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MAKing Sustainable development and WELL-being frameworks work for policy analysis

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Insights on statistical methodologies and new data sources for SDG and well-being indicators

Work Package 2

Methodological aspects of measuring SDG indicators with traditional and non-traditional data sources

Jan van den Brakel

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Partners WP 2:

1. Statistics Netherlands
2. Southampton University
3. Istat
4. Pisa University
5. Trier University
6. Destatis

Outline

1. Purpose WP 2
2. Del. 2.1
3. Del. 2.2
4. Needs for further research: Del. 2.3
5. Discussion

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1. Purpose WP2

- Overview of traditional and non-traditional data sources for SDG indicators
- Methodological development using new data sources (big data)
  - Integration of traditional and non-traditional data sources (small area estimation, nowcasting)
  - Pointing out quality aspects of big data (representativity, timeliness, …)
- Review of good and bad practices
- Identify needs for future research

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2. Del. 2.1: Aspects of existing databases, traditional and non-traditional data sources and collection of good practices

- Overview of traditional and non-traditional data sources for SDG indicators, through an inventory in Italy, the Netherlands and Germany
- Review of good and bad practices:
  - Google trends to measure propensity to move (CBDS)
  - Improving the Italian CPI using scanner data
  - Mobile phone network data (day time population, mobility, tourism, migration flows, poverty, economic growth)
  - Webscraping from websites (estimating number of innovative companies, prices)
  - Social media studies (classifying messages to measure social tension and sentiment, including a nowcast excersise with the consumer confidence index)
  - Found data: estimating unmetered photovoltaic power using time series of electricity taken from the high voltage grid and time series on solar irradiance, day length, temperature, …

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2. Del. 2.1: Aspects of existing databases, traditional and non-traditional data sources and collection of good practices

- Review of good and bad practices (cont.):
  - Found data: estimating unmetered photovoltaic power using time series of electricity taken from the high voltage grid and time series on solar irradiance, day length, temperature, …
  - Remote sensing data
    - Copernicus project on land use in Germany
    - Measuring urban sprawl using satellite data (CBDS)
    - Detecting photovoltaic solar panels in aerial images

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3. Del. 2.2: Methodological aspects of measuring SDG indicators with traditional and nontraditional data sources

- Combining survey data with non-traditional data sources:
  - Small area estimation
  - Time series methods for now-casting
- Non-traditional data sources as a primary data source
- Evaluating sustainability through an input-state-output framework as an alternative for juxtapose a large set of indicators

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4. Needs for further research (Del. 2.3)

1. Quality frame work
    - Probability samples:
        - Sampling error through variance estimation
        - Non-sampling errors: Total Survey Error (TSE) frame work
    - Non-probability data, non-traditional data, big data etc:
        - No established quality frame work
        - Extension of the TSE frame work to these new data sources: Total Error Frame-work (TEF)
        - Account for the specific features of new data sources, e.g.
            - Identification error of units of interest in fuzzy big data
            - Linkage errors
            - Feature extraction errors
            - Quantifying uncertainty under machine learning and AI alg.

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4. Needs for further research (Del. 2.3)

2. Additional methodology
    - Use of non-traditional data sources in official statistics:
        - Primary data source
        - Covariates in model-based inference procedures (SAE, time series models, now-casting)
    - Primary data source:
        - Correction for selection bias
            - Methods require structured data and strong auxiliary information
            - Need for new methods that handle these issues
            - Need for methods to obtain insight in the performance of existing methods if auxiliary information is obscured with errors (linkage errors, feature extraction errors, identification errors, …)

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4. Needs for further research (Del. 2.3)

2. Additional methodology (cont.)
    - Covariates in model-based inference procedures:
        - More empirical evidence to illustrate:
            - Efficiency of SAE methods compared to machine learning algorithms
            - Usefulness in the production of official statistics
        - Time series models:
            - Dynamic factor state-space model for high dimensionality issues
            - How to select relevant series without falling into the trap of data dredging?
            - How to account for time-varying state correlations?

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4. Needs for further research (Del. 2.3)

3. Risk appetite of NSI's
    - Well-accepted approach: probability sampling in combination with design-based inference
        - Robust for model-misspecification
        - NSI is in control over
            - Minimum required accuracy of the outcomes
            - Availability of data,
    - Use of new data sources:
        - Model-based inference to correct for selectivity or as covariates in SAE and nowcasting procedures
        - More empirical research to illustrate the benefits of such methods in the context of official statistics

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4. Needs for further research (Del. 2.3)

4. Remote sensing data
    - Successful in absence of high quality official data on well-being, poverty and SDGs
    - But also for European situations? Requires high quality remote sensed data!
    - Integration of remotely sensed data in the frame-work of SDGs and well-being measurement is predominantly experimental
    - Need for a comprehensive overview of datasets and methods to facilitate their use in official statistics

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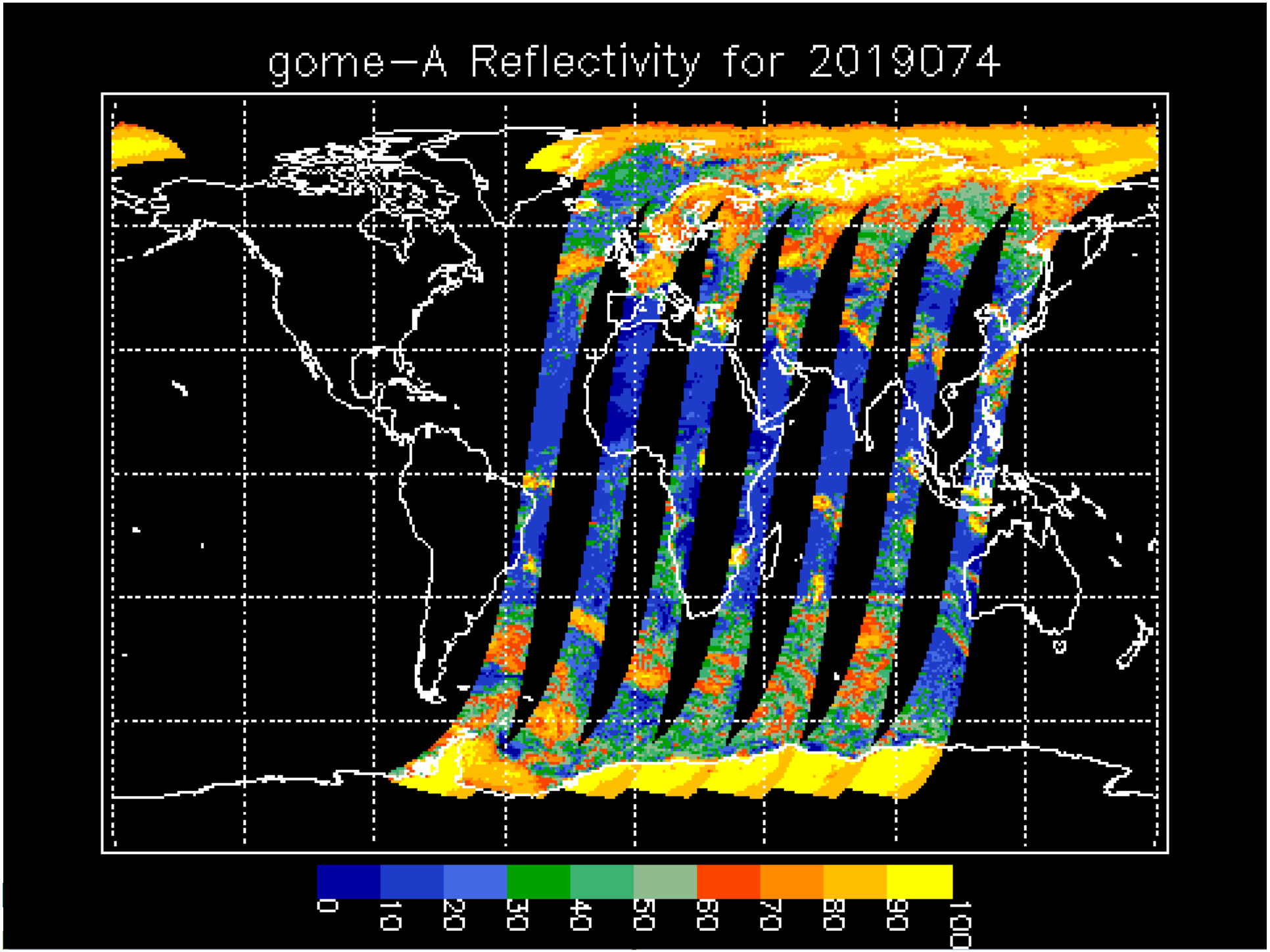
4. Needs for further research (Del. 2.3)

4. Remote sensing data (cont.)
    - Statistical purpose is predictions for well-being and SDGs:
        - spatial comparisons
        - temporal comparisons
    - Requires:
        - combining multiple images
        - comparing images of the same area over time
    - Issues:
        - spatial image inconsistency
        - temporal image inconsistency
        - computational power and data storage capacity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4. Needs for further research (Del. 2.3)

4. Remote sensing data (cont.)
    - Research:
        - methods that reduce spatial and temporal image inconsistency
        - better understanding how these error sources influence/increase uncertainty of predictions for poverty, well-being and SDGs
        - methods that account for or reduce the influence of these error sources
        - methods that quantify the increase of uncertainty on predictions for well-being, poverty and SDGs due to these error sources
        - research into methods to validate the reliability of constructs for poverty and well-being derived from remote sensed data

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4. Needs for further research (Del. 2.3)

4. Remote sensing data (cont.)
    - Data and hardware issues
        - processing images for large areas and longer periods require considerable computational power and data storage capacity
        - availability of the required AI hardware and AI knowledge is not standard available at national statistical institutes
        - satellite images of sufficient quality or resolution are only commercially available
        - to evaluate methods, geo-coded unit level data on income and poverty are required
        - to facilitate wider development of satellite-based applications an Europe wide computing infrastructure should be established

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4. Needs for further research (Del. 2.3)

5. Deep learning
    - Important for analyzing satellite and aerial images
    - Example from Del 2.1: counting solar panels and land use
    - Further research:
        - better understanding error sources to evaluate uncertainty of estimation results
        - how to create training sets, test sets and validation sets to maximize model generalizability to intended target populations
        - minimize the effect of errors in the annotating process
        - the impact of class imbalance on uncertainty measures
        - methods to quantify how these errors contribute to estimation uncertainty
        - model interpretability and transparency
        - data science and hardware knowledge for computationally intensive methods

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5. Discussion

Further needs for research

- Quality frame work for non-traditional data sources
- Needs of a new/extended framework to measure wellbeing and SDG indicators in terms of data sources, methodology, and quality requirements
- Extension of methodology to correct for selection bias
- Applications of SAE that uses non traditional data sources as covariates
- Time series methods
- Risk appetite of NSI's: empirical applications in the context of official statistics
- Methods for processing remote sensing data
- Deep learning

- Deliverable 2.3: Planned deadline February 2020