Plans for Accounting for Observational Uncertainty in ILAMB

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A Few Miscellaneous Items

- ILAMB v2.4 released, now python3 only
- ILAMB v2.3.1 is last tag for python2.7x
- Using Slack for development:

  `ilamb-community.slack.com`

- Mailing list:

  `https://www.ilamb.org/mailman/listinfo/ilamb-users`

Current Score Methodology - Bias

Relative error is normalized by the variability in the reference:

$$\varepsilon_{rel}(\mathbf{x}) = \frac{|\overline{v}_{mod}(\mathbf{x}) - \overline{v}_{ref}(\mathbf{x})|}{var(v_{ref}(t,\mathbf{x}))}$$

Spatial score:

$$s(\mathbf{x}) = e^{-\varepsilon_{rel}(\mathbf{x})}, \quad S = \frac{1}{A(\Omega)} \int_{\Omega} s(\mathbf{x}) d\Omega$$

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Problems:

- Models are penalized for any deviation from the reference, no matter how poor the reference
- For a collection of reference datasets, a perfect score is impossible
- Worse, the maximum possible score will be dependent on the number of datasets

Including Uncertainty - Accumulative Global NBP

Normalize by uncertainty (denoted $\Delta v_{ref}(t)$):

$$\varepsilon_{rel}(t) = \frac{\max(|v_{mod}(t) - v_{ref}(t)| - \Delta v_{ref}(t), 0)}{\Delta v_{ref}(t)}$$

Score:

$$s(t) = e^{-\varepsilon_{rel}(t)}, \quad S = \frac{1}{t_f - t_0} \int s(t)dt$$

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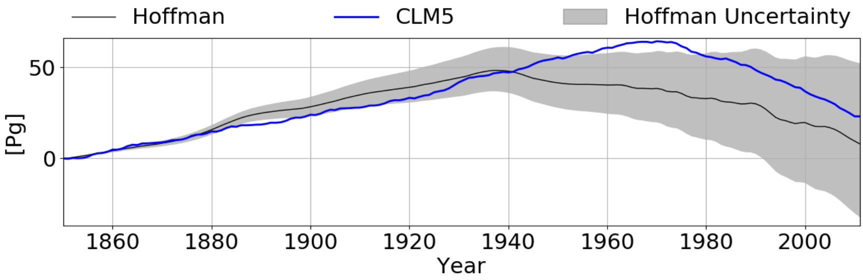
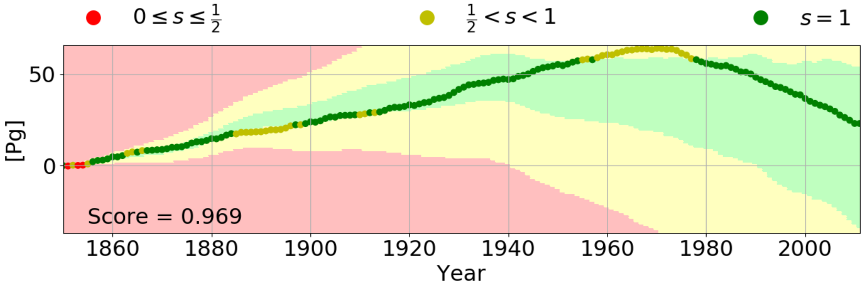
Features:

- perfect score if the model is within the uncertainty
- penalized for bias beyond the uncertainty
- we have no business discriminating models who fall within the uncertainty
- a 'large' bias is relative to our certainty only

Including Uncertainty - Accumulative Global NBP





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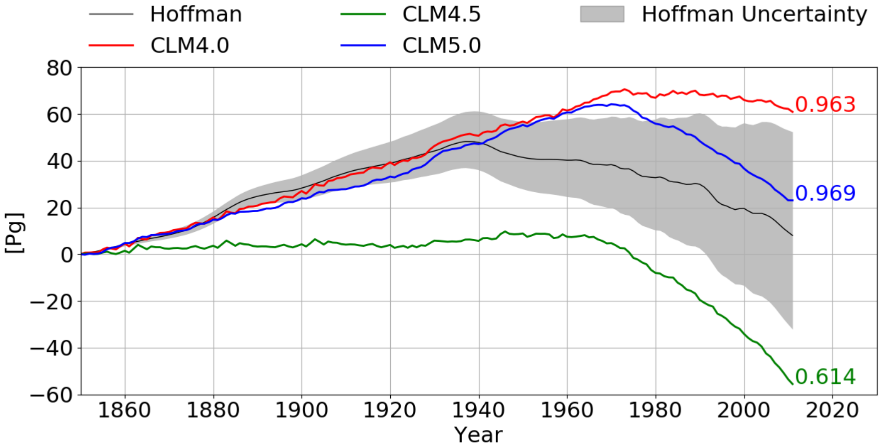

Another example - Evapotranspiration

Created a new ET 'data product':

- value = mean(GLEAM,MODIS)
- uncertainty = std(GLEAM,MODIS)

Another normalization option:

$$\varepsilon_{rel}(t,\mathbf{x}) = \frac{\max(|v_{mod}(t,\mathbf{x}) - v_{ref}(t,\mathbf{x})| - \Delta v_{ref}(t,\mathbf{x}), 0)}{var(v_{ref}(t,\mathbf{x}))}$$

Score:

$$s(\mathbf{x}) = \frac{1}{t_f - t_0}\int e^{-\varepsilon_{rel}(t,\mathbf{x})}dt, \quad S = \frac{1}{A(\Omega)}\int_\Omega s(\mathbf{x})d\Omega$$

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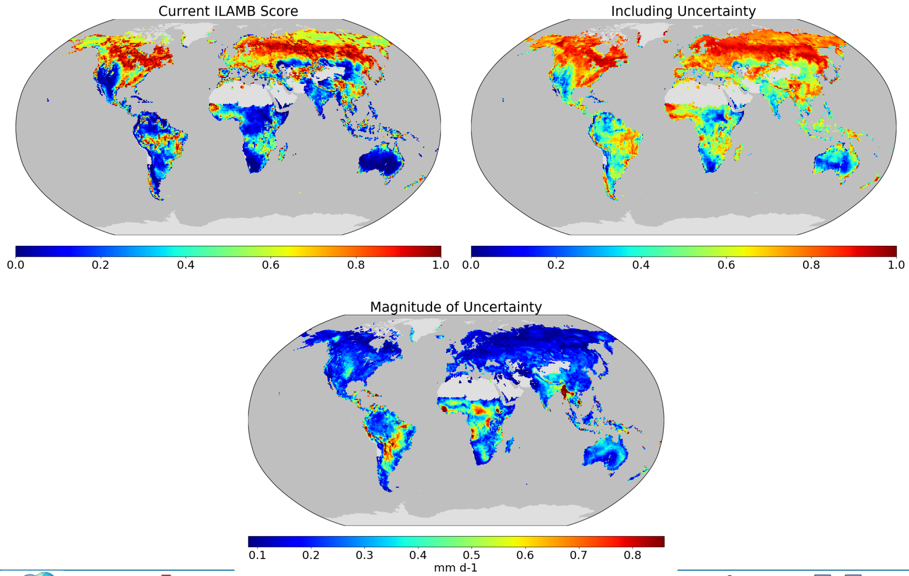

Open Questions

- Does the 'perfect in the envelope' philosophy make sense?
- What kind of relative error normalization should we use?
- In the cases where we have multiple datasets, is it valuable to generate mean composite datasets with uncertainty?
- We could make a separate ILAMB configure file and collection of data for uncertainty experiments
- Or should we rather assign expertly judged uncertainty to currently curated datasets?