Multi-layer Land Cover Data for Remote-Sensing based Vegetation Modelling for South Korea

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Abstract: Land cover data is essential input for vegetation productivity models that are often driven by coarse resolution data. In this study, we analyze how well 1 km land cover data represent land cover at 30 m for South Korea. We derive multi-layer 1 km land cover classes and coverages and analyze how much of land cover heterogeneity is represented by the successive layers. Comparison to global land cover data shows varying agreement. The multi-layer land cover data can be used for example for net primary productivity modelling. Especially, for models that can include more than one vegetation type per pixel, multi-layer land cover data and their corresponding coverages are a major asset.

1 Introduction

Land cover data are important base information for modelling vegetation productivity. They provide information about the distribution of different land cover and vegetation types on the land surface. This knowledge is essential for modelling net primary productivity (NPP), which is the net accumulation of organic matter through photosynthesis by green vegetation per unit area and unit time. NPP is one of the most important components of the carbon cycle, a key variable for ecological monitoring, and a sensitive indicator of climate and environmental change (NIEMEIJER 2002; SCHIMEL 1995).

NPP modelling is commonly based on phenological and meteorological time-series data, which can be derived from remote sensing (PRIETO-BLANCO et al. 2009; YI et al. 2013; ZHAO et al. 2005). One important input dataset for NPP modelling is land cover classification. It is needed to define the type of vegetation to be modelled with its specific parameters for a certain location. Most often, global land cover datasets are employed for NPP modelling (e.g. MATSUSHITA & TAMURA 2002; NIKLAUS et al. 2015; TUM et al. 2016; WIßKIRCHEN et al. 2013), but also regional land cover maps can be used (e.g. BAO et al. 2016; EISFELDER et al. 2014; TUM et al. 2012). The availability of regional land cover maps may be of major advantage, as global land cover data have shown weakness in describing heterogeneity in land cover characteristics on regional scale (e.g. GESSNER et al. 2015; KLEIN et al. 2012; LEINENKUGEL et al. 2014).

Land cover maps commonly define one land cover class per pixel. However, some models, such as the Biosphere Energy Transfer Hydrology model BETHY/DLR (WIßKIRCHEN et al. 2013), are able to include more than one vegetation type per pixel for NPP modelling. In previous studies, each land cover class has been translated to two fixed vegetation types, each weighted by a fixed percentage of coverage (e.g. EISFELDER et al. 2017).

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The availability of land cover products of higher spatial resolution than required for NPP modelling (e.g. SIMIC et al. 2004), allows to derive a set of land cover information at coarse resolution that provides information about both several land cover classes per pixel and their coverage.
In this study, we derive such multi-layer coarse resolution land cover information for South Korea. We first describe the method applied for deriving multi-layer land cover information including classes and coverages based on a high resolution land cover map of South Korea. We present the results and analyse the information content contained in the successive land cover layers. We also compare the land cover classification to three global land cover datasets.
In this study, we address the following research questions: (a) How well is a high resolution land cover classification represented by a derivative coarse resolution land cover classification? (b) How does this compare to global land cover classifications? (c) How much additional information is contained in successive multi-layer land cover data sets? (d) What can be concluded regarding recommendation for different land cover input data for NPP modelling?

2 Data base and processing of land cover data

2.1 High Spatial Resolution Land Cover Data

For the presented study, the Korean national land cover map issued by the Ministry of Environment was used. The national land cover map is organized with three hierarchical levels of broad (7 classes), middle (22 classes) and detailed classification (41 classes) according to their resolution. In this study, the land cover map at the broad class level, which covers the whole South-Korean territory, was used. This land cover map distinguishes seven land cover classes (forest, urban, agriculture, wetland, grassland, bare soil, and water) and was lastly updated in 2010 based on Landsat-7 data with 30 m spatial resolution (period of image recording 2008–2010). For the Landsat image processing, after the atmospheric correction the coordinate system was projected from the WGS84 UTM to the GRS80 TM (national standard), then the geospatial errors were corrected by in-situ GPS measurements and the national topographical maps (1:25,000). The mosaicked image was calibrated, normalized using the digital elevation model (DEM) to remove the topographic effects of the spectral reflections in mountainous areas. For the classification a hybrid method combining unsupervised and supervised classification algorithm was applied. These classification results were compared with the very high resolution (pan: 1 m, multispectral: 4 m) KOMPSAT-2 (Korea Multipurpose Satellite with optical sensor) images and systematic errors were corrected. The Ministry of Environment ensures an overall accuracy of higher than 75% over the whole nation in case of validation comparing with KOMPSAT-2 images.

2.2 Processing of Land Cover Input Data

For preparation as input for NPP modelling, the high spatial resolution land cover data (30 m) were rescaled to a resolution of 0.008929° ("1 km") in order to match the resolution of the commonly used LAI input data for BETHY/DLR. The example model is designed to include two land cover types within each pixel. Weight factors (range [0, 1]) define the fractional coverage of the land cover types. In order to keep a maximum of valuable land cover information for NPP modelling, thus three land cover datasets providing information on the primary (largest coverage), secondary (second largest coverage) and tertiary land cover (third largest coverage) within

each 1 km² pixel are required. Each of the land cover dataset layers is to be accompanied by the percentage cover of the land cover class within the respective 1 km² pixel. Three layers can be made use of – one more than land cover types modelled: two land cover types plus one additional layer that is included in case one of the first two land cover classes is not vegetated
An overview on the workflow for deriving the multi-layer land cover information is shown in figure 1. Land cover classes that are not vegetated (water, bare soil, urban) and for which, thus, no NPP is to be calculated were merged into one new land cover class "other". The resulting datasets contains the following classes: agriculture, forest, grassland, wetland, and other.
Finally, based on the Korean national land cover map, this procedure resulted in a total of five successive land cover datasets – each with its supplementary percentage cover dataset. The first three layers can be used as input for BETHY/DLR. In case that the previous land cover class/classes already cover 100% of the 1 km² pixel, the dummy class "no data" was introduced.

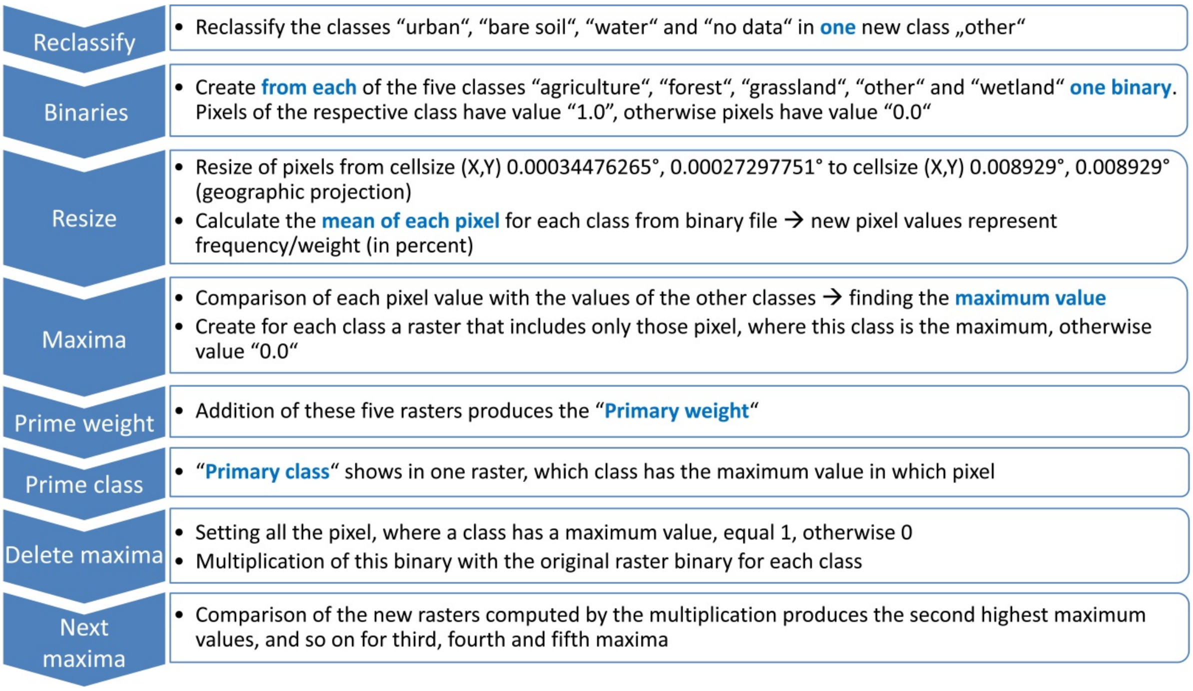

Fig. 1: Workflow for deriving coarse spatial resolution multiple land cover information and weights from high spatial resolution land cover data.

3 Results and Discussion

3.1 Multi-layer Land Cover Information

Figure 2 shows the first three land cover information data sets derived with the procedure described in section 3. The maps on the left show the land cover class assigned for the primary, secondary, and third land cover class. The maps on the right show the corresponding weight for the successive land cover classes, i.e. information about the coverage of the land cover class within the 1 km² pixel.

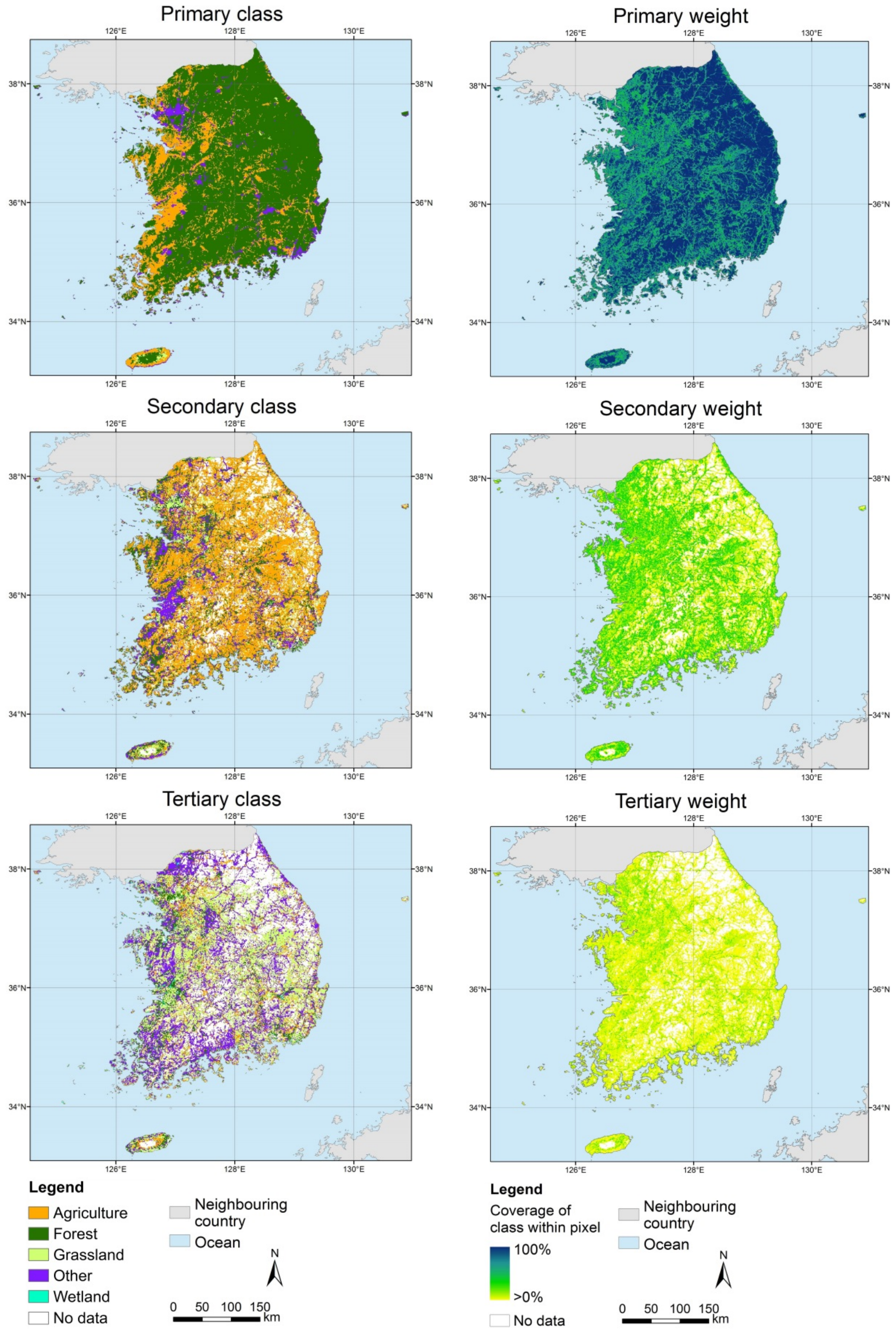

Fig 2: Left: Maps showing the primary, secondary, and tertiary (top to bottom) land cover class of each pixel for South Korea. Right: Maps showing the percentage coverage of the primary, secondary, and tertiary (top to bottom) land cover class within each pixel.

As can be seen from figure 2 (top left), the major primary land cover class within South Korea is forest, followed by agriculture. Coverage of these classes within the 1 km² pixels is up to 100% (see figure 2, top right). The most important secondary land cover class is agriculture, which spreads over large parts of South Korea but shows – in these areas – a pixel coverage of less than 50 % (figure 2, middle). The third most frequent land cover classes are “grassland” and “other”; the corresponding coverage is relatively low (figure 2, bottom).
Figure 3 shows diagrams, which illustrate the number of pixels that is classified as a certain land cover class in the sequence of primary, secondary, tertiary, quaternary, and quinary land cover class. The three main prime classes are “other”, “forest”, and “agriculture. Of these, forest is by far the most widespread primary class, with 74.8% of pixels within South Korea assigned to this class. The most frequent secondary class is “agriculture”, followed by “forest”, “other”, and “grassland”. Agriculture is secondary land cover class for more than half of the land area within South Korea. As third class, “grassland”, and “other” are most often, assigned to 31.3% and 26.3% of pixels respectively. The class “wetland” is rare, but tends to occur more often as hierarchy decreases.

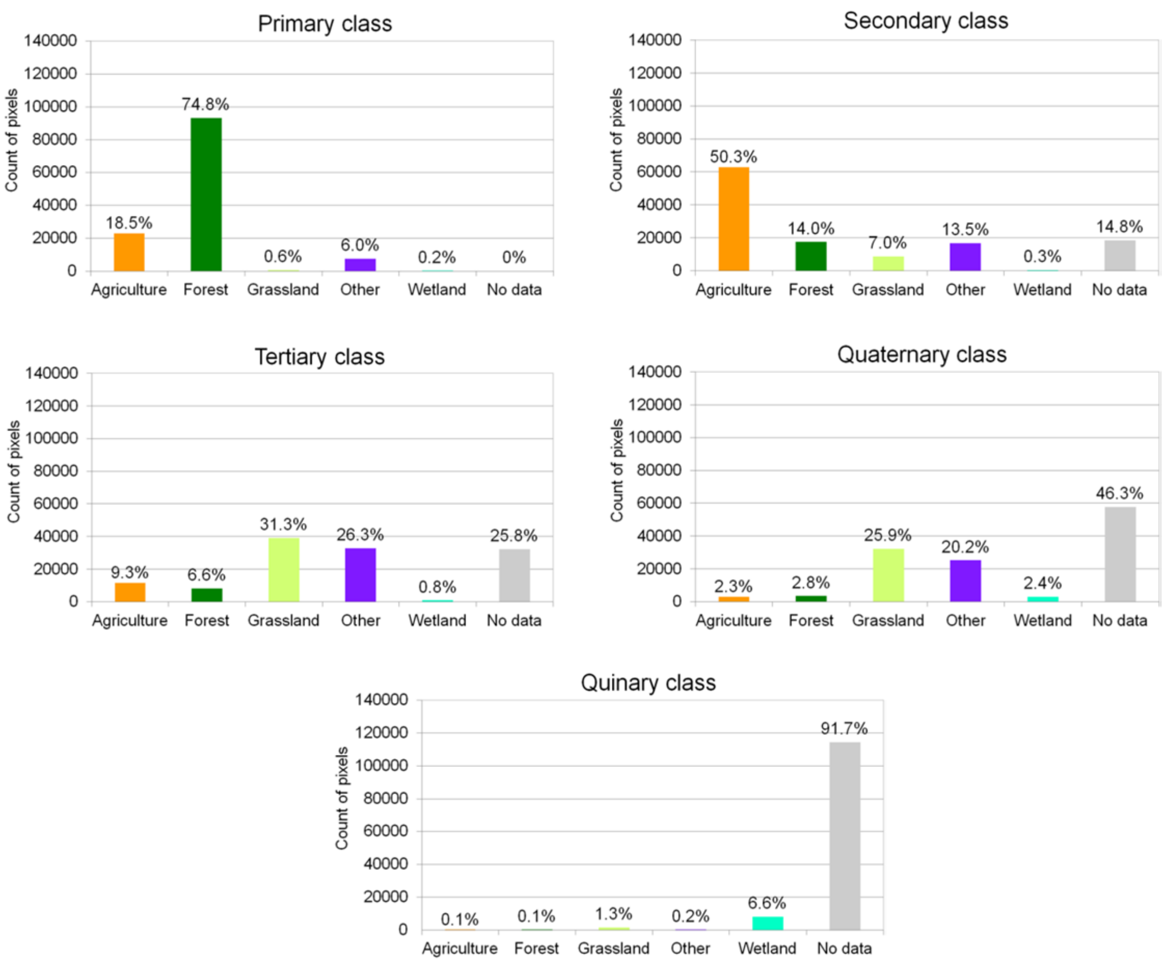

Fig. 3: Count and percentage of pixels, which have been classified as a certain land cover class (agriculture, forest, grassland, other, wetland) in the five successive land cover layers.

The diagrams from figure 3 also provide information about how many pixels have already been fully explained by the previous land cover classes. Only 14.8 % of 1 km² pixels within South Korea are fully covered by one land cover class, i.e. the assigned primary class. 25.8% of pixels are fully explained by maximum two classes, 46.3% by maximum three classes, and 91.7 % by maximum four classes.
Table 1 shows the frequency of weights assigned to the five successive land cover classes. 44.2% of pixels are covered by the primary land cover class to more than 90%. Lower weights, i.e. coverages, become less frequent for the prime class. The minimum weight for the primary class is between 30% and 40%. The secondary class has weights between >0% and 50%. The third class reaches at maximum coverage between 20% and 30%. For the majority of pixels that contain a third land cover class, its coverage is less than 10%. This is similar for the forth class. Only few 1 km² pixels within South Korea contain a fifth class, which covers not more than at maximum 10% of the 1 km² pixel.

Tab. 1: Frequency of weights assigned to the five successive land cover layers. Weights are grouped in coverage intervals of 10%. The frequency gives the percentage of pixels with a weight within the given interval.

	Frequency in %				
Coverage in %	**Primary weight**	**Secondary weight**	**Tertiary weight**	**Quaternary weight**	**Quinary weight**
>0.1 - 10	0	30.4	52.1	40.2	3.1
>10 - 20	0	18.3	10.0	1.1	0
>20 - 30	0	15.0	2.2	0	0
>30 - 40	1.3	11.1	0	0	0
>40 - 50	6.7	4.8	0	0	0
>50 - 60	10.4	0	0	0	0
>60 - 70	11.1	0	0	0	0
>70 - 80	11.9	0	0	0	0
>80 - 90	14.3	0	0	0	0
>90 - 100	44.2	0	0	0	0

3.2 Comparison to Global Land Cover Datasets

Previous comparison of global land cover datasets have revealed significant differences between products globally (GIRI et al. 2005; HEROLD et al. 2008; JUNG et al. 2006; MCCALLUM et al. 2006). In this section, we analyse how global 1 km land cover products compare to the regional land cover classification for South Korea. Three freely available global land cover datasets at coarse spatial resolution were selected for comparison: the MODIS land cover (LC) product for 2010 (FRIEDL et al. 2002), the Global Land Cover 2000 product based on SPOT-VEGETATION data (GLC 2000) (BARTHOLOMÉ & BELWARD 2005), and the ESA CCI land cover map (CCI-LC) for 2010 (UCL-GEOMATICS 2017). From the MODIS LC product, classification type 3 (LAI/fPAR) was chosen, because the land cover classification optimized for LAI/fPAR derivation is most suitable as input for NPP modelling. For comparison of area coverage, individual land cover classes were grouped to a simplified harmonized legend, as summarized in table 2.

Tab. 2: Harmonized classification for comparison and the included land cover classes from the individual legends of the high-resolution land cover map and the three global land cover datasets.

Summary class	High resolution LC	MODIS LC (Type 3)	GLC 2000	CCI-LC
Agriculture	Agriculture	Cereal Crops/Grasses (1), Broad-leaf crops (3)	Cropland (16), Mosaic of cropland and other classes (17, 18)	Rainfed cropland (10, 11, 12), Irrigated cropland (20), Mosaic cropland (>50%)/natural vegetation (30)
Forest	Forest	Forest (5, 6, 7, 8), Shrubs (2)	Tree cover (1, 2, 3, 4, 5, 6, 7, 8, 9, 10), Shrub cover (11, 12)	Tree cover (50, 60, 61, 62, 70, 71, 72, 80, 81, 82, 90), Mosaic tree and shrub/herbaceous cover (100), Shrubland, (120, 121, 122), Sparse tree (151), Sparse shrub (152)
Grassland	Grassland	Savanna (4)	Herbaceous cover (13), Sparse herbaceous or sparse shrub cover (14)	Grassland (130), Mosaic of cover types (40, 110), Lichens and mosses (140), sparse vegetation (150), Sparse herbaceous cover (153)
Wetland	Wetland	-	Regularly flooded shrub or herbaceous cover (15)	Tree cover, flooded (160, 170), Shrub or herbaceous cover, flooded (180)
Other	Urban, Bare, Water	Water (0), Non-vegetated (9), Urban (10)	Bare areas (19), Water bodies (20), Snow or Ice (21), Urban areas (22)	Urban areas (190), Bare areas (200, 201, 202), Water bodies (210), Permanent snow and ice (220)

The four maps in the top line of figure 4 show a detail of the South Korea high-resolution land cover classification with 30 m spatial resolution and the coarse resolution (~1 km) primary, secondary, and tertiary land cover classes derived in this study. Non-vegetated land cover classes from the original map were grouped in the class “other”, because a distinction of these classes is not needed for NPP modelling. The three global land cover datasets are also displayed with a simplified legend in figure 4 (see maps in bottom line).

The diagram in figure 5 shows the percent area of South Korea that is covered by the five harmonized land cover classes in the different land cover classifications. Based on the high-resolution land cover map, we observe percent coverages of 21% for agriculture, 69% for forest, 3% for grassland, and 8% for “other”; wetland is rare (0.2%). For the derived primary classes from this study, we observe a slight underestimation of agriculture (-2%), grassland (-2%), and forest (-2%), and an overestimation of forest (6%). As described in section 4.1, this can be compensated for by including the secondary and tertiary classes and applying weights.

The percent distribution of land cover classes within South Korea from the MODIS land cover product fits well to the high-resolution reference map, with a slight overestimation of agriculture (2%) and an underestimation of “other” (-2%). The ESA CCI-LC product is also relative close to the reference map, with an overestimation of agriculture (5%) and grassland (7%), and an underestimation of forest (11%). The largest discrepancy compared to the reference map and the other datasets exists for the GLC 2000. This datasets largely overestimates agriculture by 25% and underestimates other classes, mainly forest (-16%) and “other” (-7%).

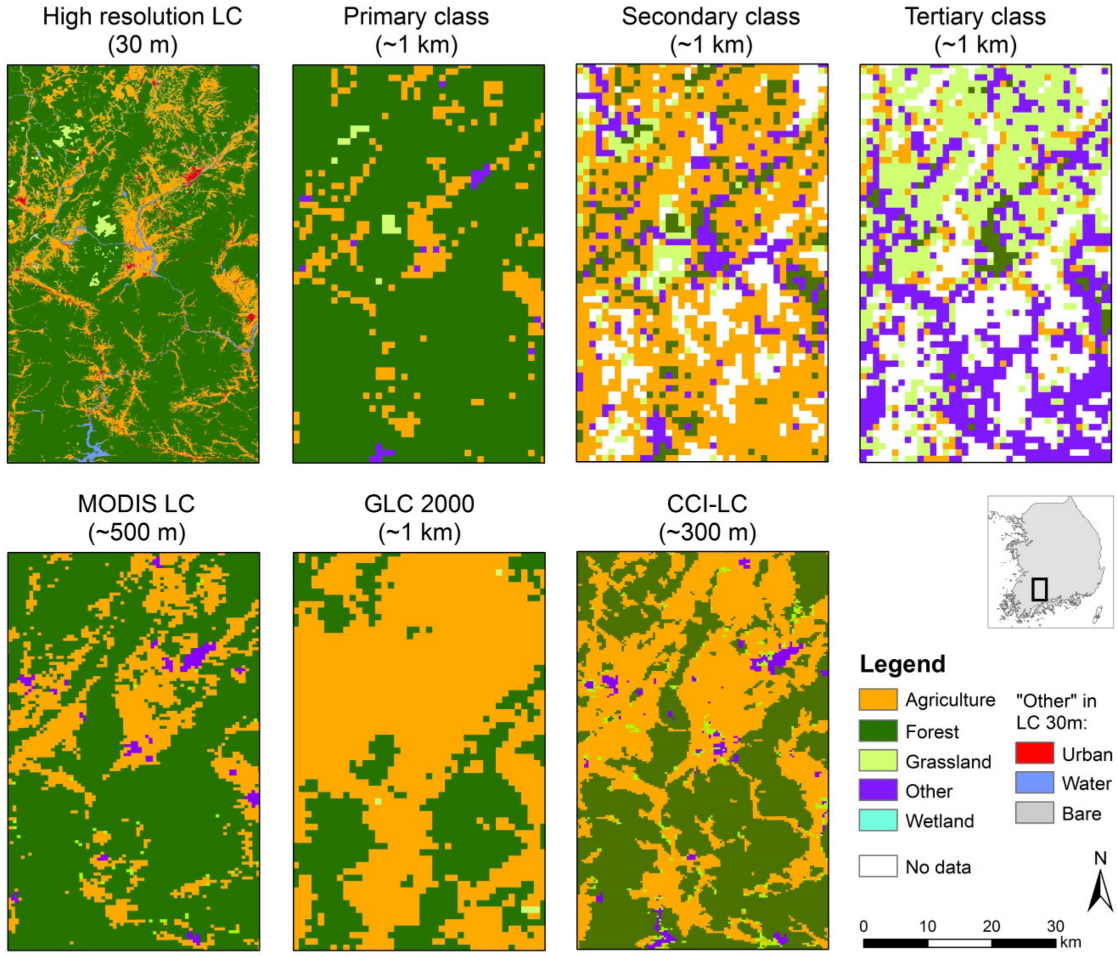

Fig. 4: Detail of the South Korea high-resolution land cover classification (top left), the primary, secondary, and tertiary land cover classes at ~1 km resolution derived in this study (top 2nd, 3rd, and 4th map), and three global land cover datasets with simplified legend for comparison bottom).

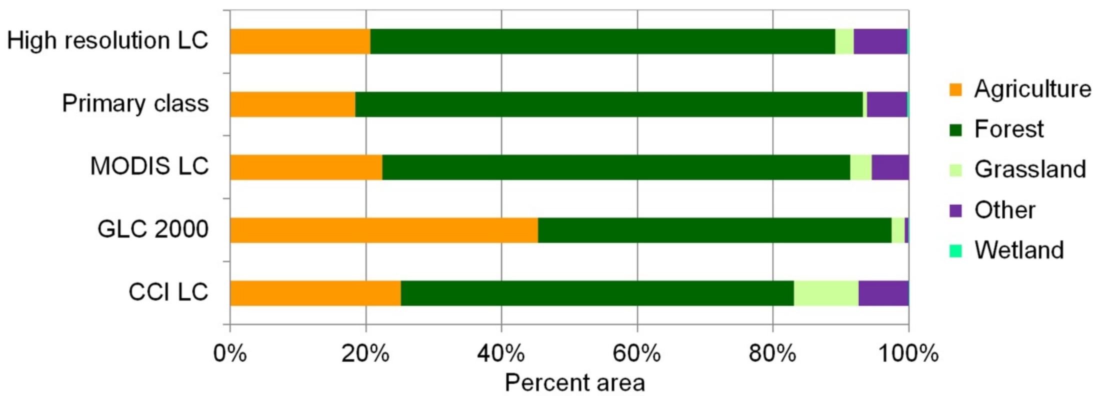

Fig. 5: Diagram showing the percent area of South Korea that is covered by the five harmonized land cover classes in the different land cover classifications.

Figure 6 shows further diagrams for comparison of the land cover classifications. The first row of diagrams shows, what percentage of the area classified as agriculture in the primary land cover class (1 km spatial resolution, derived from the Korean land cover map), is covered by which land cover class in the three global land cover products. The second and third rows show the assigned land cover classes within the three global land cover products for the area, which is classified as forest and grassland in the primary land cover class, respectively. Agriculture is given in orange, forest in dark green, grassland in light green, and "other" in violet. The class "wetland" occurs too rarely to be visible in the diagrams.

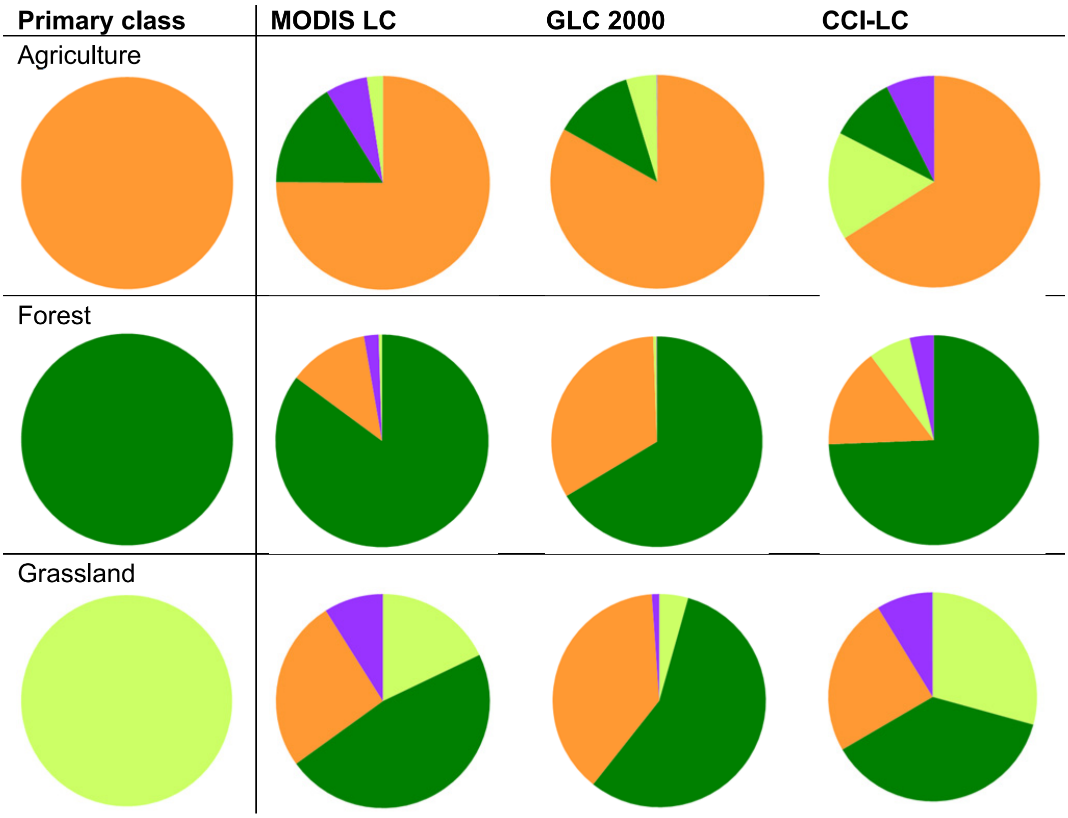

Fig. 6: Comparison of land cover products for South Korea. The diagrams show what percentage of the area classified as one of the three major land cover classes in the primary land cover class (1 km) derived from the South Korean land cover map, is covered by which land cover type (orange: agriculture, dark green: forest, light green: grassland, violet: other) in the global land cover maps.

Within this study we analysed how well a high resolution land cover classification is represented by coarse resolution land cover datasets. Of course, for NPP modelling, it is also of importance, which plant functional types are differentiated. Especially for agriculture and forest it is important to know crop types and forest types. The Landsat-based high-resolution land cover map at the coarse class level for South Korea did not differentiate crop or tree types, so we can only compare information from the global land cover maps. Different forest types assigned for South

Korea are listed in table 2 with their relative share of the forest area. The three classifications obviously vary largely with respect to forest types. None of these maps differentiates crop types.

4 Conclusions

High spatial resolution land cover data provide valuable information about the distribution of vegetation on the land surface. NPP models usually derive vegetation productivity on a coarser spatial resolution and do not take into account this wealth of information. A spatial resolution of 1 km can already be considered high resolution for NPP modelling. However, in many regions on the Earth land cover and land use patterns vary on a scale smaller than 1 km². In this study, we analyse how well a coarse resolution ~1 km land cover classification is able to represent land cover classification at higher (30 m) resolution for the study area of South Korea.

We find that the primary vegetation class at 1 km spatial resolution is only able to represent higher resolution land cover heterogeneity for 14.8% of the area. Especially widely distributed agricultural areas, which were not the majority class at 1 km² were missed. Multi-layer land cover information with secondary and tertiary classes is able to fully represent 25.8% and 46.3% of higher-resolution land cover heterogeneity. For our test case and the example classification, we thus recommend including at least two vegetation classes. With three successive layers, already a good representation of the high resolution classification can be reached, as remaining land cover proportions typically not exceed 10%. The land cover base information for NPP modelling should include both the class assignment and its sub-pixel coverage. For other study areas or land cover classifications, required classes might vary. The number of desirable classes should be defined based on both the percentage of pixels that are covered within each layer and the remaining percent of not yet captured classes.

The comparison with frequently used global land cover datasets reveals varying agreement in classes' area coverage with the regional land cover classification for South Korea. Especially the GLC 2000 shows strong discrepancy and seems not a suitable base land cover map for NPP modelling for South Korea. For different areas globally, advantages and shortcomings of various global land cover datasets may vary. For regional applications, a suitable base land cover map should be chosen carefully.

If possible, we recommend using information from regional land cover data, as demonstrated in this study. Moreover, for NPP modelling it is commonly required to know plant functional types. Different vegetation types can especially be distinguished for forest and crops. While most global land cover products distinguish different forest types, crop types are not differentiated. Here, a regional land cover classification with a more detailed legend can be of major advantage. For further improving regional NPP modelling, it would be desirable to additionally down-scale available LAI time-series based on higher resolution land cover and vegetation condition data.

We conclude that for regions with similar land cover heterogeneity to South Korea, land cover maps providing only the majority land cover class at 1 km seem not able to sufficiently represent the heterogeneity of land cover on regional scale. This deficiency becomes even the more relevant, when we consider, that some NPP models are able to include more than one vegetation type per pixel. For such models, multi-layer information about both land cover types and their pixel coverage, i.e. relative weight, are of importance to take advantage of available higher-resolution land cover information.

5 References

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