WEAKLY SUPERVISED SEMANTIC SEGMENTATION OF SATELLITE IMAGES FOR
LAND COVER MAPPING – CHALLENGES AND OPPORTUNITIES

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KEY WORDS: Land Cover Mapping, Deep Learning, Machine Learning, Data Fusion

ABSTRACT:

Fully automatic large-scale land cover mapping belongs to the core challenges addressed by the remote sensing community. Usually, the basis of this task is formed by (supervised) machine learning models. However, in spite of recent growth in the availability of satellite observations, accurate training data remains comparably scarce. On the other hand, numerous global land cover products exist and can be accessed often free-of-charge. Unfortunately, these maps are typically of a much lower resolution than modern day satellite imagery. Besides, they always come with a significant amount of noise, as they cannot be considered ground truth, but are products of previous (semi-)automatic prediction tasks. Therefore, this paper seeks to make a case for the application of weakly supervised learning strategies to get the most out of available data sources and achieve progress in high-resolution large-scale land cover mapping. Challenges and opportunities are discussed based on the SEN12MS dataset, for which also some baseline results are shown. These baselines indicate that there is still a lot of potential for dedicated approaches designed to deal with remote sensing-specific forms of weak supervision.

1. INTRODUCTION

The problem of automatic land cover mapping from remote sensing imagery is traditionally cast as a (supervised) machine learning task, especially when applied to large study areas (Cihlar, 2000). However, while the amount of available satellite data keeps on growing, training labels remain rare, because of the difficulty to create reliable land cover annotations that can be referred to as “ground truth”. On the other hand, manifold large-scale land cover datasets already exist, all of which are the result of (semi-)automated processes themselves. This introduces weakly supervised learning as a promising strategy to train well-generalizing models on available data – even if the labels come with a significant error bar or at comparably low resolutions.

In this paper, we discuss the problem of weakly supervised learning of models for land cover prediction from satellite data. For this purpose, we focus on the freely available global imagery provided by the Sentinel-1 and Sentinel-2 missions of the European Copernicus program (Torres et al., 2012, Drusch et al., 2012) and a simplified version of the land cover classification scheme of the International Geosphere-Biosphere Programme (IGBP) (Loveland, Belward, 1997), which is reflected by the SEN12MS dataset (Schmitt et al., 2019) and the 2020 IEEE-GRSS Data Fusion Contest (DFC2020) (Yokoya et al., 2020). Besides a description of the challenge and how SEN12MS and DFC2020 are addressing it, baseline results using off-the-shelf deep learning models are provided to highlight the importance of dedicated research.

2. WEAKLY SUPERVISED LEARNING

In his excellent review, (Zhou, 2018) defines weakly supervised learning as an umbrella term addressing the attempt to construct predictive models from three types of weak supervision:

- **Incomplete supervision**
  In this case, a small amount of labeled data, which is insufficient to train a good model and abundant unlabeled data are available.

- **Inexact supervision**
  In this case, some supervision information is given, but it is not as exact as necessary. An example of this is land cover labels, which have a lower resolution than the satellite observations that shall be processed.

- **Inaccurate supervision**
  In this case, annotations cannot be considered as ground-truth; i.e., at least some of the labels are erroneous.

In the context of this paper, weakly supervised learning is restricted to the cases of inexact and inaccurate supervision, which can also be seen as different forms of label noise. In contrast to that, incomplete supervision is seen as a different case, which is addressed by semi-supervised learning (Zhu, Goldberg, 2009), which is not covered here. As shown in the following sections, dealing with different forms of noisy samples has become a well-addressed field in machine learning and should receive quite some attention by remote sensing researchers as well.

2.1 Machine Learning with Noisy Samples

Weakly supervised learning in the above-defined sense, i.e., learning from inexact and inaccurate samples, has become a sub-field in machine learning research that has been drawing a significant amount of interest. While there are some studies, which indicate that deep neural networks are relatively robust to label noise (Rolnick et al., 2018), many researchers investigate approaches to deal with this challenge based on insights from robust statistics and dedicated mathematical modelling. Thus, popular solutions in this context are either the formulation of robust loss functions, e.g. (Ghosh et al., 2017), the iterative improvement of training data via bootstrapping (Reed et al.,
2.2 Relevance for the Remote Sensing of Land Cover

Remote sensing has long been a primary source of big data (Chi et al., 2016), with the numbers of available observations and measurements of our planet continuously on the rise. Driven by this development, deep learning has drawn significant attention from the research community (Zhu et al., 2017). However, as highlighted by (Reichstein et al., 2019), the lack of dedicated large training or benchmark datasets still remains one of the grand challenges in the creation of operational models for real-world applications. On the other hand, past efforts of remote sensing scientists and practitioners have led to the production of numerous large-scale – or even global – land cover maps. As nicely summarized by (Grekousis et al., 2015), the resolutions of those maps typically range from 30m to 1,000m per pixel with overall accuracies between 64% and 88%. In other words, plenty of noisy training labels are potentially available free of charge! Inspired by the generic techniques for machine learning from noisy samples described in the previous section, one would think that weakly supervised learning of land cover prediction models using these available datasets as training input would have become a major theme in modern day remote sensing research. Interestingly, however, the literature dedicated to this challenge is still rather scarce. While most papers addressing weak supervision in a remote sensing context deal with object detection, e.g. (Zhang et al., 2015, Kellenberger et al., 2019), the few papers addressing weakly supervised semantic segmentation usually rely on sparse or even only image-level annotations, e.g. (Fu et al., 2018, Wang et al., 2020), instead of coarse and/or noisy labels available in a dense manner. A quite notable exception is the work by (Robinson et al., 2019), who fused low-resolution and high-resolution labels in order to produce a high-resolution land cover map of the contiguous United States. Their approach is based on what they called super-resolution loss in an earlier contribution (Malkin et al., 2019), which allows to predict high-resolution land cover from low-resolution labels by modeling the expected distribution of high-resolution land cover and using its distance to the predicted distribution as an additional loss term.

Using the SEN12MS dataset, which combines noisy land cover labels with a resolution of 500m with Sentinel-1 SAR and Sentinel-2 optical data, as an example, this paper seeks to provide a basis for further explorations of weakly supervised semantic segmentation of satellite images for land cover prediction.

3. WEAKLY SUPERVISED LEARNING FOR LAND COVER MAPPING WITH SEN12MS

The SEN12MS dataset (Schmitt et al., 2019) was published in 2019 as the largest curated dataset dedicated to deep learning in remote sensing at that time. It consists of 180,662 patch triplets sampled over all meteorological seasons and all inhabited continents in order to represent a global distribution. Every triplet consists of a dual-polarimetric Sentinel-1 SAR image, a multi-spectral Sentinel-2 image tensor, and four different land cover maps following different internationally established classification schemes. In the frame of the 2020 IEEE-GRSS Data Fusion Contest (DFC2020), the organizers defined the weakly supervised training of globally applicable land cover prediction models as the contest goal (Yokoya et al., 2020).

3.1 The Simplified IGBP Land Cover Classification Scheme

For the DFC2020 the IGBP classification scheme, which originally is comprised of 17 classes (Loveland, Belward, 1997), was aggregated to 10 less fine-grained classes (see Tab. 1). This simplified IGBP scheme is similar to the classification scheme adopted by the authors of the FROM-GLC10 dataset (Gong et al., 2019), which constitutes the first global land cover map with a resolution of 10m (at an overall validation accuracy of about 73%). Both schemes differ in only one class: While the simplified IGBP scheme contains a Savanna class, the FROM-GLC10 scheme contains a Tundra class. However, both classes are not applicable on a global scale and rather restricted to certain geographical regions: According to the Encyclopedia Britannica, a savanna “is characterized by an open tree canopy (i.e., scattered trees) above a continuous tall grass understory (the vegetation layer between the forest canopy and the ground)”. Mostly found “in Africa, South America, Australia, India, the Myanmar (Burma)-Thailand region in Asia, and Madagascar”, savannas thus are not a generic land cover type and therefore not a great target for purely image-based classification approaches. Above that, they are also not suitable for pixel-based classification approaches, since at a resolution of 10m no Savanna pixels exist – one will either find pixels containing trees (i.e. the Forest class in simplified IGBP terms), or grass (i.e. Grassland). At a resolution of 500m, however, the mixing of the spectral responses of sparse trees and grass understory can well lead to a distinct spectral Savanna profile.

As can be seen in Fig. 1, in the MODIS-derived IGBP land cover map, which constitutes the basis of the SEN12MS land cover annotations, the Savanna class is way more widely spread than one would expect based on the above-mentioned definition, making it the largest class in the dataset (see also Section 3.2 for more details). For generic solutions to global land cover mapping, it will thus be advisable to adapt suitable strategies that either ignore training pixels with Savanna label, or that allow a transformation of Savanna into globally applicable classes such as Grassland, or Forest. Since there is certainly no one-to-one mapping between Savanna and the alternative classes, statistical strategies such as, e.g., the one proposed by (Malkin et al., 2019) are in need.

3.2 SEN12MS

The distribution of the pixels contained in the SEN12MS dataset over the 10 classes of the simplified IGBP scheme is shown in Fig. 2. While the distribution is relatively balanced in terms of the classes Forest, Grassland, Croplands, and Urban, the classes Shrubland, Barren, and Water are slightly less frequent. The major outliers are the classes Wetlands and Snow/Ice, which hardly exist, and the largest class Savanna, which accounts for almost a quarter of all pixels in the dataset.

The reason for this imbalancing are multifaceted: Firstly, wetlands, for example, are simply relatively rare in reality. Apart from that, water areas were purposely undersampled because of the simplicity to map them, whereas urban areas were purposefully oversampled because of their heterogeneity and also their importance to geographical science. As discussed in Section 3.1, the Savanna class is over-represented because the
global, MODIS-derived IGBP land cover map, which constitutes the basis of the SEN12MS land cover annotations, contains much more savanna areas than one would expect. This has to be considered when using the dataset as basis for the development of land cover-oriented semantic segmentation models.

3.3 DFC2020

For the IEEE-GRSS 2020 Data Fusion Contest, a high-resolution (GSD: 10m) dataset for validation and testing was generated in a semi-manual manner, following the simplified IGBP scheme as well. While the DFC2020 validation and test labels and all relevant meta-information will only officially be published after the end of the contest in April 2020, the class distributions of the data are already shown in Fig. 2 for sake of comparison with SEN12MS. It can be seen that the distributions are fairly similar. The most important exception is the complete absence of the Savanna class. This is due to the fact that the DFC2020 maps were created in a semi-manual manner and on a pixel-level basis. Thus, at a resolution of 10m, Savanna cannot exist; a pixel will either be occupied by a tree (class Forest), or by Grassland. Another interesting difference between the SEN12MS and the DFC2020 datasets is the fact that the high-resolution DFC2020 patches either contain a single class (e.g. in homogeneous Forest or Water areas) – or more than five classes, whereas the low-resolution MODIS-derived labels of SEN12MS mostly contain one to three classes. This is a clear hint towards the significant resolution difference.

3.4 Predicting High-Resolution Land Cover from Low-Resolution Labels

With the availability of SEN12MS for training and DFC2020 for validation and/or testing, a wide range of possibilities for weakly supervised training of high-resolution land cover prediction models opens up. To make full use of them it is crucial to have a common understanding of the data structures. A summary is given in Tab. 2. While it is perfectly possible to keep all 180,662 patches of SEN12MS in a single dataset purely used for training, and all 6,114 patches of DFC2020 in another dataset purely used for testing, we suggest to make use of the splits proposed in this paper in future work to ensure comparability between achieved results in a benchmarking sense. The list of hold-out scenes for SEN12MS can be found in the appendix, and the DFC2020 data is provided in separate validation and test packages at https://ieee-dataport.org/competitions/2020-ieee-grss-data-fusion-contest.

4. BASELINE RESULTS

To provide a first intuition about what is possible when using the SEN12MS and DFC2020 datasets for weakly supervised learning, first results are collected in this section. They shall also serve as examples for future benchmarking purposes. While land cover maps are traditionally assessed via the overall accuracy (OA) measure, we propose to use the less optimistic average accuracy (AA) for comparison, as it gives less weight to large classes, which are rather simple to classify, e.g. Forest and Water.

To implement the considerations about the difficult Savanna class described in Section 3, during training of all machine learning models, Savanna pixels were not used.

With respect to the satellite input data, the following pre-processing was applied: The Sentinel-1 backscatter values were clipped and normalized to the interval $[−25, 0]$ before rescaling to $[0, 1]$. In a similar manner, we clipped the intensity values of the Sentinel-2 top-of-atmosphere observations to $[0, 10^4]$, corresponding to a maximum of 100% surface reflectance before rescaling. It is important to note that we made only use of the 10 surface-related Sentinel-2 bands (i.e. the bands with an original resolution of 10m and 20m), while the atmosphere-related bands (with an original resolution of 60m) B1, B9 and B10 were not used.

4.1 Low-resolution vs. high-resolution labels

As a sanity check and the lower end of what is possible, the low-resolution MODIS-derived labels can simply be tested against the high-resolution DFC2020 validation set. The results are shown in the leftmost column of Tab. 3. While frequent and easy-to-determine classes such as Forest, Urban, and Water show relatively good agreement between the low-resolution labels and the high-resolution reference, less frequent classes, which are harder to identify (e.g. Shrubland, Barren, and Wetlands) cause the average accuracy to drop to a mere 37.2%. On the other hand, it seems a bit surprising that the Croplands class also shows a satisfying agreement, although empty fields could certainly be confused with Barren or crops growing up with Grassland. On the opposite, the Grassland class shows an unexpectedly bad accuracy, which may be due to a confusion with Wetlands or Croplands pixels in the high-resolution reference. More details can be seen from the class...
| IGBP Class Number | IGBP Class Name                        | Simplified Class Number | Simplified Class Name | Color  |
|-------------------|----------------------------------------|-------------------------|-----------------------|--------|
| 1                 | Evergreen Needleleaf Forest            | 1                       | Forest                | 009900 |
| 2                 | Evergreen Broadleaf Forest             | 2                       | Shrubland             | e6b044 |
| 3                 | Deciduous Needleleaf Forest            | 3                       | Savanna               | bdf1f3 |
| 4                 | Deciduous Broadleaf Forest             | 4                       | Grassland             | b6f0f5 |
| 5                 | Mixed Forest                          | 5                       | Wetlands              | 27f878 |
| 6                 | Closed Shrublands                     | 6                       | Croplands             | c2f4f4 |
| 7                 | Open Shrublands                       | 7                       | Urban/Built-up        | a5a5a5 |
| 8                 | Woody Savannas                        | 8                       | Snow/Ice              | 69f8f8 |
| 9                 | Savanna                               | 9                       | Barren                | 0f8a84 |
| 10                | Grasslands                            | 10                      | Water                 | 1c0dff |

Table 1. The simplified IGBP land cover classification scheme.

| Dataset          | Size  | Comment                                                                 |
|------------------|-------|-------------------------------------------------------------------------|
| SEN12MS training | 162,556 | subset of SEN12MS dedicated to training                                  |
| SEN12MS hold-out | 18,106 | hold-out set with low-res labels; similar spatial and temporal distribution as the overall dataset; used for validation or testing |
| DFC2020 validation | 986  | used for testing in the first phase of DFC2020, and for validation in the second phase |
| DFC2020 testing  | 5,128  | used for testing in the second phase of DFC2020                         |

Table 2. The different sub-datasets that can be built from the SEN12MS and DFC2020 data.

4.2 Off-the-Shelf Models for Semantic Segmentation

To provide a baseline for future developments, Tab. 3 also contains the results for off-the-shelf models for semantic segmentation. All of them were trained on the SEN12MS training subset, validated with the SEN12MS validation subset, and tested on the DFC2020 validation set, which was already officially available during the writing of this paper. We implemented the ignoring of the Savanna pixels during training using a masked-cross-entropy loss.

- **DeepLabv3+ (DLv3)**
  Achieving top-ranking results on various semantic segmentation benchmarks, DeepLabv3+ (Chen et al., 2018) represents a state-of-the-art semantic segmentation architecture and was, thus, used for our baseline experiments. Our implementation used a ResNet-101 backbone with ImageNet pre-trained weights as an initialization. In order for results to be comparable, we fixed the hyperparameters for training. Training was conducted for ten epochs.

- **Unet**
  In addition to DLv3 we further applied a Unet type architecture (Ronneberger et al., 2015) to the segmentation task. We adopted the last layer to contain nine segmentation maps and masked the loss function to ignore the neglected tenth class. The model contains \( \approx 31 \) million (random initialized) parameters, and is therefore significantly larger then the DLv3. Another important difference is the utilization of long skip connections in the Unet architecture, which is expected to have a positive influence on preserving fine spatial details.

Our Pytorch-based implementations of the two baseline networks are available at https://github.com/lukasliebel/dfc2020_baseline.

Figure 5 shows how the test accuracy on the DFC2020 validation set changes over time for the different models. Since the training is carried out on the low-resolution MODIS-derived land cover labels without any specific adaptations to cope with the situation of weak supervision, no clear trend can be observed – the evolution of the networks remains unstable. In order to fill Tab. 3, we select the checkpoint with the best test accuracy for evaluation. This should be seen as the upper bound of what is achievable with off-the-shelf semantic segmentation networks and does not allow a judgment between the models.
### Table 3. Class-wise and average accuracies achieved on the DFC2020 validation dataset for different benchmarks.

| Class       | LR-HR | DLv3 S2 only | DLv3 S1+S2 | Unet S1+S2 | k-means S2 only | k-means S1+S2 | RF S2 only | RF S1+S2 |
|-------------|-------|--------------|------------|------------|-----------------|---------------|------------|----------|
| Forest      | 51.6% | 71.4%        | 61.2%      | 67.3%      | 55.4%           | 80.7%         | 93.3%      | 80.1%    |
| Shrubland   | 7.7%  | 2.3%         | 3.8%       | 0.0%       | 3.7%            | 0.3%          | 44.7%      | 0.9%     |
| Savanna     | -     | -            | -          | -          | -               | -             | -          | -        |
| Grassland   | 6.7%  | 64.4%        | 48.2%      | 76.7%      | 77.2%           | 21.2%         | 49.8%      | 78.0%    |
| Wetlands    | 0.6%  | 2.4%         | 3.8%       | 3.7%       | 3.2%            | 38.2%         | 1.3%       | 0.0%     |
| Croplands   | 64.4% | 53.5%        | 61.9%      | 65.7%      | 50.7%           | 33.4%         | 40.3%      | 80.7%    |
| Urban       | 71.5% | 71.0%        | 62.8%      | 80.9%      | 73.1%           | 38.8%         | 50.7%      | 91.8%    |
| Snow/Ice    | 0.3%  | 0.2%         | 1.0%       | 0.6%       | 0.8%            | 0.4%          | 9.8%       | 0.0%     |
| Barren      | 95.1% | 88.9%        | 95.8%      | 89.4%      | 92.7%           | 73.1%         | 48.7%      | 99.9%    |
| Water       | 95.1% | 88.9%        | 95.8%      | 89.4%      | 92.7%           | 73.1%         | 48.7%      | 99.9%    |
| Average     | 37.2% | 44.2%        | 42.3%      | 48.1%      | 44.6%           | 35.8%         | 42.3%      | 54.0%    |

**Figure 2.** The distribution for the different land cover classes (top) as well as the number of different classes per image patch (bottom). Note that the SEN12MS training subset contains approximately 0.01% of Snow/Ice pixels.

The confusion matrix achieved by the best deep semantic segmentation network (i.e. the Unet relying on only Sentinel-2) is shown in Fig. 4.

The results show that even off-the-shelf semantic segmentation models produce results that are significantly better than the low-resolution reference. The most notable improvement is observed for the Grassland class, with also Forest, Croplands, Urban, and Water performing reasonably well. On the downside, Wetlands and Barren are not really mapped well, whereas Shrubland becomes even worse than in the low-resolution input. The main source of confusion is the Grassland class, which collects most predictions from Shrubland, Wetlands and Barren classes. With erroneous Grassland predictions also affecting the Forest, Shrubland and Croplands reference classes, this land cover type will need more attention in future model designs.

**Figure 3.** Class transition matrix from low-resolution, MODIS-derived labels to high-resolution DFC2020 labels. Figure 6 provides a visual impression of the mapping quality, taking a prediction example after the first epoch. While the off-the-shelf deep semantic segmentation models are able to recover the general scene structure, fine details get completely lost.

### 4.3 Overfitting on the Validation Set

Besides training a generic, region-agnostic semantic segmentation network on the SEN12MS dataset, another potential solution for large-scale high-resolution land cover mapping would be to train regional classifiers on regional low-resolution labels and predict high-resolution land cover only within that region. While this is accepted practice in remote sensing, this would equal the intentional overfitting to the validation set in the machine learning context. To provide another baseline for the problem at hand (i.e. high-resolution land cover mapping based on the availability of noisy, low-resolution labels), we trained two shallow classifiers – one unsupervised, one supervised – on the DFC2020 validation set. It has to be noted that only the low-resolution MODIS-derived land cover labels are used as annotations in these experiments, while the high-resolution labels are only used to calculate the evaluation metrics. The two setups are described in the following. Both used just the above-described 12 channels of Sentinel-1 and Sentinel-2 as pixel-wise input features.
Figure 4. Confusion matrix of the Unet model using only Sentinel-2 data as input.

Figure 5. Comparison of the Average Accuracy metric achieved on both the DFC2020 validation as well as the SEN12MS hold-out set over the training process for the different deep semantic segmentation networks described in section 4.2. The monotonously improving trend observed on the low-resolution data is not reflected by the validation against the high-resolution land cover labels.

- k-means clustering
  \( k = 9 \) clusters, set according to the observed number of classes in the MODIS labels of the DFC2020 validation split (excluding Savanna class). The cluster segments are learned completely unsupervised. The re-ordering of cluster labels is done via the Kuhn-Munkres algorithm (Hungarian method) (Munkres, 1957), with the given low-resolution MODIS-derived labels serving as a reference. Clustering is done with the best-fitting of 10 \( k \)-means++ initializations (Arthur, Vassilvitskii, 2007), each fitted for up to 300 iterations.

- Random Forests (RF)
  Supervised training on low-resolution MODIS-derived labels of the DFC2020 validation set. The model consists of an ensemble of 100 trees, each with a maximum depth of 10 nodes.

As can be seen from Tab. 3, shallow classifiers doing simple pixel-wise classification clearly outperform the weak labels they were trained on. Interestingly, the supervised RF approach fails totally on some classes such as Wetlands while achieving near-perfect accuracy on others, like Water. k-means clustering performs comparatively well on some classes such as Shrubland or Barren. The predicted maps displayed in Fig. 6 show a fair amount of spatial coherence, even though the classification has been conducted on a per-pixel base. Importantly, the pixel-wise approach is less affected by the weak label’s low spatial resolution than the CNN approaches. However, it is important to keep in mind that the shallow classifiers here have been specifically trained on the region of interest, whereas the deep models need to bridge a generalization gap in order to perform well. Thus, the pixel-based shallow learning approach is generally less suitable for large-scale (or even global) mapping.

4.4 Data Fusion

All machine learning models have used either the ten surface-related bands of Sentinel-2 as input, or have relied on a form of early data fusion by combining this Sentinel-2 input with the two polarimetric channels of Sentinel-1. As can be seen from Tab. 3, the fusion of Sentinel-1 and Sentinel-2 data often leads to slightly better results than what is achievable if only Sentinel-2 is used. The fact that the fusion doesn’t always help to improve the metrics achieved with the deep learning models should not be misunderstood: Since Tab. 3 collects the best validation results, a fair comparison among the four deep semantic segmentation setups is not ensured.

5. DISCUSSION

The baseline results presented in Section 4 show that mapping land cover on a global scale with models learned on inaccurate and inexact training labels remains an exciting challenge. We see three main challenges in that regard, which are addressed in the following.

5.1 The Need for a Generic Land Cover Classification Scheme

Before any methodological issue, one of the main difficulties is to define classification schemes that are generic enough to be applied to every geographical region on Earth. As both (Hansen, Reed, 2010) and (Congalton et al., 2014) elaborate, differences in class definitions can lead to serious errors, contradictions, and a lack of comparability between different map products. Although the IGBP scheme is a well-established standard that has been used for many years, it is not the optimal choice for fully automatic, global, image-based land cover mapping due to the misleading Savanna class. Thus, such classes must either be replaced by more generic ones, or image-based mapping has to be combined with additional geographical considerations, e.g. by using different sub-schemes in different regions of the world. As an intermediate solution, we propose to use the simplified IGBP scheme without Savanna class.

5.2 Challenging Classes

In addition to the general problem of land cover class definitions, it is interesting to note that two classes get consistently bad metrics throughout all classification methods (cf. Tab. 3): Wetlands and Barren. As can be seen in Fig. 2, those two classes are the least frequent in the SEN12MS dataset (except the understandably rare Snow/Ice class). On the other hand, Wetlands are massively over-represented in the DFC2020 validation set.

The problem can further be understood when looking at Figs. 1 and 6: In the MODIS-derived IGBP land cover map,
Figure 6. Land cover mapping results achieved with the baseline models for two example patches. Note that for Unet and DLv3 the models achieved after the first training epoch were used to predict the maps shown in this figure.

Quite some regions in boreal latitudes are mapped as Savanna, while the high-resolution reference classifies some of these areas into Wetlands. If Savanna pixels are not dealt with appropriately during training, e.g. if they are simply used or excluded without any semantic transformation into other classes, this will of course negatively impact the classifiers’ capabilities to correctly deal with this class confusion.

Finally, Fig. 3 shows that both classes seem to be significantly mislabeled in the low-resolution land cover maps – most of the time they are used to label pixels actually containing water.

Besides those two problematic classes it is also interesting to note that the Shrubland class is not well mapped by most models – besides unsupervised k-means clustering. A probable explanation for this is that k-means is more robust to the class imbalance problem.

Last, but not least, it seems very promising that the Grassland class is apparently not well represented by the low-resolution MODIS-derived labels, but can be well predicted by most models. This indicates the potential of the topic addressed in this paper.

5.3 Generic Models for Global Mapping

As both Tab. 3 and Fig. 6 show, the pixel-based shallow learning models trained on the low-resolution labels of the DFC2020 validation set outperformed the deep learning models trained on the SEN12MS training set. However, this has to be put into perspective: Clearly, the overfitting to a specific, small-scale dataset can provide a satisfying solution for regional mapping tasks, as even shallow models can generalize well from noisy labels to accurate predictions. If the goal, however, is a fully automatic global mapping with a once-and-for-all classifier, more generic models are in need. The results achieved for the deep semantic segmentation baselines still lack high spatial accuracy, but already indicate their potential for the task, given that only off-the-shelf architectures were used. As both training and validation were carried out with only weak supervision on low-resolution labels sampled at locations spatially disjunct from the DFC2020 data, they are able to tackle not only the generalization from low-resolution to high-resolution labels, but also from one region of the Earth to other regions. If models specifically adapted to the weakly supervised learning case were used or if at least validation could be carried out with strong supervision, i.e. high-resolution labels, a significant improvement is expected.

6. SUMMARY & CONCLUSION

In this paper, we have used the SEN12MS dataset and the validation data provided in the frame of the IEEE-GRSS 2020 Data Fusion Contest to address the challenge of learning semantic segmentation models for global land cover mapping from inaccurate and inexact labels. While standard shallow and deep learning approaches were shown to already provide promising mapping capabilities, the results are not satisfying enough yet to consider off-the-shelf approaches for operational solutions. Therefore, we argue that specific models from the field of weakly supervised machine learning must be developed and expect that they will contribute greatly to a regular and fully automatic satellite-based monitoring of global land cover.
ACKNOWLEDGEMENTS

The authors would like to thank the Chairs of the IEEE-GRSS IADFC, Naoto Yokoya, Ronny Hänsch and Pedram Ghamisi, for making the challenge of weakly supervised learning for global land cover mapping the topic of the 2020 IEEE-GRSS Data Fusion Contest; and for numerous fruitful discussions during the design of the contest.

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APPENDIX

Hold-out scenes for SEN12MS

We suggest to use following scenes as hold-out set when working on SEN12MS only. The identifier _a1_ must be replaced by _a2_, or _a3_ to access the Sentinel-2 and MODIS-derived land cover instead of the Sentinel-1 data.

| Scene ID | Year | Season |
|----------|------|--------|
| ROIs1158 | 2015 | spring |
| ROIs1158 | 2015 | summer |
| ROIs1158 | 2015 | fall |
| ROIs1158 | 2015 | winter |
| ROIs1868 | 2015 | spring |
| ROIs1868 | 2015 | summer |
| ROIs1868 | 2015 | fall |
| ROIs1868 | 2015 | winter |

Notes:
- SEN12MS is the dataset used for the challenge.
- The scenes are divided into four seasons: spring, summer, fall, and winter.
- Each season has a corresponding label set for training and testing.
- The _a1_ identifier is used to access the Sentinel-2 data, and _a2_ or _a3_ to access the MODIS data.