When is a finer spatial resolution justified in remote sensing analysis?

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Check out the code

Introduction

Remote sensing plays a critical role in supporting *evidence-informed* policy-making, through the production of various types of land cover classification maps to quantify and monitor phenomena such as **deforestation** or **urbanization**.

A prevailing assumption in the field is that **higher spatial resolution** EO products (*e.g. Dynamic World provided at 10 m*) are inherently valuable, and often necessary to produce such reports and conduct research, as they yield more accurate results. This often comes at **storage** costs of ever-increasing **massive data volumes** and **high computational load** costs for **analysis**. When quantifying aggregated target values, e.g. Forest Fraction estimates in a region from such classification maps, to what extent does the spatial resolution of the classification map matter?

In this study, we examine the effects of **spatial down-sampling** under **systematic (non-random) regular sampling** schemes on the estimates of fractions. We assess classification **accuracy** by evaluating **standard error variances** derived from Ripley's formulation (Eq. 1) [1], computed using two numerical methods: Monte Carlo Integration (a random stochastic approach) and Gauss Quadrature (a systematic deterministic approach). The analysis is carried out for two use cases: deforestation in Brazil, and impervious surface mapping in Germany.

Research Questions

RQ1. How does **spatial down-sampling** of the classification map, in steps, **affect** the estimates of
a. **Impervious fraction** (from 20-m to 10-km resolution)?
b. **Forest fraction** (from 30-m to 12-km resolution)?

RQ2. How does the **standard error** of the fraction estimates, computed using (Eq. 1), **vary** with down-sampling under systematic (non-random) regular sampling schemes?

RQ3. **What** is the **threshold resolution** beyond which the estimated fraction becomes unacceptable to assess temporal changes in mean values?

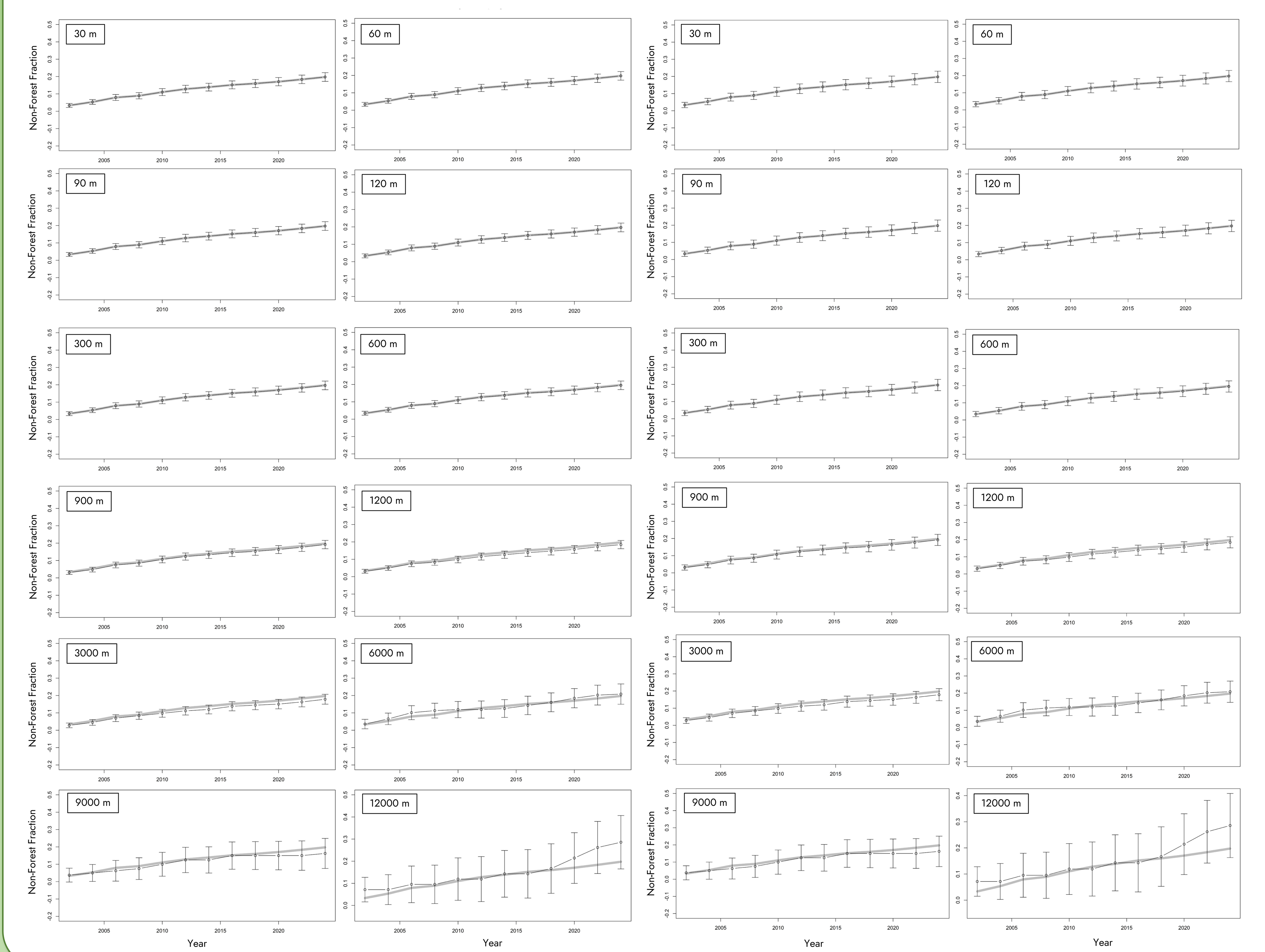
RQ4. How do results depend on whether **Monte Carlo Integration** or **Gauss Quadrature** are used for computing block mean **covariances in** (Eq. 1)?

Imperviousness in Münster, Germany

Regular Sampling with Monte Carlo Integration | Regular Sampling with Gauss Quadrature

Deforestation in Minaçu, Brazil

Regular Sampling with Monte Carlo Integration | Regular Sampling with Gauss Quadrature



References

[1] Equation 3.4 in Ripley, B. D. (1981). *Spatial Statistics*. New York: John Wiley & Sons.

[2] Copernicus Land Monitoring Service (CLMS). (2023). *High Resolution Layer Imperviousness (Imperviousness Density 2006, 2009, 2012, 2015, 2018)* [Dataset]. European Environment Agency (EEA). Retrieved from https://land.copernicus.eu/en/products/high-resolution-layer-imperviousness

[3] INPE (National Institute for Space Research). (2020). *Terrabrasilis Cerrado PRODES Yearly Deforestation (2001–2019)* [Dataset]. Brazilian Institute of Geography and Statistics (IBGE). Retrieved from https://terrabrasilis.dpi.inpe.br/download/dataset/cerrado-prodes/vector/yearly_deforestation.zip

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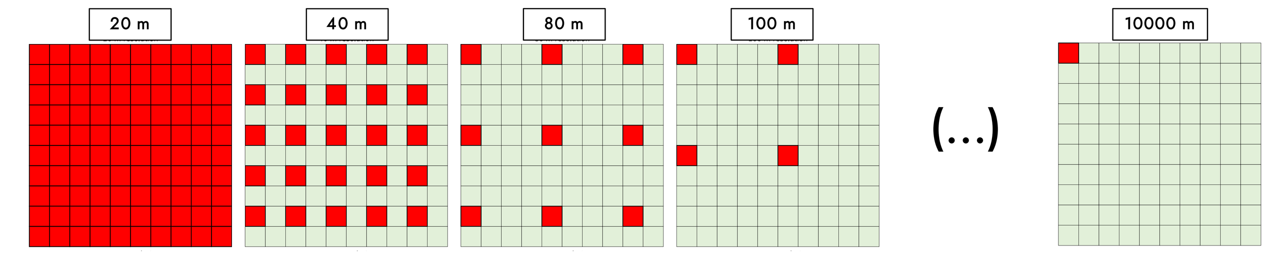
Methodology

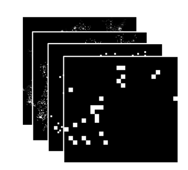
Acquire the **time-series datasets** from their portals → Clip to study area and create **time-series of binary maps** → **Down-sample** each time-stamp to progressively *lower* **spatial resolution**

The acquired time-series datasets are: the Copernicus "**High Resolution Imperviousness Density Layer**" [2] subset to Münster, Germany; and the INPE "**PRODES (Deforestation)** Annual increase in native vegetation suppression" [3] subset to Minaçu, Brazil. The **native** resolution of the maps is taken as the population value or 'truth' and is **down-sampled** using a **regular (systematic) sampling** at different, **lower spatial resolutions**.



Classes	Temporal Extent	Spatial Resolutions
Impervious vs. Non-Impervious	2006 - 2018	**20-**, 40-, 80-, 100-, 200-, 400-, 800-m, 1-, 2-, 4- 8-, 10-km
Forest vs. Non-Forest	2002 - 2024	**30-**, 60-, 90-, 120-, 300-, 600-, 900-m, 1.2-, 3-, 6-, 9-, 12-km

For each **spatial resolution**,



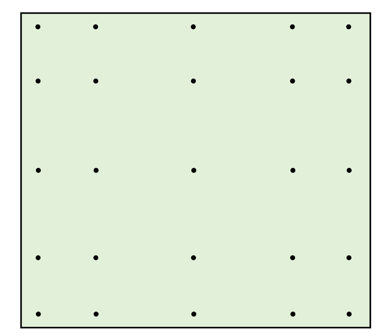
→ Compute **standard error of mean** from Eq.1 for **systematic sampling** at each time-stamp, where $se = \sqrt{var}$ → Plot the **fraction** and **standard error** for each time-stamp at every **resolution**

sample-sample covariance | **block-sample** covariance | **block-block** covariance

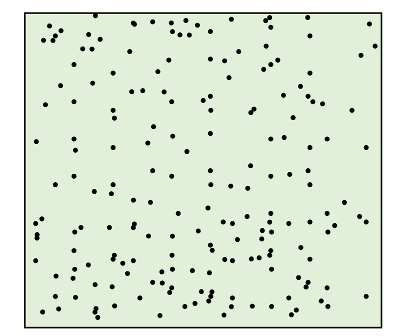
$$var\left(\bar{Z} - \tilde{Z}(A)\right) = \frac{1}{n^2}\sum_{\boldsymbol{u},\boldsymbol{v}} C(\boldsymbol{u},\boldsymbol{v}) - 2\sum_{\boldsymbol{u}} \frac{1}{an}\int_A C(\boldsymbol{u},\boldsymbol{y})\, d\boldsymbol{y} + \frac{1}{a^2}\int_A \int_A C(\boldsymbol{x},\boldsymbol{y})\, d\boldsymbol{x}\, d\boldsymbol{y} \quad \text{(Eq. 1)}$$

For **Eq. 1**, two **numerical methods** which use different block discretizations to **estimate** the continuous integrals of the **block-sample** and **block-block covariances**

Gauss Quadrature
(Weighted, Regular, Symmetric, Deterministic)

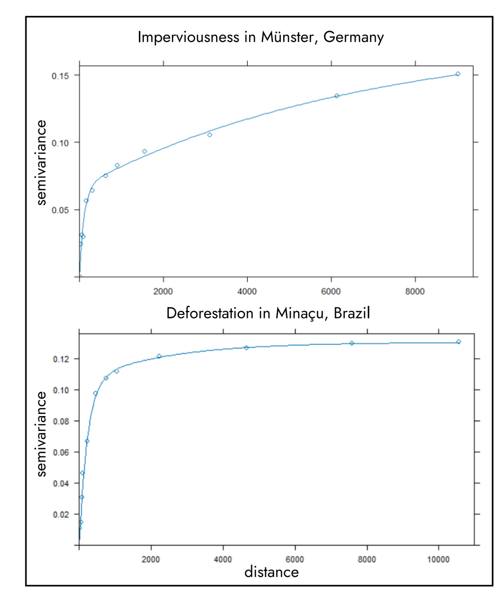


Monte Carlo
(Random, Stochastic)



Discussion & Conclusion

- **Down-sampling** using **systematic sampling schemes** produces spatial mean estimates nearly indistinguishable from the full-resolution estimates.
- In the **first case** study, the **impervious fraction** remains stable when down- sampling from **20- to 400-m resolution**. In the **second case** study, the **non-forest fraction** similarly remains stable from **30- to 600-m**. For both cases, this implies a **reduction** in **computational load** by a **factor** of **20²** with minimal loss of accuracy.



- For **more complex covariance structures**, such as the **double exponential variogram model** encountered in these cases, Monte Carlo Integration better captures the **fine-scale, short-distance spatial variability**.