

# Statistical upscaling of terrestrial greenhouse gas emissions

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# Upscaling

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- Upscaling is taken as synonymous to *aggregation*, where the interest is in obtaining an integrated value of a variable over an area or volume of a given size and/or a time interval of given length
  - Example: chambers may measure emission over 30 minutes for a 0.25 m<sup>2</sup> surface, whereas the interest is in annual values for a large region or country
  - Upscaling is based on 'point' observations, but perhaps auxiliary information can be used to improve accuracy
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# Two fundamentally different approaches to

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## upscaling **Design-based**

- Makes no assumption about space-time variability structure ('model-free')
- Does not suffer from making wrong assumptions
- Locations of observations must be selected with probability sampling, usually simple random sampling
- Simple random sampling may be replaced with more efficient designs (e.g. stratified sampling, two-phase random sampling, cluster sampling)
- Widespread misconception that design-based methods cannot be applied when there is spatial (temporal) correlation
- ~~Problems with scarce data and preferential sampling~~

# Two fundamentally different approaches to

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## 2. upscaling Model-based

- Assumes a (statistical) model that characterises the space-time behaviour of the variable of interest
- Statistical model because space-time behaviour is partially unpredictable: include stochastic term to represent uncertainty
- Model also includes a deterministic trend, ranging from an unknown constant to a complex process model such as DNDC:  $Z(x,t) = m(x,t) + \varepsilon(x,t)$
- Given the model, trend and observations, estimates of upscaled variable are obtained with block-kriging
- Model-based more flexible and potentially more efficient than design-based, but makes assumptions

# Model-based upscaling: two main steps

point-support data at measurement locations

interpolation

spatial coverage of point-support data

aggregation

spatial coverage of block-support data

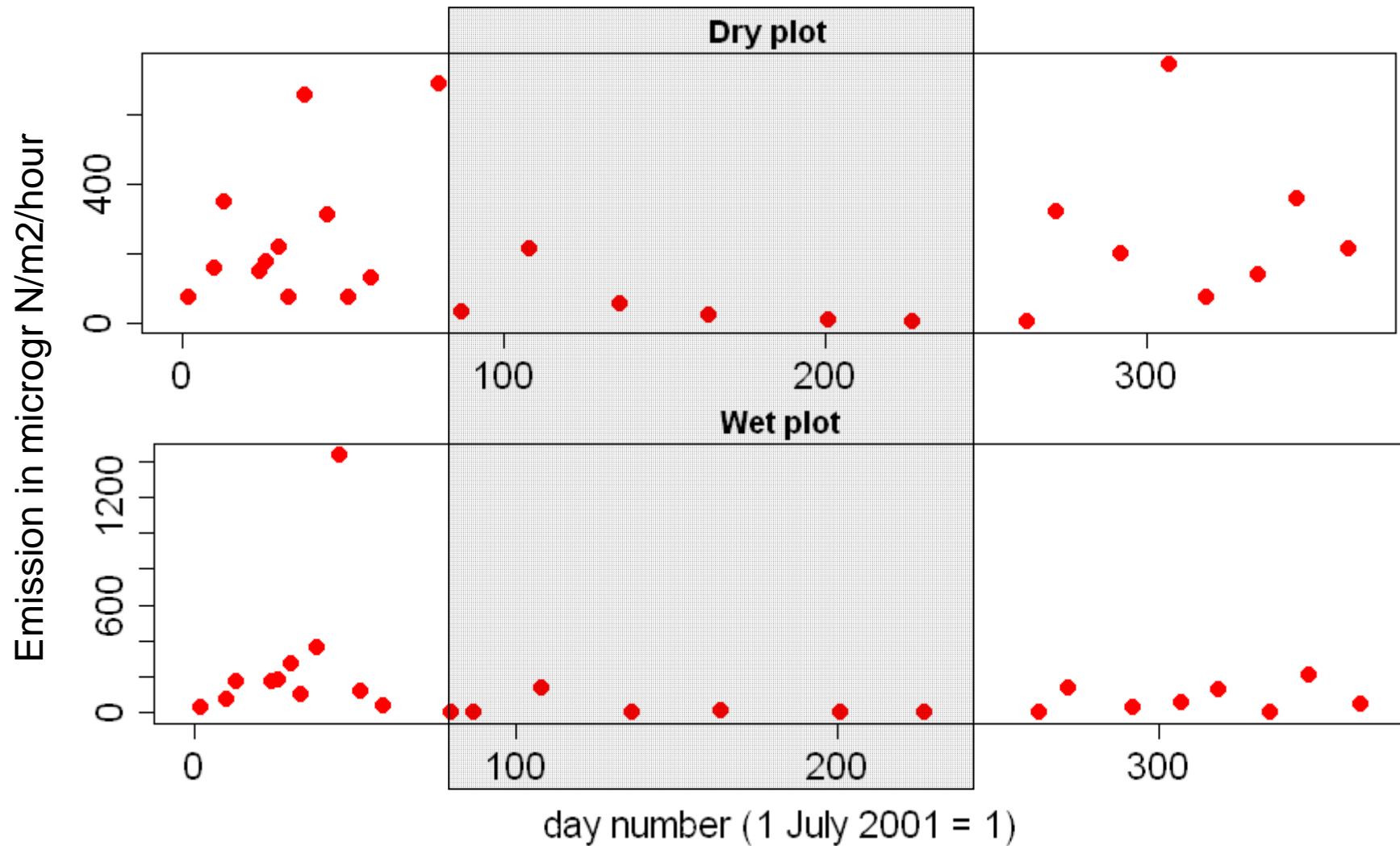
**HARD**  
**EASY**

## Example design-based upscaling

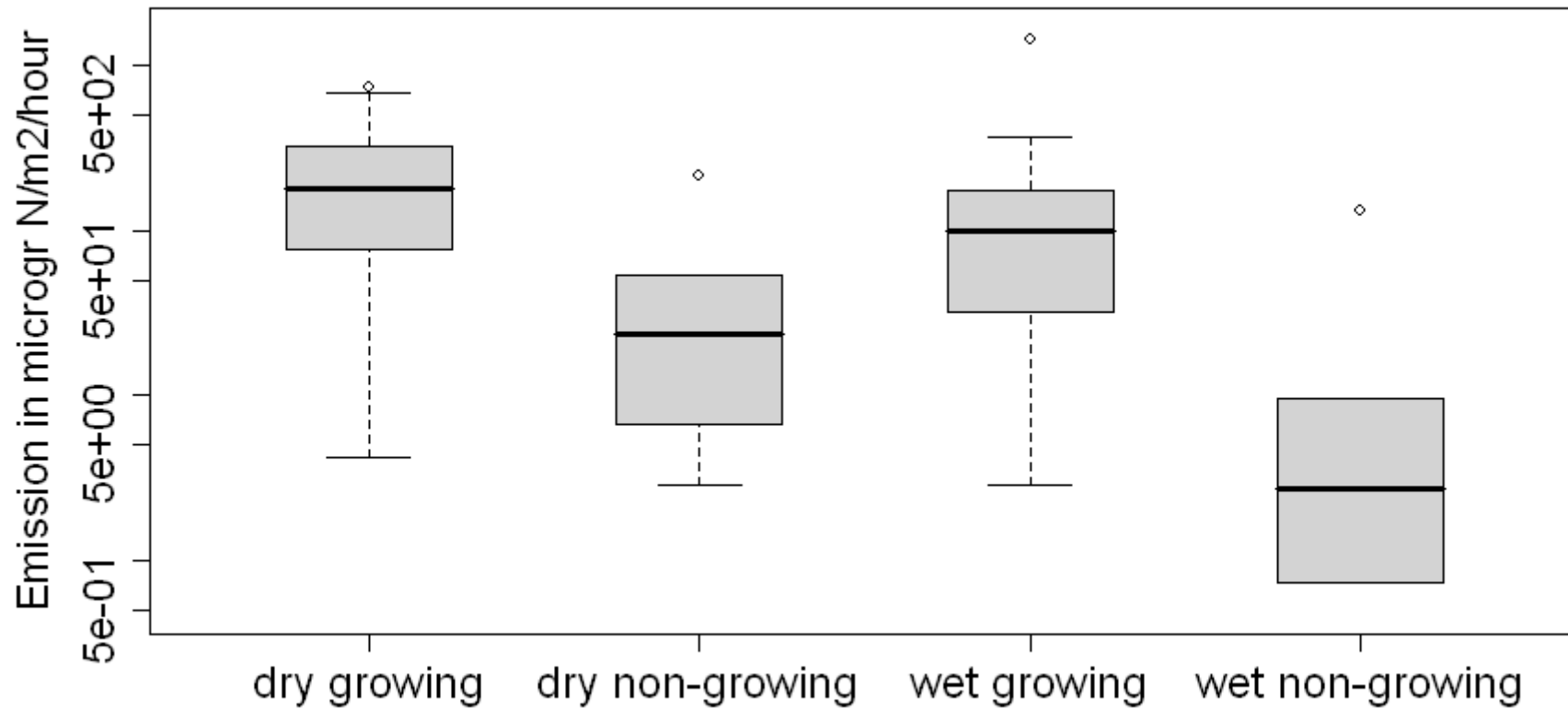
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- Aggregation over time only: from half-hour chamber measurements to annual average (1 July 2001 to 30 June 2002)
- N<sub>2</sub>O measured at 26 times for two grassland parcels (dry and wet) in Western Dutch peat soil area
- Assume stratified random sampling with two strata: growing season (1 March to 30 September) and non-growing season
- Higher sampling density in growing season

# Measurements over time



# Box plots show differences between plots and season





# Statistical inference

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$$\mu = \frac{T_{\sigma g}}{T} \mu_{\sigma g} + \frac{T_n}{T} \mu_n$$

$$\hat{\sigma}_{\sigma g}^2 = s_{\sigma g}^2 = \frac{1}{n_{\sigma g} - 1} \sum_{i=1}^{n_{\sigma g}} (x_{\sigma gi} - \bar{x}_{\sigma g})^2$$

$$\hat{\mu}_{\sigma g} = \bar{x}_{\sigma g} = \frac{1}{n_{\sigma g}} \sum_{i=1}^{n_{\sigma g}} x_{\sigma gi}$$

$$\hat{\mu} = \frac{T_{\sigma g}}{T} \hat{\mu}_{\sigma g} + \frac{T_n}{T} \hat{\mu}_n$$

$$\sigma(\mu_{\sigma g} - \hat{\mu}_{\sigma g}) = \frac{\sigma_{\sigma g}}{\sqrt{n_{\sigma g}}}$$

$$\sigma(\mu - \hat{\mu}) = \sqrt{\left(\frac{T_{\sigma g}}{T}\right)^2 \frac{\sigma_{\sigma g}^2}{n_{\sigma g}} + \left(\frac{T_n}{T}\right)^2 \frac{\sigma_n^2}{n_n}}$$

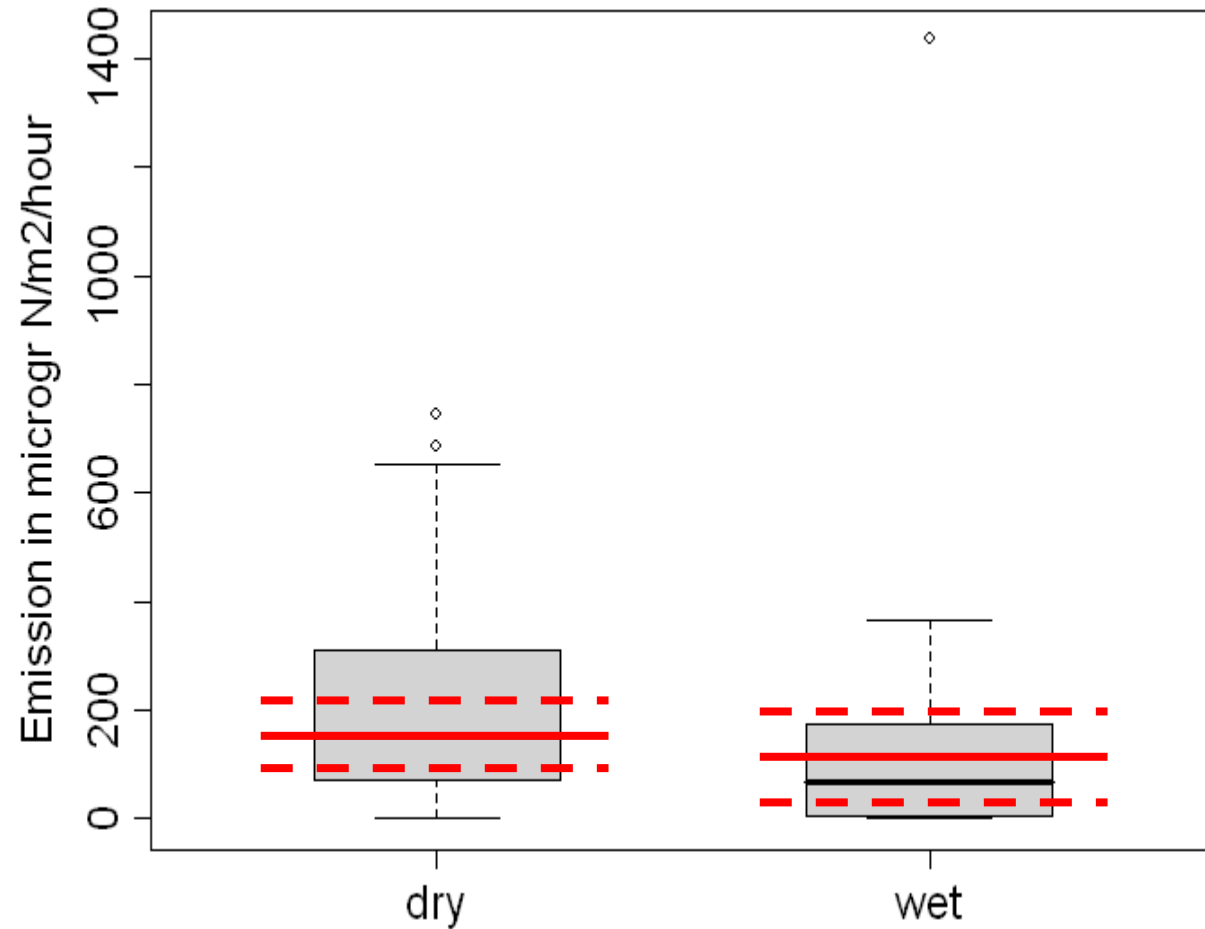
# Results (recall n=26)

$$\hat{\mu}_{\text{dry}} = 168.6$$

$$\sigma(\mu_{\text{dry}} - \hat{\mu}_{\text{dry}}) = 31.8$$

$$\hat{\mu}_{\text{wet}} = 112.5$$

$$\sigma(\mu_{\text{wet}} - \hat{\mu}_{\text{wet}}) = 40.6$$



## Example model-based upscaling

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- N<sub>2</sub>O emission in natural areas in Europe, data from (after screening 115 observations remain):
  - NOFRETETE
  - Stehfest and Bouwman
  - Denier van der Gon
  
- Candidate predictors (auxiliary information incorporated in trend):
  - Climate (precipitation, nr frost days, temperature)
  - Soil (pH, organic carbon, texture, CN ratio, bulk density)
  - N deposition
  - Vegetation type (coniferous, deciduous, grass&heath)
  
- Use regression kriging

# Regression-kriging

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target variable = f(explanatory variables) + stochastic residual

possibly spatially  
autocorrelated



Example:

$$\log(\text{N}_2\text{O}) = \beta_0 + \beta_1 \cdot f(\text{Prec}) + \beta_2 \cdot \log(\text{N}_{\text{dep}}) + \beta_3 \cdot \text{pH}_{\text{soil}} + \beta_4 \cdot \text{OrgC}_{\text{soil}} + \beta_5 \cdot \text{vegtype} + \beta_6 \cdot \text{nr}_{\text{frost days}} + \varepsilon$$

# Steps in regression kriging upscaling

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- Build and fit regression model using emission and predictor data (auxiliary information)
- Run regression model for the whole of (natural) Europe
- Compute regression residuals at measurement locations
- Estimate spatial correlation structure of residuals
- Interpolate residuals using kriging
- Add interpolated residual to regression model output
- Slightly better approach is to integrate estimation of regression coefficients and kriging of residuals (WLS instead of OLS)
- Aggregate resulting map to desired support (e.g. compute average emission over regions or nations)

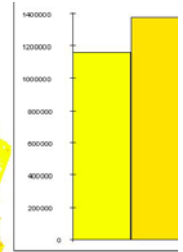
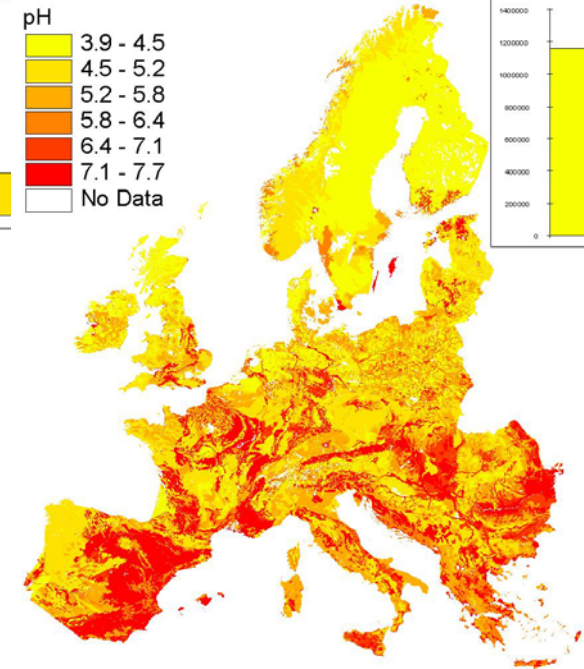
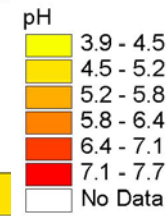
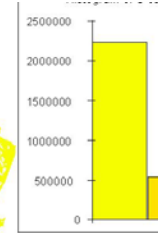
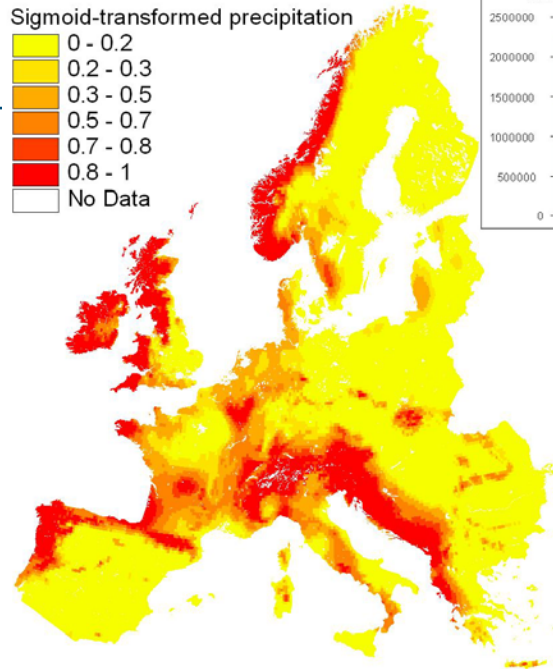
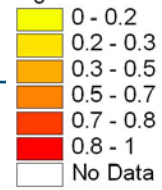
# Regression model and parameter estimates based on 115 observations across Europe

$$\log(\text{N}_2\text{O}) = \beta_0 + \beta_1 \cdot \text{Sigmoid}(\text{Prec}) + \beta_2 \cdot \log(\text{N}_{\text{dep}}) + \beta_3 \cdot \text{pH}_{\text{soil}} + \beta_4 \cdot \text{OrgC}_{\text{soil}} + \beta_5 \cdot \text{Indicator}(\text{deciduous}) + \beta_6 \cdot \frac{\text{nr frost days}}{365} + \varepsilon$$

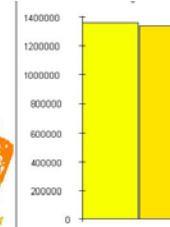
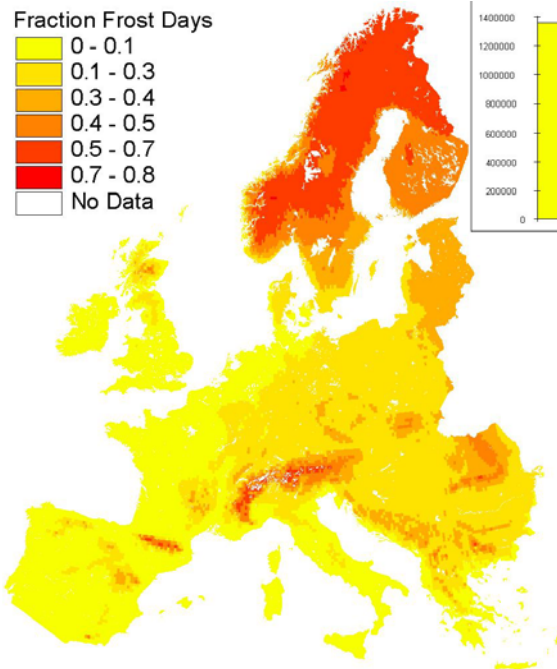
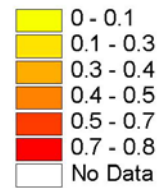
$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$	$\beta_6$
0.170	-0.246	0.214	-0.082	0.010	0.287	0.725

# Predictor maps

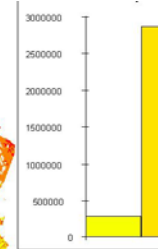
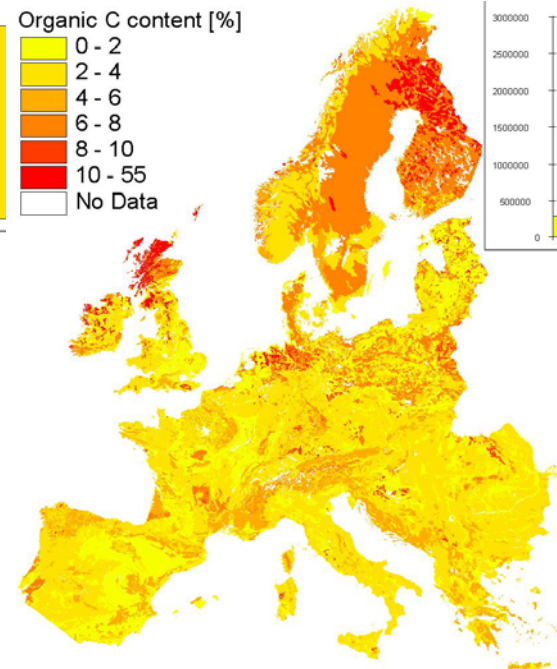
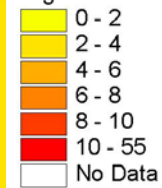
Sigmoid-transformed precipitation



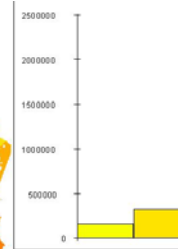
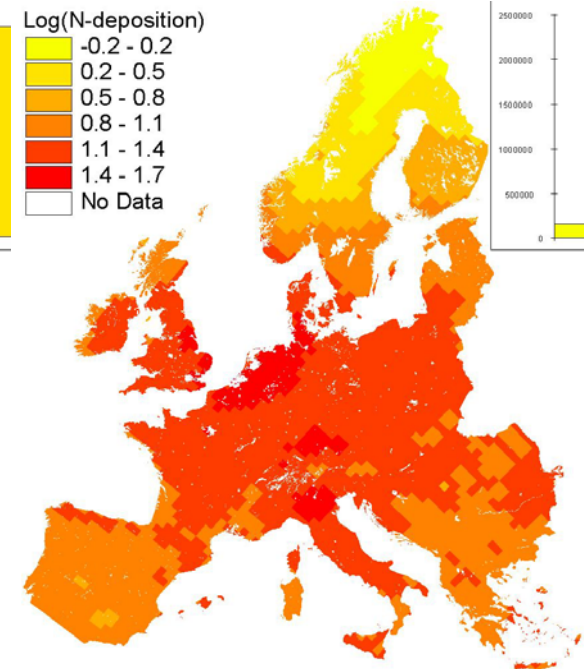
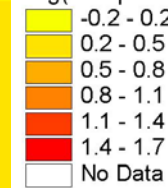
Fraction Frost Days



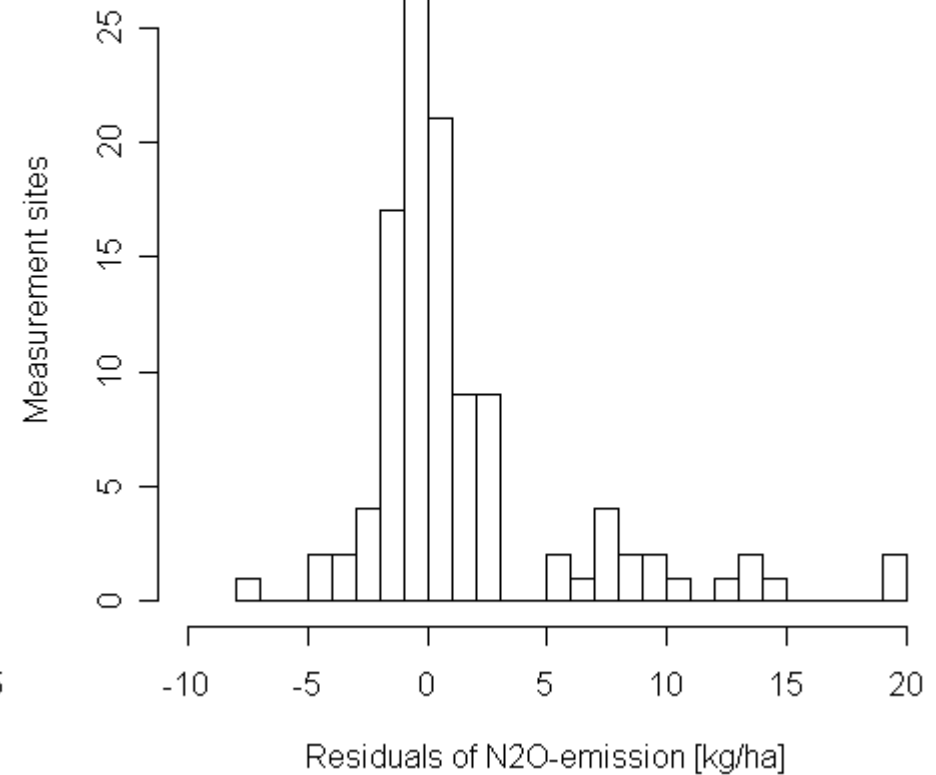
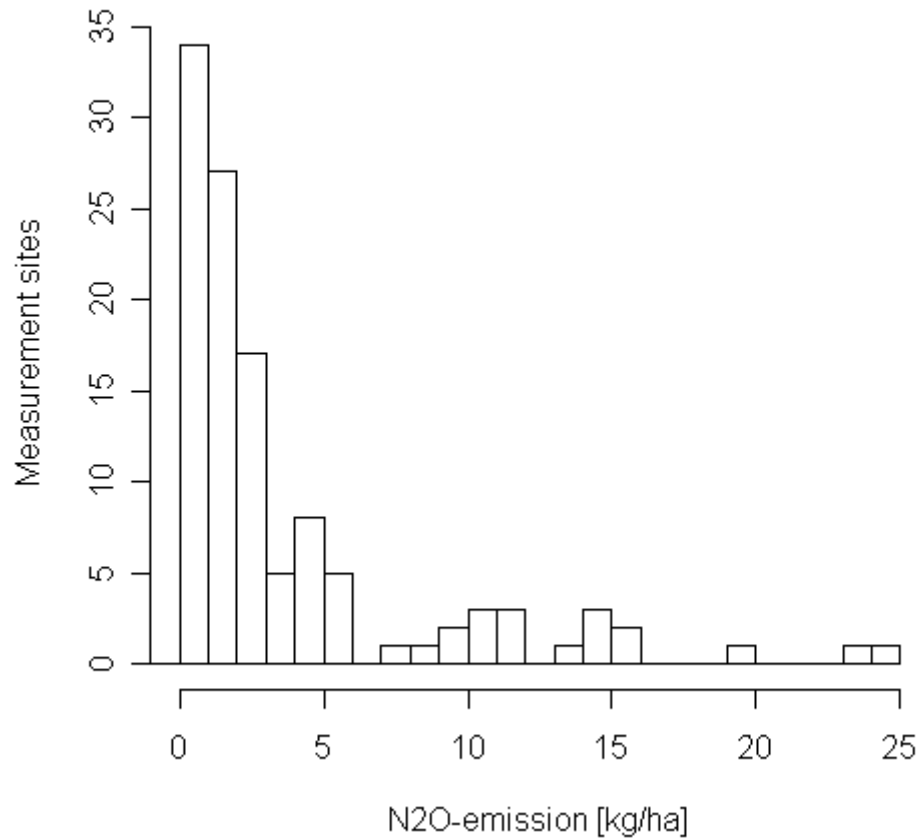
Organic C content [%]



Log(N-deposition)



# Regression explains little variation ( $R^2=0.20$ )

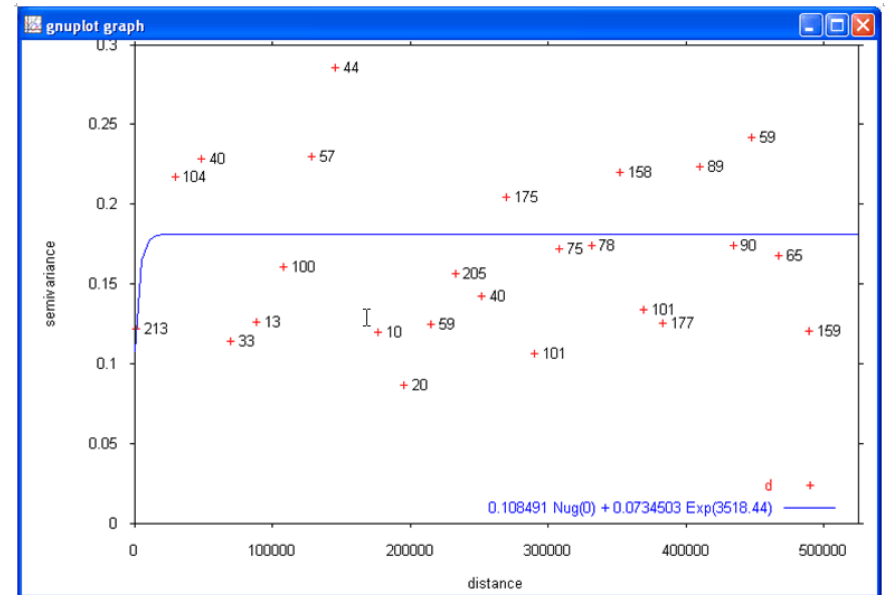
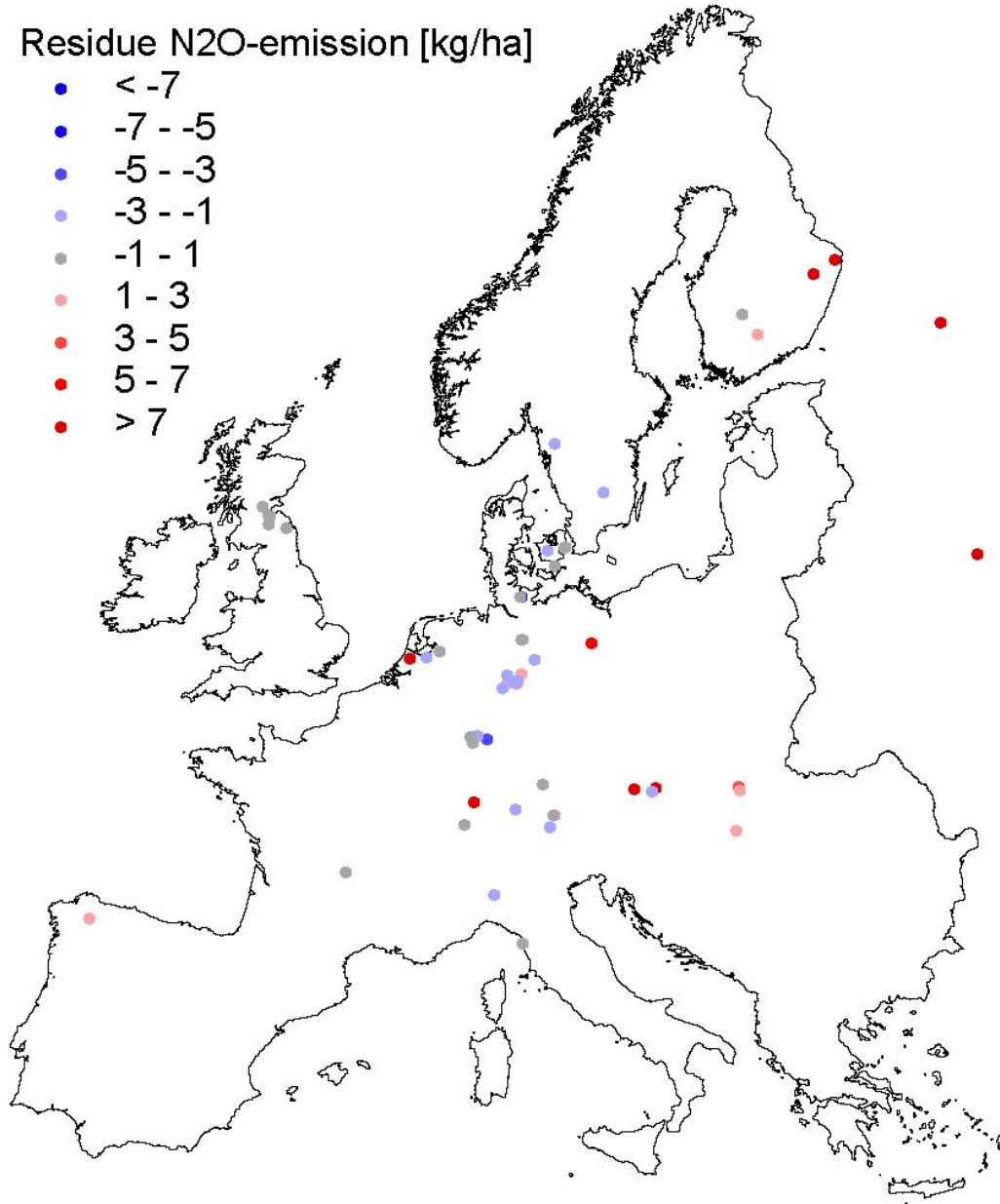




# Residual weakly spatially correlated

Residue N<sub>2</sub>O-emission [kg/ha]

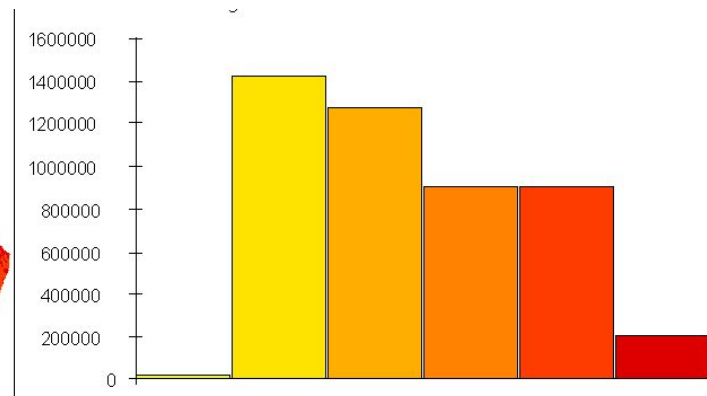
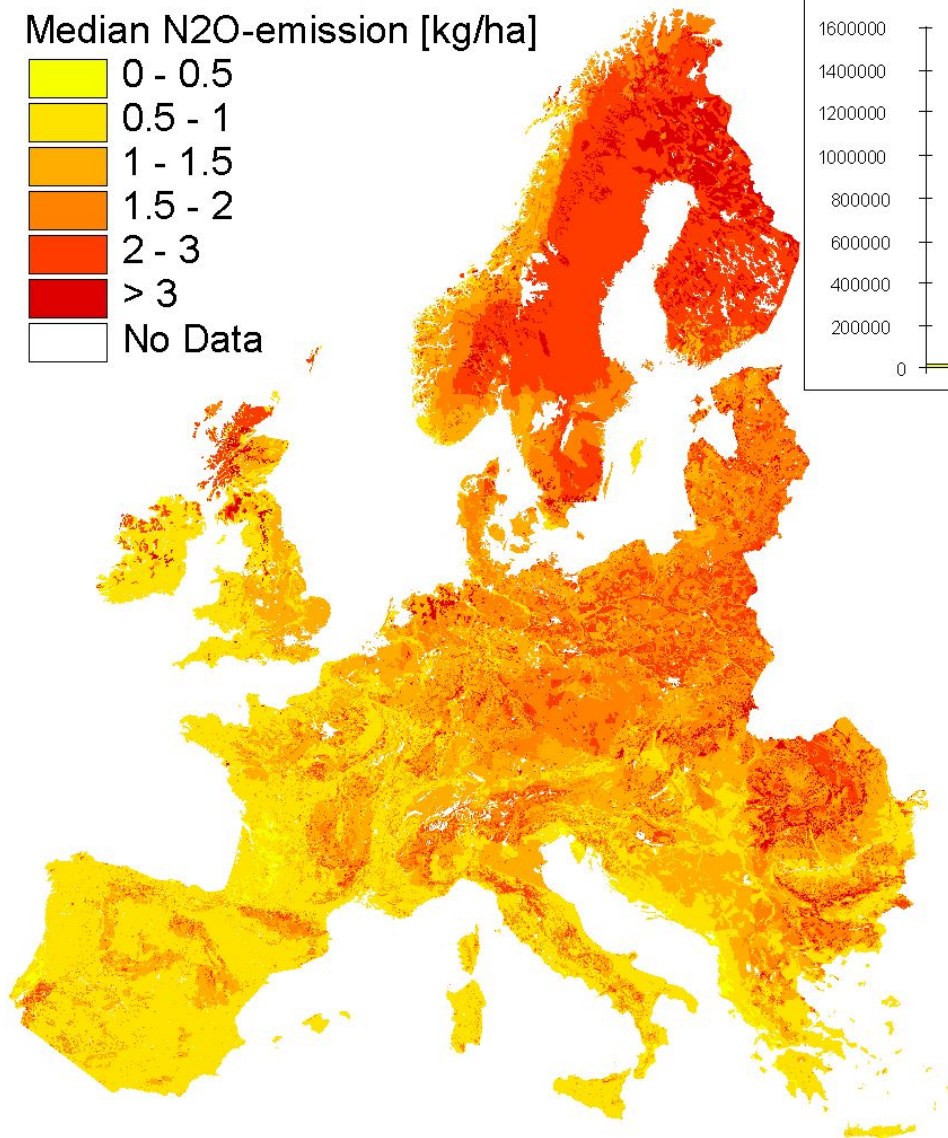
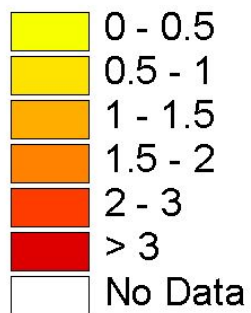
- < -7
- -7 - -5
- -5 - -3
- -3 - -1
- -1 - 1
- 1 - 3
- 3 - 5
- 5 - 7
- > 7



# Regression kriging result: median N<sub>2</sub>O emission

(natural areas only)

Median N<sub>2</sub>O-emission [kg/ha]

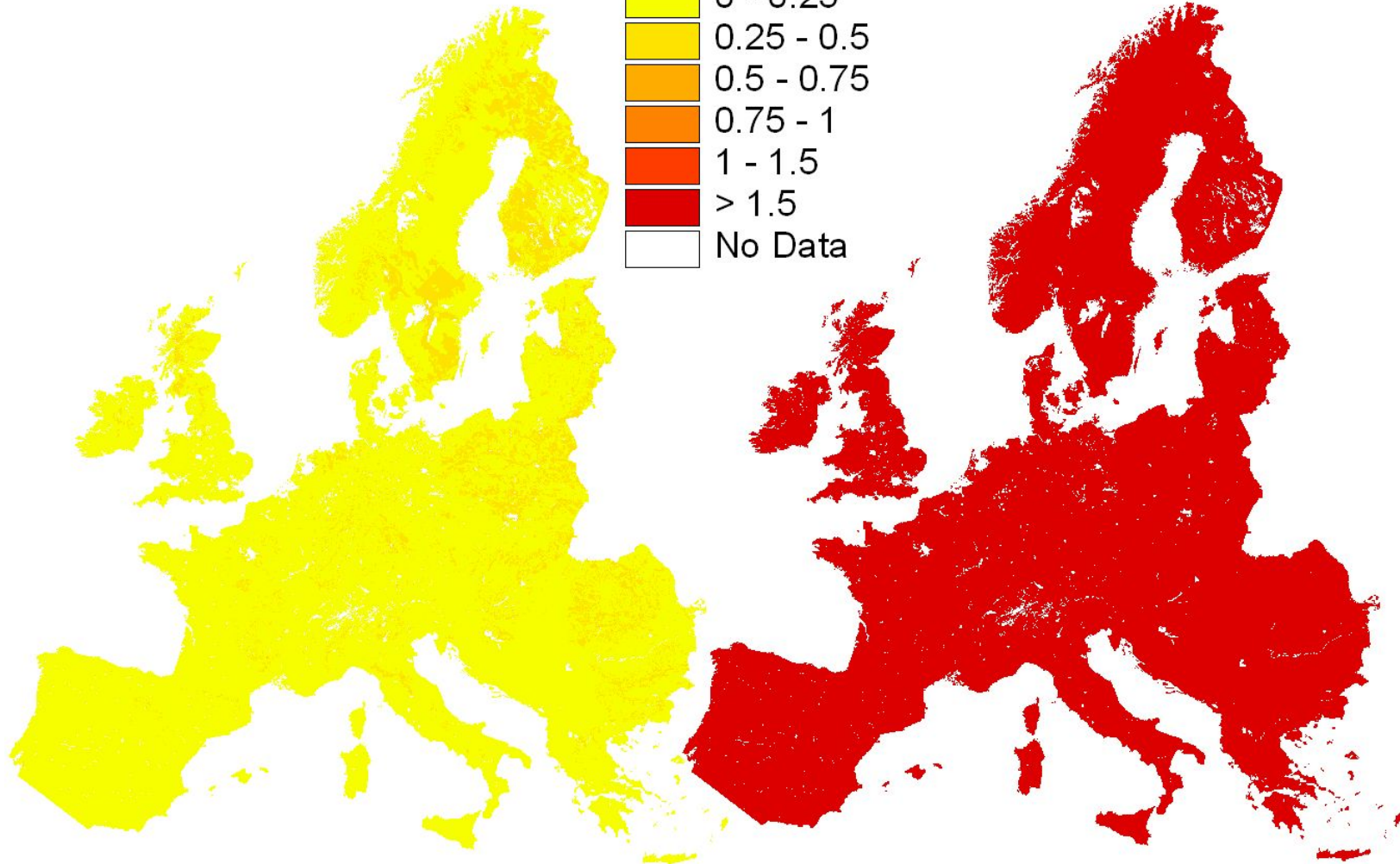
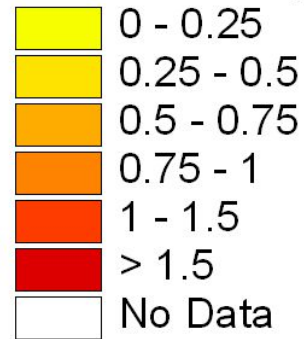


# Large uncertainties (but note: point support!)

10 Percentile

N<sub>2</sub>O-emission [kg/ha]

90 Percentile



# Conclusions

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- Design-based upscaling attractive because it does not suffer from making wrong assumptions
- It is also suitable for validation because independence guaranteed (provided data are not used twice)
- However, measurements must be selected using probability sampling, this is rare in GHG emission research
- Time to critically evaluate measurement strategies?
- Model-based upscaling currently more suitable for GHG emission research, but model-building and data selection requires attention
- Do not expect good results with scarce and/or poor data!

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# Thank you