M4 Approach to trend estimation for QSR 2023

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Rationale

Aim: estimate trends in abundance of cetacean species to aid in the QSR 2023 assessment

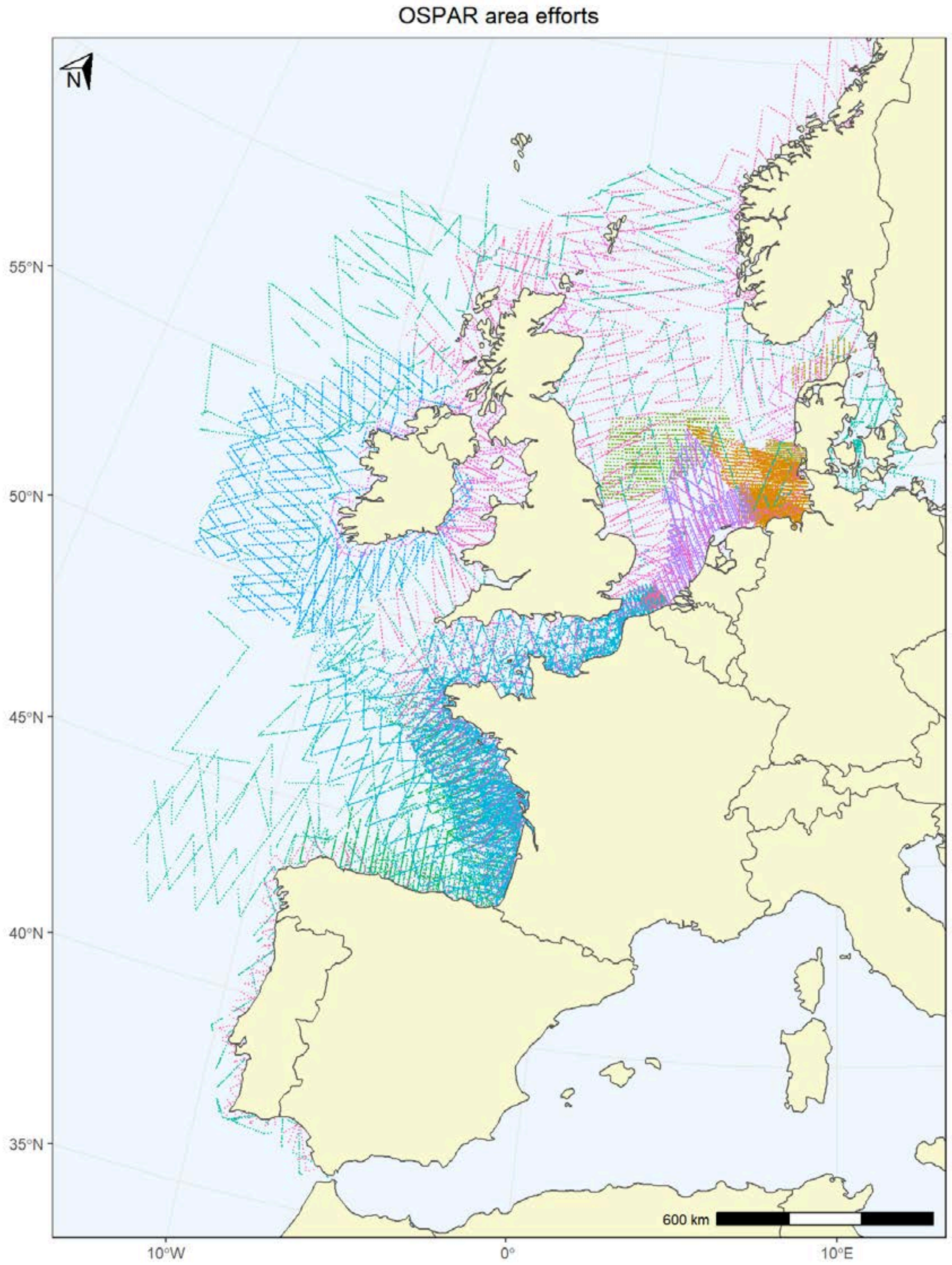
Problem: no co-ordinated surveys on relevant temporal and spatial scale

Possible solution: density surface modelling of all available survey data

Effort Map

Segments of
10 km

Line transect
surveys with
distance
sampling
protocol



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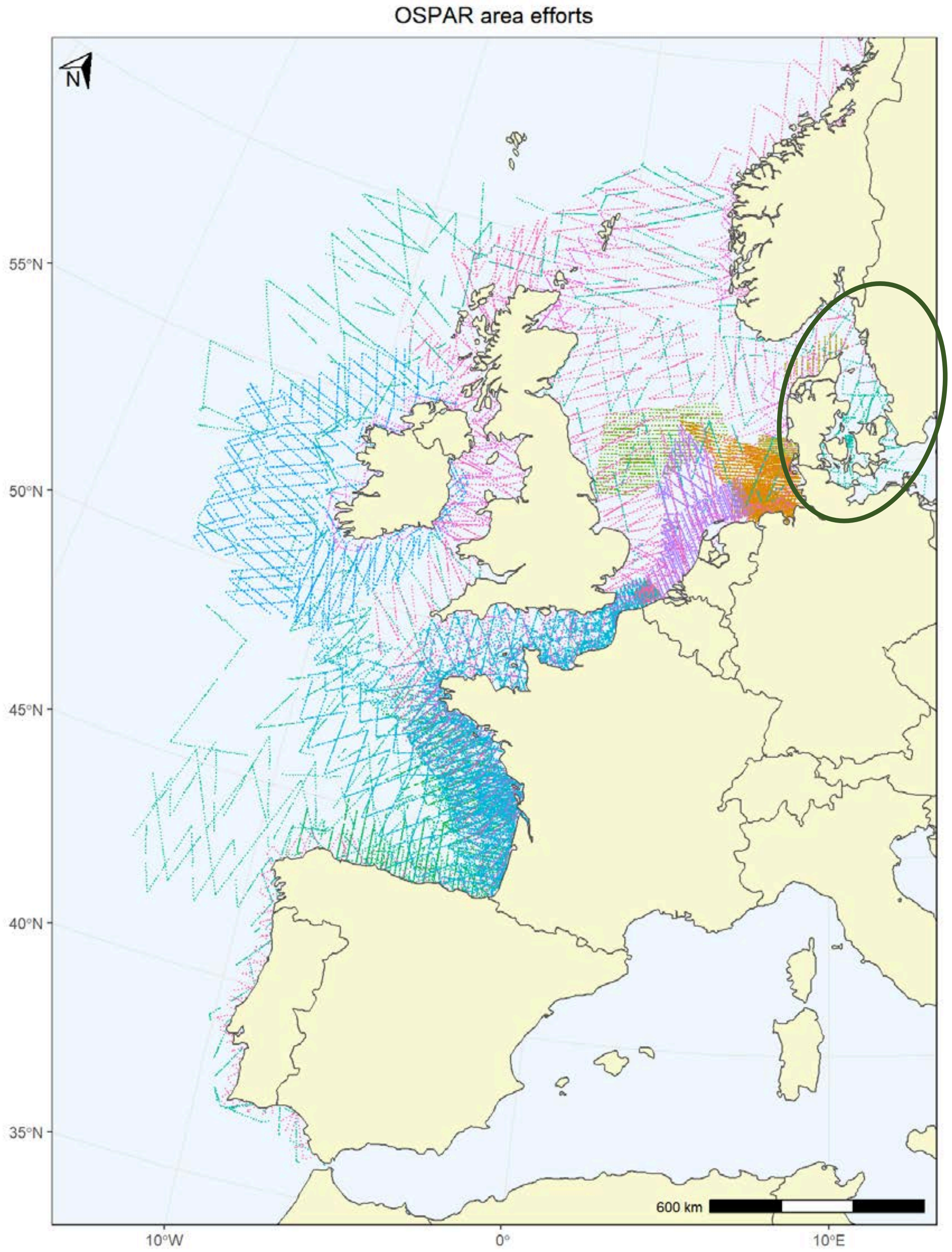

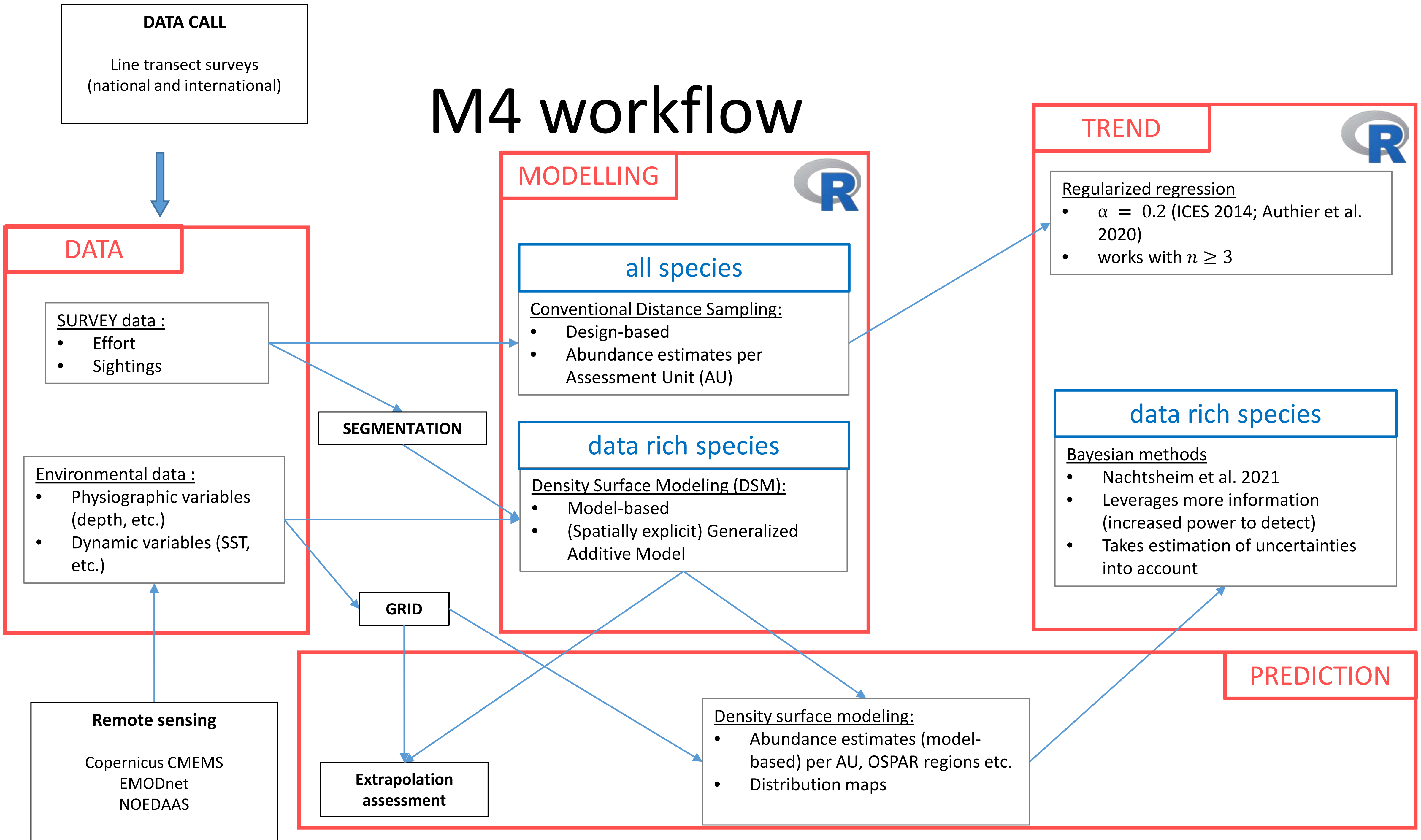

M4 workflow
DATA CALL
Line transect surveys
(national and international)
DATA
SURVEY data :
• Effort
• Sightings
Environmental data :
• Physiographic variables (depth, etc.)
• Dynamic variables (SST, etc.)
Remote sensing
Copernicus CMEMS
EMODnet
NOEDAAS
SEGMENTATION
GRID
MODELLING
all species
Conventional Distance Sampling:
• Design-based
• Abundance estimates per Assessment Unit (AU)
data rich species
Density Surface Modeling (DSM):
• Model-based
• (Spatially explicit) Generalized Additive Model
TREND
Regularized regression
• $\alpha = 0.2$ (ICES 2014; Authier et al. 2020)
• works with $n \geq 3$
data rich species
Bayesian methods
• Nachtsheim et al. 2021
• Leverages more information (increased power to detect)
• Takes estimation of uncertainties into account
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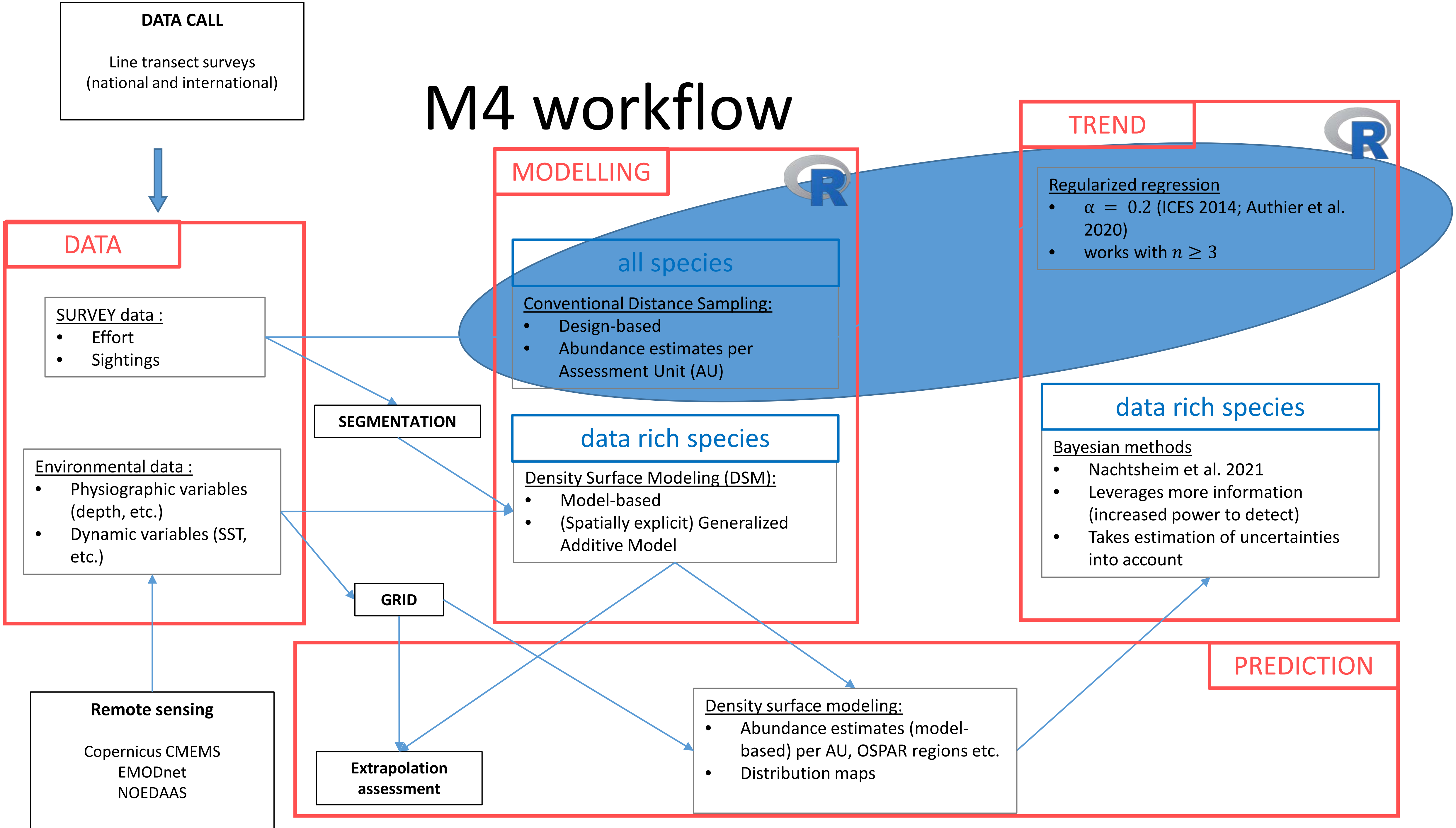
Extrapolation assessment
Density surface modeling:
• Abundance estimates (model-based) per AU, OSPAR regions etc.
• Distribution maps



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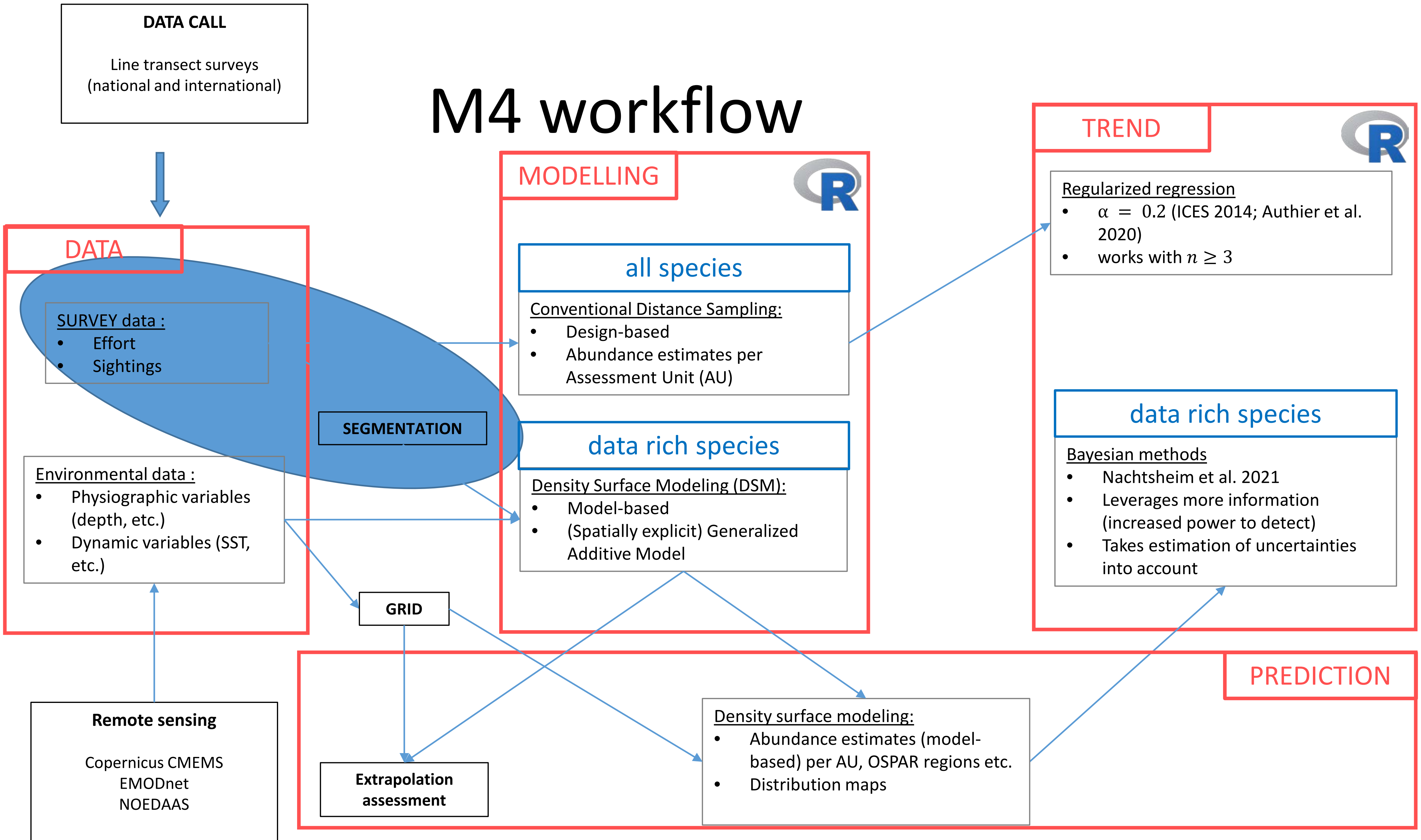
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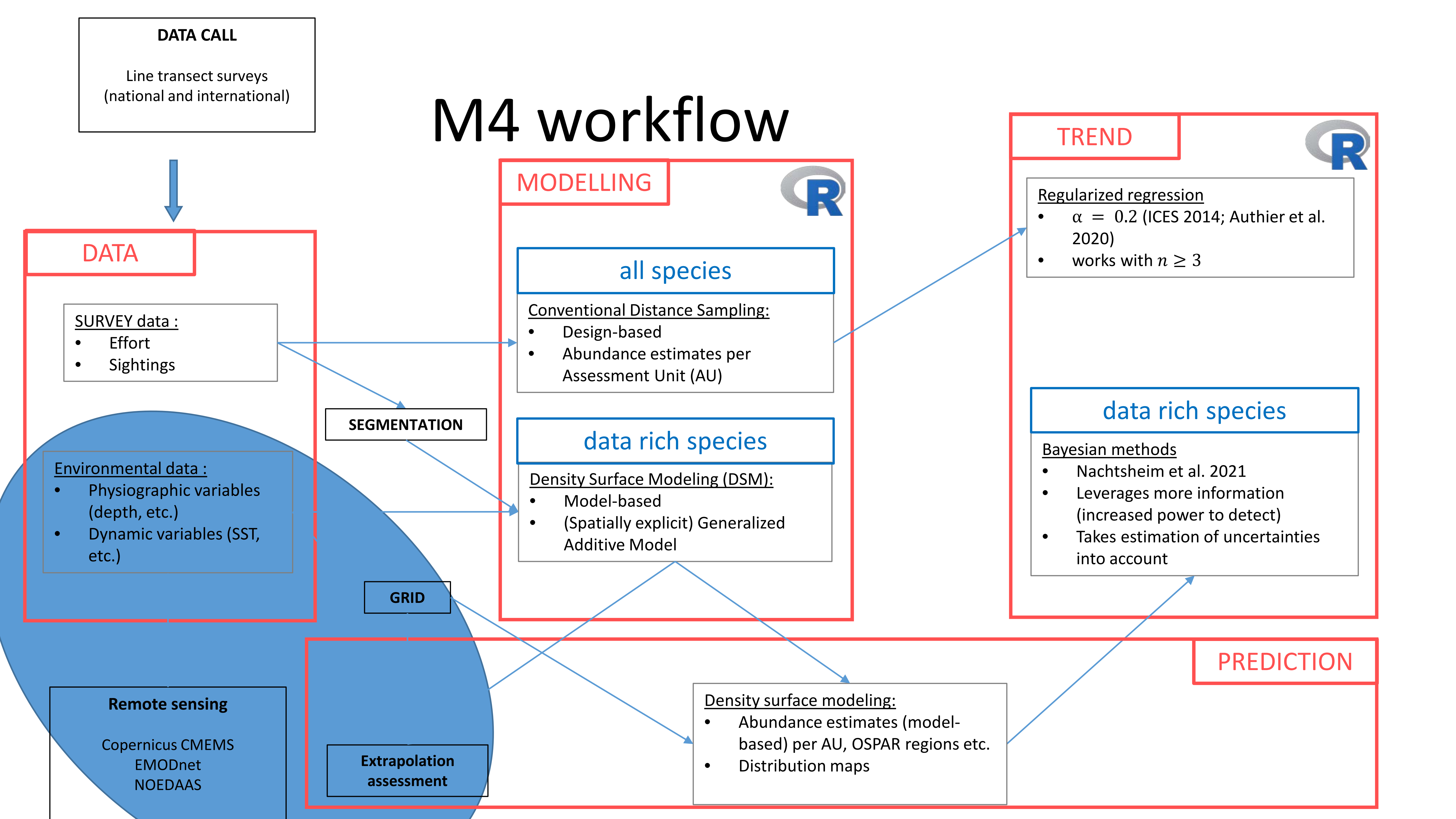
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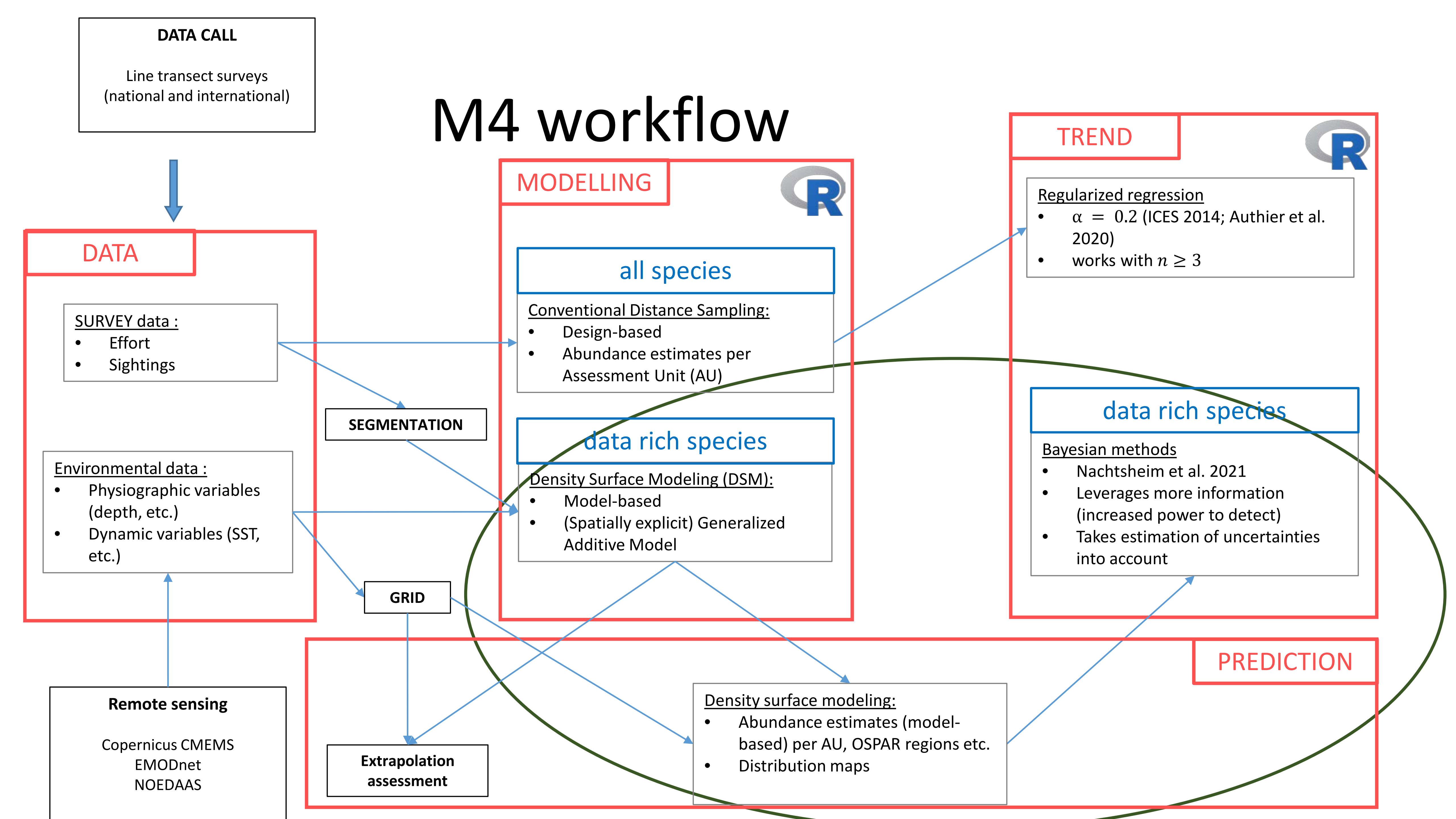
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DSM (density surface modelling)

For i-th segment in year t at spatial location j, let y_{ijt} be the count of detected animals

$$y_{ijt} \sim \mathrm{NegBin}\left(\omega, \mathrm{Effort}_{ijt} \times \lambda_{ijt}\right)$$

λ_{ijl} = true density at spatial location j in year t

ω: overdispersion parameter (accommodates outliers)

Effort_{ijt}: effective area sampled; includes linear effort, $g(0)$ and esw

λ_{ijl} incorporates environmental covariates

DSM (density surface modelling)

Let λ_{ijl} be the true density on segment i at spatial location j in year t

$$\log(\lambda_{ijt}) = \beta_0 + \sum_k f_k(x_{ijtk}) + \cdots$$

β_0: intercept

$f_k(.)$: environmental relationship between density and k-th covariate x_{ijtk} associated with i-th segment in year t at spatial location j

... : spatial-temporal effects (not accounted for by covariates), *etc.*

DSM

8 Covariates x_{ijtk}:

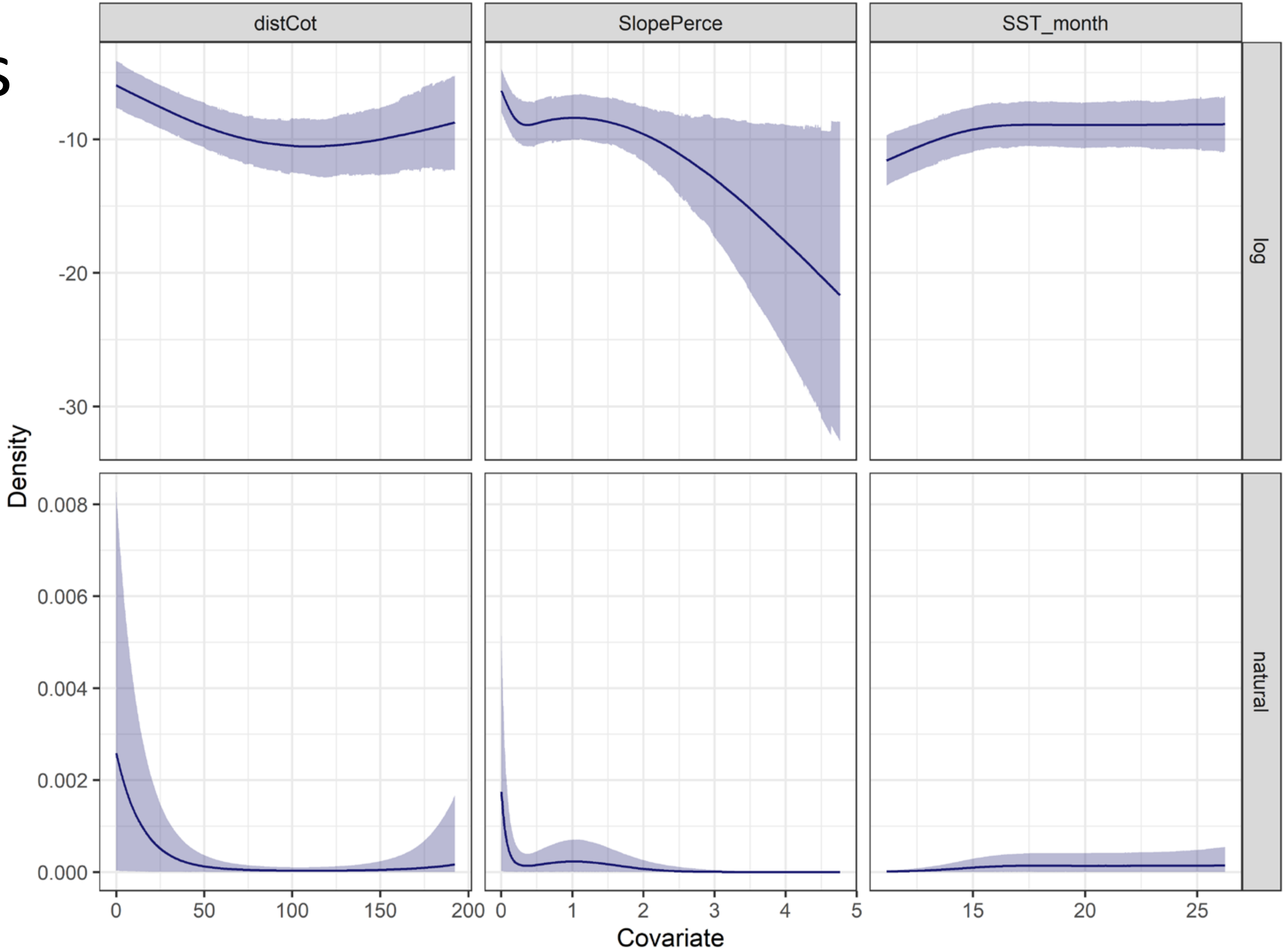
Physiographic (time-invariant)

- Bathymetry (depth)
- Slope
- Aspect
- Topographic complexity Index

Dynamic (time-varying, monthly resolution)

- SST
- SST gradient
- Net Primary Productivity
- Eddy Kinetic Enerdy

Examples of $f_k(.)$



DSM: estimate a trend

For each year t between 2005 – 2019,

(i) predict total abundance A_t over a spatial area from the fitted DSM and covariates (cookie-cutter approach)

The DSM may be viewed as an « instrument » to obtain estimates at regular time intervals here (using information from covariates)

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Estimate a trend on $\{A_t, \Sigma\}$ from (i) and (ii) above using appropriate methods (*e.g.* State Space Modelling)

GES assessment

Once a trend has been estimated (irrespective of how it has been estimated),

Compare trend to threshold

Note: the threshold is defined **independently** of the data used to estimate the trend

Thresholds 040xAddx_Threshold_proposal_m4

For each assessment unit, maintain [**insert species name**] population size at or above baseline levels (using the earliest reliable population estimate, e.g. from SCANS or SCANS II/CODA, as the baseline)

with no absolute decrease of >30%

and a rate of decrease no greater than 30% over three generations.

Importantly, although thresholds are defining over three generations, it is not necessary to wait for three generations for the assessment.

Harbour porpoise : 7.5 years

Species name	Temporal scale	Temporal scale (years)	Threshold (decline, in percent)
Harbour porpoise	yearly	1	-1.6
Harbour porpoise	MSFD	6	-9.1
Harbour porpoise	SCANS	10	-14.7
Harbour porpoise	3-generations	22	-30.0

Thresholds 040xAddx_Threshold_proposal_m4

However, the best available baseline will not always refer to a favourable status,

e.g. in the case of assessment units containing species which are considered to be endangered, critically endangered or vulnerable,

due to small population size and/or a known high level of pressure (*e.g.* the Iberian harbour porpoise).

In such cases ***no further population decline should be allowed***.

Thanks for your attention