Sampling for monitoring: on design-based, model-based and mixed approaches

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Outline

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Introduction

Pure design-based approach for compliance monitoring

Pure model-based approach for trend monitoring

Mixed approach for trend monitoring

Conclusions

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KEN LIVINGSTONE ABOUT THE CLIMATE PROBLEM:
"'We've most probably passed the tipping point'

Types of monitoring

- status monitoring
- trend monitoring
- compliance monitoring

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Sampling and estimation

- Statistical literature: strong focus on estimation (prediction); the data are already there
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Major design decision: Design-based or model-based approach?

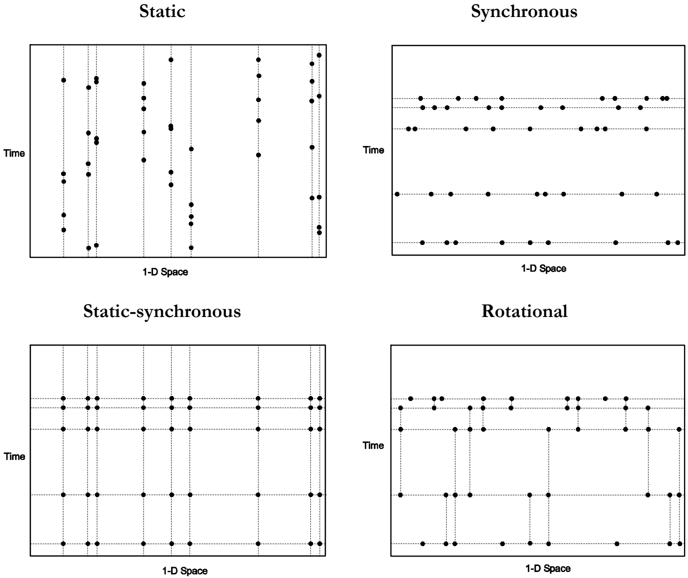
Definition of design-based and model-based approach

Type of approach	Sampling unit selection	Statistical inference
Design-based	Probability sampling	Design-based
Model-based	Purposive	Model-based

Four statistical approaches in space–time

		Space	
	Statistical approach	Design-based	Model-based
Time	Design-based	$\mathrm{D_S D_T}$	$\mathrm{M_S D_T}$
	Model-based	$\mathrm{D_S M_T}$	$\mathrm{M_S M_T}$

Basic sample patterns in space–time



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Surface water in Dutch polder

ALTERRA WAGENINGEN UR

Aim

- Testing quality of surface water against WFD-standards
- Does *spatio-temporal mean* concentration of N-total and P-total during summer-halfyear comply with MAR-values (N: 2.2 mg/l; P: 0.15 mg/l)?
- H_0: 'water is dirty' ($c > c_{\mathrm{MAR}}$)

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Why $\mathrm{D_S D_T}$-approach?

- space–time mean: global quantity
- for compliance monitoring validity more important than efficiency
- too few data for space-time modelling

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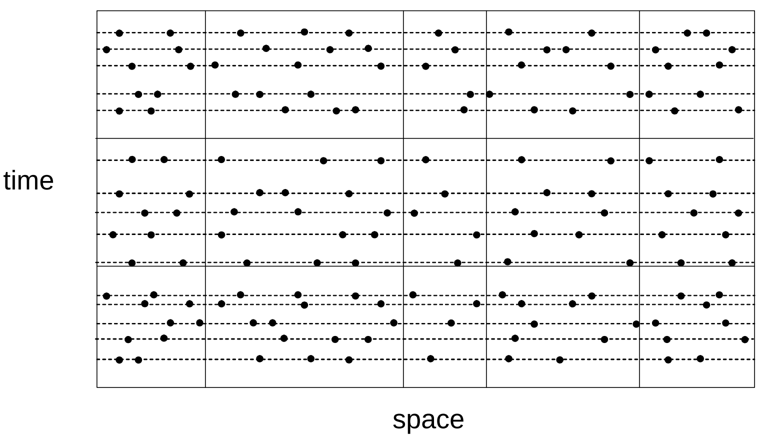
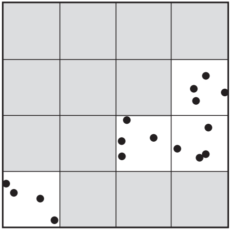
Synchronous pattern, STSI in space, STSI in time



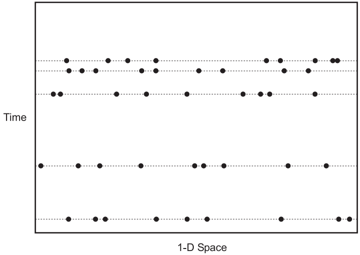
Why synchronous pattern?

Unbiased estimation of sampling variance (if samples independent!)

Two-stage sampling in space



Synchronous samping in space–time



Estimation of sampling variance

- For SI in both stages:

$$\hat{V}(\hat{\bar{y}}) = \frac{1}{r}\{\hat{V}_{\mathcal{T}} + \frac{1}{n}\hat{V}_{\mathcal{S}}\}$$

- r: number of sampling times (psu's)
- n: number of sampling locations per sampling time (ssu's)
- $\hat{V}_{\mathcal{T}}$: temporal variance of spatial means
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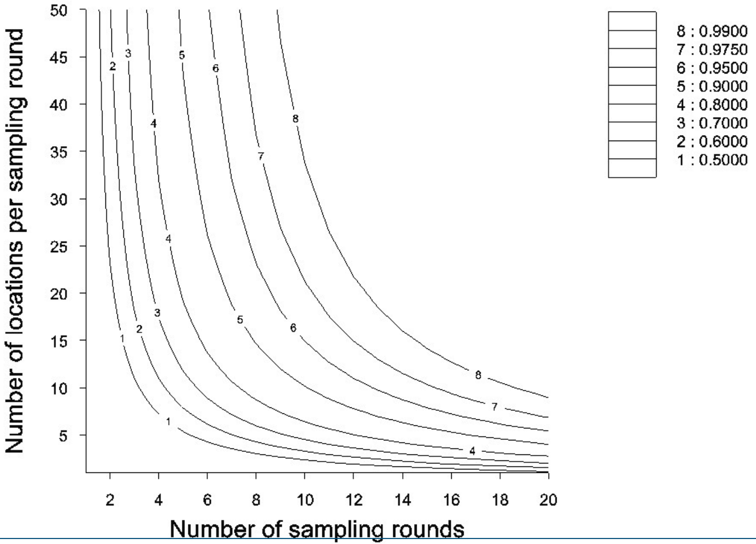
Contourplot of power for N



D.J. Brus & M. Knotters (2008), Water Resources Research 44

Outline

Monitoring-networks in the Netherlands

	Number of locations	Sampling interval
Groundwater	371 (1 per 100 km^2)	4 y (25 m)
Soil and freatic groundwater	200	6 y

- Static-synchronous pattern
- Purposive sampling of locations

C.J.F. ter Braak, D.J. Brus & E. Pebesma (2008), JABES 13, p. 159-176

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Research question

"What is the efficiency of the networks compared to alternatives"

- Other sampling densities (space) and sampling frequencies (time)
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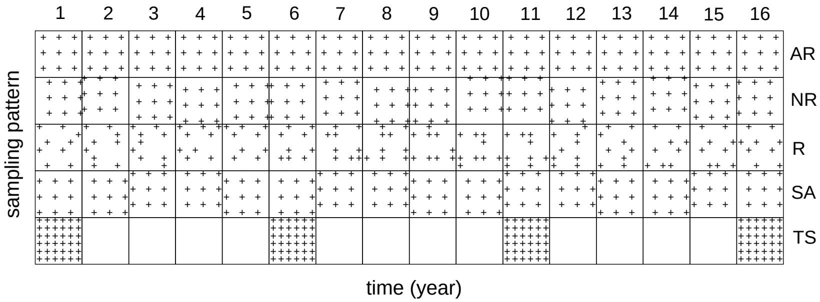
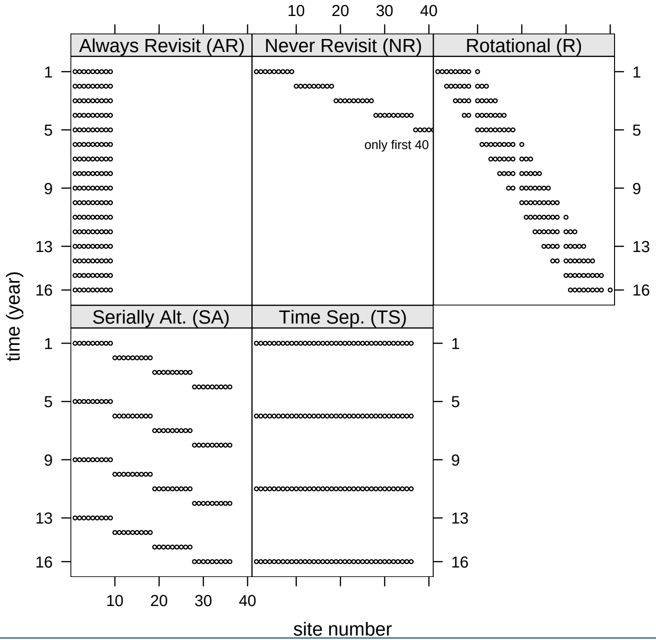

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
AR
NR
R
SA
TS
sampling pattern
time (year)



Always Revisit (AR)
Never Revisit (NR)
Rotational (R)
Serially Alt. (SA)
Time Sep. (TS)
only first 40
time (year)
site number
1
5
9
13
16
10
20
30
40

Pure model-based ($\mathrm{M_S M_T}$) approach

Geostatistical space–time model:

$$Y(\mathbf{s},t) = \mu(\mathbf{s},t) + \varepsilon(\mathbf{s},t)$$

$$\mu(\mathbf{s},t) = \sum_{j=1}^{p} \beta_j x_j(\mathbf{s},t)$$

Special case: $x_1(\mathbf{s},t) = 1, x_2(\mathbf{s},t) = t \rightarrow$

$$Y(\mathbf{s},t) = \beta_1 + \beta_2 t + \varepsilon(\mathbf{s},t)$$

SMTT, either defined as *model-parameter* or as *population parameter*, can be estimated by Universal Kriging

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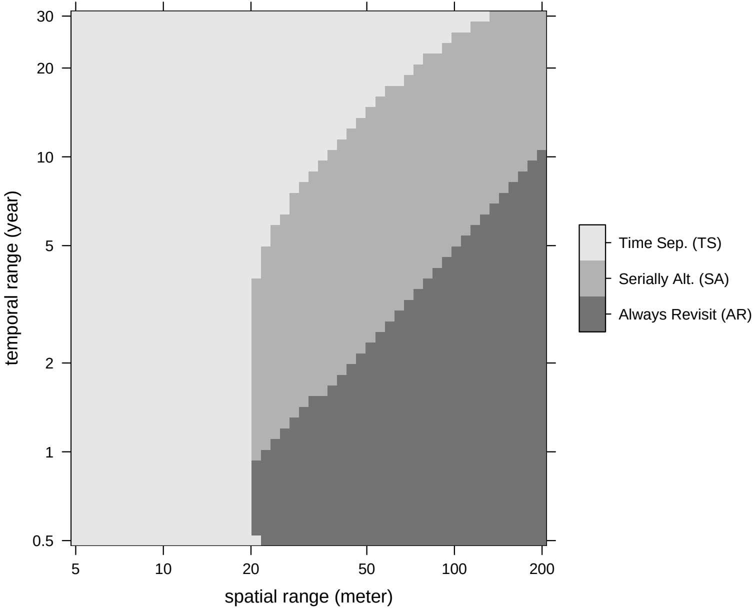
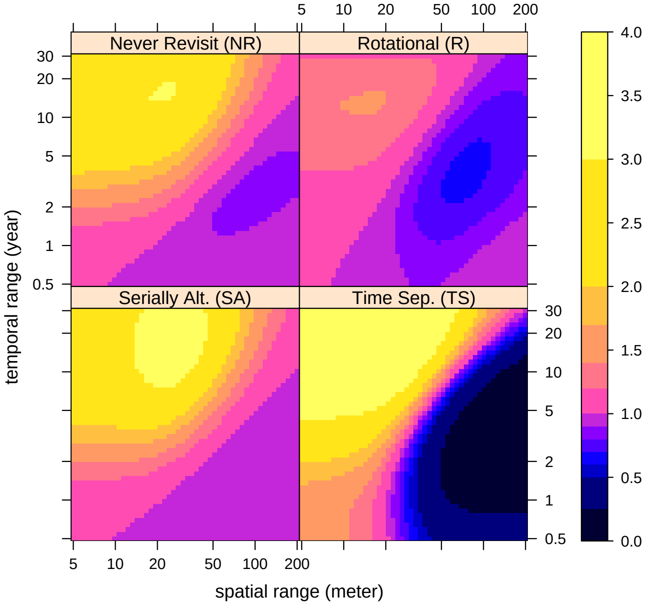


temporal range (year)
30
20
10
5
2
1
0.5
5
10
20
50
100
200
spatial range (meter)
Time Sep. (TS)
Serially Alt. (SA)
Always Revisit (AR)


Never Revisit (NR)
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Time Sep. (TS)
temporal range (year)
spatial range (meter)
5
10
20
50
100
200
0.5
1
2
5
10
20
30
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

Some characteristics of AR, TS and SA

	# of time series	Sampling density	Sampling frequency
AR	few	low	high
TS	many	high	low
SA	many	low	low

Outline

Mixed $\mathrm{D_S M_T}$ approach

- Probability sampling in space, design-based estimation of spatial means
- Purposive sampling in time, constant time interval: first sampling round at start (T_1), last round at end (T_2) of monitoring period
- Linear Regression Model for spatial means at $t = T_1 \cdots T_2$

$$m_A\{Y(t)\} = \beta_1 + \beta_2 t + \eta(t) + \varepsilon(t)$$

$$\eta(t) \sim G(\mathbf{0}, \mathbf{C}_\xi)$$

$$\varepsilon(t) \sim G(\mathbf{0}, \mathbf{C}_p)$$

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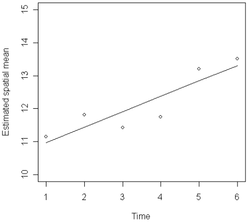
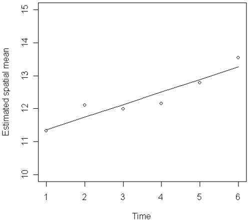
Number of sampling locations per round: 10

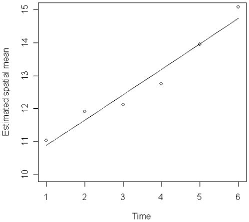
0.469



0.380

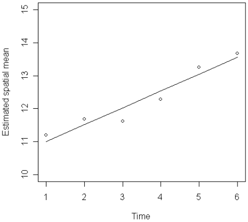


0.768

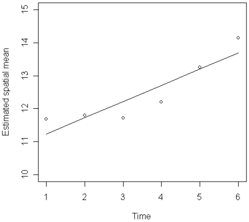


Number of sampling locations per round: 50

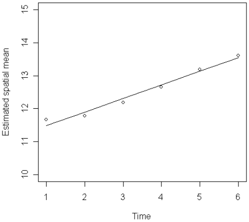
0.508



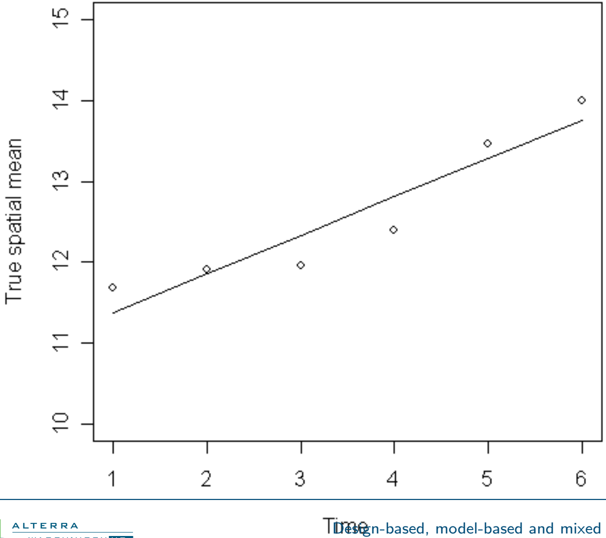
0.490



0.412



All locations; temporal trend: 0.475



Estimators for trend and variance of trend

$$\mathbf{b} = (\mathbf{X}^T \mathbf{C}_{\xi p}^{-1} \mathbf{X})^{-1} (\mathbf{X}^T \mathbf{C}_{\xi p}^{-1} \mathbf{y})$$

$$\mathrm{Var}(\mathbf{b}) = (\mathbf{X}^T \mathbf{C}_{\xi p}^{-1} \mathbf{X})^{-1}$$

$$\mathbf{C}_{\xi p} = \mathbf{C}_{\xi} + \mathbf{C}_{p}$$

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Simple cost model

$$C = c_{\text{round}} \cdot r + c_{\text{site}} \cdot r \cdot n$$

- c_{round}: costs per sampling round
- c_{site}: costs per sampling site
- r: number of sampling rounds
- n: number of sampling sites per sampling round

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Experiment

- Total costs: 1000
- Number of sampling rounds $r = 2 \ldots 50$
- c_{round}: 10, 100; c_{site}: 1
- Model variance of residuals $\sigma^2_\xi\{\eta(t)\} = 0.01 \cdots 1$
- Exponential correlogram for residuals $\eta(t)$
- Spatial variance $v_A\{y(t)\} = 0.25 \cdots 25$
- Constant spatial variance: $v_A\{y(t_i)\} = v_A\{y(t_j)\}$
- Simple random sampling in space: sampling variance of estimated spatial mean $\sigma^2_p\{\hat{m}_A(y)\} = v_A\{y(t)\}/n$
- Systematic sampling in time: first round at start, last round at end of monitoring period

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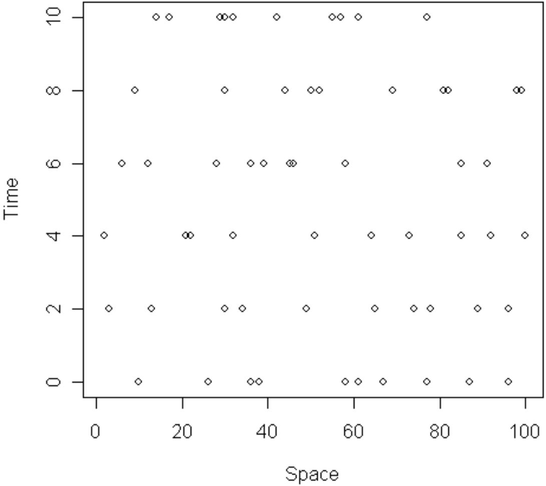
- Systematic sampling in time: first round at start, last round at end of monitoring period

Synchronous pattern, independent SI samples

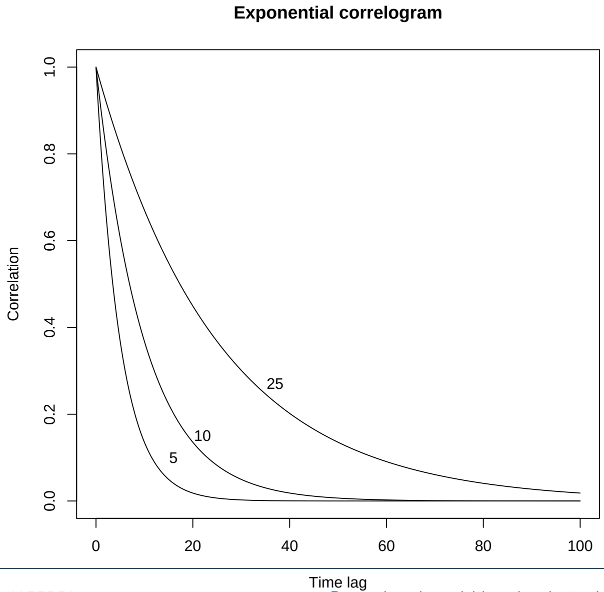


Synchronous pattern, independent samples

- Synchronous pattern (Never Revisit), independent samples $\rightarrow$

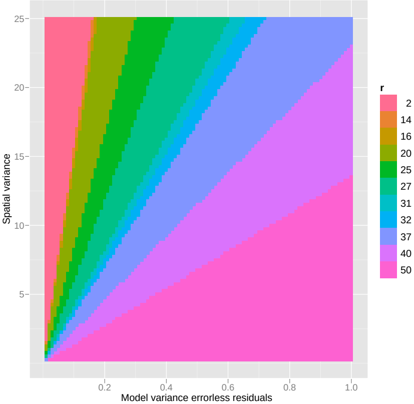
$$\mathsf{Cov}_p\{\varepsilon(t_i), \varepsilon(t_j)\} = 0, i \neq j$$

Correlogram of model residuals $\eta(t)$

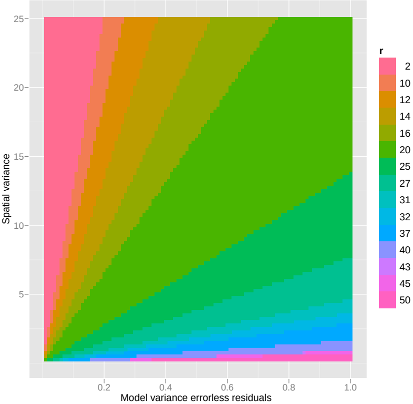


Optimal number of sampling rounds; $c_{\text{round}} = 10$

Pure nugget



Exponential(5)



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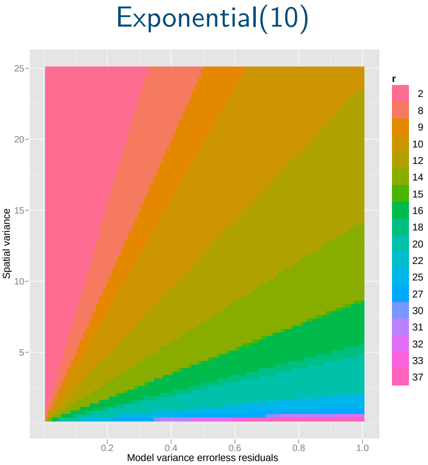
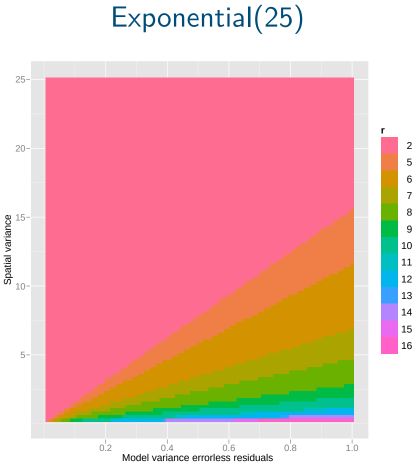
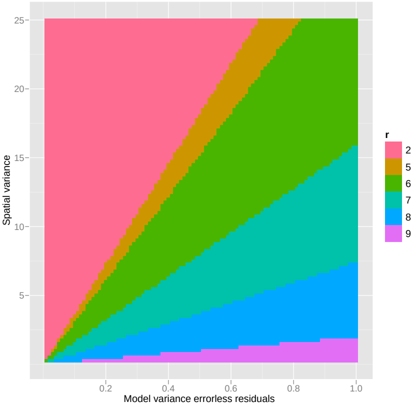


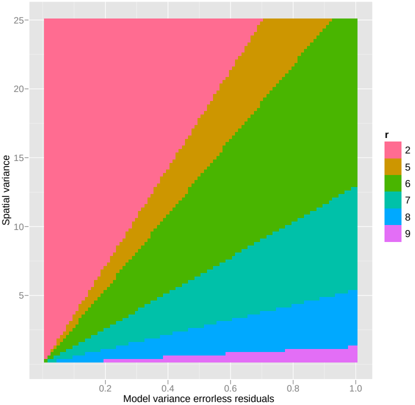


Optimal number of sampling rounds; $c_{\mathrm{round}} = 100$

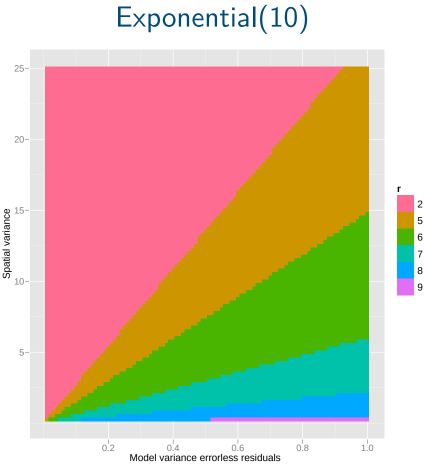
Pure nugget

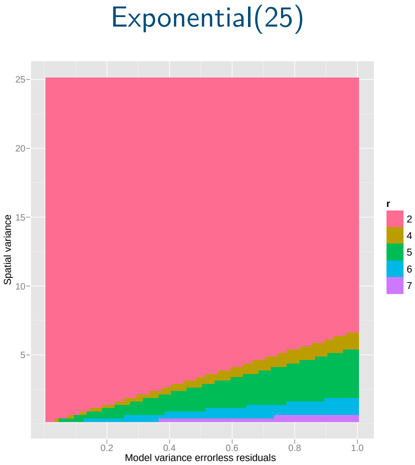


Exponential(5)



Optimal number of sampling rounds; $c_{\mathrm{round}} = 100$





Results

- Optimal number of sampling rounds not always 2!
- Optimal number of sampling rounds is determined by ratio of spatial variance of target variable and model variance of residuals (given the cost model parameters)
- The smaller the ratio, the larger the optimal number of sampling rounds
- Given a ratio, the stronger the temporal correlation, the smaller the optimal number of sampling rounds

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Conclusions

- Model in $\mathrm{D_S M_T}$ approach less complicated than in $\mathrm{M_S M_T}$ approach, fewer assumptions required $\longrightarrow$ better validity properties
- Mixed $\mathrm{D_S M_T}$ approach with probability sampling in space seems promising for estimating Temporal Trend of Spatial Means
- Further research:
  - other spatial sampling designs
  - optimization of r and n in static-synchronous and rotational patterns
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Outline

Conclusions

- For compliance monitoring of global quantities a full design-based approach can be advantageous
- For trend monitoring: full model-based or mixed $(\mathrm{D_S M_T})$ approach most appropriate
- Full model-based approach: Serially alternating pattern good option
- Mixed $(\mathrm{D_S M_T})$ approach: model more simple, better validity, but less efficient?

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Message to take home

Start thinking before you go into the field!

Thanks for your attention