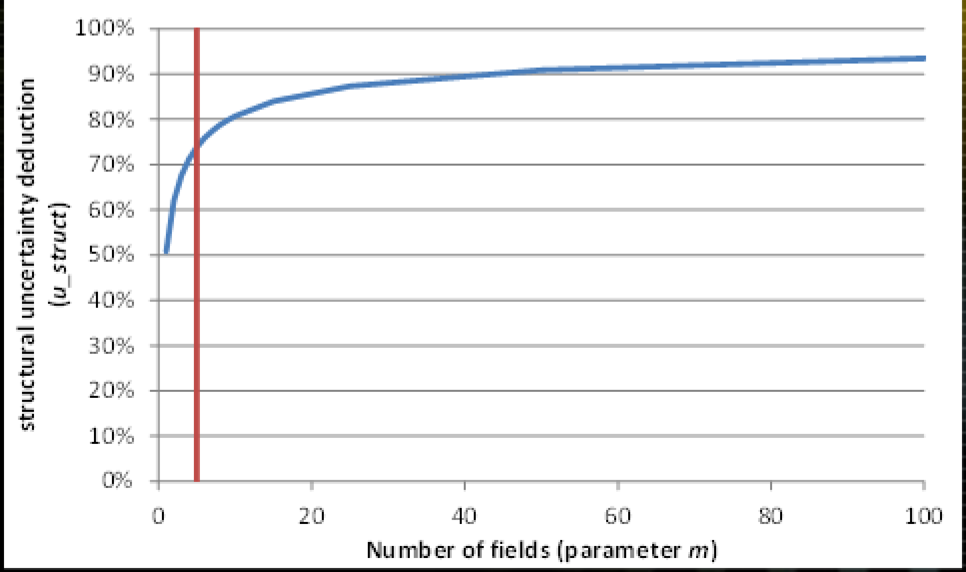


- Projects with multiple fields are likely given transaction costs
- Aggregation of multiple fields will affect uncertainty deductions…

DNDC CA Rice Example: Structural Uncertainty Deduction

- Used CA rice validation to derive structural uncertainty at 95% confidence interval

$$u_{struct}(m) = e^{\frac{-0.346}{\sqrt{m}} \cdot 1.96}$$



Number of fields (m)	u_{struct}	Eligibility
1	51%	Not eligible
2	62%	
3	68%	
4	71%	
5	74%	
6	76%	Eligible
7	77%	
8	79%	
9	80%	
10	81%	
15	84%	
25	87%	
50	91%	
100	93%	
1000	98%	

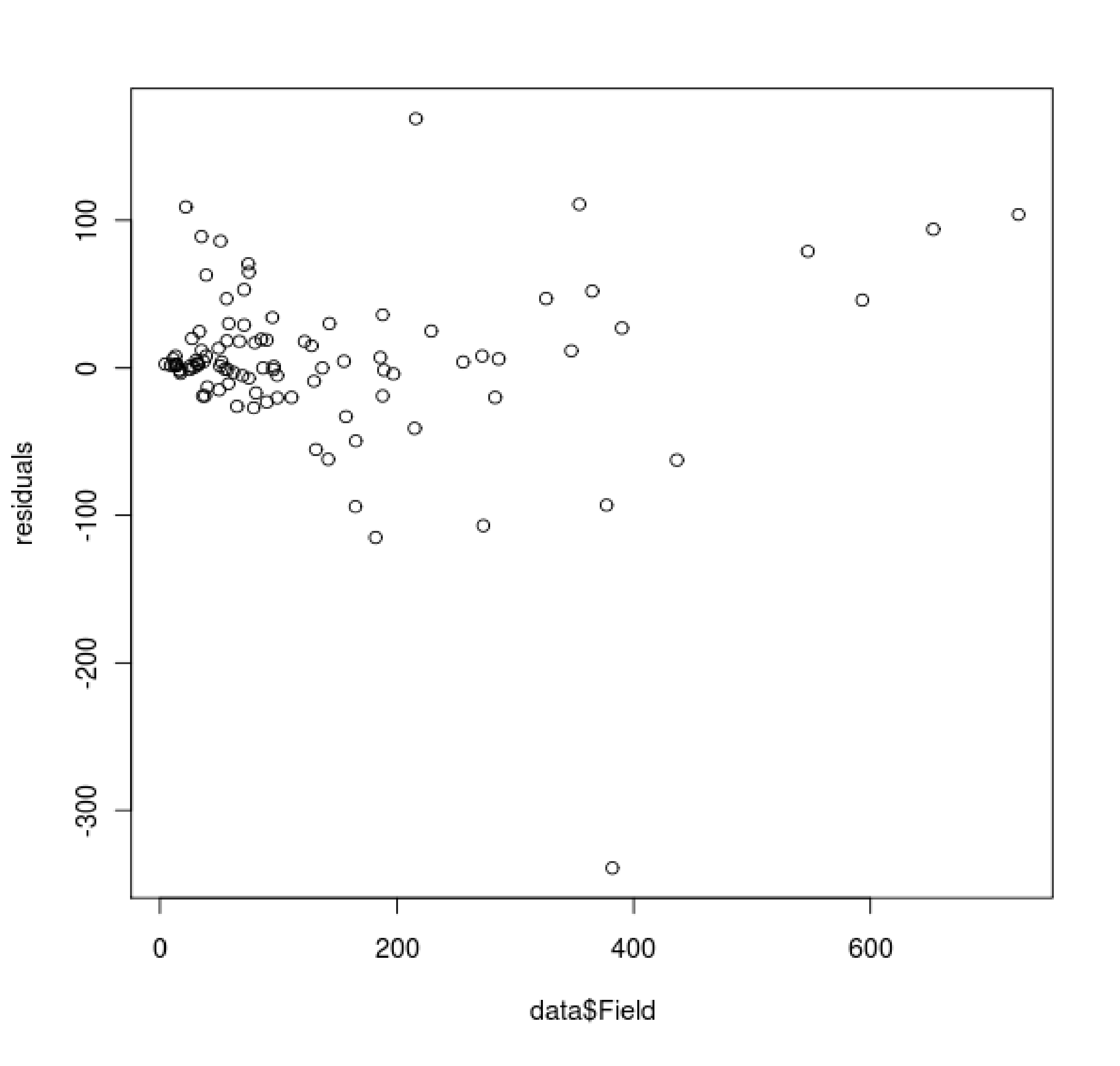
Accounting for interactions between model structural uncertainties and uncertainty from input parameters…

- Simplest assumption (and most conservative) is to combine both sources of uncertainty

$$ER_y = \mu_{struct} * \sum_{i=1}^{m} \mu_{inputs\_i} * (GHG_{BSL,i} - GHG_{P,i}) * A_i$$

- Alternative approach is to account for correlation between sources of uncertainty

Rice Validation Example:



Larger errors with higher emissions

Soil texture has significant impact on magnitude of emissions.

Does structural uncertainty increase with coarser soils???

Characteristics of Approach:

- Based on process-based biogeochemical model
- Model uncertainty is handled through deduction system
- Explicit quantification of uncertainty using measured data is required
  - ✓ Only specific practices and geographic regions are included
- Incentivizes “aggregation” of fields within one project
  - ✓ Fields managed by different growers are combined within one project through an third party: “aggregating entity”
  - ✓ More fields => Smaller uncertainty => More credits

Next Steps for White Paper…

- Add example of model structural uncertainty calculations
- Assess Mixed Effects Approach for extending model applicability
- Expand discussion in annotated outline sections
- Get and incorporate feedback from C-AGG community.
- C-AGG workgroup for further discussion??

Thank you!

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C-AGG Feedback…

- **Process Model Calibration and Validation: What is sufficient?**
  - ✓ Short summary of parameterization, calibration and validation process
  - ✓ How do we demonstrate that models have been sufficiently calibrated?
  - ✓ When is re-calibration needed? Differences in crop varieties, differences in cultural practices, soil biophysical and climate drivers…What statistical approaches should be used to assess the need for re-calibration? (See mixed effects discussion)

C-AGG Feedback…

- **Quantifying model structural uncertainty**
  - ✓ Should the structural uncertainty be estimated for both absolute emissions and emission reductions?
  - ✓ What is the appropriate uncertainty metric? RMSE or % deviation. Dividing the error in different components: lack of correlation, non-unity slope, and bias
  - ✓ How to define confidence intervals? As a factor of the average or absolute amount (related to assumption on distribution)
  - ✓ Minimum number of validation points for deriving structural uncertainty metrics?
  - ✓ Using local/regional/global datasets: (relates to the question regarding recalibration)

C-AGG Feedback…

- ✓ Discuss sources of uncertainty in input data for process models?
- ✓ Applying Monte Carlo approach to changes in emissions (given the context of offset protocols)
  - ➢ How to estimate parameter pdfs?
  - ➢ Accounting for covariates in input parameters (e.g. soil SOM and clay fraction)?
- ✓ Discuss tradeoffs between measurements and other input. Examine approaches for integrating a sensitivity analysis of parameters with costs to measure parameters and thus create a graph of uncertainty vs. cost