# **EFFECTS OF DIFFERENT LAND USE** DATA ON BIODIVERSITY METRICS IN MonViA **AGRICULTURAL LANDSCAPES: TOWARDS (GEO)DATA FITNESS FOR USE**



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#### BACKGROUND

- crop type information like Integrated Public Administration and Control System (IACS) data are partly restricted for Germany.
- Freely available Crop Type Classifications (CTC) derived from remote sensing imagery represent crucial input data for agricultural biodiversity metrics.

#### **METHODS**

CTC\* IACS\* (\*flexible Input data) IACS (n=226) IACS (n=20) CTC (n=19) CTC (n=19) Biodiv. Biodiv. Metrics Metrics (IACS) (CTC)

## **Zonal Statistics:** Majority voting of

CTC on IACS geometry **Aggregation:** Assignment of IACS

classes to CTC classes

**Calculation of Biodiversity Metrics:** Number of Crops and Shannon Evenness Index for IACS and CTC per hexagon as reference unit

### **CONCLUSIONS**

- For the first time, area-wide biodiversity metrics deviated from remote sensing-based are Crop Type Classifications and are evaluated through a data fitness for use approach.
- IACS data can be replaced by freely available remote sensing-based Crop Type Classifications, which can be used in regions where IACS is not available.

#### GOALS

- Analyzing effects of different input data in the form of IACS and CTCs (Schwieder et al., (2022) (SWD)) and Preidl et al., (2020) (PRE)) for the Number of Crops (NoC) and the Shannon Evenness Index (SEI) by data quality metrics (R<sup>2</sup>, RMSE) for Lower Saxony (LS) and Brandenburg (BB) 2017 – 2019.
- Differences between the two presented CTCs due to:
  - spatial discrepancies (resolutions)
  - different sampling schemes
  - different input data
  - number and definition of classes
- Designing best practice guidelines and algorithms for data fitness for use assessment.

Differences **Calculation of Accuracy Metrics:** Accuracy of Biodiv. R<sup>2</sup>, RMSE of the differences of Metrics biodiversity metrics for IACS and CTC Metrics

Application Matrix: Summary of Summary of Accuracy Metrics accuracy metrics in tables and figures

Fig. 1: Method workflow for flexible input data (e.g. Crop Type Classification (CTC), IACS) to compare biodiversity metrics by accuracy metrics.



Fig. 2: Application example for biodiversity metric Number of Crops

**OUTLOOK** 

- The flexible workflow is an approach to generate information on data usability from a user perspective.
- Within the FAIRagro project, a multidimensional application data matrix framework will be built, formalized and transferred to additional quality metadata.





**Difference Number of Crops (IACS – PRE)** 



#### **RESULTS + DISCUSSION**

#### Number of Crops (IACS – PRE)

y = 0.25 + 0.95 x		•			
$R^2 = 0.73$	•	•	•	•	•

Shannon Evenness Index (IACS – PRE)





Fig. 3: Difference of Number of Crops (NoC) per hexagon (n = 46,543) of Preidl (PRE) subtracted from IACS for Lower Saxony 2019. Positive differences (green): NoC according to IACS is greater, negative differences (brown): Preidl data generate a greater NoC per hexagon.

**Fig. 4:** Difference of Number of Crops (NoC) (n = 46,543) from Preidl vs. from IACS for Lower Saxony 2019. Positive differences (green): NoC according to IACS is greater, negative differences (brown): Preidl data generate a greater NoC per hexagon.

**Fig. 5:** Difference of Shannon Evenness Index (SEI) (n = 46,543) from Preidl vs. from IACS for Lower Saxony 2019. Positive differences (green): higher SEI values for IACS, negative differences (brown): higher SEI values for Preidl (PRE).



#### Summary of Data Quality Metrics

- Derivation of area-wide biodiversity metrics based on Crop Type Classifications (Fig. 3).
- Comparison of biodiversity metrics based on PRE and IACS show that the most frequent difference is 0 (Fig. 3-5)



Fig. 6: Data quality metric R<sup>2</sup> as a measure of the similarity of the Number of Crops (NoC, top) and Shannon Evenness Index (SEI, bottom) based on the Crop Types Classifications (Preidl (PRE): green, Schwieder (SWD): blue) versus based on IACS for Lower Saxony (left) and Brandenburg (right) 2017-2019.

 $\rightarrow$  highlights hexagons with **no discrepancies** between the input data

- Summary of Data Quality Metrics (Fig. 6):
  - higher R<sup>2</sup> values for Lower Saxony than for Brandenburg
  - higher R<sup>2</sup> values for SEI than for NoC
  - higher R<sup>2</sup> values for SWD than for PRE
- **High correlation** for the Number of Crops (Fig. 4) and the Shannon Evenness Index (Fig. 5) for PRE and IACS as input data for Lower Saxony and Brandenburg for 2017 – 2019. (Fig. 6)



- 1: Blickensdörfer, Lukas & Schwieder, Marcel & Pflugmacher, Dirk & Nendel, Claas & Erasmi, Stefan & Hostert, Patrick. (2022). Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany. Remote Sensing of Environment. 269. 112831. 10.1016/j.rse.2021.112831.
- 2: Preidl, Sebastian; Lange, Maximilian; Doktor, Daniel (2020): Introducing APiC for regionalised land cover mapping on the national scale using Sentinel-2A imagery. In: Remote Sensing of Environment 240, S. 111673. DOI: 10.1016/j.rse.2020.111673.
- 3: Schwieder, Marcel; Erasmi, Stefan; Nendel, Claas; Hostert, Patrick (2022): National-scale crop type maps for Germany from combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data (2020).

NFORMATIONS-UND OORDINATIONSZENTRUM

11ELTALT

DOISCHE

4: Asam, Sarah; Gessner, Ursula; Almengor González, Roger; Wenzl, Martina; Kriese, Jennifer; Kuenzer, Claudia (2022): Mapping Crop Types of Germany by Combining Temporal Statistical Metrics of Sentinel-1 and Sentinel-2 Time Series with LPIS Data. In: Remote Sensing 14 (13), S. 2981. DOI: 10.3390/rs14132981.









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