Supplemental Material

National-scale mapping of building height

using Sentinel-1+2 time series

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Structure

A1: Choice of machine learning method
A2: Feature selection
A3: Mean building height and population density
A1. Choice of machine learning method

Random Forest Regression (RFR) and Support Vector Regression (SVR) are two widely used machine learning methods employed in the field of remote sensing. Based on the Berlin dataset, we have evaluated which method to use for predicting building height. This assessment complements the preliminary analysis as presented in section 4.3.3.a. and 5.1 of the main paper. We inter-compared the performance of the radar features, the optical features, as well as a synergistic combination of both on the Berlin dataset. For this, we tested two machine learning methods:

1) We trained SVR models using 90% of the training data. The SVR hyper-parameters were tuned using grid search with 10-fold cross-validation. The remaining subsample was used for model inspection. For clarity of presentation, Figure 6 from the main paper is reproduced here as Figure A1.

2) Analogous, we trained RFR models with 500 trees of maximal depth, and used a third of all available features at each tree node to find the optimal splits (Figure A2).

![Figure A1](image1)

**Figure A1.** Support Vector Regression model comparison using radar-only (a), optical-only (b), and both data sources combined (c). White Line = one-to-one; red line: ordinary least squares regression, orange line: ordinary least squares regression through origin; green line: weighted least squares regression; cyan line: weighted least squares regression through origin; RMSE: Root Mean Squared Error, RMSE’ = weighted RMSE; weights were obtained from the frequency of occurrence within the reference dataset.

![Figure A2](image2)

**Figure A2.** The same as Figure A1, but using Random Forest Regression.
The OLS estimates suggest the superiority of RFR as compared to SVR. However, the frequency-weighted RMSE indicates the opposite. When inspecting the map representation of the building height prediction, we observed a largely consistent behavior between the methods, except for large commercial buildings (Figure A3). We presume that this is because the buildings are larger than the radius used for generating the morphological metrics, and as such, the prediction can only rely on the spectral/backscatter signal of the roofing material (i.e., no building shadows nor trihedral scattering mechanisms are present). Obviously, the RFR substantially overestimated building height in these cases, whereas more reasonable heights were predicted by SVR – although not highly accurate either.

![Figure A3. Building height prediction using the combined radar + optical model using Support Vector Regression (a) and Random Forest Regression (b) for a large commercial building in Berlin as shown in c): © Google Earth.](image)

This is further corroborated by Figure A4. The mean absolute percentage error indicates that RFR is performing worse for specific building heights, e.g., for short buildings (4-5 m) as well as for 9-12 m tall buildings, which appears to be a typical height for commercial buildings. For tall buildings > 30 m however, RFR may be superior. However, due to the rare occurrence of these buildings in Germany, we opted to select SVR for producing the wall-to-wall building height map.
Figure A4. Mean Absolute Percentage Error (MAPE) per reference height for the radar-only (a), optical-only (b), and combined models (c). Black Line = Support Vector Regression (SVR); red line: Random Forest Regression (RFR); grey bars: histogram of reference building height. The legend displays the total MAPE, as well as the MAPE weighted by the frequency of occurrence within the reference dataset.

A2. Feature selection

1) Methods

a) Pre-selection

The large feature space generated may result in overfitting and computational complexity related to the “curse of dimensionality” (Rust 1997). As a consequence, we reduced dimensionality using a two-step feature reduction approach. In the first step, we aimed at quickly eliminating the least important features using a fairly fast training technique that provides a feature ranking. For this, we employed a Random Forest regression (RFR) on a random 10% subsample (500 trees, 1% of features tested at each split for fast computation) and retained all features that contribute more than 1‰ feature importance, i.e. we only removed features that did not contribute information at all.

b) Model selection

In the second step, we switched to our target machine learning algorithm, i.e. Support Vector Machine regression (SVR). Similarly to Schug et al. (2020), feature reduction was achieved by repeatedly training models using random feature subsets. We trained 100 SVR models, and randomly selected 50 pre-selected features as a reasonable compromise between testing many feature combinations and performing costly feature reduction strategies like forward, backward, or exhaustive feature selection. For each mode, the SVR hyper-parameters were tuned using grid search with 10-fold cross-validation. The training was performed on 90% of the training data.
The remaining subsample was used for model selection, wherein the model with best performance in terms of regression slope, offset, $R^2$, and RMSE was eventually selected.

2) Results

a) Pre-selection

Figure A5a-c shows the feature importance for the three different feature dimensions, i.e. spectral (a), temporal (b), and spatial (c) domains. Within each domain, boxplots are grouped according to spectral band, statistical aggregation and morphological metric, respectively. Within each domain, there are features that contribute more than others. Highest spectral contribution stems from the SAR data wherein both polarizations show high feature importance. However, optical data contribute valuable information, too. Especially vegetation-sensitive bands/indices contribute more, e.g. the near infrared band, NDVI or Tasseled Cap Greenness. Other optical indices seem to contribute less, which are mainly shortwave infrared bands, the first red-edge band, and Tasseled Cap Wetness. In the temporal domain, all metrics that indicate temporal snapshots and average state contribute equally well. The variability and distribution parameters contribute less. In the spatial domain, clear patterns are present. Blackhat and tophat metrics are least important, while closing, erosion and opening metrics contribute most information to the model. Within each group, positive outliers are present, which indicate a high usefulness of specific domain combinations. Thus, when selecting all features that contribute more than 1‰ feature importance, almost no group is entirely eliminated. However, more important groups are selected at a higher rate (Figure A5d-f), e.g. SAR bands, temporal snapshot statistics or erosion and dilation metrics. The full list of pre-selected features with feature importance ranking is presented in Table A1.
Figure A5. Feature pre-selection using Random Forest Feature Importance. Top: Boxplots of Feature Importance for the spectral (a), temporal (b) and spatial (c) domains, represented through bands/indices, aggregation statistics, and texture metrics, respectively; the y-axis is drawn logarithmic, thus outliers with 0% Feature Importance are omitted from this plot. Bottom: Number of selected features for the spectral (d), temporal (e) and spatial (f) domains. See Table A1 for a list with all pre-selected features.

b) Model selection

The performance indicators vary considerably from model to model (Figure A6a-d), indicating that not every sub-combination of features is equally meaningful. Most reduced models perform worse than the full model using all 1,638 features (horizontal red lines). However, a few feature subsets do indeed perform better, indicating that some features interact adversely. The selection of the best model is trivial as it showed superior performance in all chosen indicators (bullseye signature).

The 50 randomly selected features of the best performing model are shown in Figure A6, grouped according to domain (see supplemental material for the full list). Several groups were entirely eliminated, while other groups are selected at higher or lower rates than present in the pre-selection. Among high-ranking groups in the pre-selection, NDVI was entirely eliminated and median and maximum statistics were selected at a lower rate. Low-wavelength bands (blue, green), the 2nd red-edge band, kurtosis and closing were selected at a higher rate as compared to the pre-selection. The full list of selected features is presented in Table A2.
Figure A6. Model selection using Support Vector Machine Regression. Top: Model performance of 100 models trained on 50 randomly chosen feature subsets in terms of regression offset (a), slope (b), $R^2$ (c) and RMSE (d); the best-performing model is highlighted with bull’s eye signature; the full model as shown in Figure 6f is highlighted with the red horizontal line. Bottom: feature subset of the best-performing model; number of selected features for the spectral (e), temporal (f) and spatial (g) domains. See Table A2 for a list with all 50 selected features.

3) Discussion

Along all feature dimensions, i.e. spectral, temporal and spatial domains, distinct features were selected at a higher rate. In the spectral dimension, both radar polarizations appear very relevant. This is likely due to the fairly direct relationship between backscatter and vertical structure (Li et al. 2020). There are also important optical bands and indices. Low-wavelength bands were likely selected as they capture brightness gradients, and vegetation-sensitive bands and indices were selected. These bands likely provide explanatory power to the machine learning model with regards to typical roof materials and vegetation compositions of particular settlement types. Short-wave infrared bands were not selected at all, which probability is due to its sensitivity to vegetation and water content, which is already covered by the near-infrared bands or not relevant for predicting building height, respectively.

Within the temporal dimension, temporal variability and data distribution statistics were selected at a lower rate, whereas most quantiles and the average are very important. The quantiles represent different temporal snapshots, and their combination implicitly include the temporal variability while also providing spectral information. Variability and distribution statistics were likely not selected as they provide redundant information
when several quantiles are available. Similarly, the median was hardly selected, whereas the average was very dominant, which is likely due to redundancy.

In the spatial dimension, two texture metrics were hardly selected (blackhat, tophat), while three metrics appear very important (erosion, opening, closing). The tophat and blackhat metrics are operations that enhance bright and dark elements in a dark and bright background, respectively. When applied to highly structured urban landscapes, the resulting images appear sharpened, which is probably an undesired property as most information content is rather encoded in the spatial neighborhood (e.g. shadow effects). The erosion (dilation) operation assigns the minimum value in the structuring element to the central pixel, i.e. in a city, it selects the darkest pixel / shadow (brightest pixel / roof). The opening operator performs a dilation on the eroded image, i.e. in a city, it selects the brightest of the selected shadows, whereas the closing operator preforms an erosion on the dilated image, i.e. in a city, it selects the darkest of the selected roofs. By combining those three texture metrics with each other, one can assume that some logical height derivation is possible, especially if complementary spectral and temporal information is added.

4) Full list of selected features

a) Pre-selection

| Rank | Band/Index | Aggregation Statistic | Texture Metric | Feature Importance |
|------|------------|-----------------------|----------------|-------------------|
| 1    | VH         | 90%                   | Closing        | 0.011183          |
| 2    | VH         | 50%                   | Closing        | 0.009906          |
| 3    | VV         | 75%                   | Closing        | 0.009331          |
| 4    | VH         | 75%                   | Closing        | 0.008569          |
| 5    | VH         | Average               | Closing        | 0.008182          |
| 6    | VH         | Average               | Dilation       | 0.007332          |
| 7    | VV         | 25%                   | Closing        | 0.007228          |
| 8    | VV         | 25%                   | Dilation       | 0.007205          |
|    |    |    |    |
|----|----|----|----|
| 9  | VH | 75% | Dilation | 0.006987 |
| 10 | VH | 50% | Dilation | 0.006302 |
| 11 | VV | 10% | Closing  | 0.006048 |
| 12 | VV | 50% | Closing  | 0.006022 |
| 13 | TC Green | 0% | Opening  | 0.005762 |
| 14 | NIR | 75% | Opening  | 0.005686 |
| 15 | RE2 | 10% | Opening  | 0.005669 |
| 16 | VH | 100% | Closing  | 0.005659 |
| 17 | VV | 90% | Opening  | 0.005446 |
| 18 | NIR2 | 75% | Opening  | 0.005398 |
| 19 | NIR2 | 90% | Erosion  | 0.005383 |
| 20 | NIR2 | Average | Erosion | 0.005233 |
| 21 | VV | 100% | Opening  | 0.005159 |
| 22 | TC Green | 50% | Opening  | 0.00506 |
| 23 | VV | 100% | Closing  | 0.005044 |
| 24 | VV | 0%   | Closing  | 0.004993 |
| 25 | NIR | Average | Opening | 0.004884 |
| 26 | RE3 | 75% | Opening  | 0.004871 |
| 27 | NIR2 | 10% | Opening  | 0.004866 |
| 28 | NIR2 | 50% | Erosion  | 0.004842 |
| 29 | VV | Average | Closing | 0.004751 |
| 30 | VV | 75% | Dilation | 0.004743 |
| 31 | NIR | 100% | Opening  | 0.004738 |
| 32 | TC Green | 25% | Opening  | 0.004705 |
| 33 | VV | Average | Opening | 0.004696 |
|   |   |   |   |
|---|---|---|---|
| 34 | VV | 10% | Dilation | 0.004659 |
| 35 | NIR2 | 50% | Opening | 0.004634 |
| 36 | RE3 | 50% | Erosion | 0.004629 |
| 37 | NDVI | Average | Opening | 0.004592 |
| 38 | RE2 | 0% | Opening | 0.004566 |
| 39 | VH | 25% | Closing | 0.004427 |
| 40 | NIR2 | 90% | Opening | 0.004343 |
| 41 | NIR | 25% | Opening | 0.004325 |
| 42 | NIR2 | 100% | Erosion | 0.00432 |
| 43 | RE3 | Average | Opening | 0.004276 |
| 44 | VH | 25% | Dilation | 0.004274 |
| 45 | RE3 | 90% | Opening | 0.004273 |
| 46 | NIR2 | 75% | Erosion | 0.00426 |
| 47 | TC Green | 10% | Opening | 0.004218 |
| 48 | SWIR1 | 75% | Erosion | 0.004001 |
| 49 | NIR2 | 10% | Erosion | 0.003994 |
| 50 | NDVI | 0% | Opening | 0.00395 |
| 51 | NIR | Average | Erosion | 0.003941 |
| 52 | NIR | 10% | Opening | 0.003913 |
| 53 | RE2 | 50% | Erosion | 0.003815 |
| 54 | RE2 | Average | Erosion | 0.003752 |
| 55 | NIR2 | Average | Opening | 0.00375 |
| 56 | TC Green | Average | Opening | 0.003738 |
| 57 | NIR | 100% | Erosion | 0.003737 |
| 58 | NDVI | 10% | Opening | 0.003725 |
|   | Sensor | Percentage | Operation  | Result  |
|---|--------|------------|------------|---------|
| 59 | VH     | 10%        | Dilation   | 0.003677|
| 60 | NIR    | 50%        | Erosion    | 0.00362 |
| 61 | VH     | Kurtosis   | Opening    | 0.003618|
| 62 | VH     | 10%        | Closing    | 0.003559|
| 63 | NIR    | 50%        | Opening    | 0.00349 |
| 64 | VV     | 25%        | Opening    | 0.003451|
| 65 | NDVI   | 50%        | Opening    | 0.003375|
| 66 | VH     | 90%        | Dilation   | 0.003367|
| 67 | Blue   | Average    | Closing    | 0.00334 |
| 68 | RE3    | 90%        | Erosion    | 0.003323|
| 69 | VH     | 75%        | Opening    | 0.003277|
| 70 | NIR    | 25%        | Erosion    | 0.003271|
| 71 | NIR2   | 25%        | Opening    | 0.003266|
| 72 | NIR2   | 100%       | Opening    | 0.003217|
| 73 | TC Green| 75%        | Erosion    | 0.003214|
| 74 | NIR    | 90%        | Opening    | 0.003184|
| 75 | TC Bright| 100%       | Erosion    | 0.003146|
| 76 | VV     | 75%        | Opening    | 0.003117|
| 77 | VV     | 0%         | Dilation   | 0.0031  |
| 78 | VV     | 90%        | Closing    | 0.003094|
| 79 | TC Bright| 50%        | Erosion    | 0.003082|
| 80 | SWIR2  | 25%        | Erosion    | 0.003072|
| 81 | RED    | 10%        | Closing    | 0.003054|
| 82 | TC Green| 100%       | Opening    | 0.003034|
| 83 | NIR2   | 0%         | Opening    | 0.003018|
| Row | Object | Percentage | Operation | Erosion  |
|-----|--------|------------|-----------|----------|
| 84  | RE3    | 100%       | Erosion   | 0.002983 |
| 85  | RE3    | Average    | Erosion   | 0.00297  |
| 86  | VH     | 100%       | Opening   | 0.002951 |
| 87  | TC Bright | 75%     | Erosion   | 0.002849 |
| 88  | TC Bright | Average  | Erosion   | 0.002829 |
| 89  | VV     | 90%        | Dilation  | 0.002825 |
| 90  | VV     | Average    | Dilation  | 0.002805 |
| 91  | TC Bright | 90%     | Erosion   | 0.002805 |
| 92  | NIR    | 75%        | Erosion   | 0.002803 |
| 93  | TC Green | 10%    | Closing   | 0.002775 |
| 94  | VV     | 100%       | Erosion   | 0.002774 |
| 95  | VH     | Kurtosis   | Erosion   | 0.002753 |
| 96  | TC Bright | 50%     | Opening   | 0.002715 |
| 97  | NDVI   | 0%         | Erosion   | 0.002715 |
| 98  | TC Green | 50%    | Erosion   | 0.002705 |
| 99  | Blue   | 10%        | Closing   | 0.002692 |
| 100 | TC Green | 75%    | Opening   | 0.002627 |
| 101 | TC Green | 90%    | Opening   | 0.002605 |
| 102 | NDVI   | Range      | Closing   | 0.002578 |
| 103 | RE3    | 25%        | Erosion   | 0.00257  |
| 104 | SWIR1  | 50%        | Erosion   | 0.002567 |
| 105 | VH     | IQR        | Closing   | 0.002548 |
| 106 | RED    | 0%         | Closing   | 0.002528 |
| 107 | RE3    | 75%        | Erosion   | 0.002522 |
| 108 | NIR    | 0%         | Opening   | 0.00251  |
|   | Process  | Percentage | Result   | Value    |
|---|----------|------------|----------|----------|
| 109 | TC Green | 10%        | Erosion  | 0.002454 |
| 110 | VV       | 50%        | Opening  | 0.002424 |
| 111 | RE2      | 90%        | Erosion  | 0.002421 |
| 112 | RE3      | 25%        | Opening  | 0.002351 |
| 113 | NDBI     | 50%        | Closing  | 0.002279 |
| 114 | VH       | 0%         | Closing  | 0.002277 |
| 115 | RE3      | 100%       | Opening  | 0.002263 |
| 116 | RE1      | Average    | Erosion  | 0.002223 |
| 117 | Blue     | 0%         | Gradient | 0.002208 |
| 118 | RE3      | 10%        | Erosion  | 0.002202 |
| 119 | RE2      | 75%        | Opening  | 0.002196 |
| 120 | RE2      | 50%        | Opening  | 0.002182 |
| 121 | NDVI     | 25%        | Opening  | 0.002177 |
| 122 | RE2      | 90%        | Opening  | 0.002171 |
| 123 | SWIR2    | 50%        | Erosion  | 0.002134 |
| 124 | NIR      | 0%         | Erosion  | 0.002134 |
| 125 | RE2      | Average    | Opening  | 0.002133 |
| 126 | TC Bright| 75%        | Opening  | 0.00213 |
| 127 | NIR2     | 100%       | Blackhat | 0.002094 |
| 128 | VH       | Average    | Opening  | 0.002058 |
| 129 | VV       | 50%        | Dilation | 0.002058 |
| 130 | TC Green | 25%        | Erosion  | 0.002051 |
| 131 | RE2      | 100%       | Erosion  | 0.00205 |
| 132 | RE2      | 10%        | Erosion  | 0.002043 |
| 133 | NIR2     | 25%        | Erosion  | 0.002039 |
| Page | Measurements          | Description | Value   |
|------|-----------------------|-------------|---------|
| 134  | NDBI 100%             | Closing     | 0.002032 |
| 135  | VV Average            | Erosion     | 0.001995 |
| 136  | RE2 75%               | Erosion     | 0.00199  |
| 137  | Green 0%              | Gradient    | 0.00199  |
| 138  | NDVI 75%              | Opening     | 0.001954 |
| 139  | NDVI 90%              | Erosion     | 0.001858 |
| 140  | NDBI 10%              | Closing     | 0.001834 |
| 141  | RE3 0%                | Opening     | 0.001809 |
| 142  | TC Green Average      | Erosion     | 0.001805 |
| 143  | VH 100%               | Erosion     | 0.001805 |
| 144  | VV Kurtosis           | Opening     | 0.001775 |
| 145  | VV 10%                | Opening     | 0.001774 |
| 146  | TC Bright 25%         | Erosion     | 0.001773 |
| 147  | RED 75%               | Closing     | 0.001768 |
| 148  | Green 75%             | Erosion     | 0.001748 |
| 149  | VH 50%                | Opening     | 0.001738 |
| 150  | TC Bright 100%        | Opening     | 0.001733 |
| 151  | NDBI Range            | Closing     | 0.001717 |
| 152  | Blue 0%               | Dilation    | 0.001706 |
| 153  | RE3 IQR               | Opening     | 0.001702 |
| 154  | NDBI 75%              | Closing     | 0.001699 |
| 155  | TC Green 0%           | Closing     | 0.001673 |
| 156  | RE1 50%               | Erosion     | 0.001658 |
| 157  | RE1 75%               | Erosion     | 0.001653 |
| 158  | NDBI 50%              | Dilation    | 0.001642 |
|   |   |   |   |
|---|---|---|---|
| 159 | VH | Std. dev. | Gradient | 0.001642 |
| 160 | NDVI | 100% | Erosion | 0.001639 |
| 161 | TC Green | 0% | Erosion | 0.001638 |
| 162 | NDBI | 90% | Closing | 0.001637 |
| 163 | NDBI | Average | Closing | 0.001634 |
| 164 | NIR2 | Std. dev. | Blackhat | 0.001612 |
| 165 | RE2 | 100% | Opening | 0.001604 |
| 166 | SWIR1 | 25% | Erosion | 0.001595 |
| 167 | VH | 100% | Dilation | 0.001584 |
| 168 | VV | 90% | Erosion | 0.001571 |
| 169 | NDBI | 90% | Opening | 0.001547 |
| 170 | RE2 | 25% | Erosion | 0.001541 |
| 171 | TC Green | 75% | Closing | 0.001535 |
| 172 | NDBI | 75% | Opening | 0.001532 |
| 173 | NIR | 90% | Erosion | 0.001522 |
| 174 | RE3 | 50% | Opening | 0.001518 |
| 175 | NDBI | 0% | Closing | 0.001503 |
| 176 | SWIR2 | 10% | Erosion | 0.001501 |
| 177 | NDVI | 50% | Erosion | 0.001499 |
| 178 | NDVI | 100% | Opening | 0.001496 |
| 179 | Green | Average | Erosion | 0.00149 |
| 180 | NDVI | 10% | Closing | 0.001472 |
| 181 | NDVI | 90% | Opening | 0.001469 |
| 182 | NIR | 10% | Erosion | 0.001468 |
| 183 | RED | 0% | Gradient | 0.001455 |
| 184 | RE3   | 10% | Opening | 0.001454 |
| 185 | SWIR2 | 100%| Erosion | 0.001453 |
| 186 | NDBI  | Average | Dilation | 0.001442 |
| 187 | Green | 10% | Dilation | 0.001433 |
| 188 | NIR2  | 90% | Gradient | 0.001425 |
| 189 | NDVI  | 25% | Erosion | 0.001413 |
| 190 | Green | 10% | Gradient | 0.001407 |
| 191 | VV    | 75% | Erosion | 0.001406 |
| 192 | NDVI  | 90% | Closing | 0.001387 |
| 193 | Blue  | 25% | Closing | 0.00138 |
| 194 | NIR   | Std. dev. | Dilation | 0.001368 |
| 195 | SWIR1 | 90% | Erosion | 0.001363 |
| 196 | VH    | 90% | Opening | 0.001358 |
| 197 | TC Green | 100% | Erosion | 0.001341 |
| 198 | NDVI  | Average | Erosion | 0.001334 |
| 199 | RE2   | Range | Opening | 0.001298 |
| 200 | Green | 25% | Dilation | 0.001296 |
| 201 | RE2   | 25% | Opening | 0.001275 |
| 202 | Blue  | 10% | Dilation | 0.001273 |
| 203 | VV    | 25% | Erosion | 0.001255 |
| 204 | Green | 50% | Erosion | 0.001253 |
| 205 | NDBI  | 0% | Dilation | 0.001252 |
| 206 | TC Green | 75% | Blackhat | 0.001251 |
| 207 | RED   | 50% | Gradient | 0.001248 |
| 208 | mNDWI | Average | Gradient | 0.001242 |
|   |   |   |   |
|---|---|---|---|
| 209 | TC Bright | 90% | Opening | 0.00124 |
| 210 | VH | 0% | Dilation | 0.001234 |
| 211 | NDVI | IQR | Blackhat | 0.001226 |
| 212 | VV | Kurtosis | Erosion | 0.001223 |
| 213 | SWIR2 | 25% | Closing | 0.001218 |
| 214 | SWIR1 | 100% | Opening | 0.001215 |
| 215 | SWIR1 | Average | Opening | 0.001192 |
| 216 | NDVI | Std. dev. | Closing | 0.001191 |
| 217 | NDBI | 90% | Dilation | 0.001178 |
| 218 | Blue | 10% | Gradient | 0.001178 |
| 219 | RED | 10% | Gradient | 0.00117 |
| 220 | mNDWI | 75% | Gradient | 0.001163 |
| 221 | SWIR2 | 50% | Opening | 0.001161 |
| 222 | RED | 75% | Erosion | 0.001157 |
| 223 | VH | 75% | Gradient | 0.001156 |
| 224 | mNDWI | 50% | Gradient | 0.001154 |
| 225 | RE3 | 0% | Erosion | 0.001147 |
| 226 | VH | IQR | Dilation | 0.00114 |
| 227 | NDVI | 90% | Gradient | 0.001139 |
| 228 | NDBI | 100% | Opening | 0.001136 |
| 229 | VV | 75% | Gradient | 0.001127 |
| 230 | RED | 25% | Gradient | 0.001127 |
| 231 | TC Green | 25% | Closing | 0.001121 |
| 232 | NIR2 | IQR | Blackhat | 0.001119 |
| 233 | mNDWI | 25% | Gradient | 0.001106 |
|  | VV  | 0%  | Opening | 0.001101 |
|---|-----|-----|---------|----------|
|  | VH  | 50% | Tophat  | 0.001088 |
|  | RED | 90% | Erosion | 0.001084 |
|  | TC Green | 50% | Closing | 0.001081 |
|  | NDVI | 75% | Erosion | 0.001076 |
|  | mNDWI | 0%  | Gradient | 0.001072 |
|  | RE3 | Std. dev. | Blackhat | 0.001065 |
|  | Blue | 25% | Dilation | 0.001055 |
|  | Green | 10% | Closing | 0.001055 |
|  | RE1 | 100% | Erosion | 0.001055 |
|  | NDVI | 0%  | Closing | 0.001044 |
|  | Blue | Average | Gradient | 0.001043 |
|  | NIR2 | 0%  | Erosion | 0.00104  |
|  | VH  | 0%  | Opening | 0.001038 |
|  | Green | 25% | Closing | 0.001022 |
|  | Green | 0%  | Closing | 0.001012 |
|  | mNDWI | Range | Closing | 0.001012 |
|  | Green | Average | Opening | 0.001012 |
|  | NDVI | 0%  | Dilation | 0.001009 |
|  | RE1 | 90% | Opening | 0.001005 |
|  | NIR2 | 90% | Blackhat | 0.001004 |
|  | TC Green | 90% | Blackhat | 0.001004 |

b) Model selection
Table A2. Selected features using evaluation of random feature subsets. Note that this method does not provide a feature ranking, i.e. the order of features in this list is arbitrary.

| Band/Index | Aggregation Statistic | Texture Metric |
|------------|------------------------|----------------|
| VH         | Average                | Opening        |
| RED        | 90%                    | Erosion        |
| NIR2       | 100%                   | Blackhat       |
| TC Green   | 50%                    | Closing        |
| VV         | 10%                    | Opening        |
| RE3        | 75%                    | Erosion        |
| NIR2       | 90%                    | Erosion        |
| VV         | Average                | Closing        |
| Blue       | 0%                     | Gradient       |
| Green      | 0%                     | Closing        |
| TC Green   | Average                | Opening        |
| TC Green   | 0%                     | Closing        |
| RE2        | 75%                    | Erosion        |
| RE2        | 90%                    | Opening        |
| Blue       | 25%                    | Closing        |
| TC Bright  | 25%                    | Erosion        |
| NIR        | Average                | Opening        |
| RE3        | Average                | Erosion        |
| Green      | Average                | Erosion        |
| RE2        | 10%                    | Opening        |
| NIR        | 10%                    | Opening        |
| VV         | 75%                    | Closing        |
| VV         | 75%                    | Closing        |
| Parameter       | Value | Operator |
|-----------------|-------|----------|
| mNDWI           | 25%   | Gradient |
| VV              |       | Opening  |
| VH              |       | Closing  |
| VH              | 25%   | Dilation |
| Blue            | 0%    | Dilation |
| NIR             | 90%   | Opening  |
| Blue            | 25%   | Dilation |
| TC Green        | 25%   | Erosion  |
| NIR2            | 75%   | Erosion  |
| RE2             | 10%   | Erosion  |
| VH              |       | Dilation |
| VV              |       | Opening  |
| VH              | 10%   | Closing  |
| VV              | 0%    | Dilation |
| NIR             | 0%    | Erosion  |
| NIR2            | 90%   | Gradient |
| RE2             |       | Opening  |
| VH              |       | Dilation |
| VV              |       | Opening  |
| mNDWI           | 25%   | Gradient |
| NIR             | 10%   | Erosion  |
| Green           | 0%    | Closing  |
| Green           |       | Opening  |
| VH              | 25%   | Closing  |
| RE2             | 100%  | Erosion  |
A3. Mean building height and population density

![Graph showing population density vs. mean building height in NUTS units.](image)

Figure A7. Population density vs. mean building height in NUTS units. NUTS-1 to 3 represent states, government regions and districts, respectively. x-axes are drawn logarithmic. Population density was acquired from official German and European statistical surveys (Eurostat 2020a, b; Statistische Ämter des Bundes und der Länder 2020).

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