Detecting old-growth forests with geospatial foundation model embeddings and spatial validation

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UNIVERSITY OF CAMBRIDGE

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Mapping Europe's remaining old-growth forests (OGF) is a EU Biodiversity Strategy 2030 priority

Area of Interest (AOI): Făgăraș Mountains, Romania

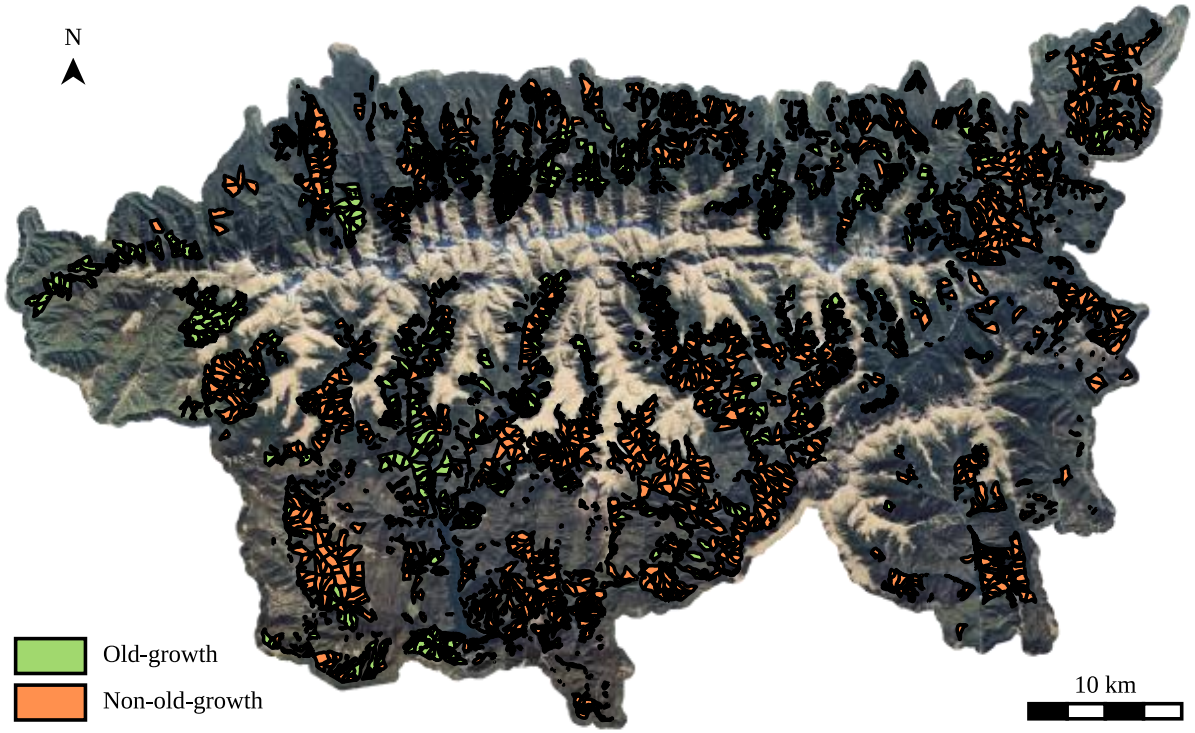
Disagreement on OGF area in AOI

Study	Extent	Method	Area (ha)	% AOI
Sabatini et al. (2018)	Europe	Machine learning	22,376	11%
Munteanu et al. (2022)	Romania	Machine learning	59,707	29%
Schickhofer et al. (2019)	Romania	Rule-based	49,501	23%
Kathmann et al. (2017)	Romania	Rule-based	60,694	29%

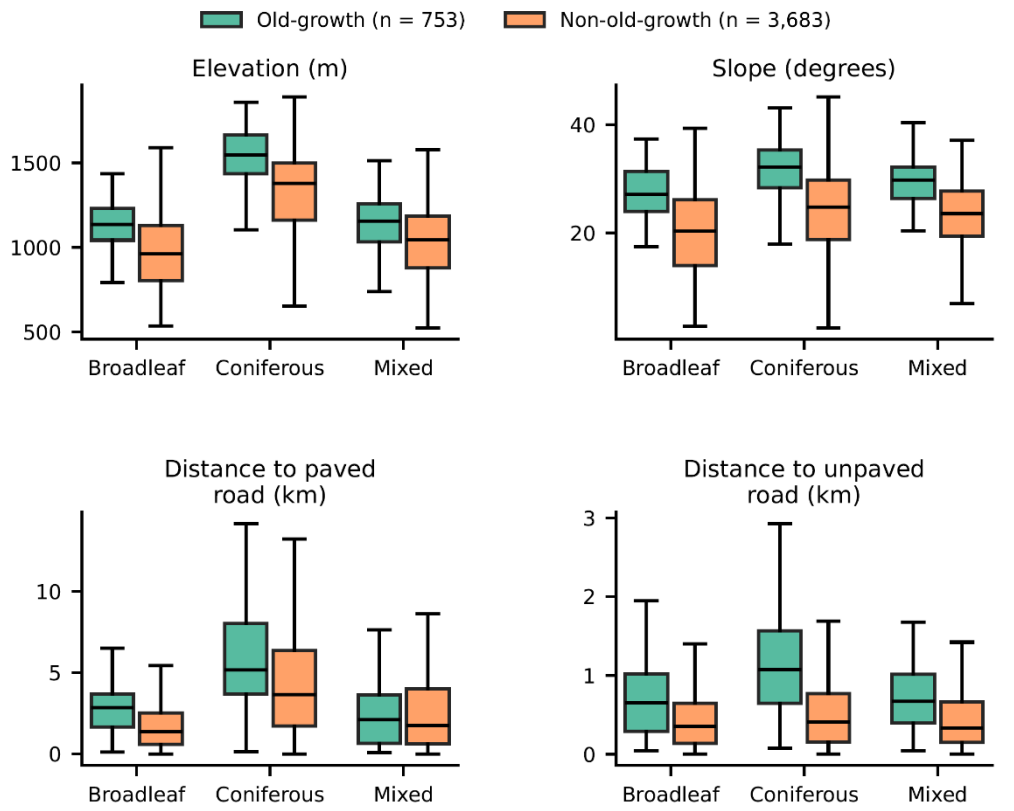
RQ1. How accurate are existing old-growth forest detection models when validated against locally-informed reference labels?

Both coniferous and broadleaf OGF are at higher altitudes, on steeper slopes and further from roads

Ground-truth constructed from inventories and surveys

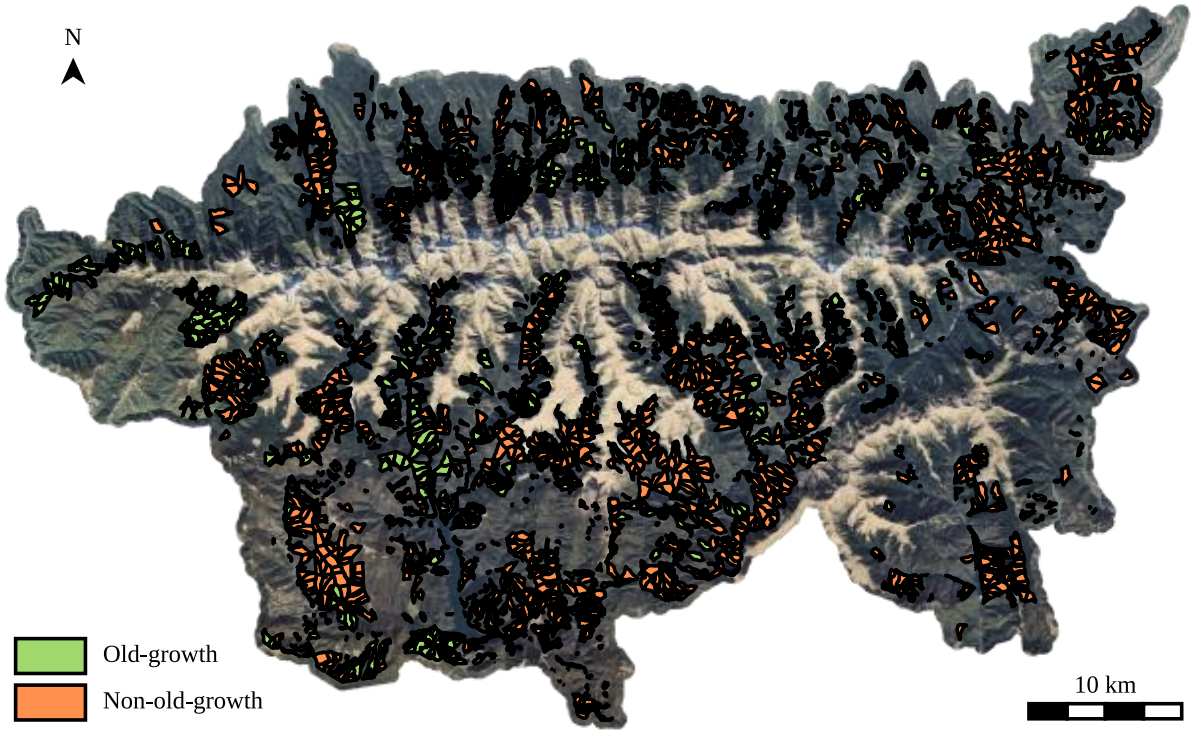


Forest parcel statistics disaggregated by forest type

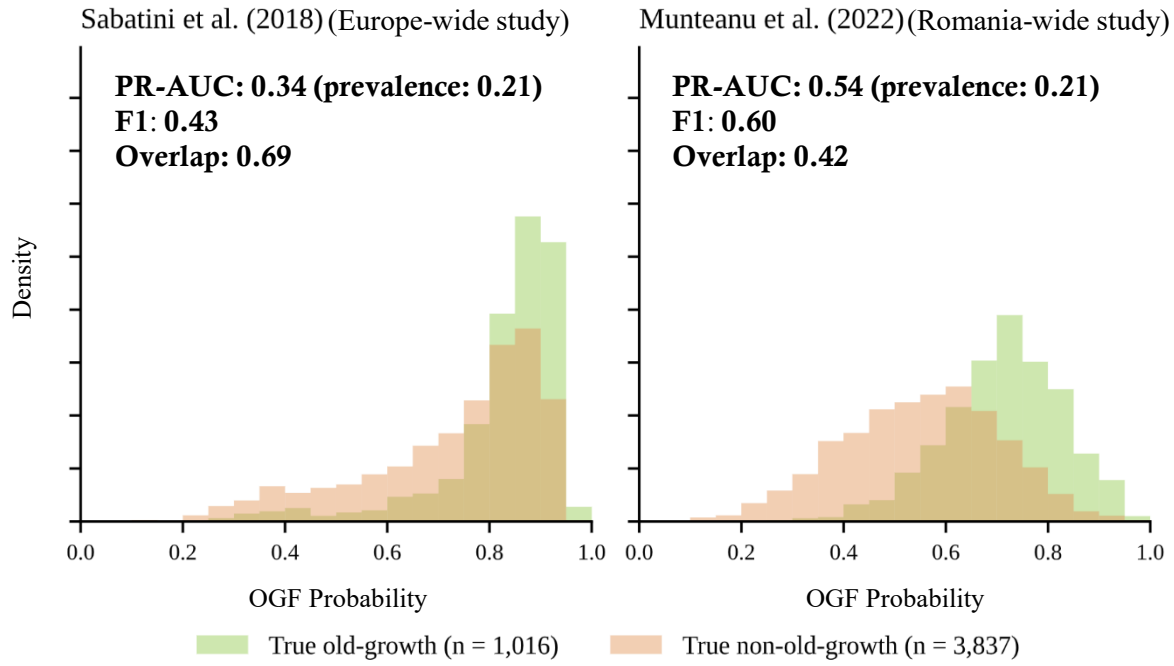


Existing continental and national products perform poorly against our locally-informed ground truth

Ground-truth constructed from inventories and surveys



Model predictions for known old-growth and non-old growth forest parcels (0 = non-old growth; 1 = old growth)



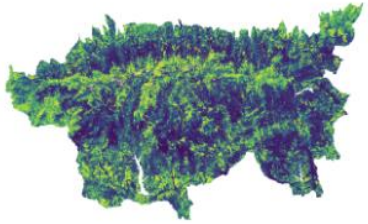
Experimental design: four feature sets and four models

RQ2. To what extent can earth observation (EO) data, including geospatial foundation models (GFM), predict old-growth forests, beyond terrain and access covariates?

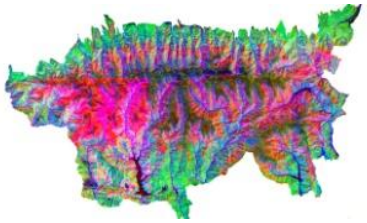
RQ3. Do patch-based models (CNNs) perform better than pixel-based models (XGBoost)?

1. Baseline covariates
e.g. altitude, slope, distance to roads

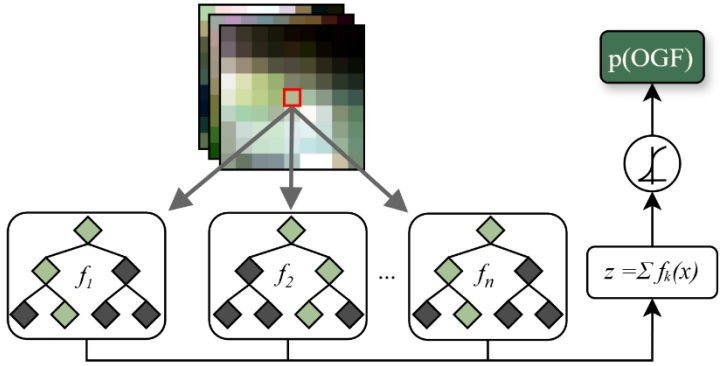
2. Baseline + conventional EO
e.g. optical, SAR, vegetation indices



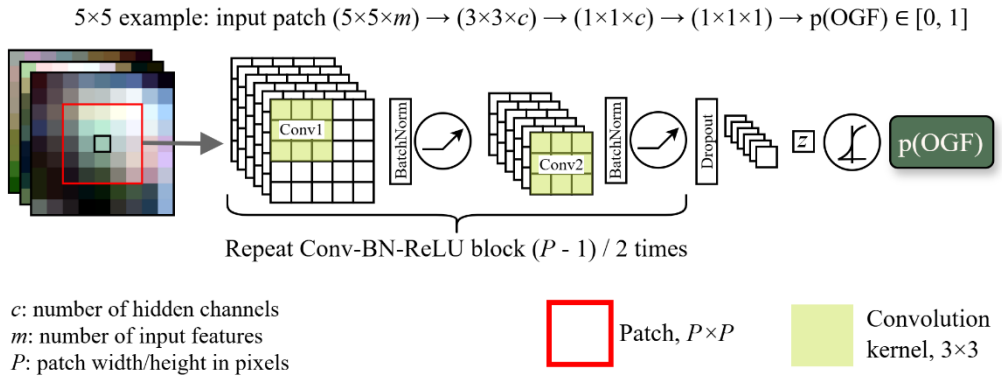
3. Baseline + AlphaEarth
4. Baseline + TESSERA
Learned spatio-temporal representations



1. Pixel-based model: XGBoost

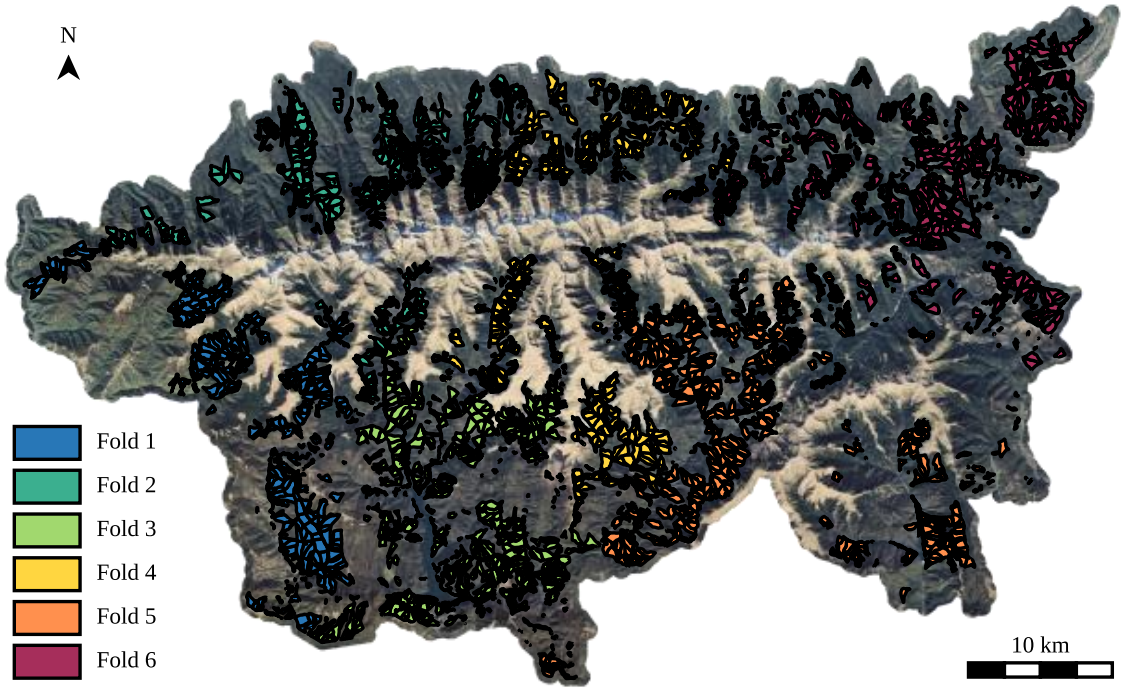


2-4. Patch-based models: 3×3, 5×5 and 7×7 CNNs

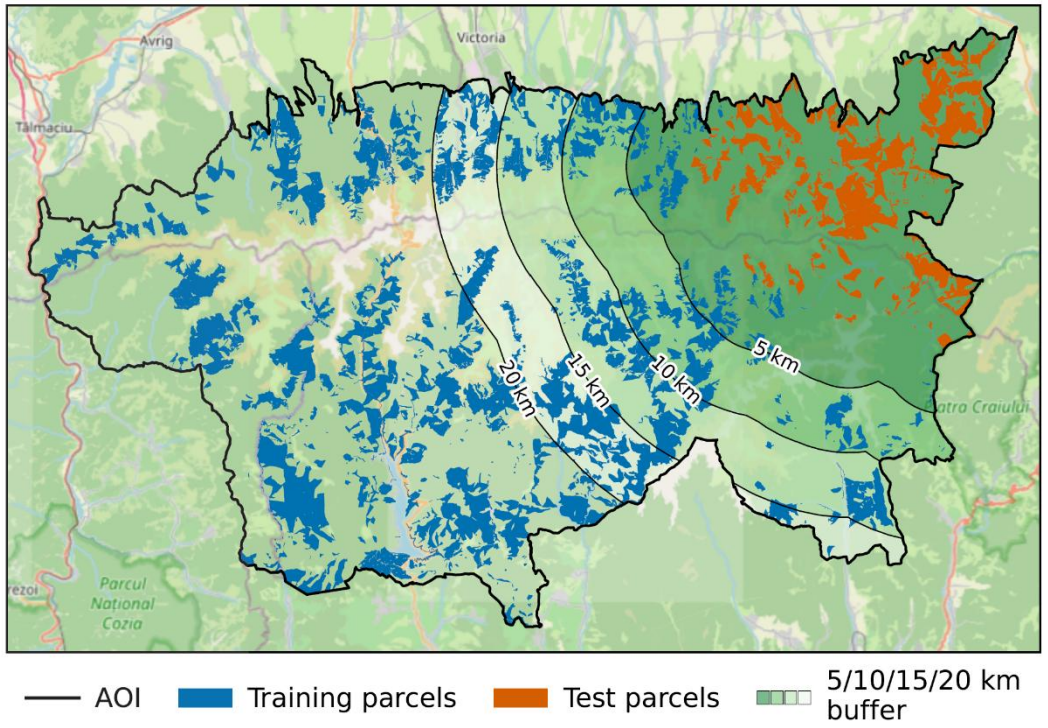


Dealing with spatial autocorrelation: (1) measure (2) mitigate (3) honesty

Nested six-fold blocked cross validation

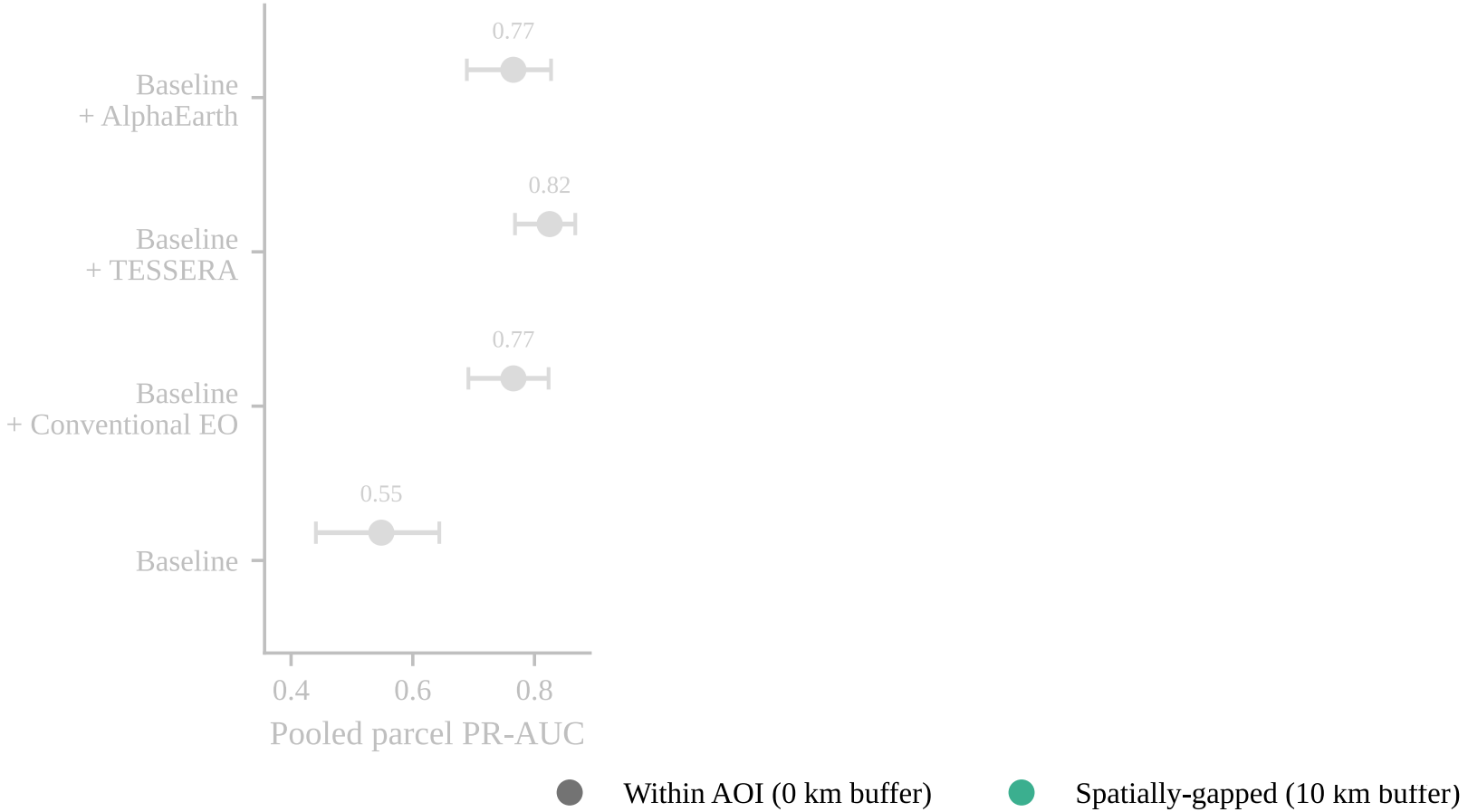


Train-test buffer sensitivity analysis



[1]Ploton et al. (2020), [2] Roberts et al. (2016)

Finding 1: Conventional EO and embeddings contain an old-growth signal beyond terrain and access covariates



*** = a statistically significant difference; PR-AUC = Average Precision**

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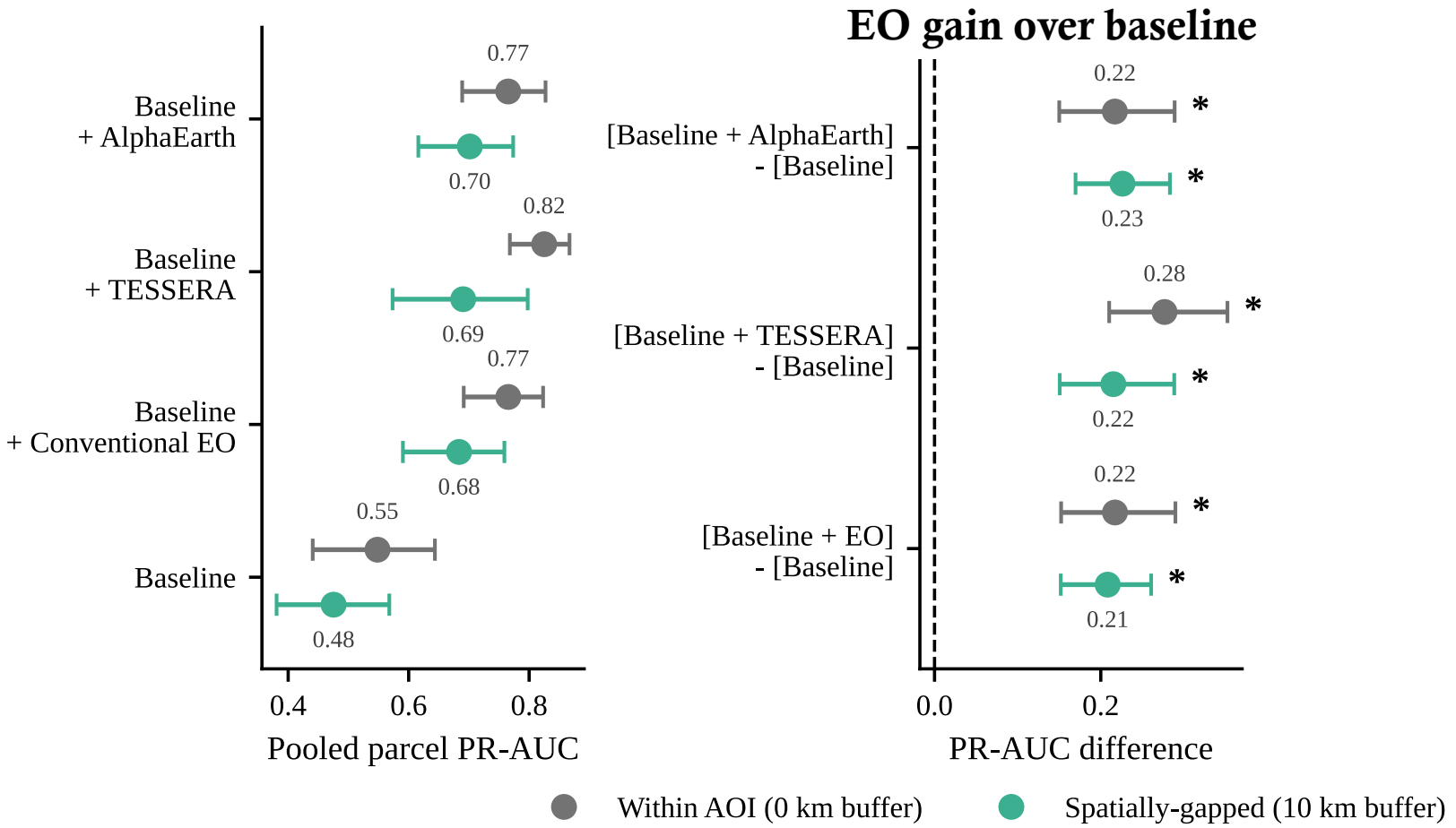

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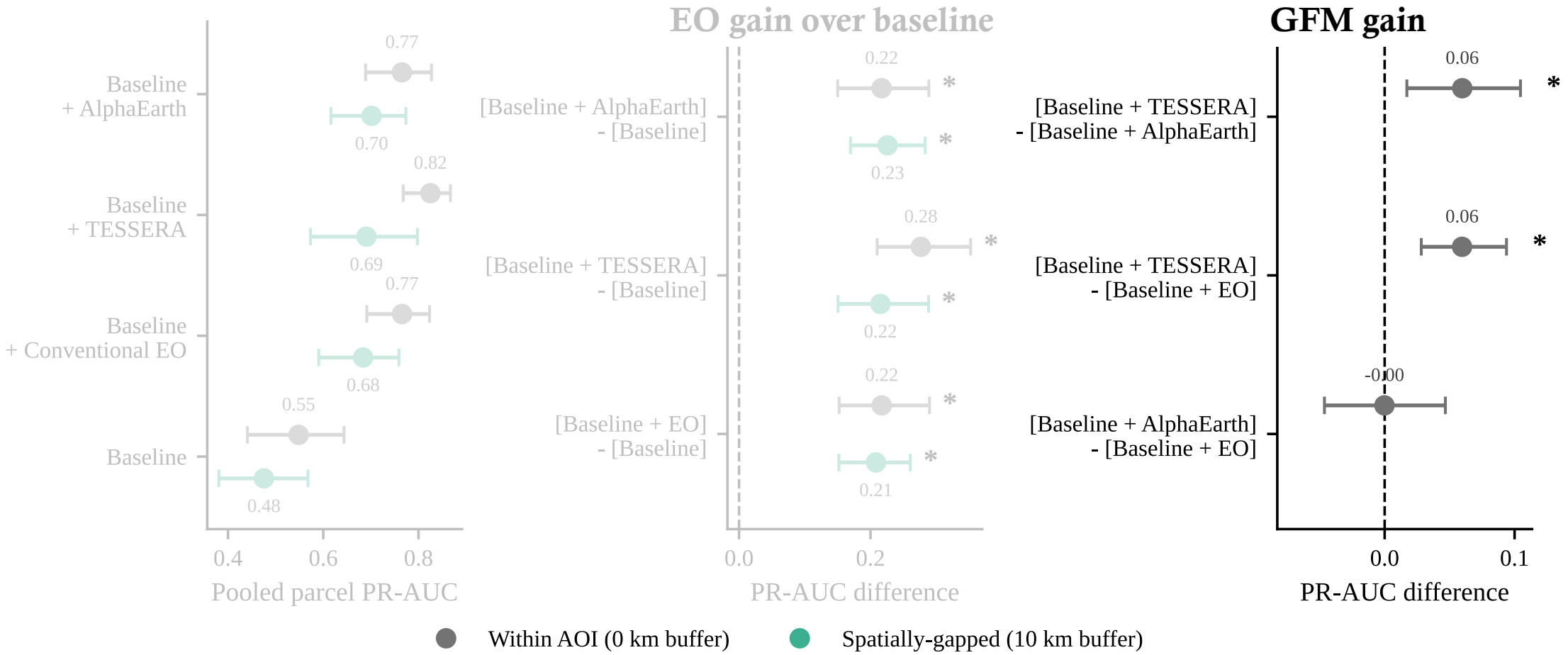
Finding 2: TESSERA outperforms at interpolation; but indistinguishable from conventional EO beyond 10 km



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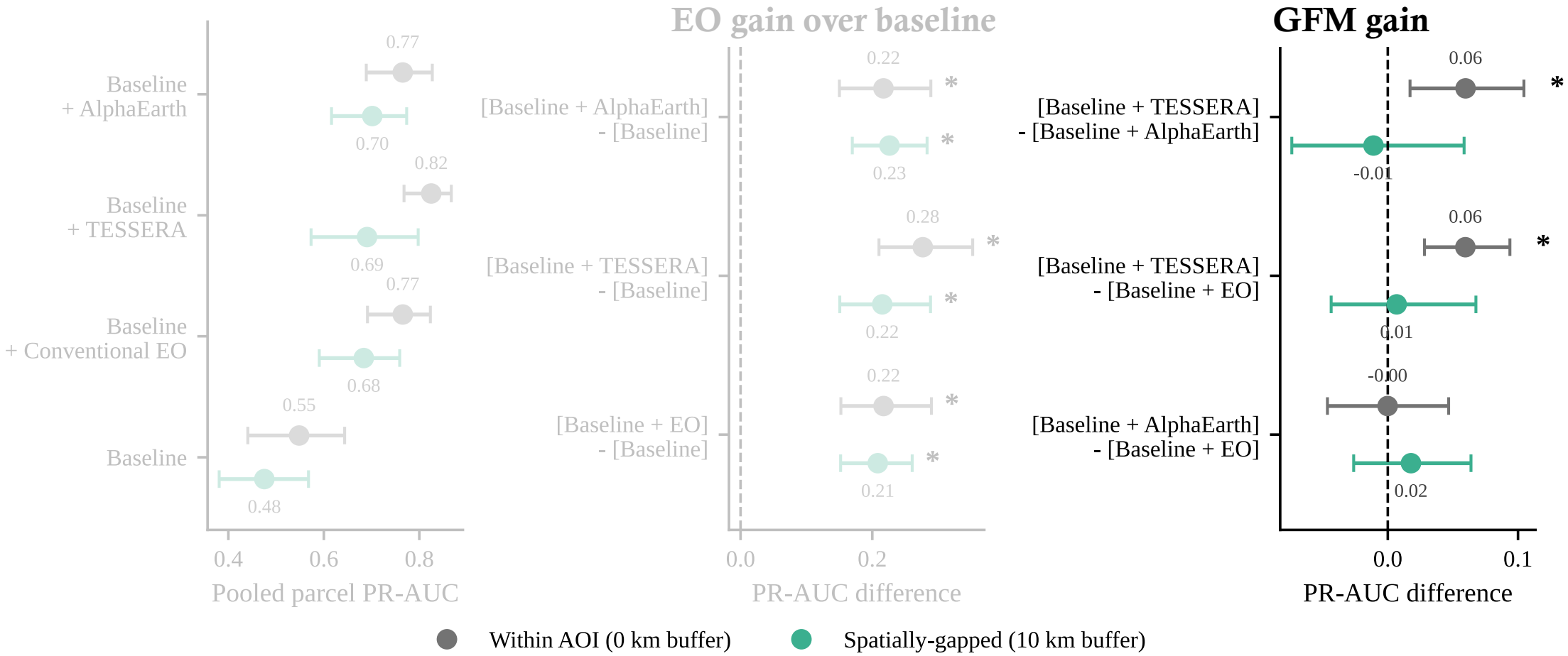

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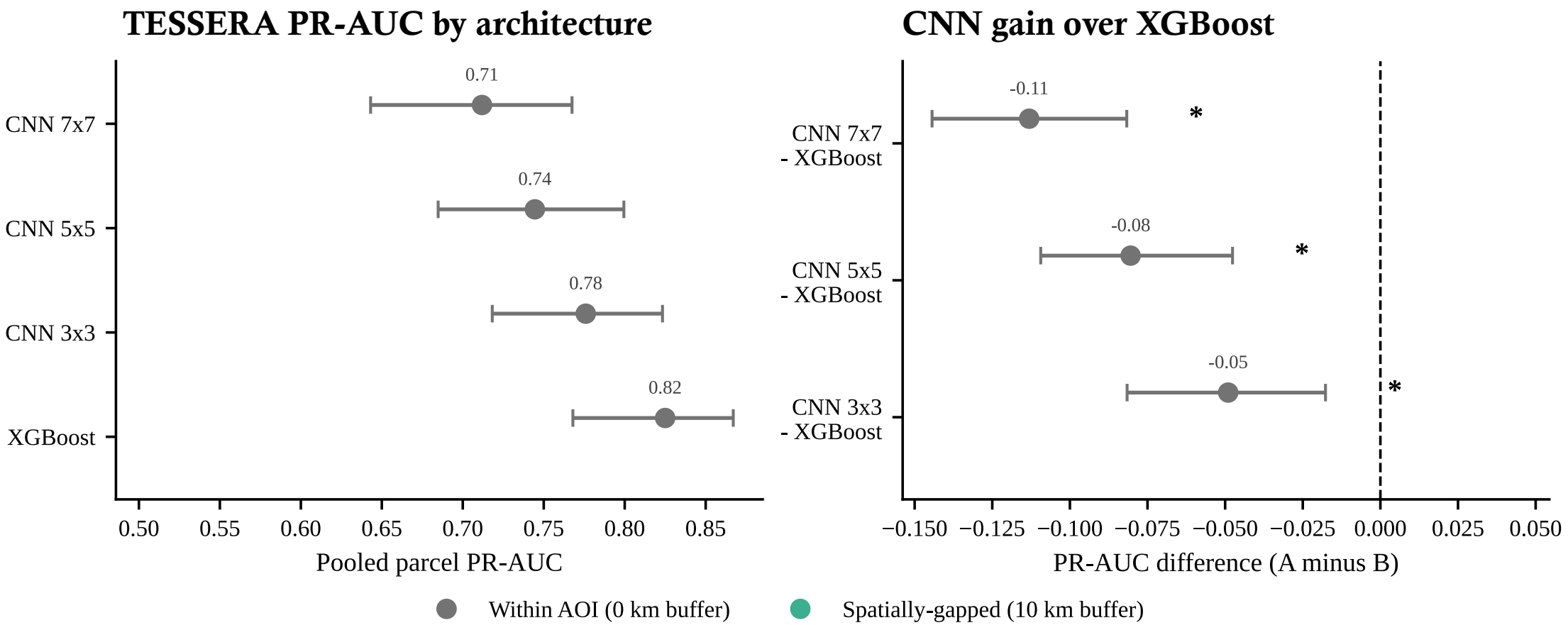
Finding 3: Adding spatial context does not improve (and potentially impairs) performance



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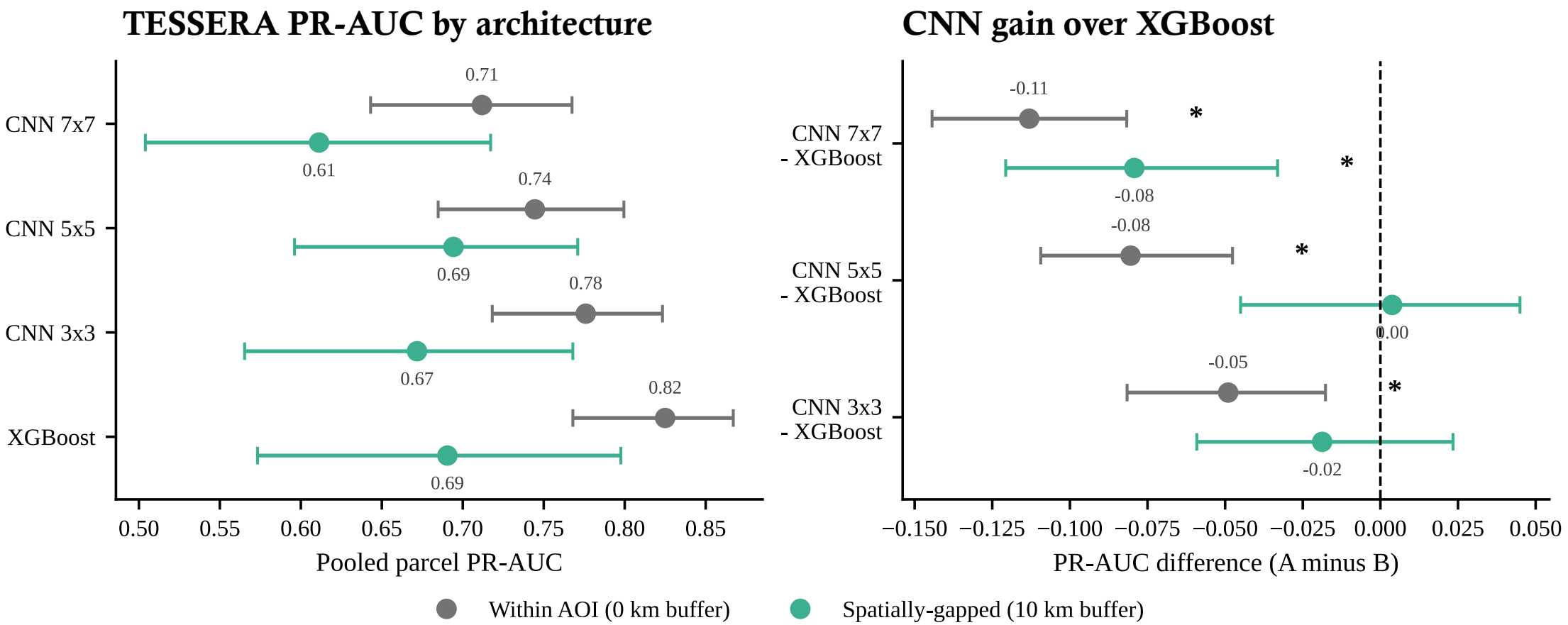

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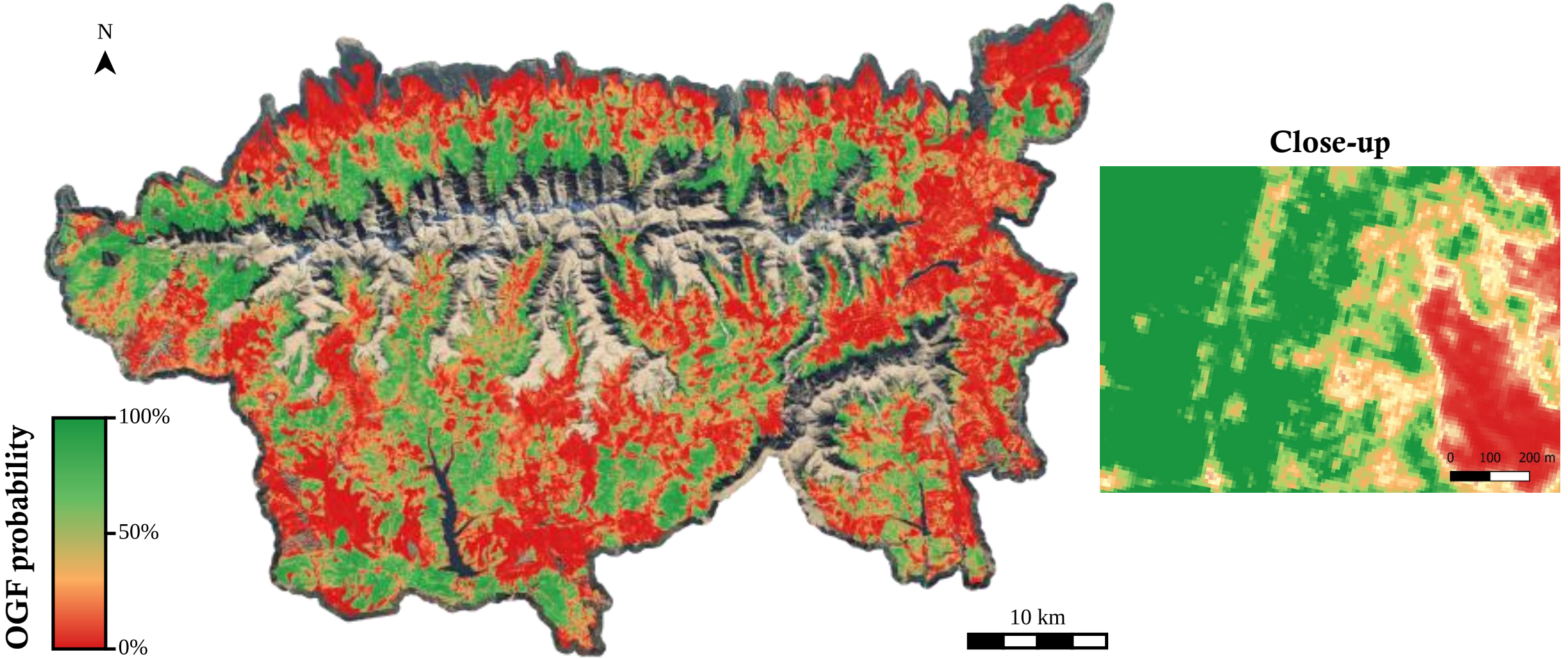
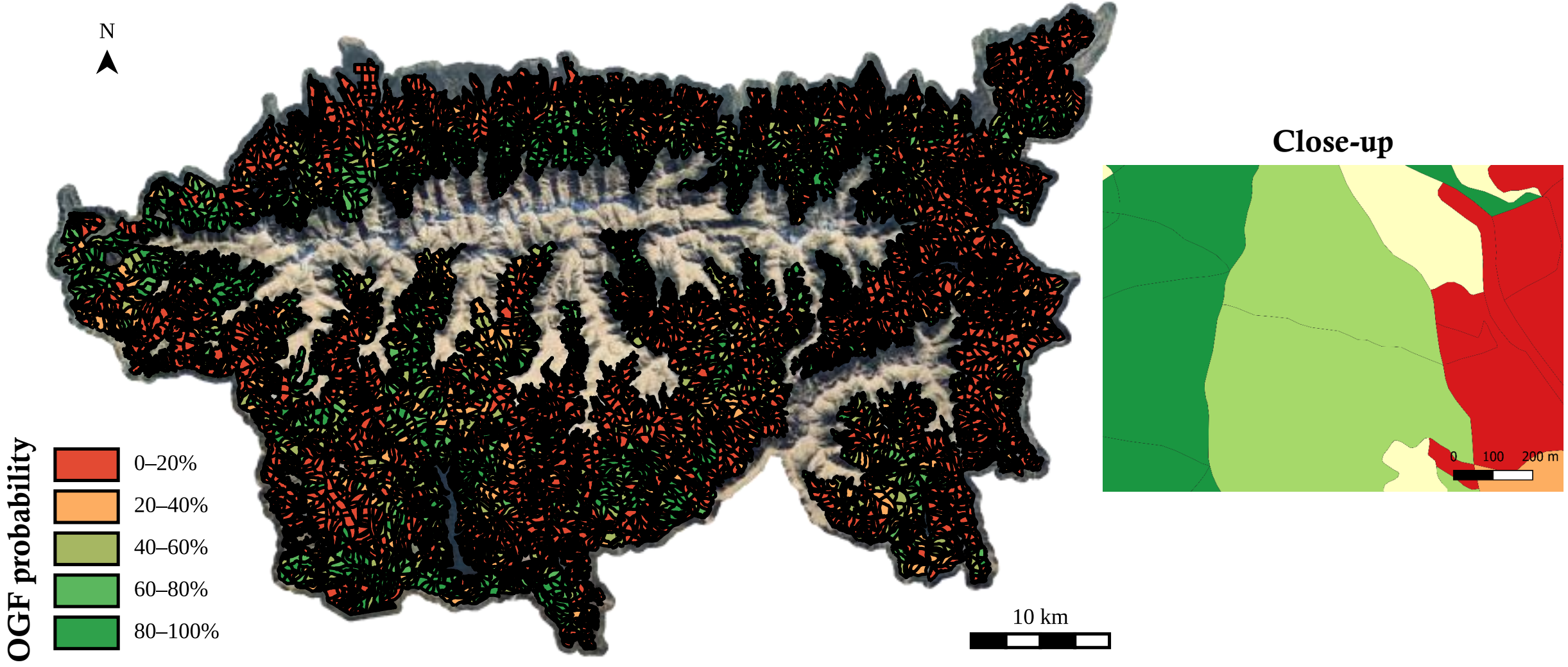
Pixel-level inference across the AOI with calibrated XGBoost + TESSERA model…



…pixels aggregated to forest parcels; estimated old-growth area of 50 kha (95% CI: 36-62 kha)

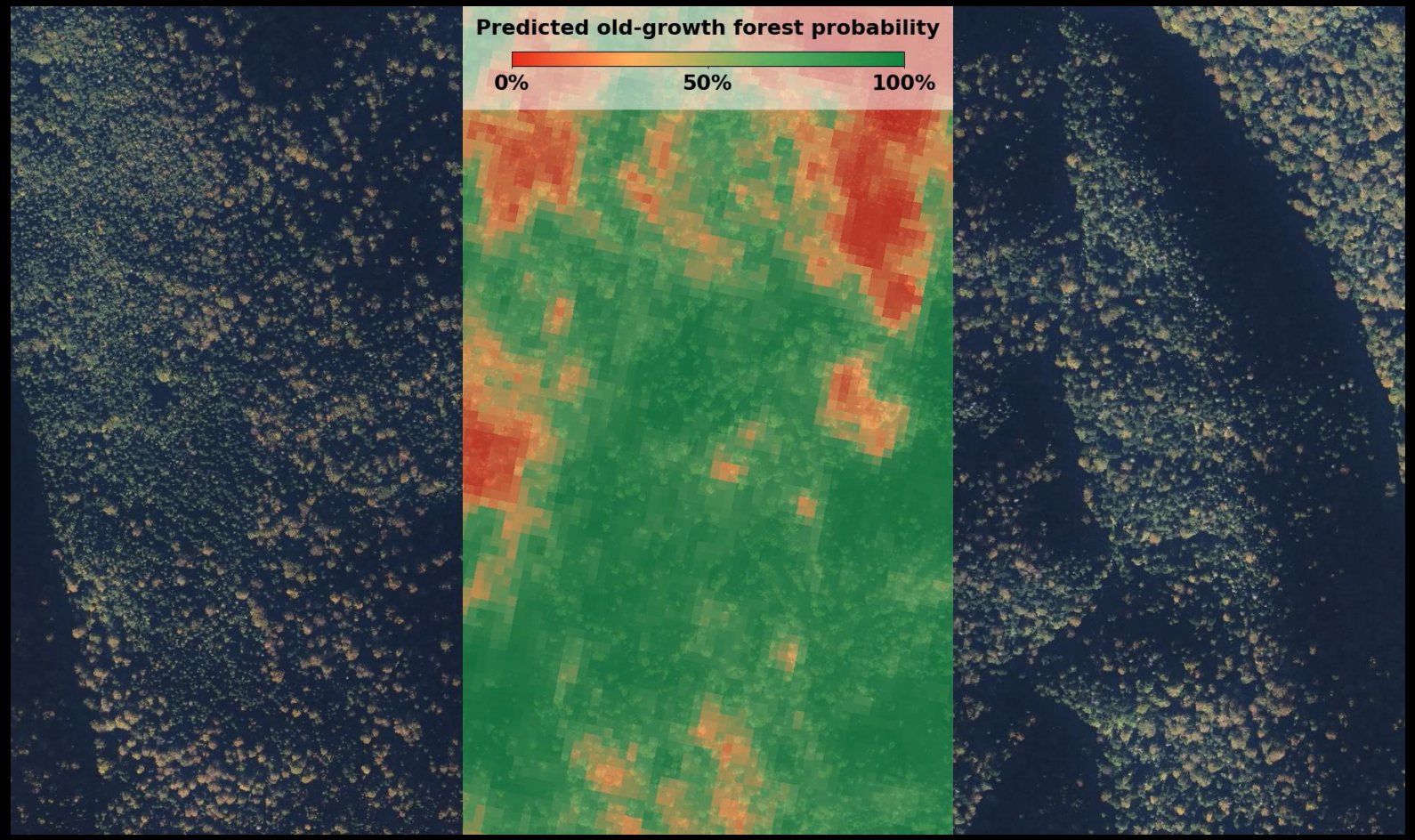


Key messages

1. Use large-scale (global/continental/national) maps with caution.
2. A temperate montane old-growth forest signal exists within a 10 m EO pixel, independent of terrain, access and location.
3. Spatial validation can reverse apparent gains from geospatial foundation model embeddings.

[1] Ploton et al. (2020), [2] Roberts et al. (2016), [3] Meyer and Pebesma (2021, 2022)

Thank you



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