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Comparison and Assessment of Coarse Resolution Land Cover Maps for Northern Eurasia

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Abstract

Information on land cover at global and continental scales is critical for addressing a range of ecological and socioeconomic research questions. Coarse spatial resolution sensors and algorithms for global land cover mapping have evolved rapidly in the last decade, but efforts to evaluate map uncertainties have been limited, especially in remote regions like Northern Eurasia. In this study we assessed four global land cover datasets: GLC-2000, GLOBCOVER, and the MODIS Collection 4 and Collection 5 Land Cover Products using Landsat-based reference maps at six test sites distributed across Northern Eurasia. We developed a common legend based on dominant life form (Tree, Shrub, and Herbaceous) to bridge differences in global map legends, and assessed map performance at the pixel, pixel-block, test site, and continental scale. Accuracy assessment for pixel and pixel-blocks was based on sub-pixel proportions of land cover to evaluate biases associated with coarse resolution. Total pixel-level agreement between global maps and test sites ranged from 0.67-0.74, and kappa ranged from 0.41-0.52 indicating fair to moderate agreement. The representation of tree-dominated classes was most accurate, while differences in the classification of non-tree classes accounted for most of the disagreement among global datasets. Tree-dominated classes tended to be over-represented at test sites as a result of the coarse spatial resolution. Accuracy estimates for pure (coarse-resolution) pixels and sampling units between 2 x 2 and 5 x 5 pixel blocks were 7-45% higher than pixel-level results, indicating that accuracy estimates from global maps based on homogeneous or dominant land cover types are likely too optimistic. If global maps are compared at our test sites using pixel-blocks of equal area, e.g. 3 x 3 km

47 then the overall agreement of GLOBCOVER (0.80) is similar to that of GLC-2000
48 (0.81), and MODIS V5 (0.81), and is higher than that of MODIS V4 (0.75). Because the
49 choice of evaluation criteria and sampling unit can lead to significantly different
50 estimates of map accuracy, a better understanding of the effect of accuracy measure
51 selection is needed. Knowledge of biases in different global products is important for
52 their applications in global assessments and informing policy decisions.

1 Introduction

Information on land cover at global and continental scales is critical for addressing a range of important science questions from effects of vegetation on the carbon cycle, surface energy, and water balance, to understanding socioeconomic causes and consequences of land-use and land-cover change. The need for accurate land-cover information is particularly acute in Northern Eurasia. The area is a locus for climate change, and there is mounting evidence of significant recent changes in vegetation distribution, growing season duration, and patterns of snow cover and permafrost (i.e. Chapin et al. 2005; Groisman et al. 2009). The region also has unique, but often poorly characterized features, including vast expanses of larch (*Larix* spp.) forests, permafrost, wetlands, widespread disturbances (fire, harvest, pollution damage, insect damage), and drastic changes in land use following profound region-wide socioeconomic changes in the 1990s (e.g. Forbes et al. 2004; Kuemmerle et al. 2008; Kuemmerle et al. 2009).

Since the mid 1990s substantial advances have been made towards the development of global vegetation and land cover datasets from moderate resolution satellite sensors. The first satellite-based global land cover maps were produced with data from the advanced high-resolution radiometer (AVHRR) (DeFries and Townshend 1994; Hansen et al. 2000; Loveland et al. 2000). In 1998 and 1999, AVHRR was followed by VEGETATION-1 onboard the fourth Satellite Pour l'Observation de la Terre (SPOT) and the Moderate Resolution Imaging Spectroradiometer (MODIS), which started the concurrent development of two additional global land cover products: GLC-2000 (Bartholome and Belward 2005) and the MODIS Global Land Cover Product (Friedl et al. 2002). More

recently, two new global land cover datasets have been released: GLOBCOVER derived from Medium Resolution Imaging Spectrometer (MERIS) data (Arino et al. 2008) and the MODIS C5 Land Cover Product (Friedl et al. 2010). The most important change in the evolution of these datasets is the increase in spatial resolution from ~1km (MODIS C4 and GLC-2000) to ~500m (MODIS C5) and ~300m (GLOBCOVER). The finer resolution of these maps is expected to improve global land cover characterization.

The availability of multiple relatively similar land cover data sets provides the user community with a choice, but it is not clear for most users which map suits their particular application best (Herold et al. 2008; Jung et al. 2006). Ultimately, the selection is often based on map legends rather than accuracy, in part because it is difficult to ascertain which map is the most accurate. Map developers commonly report overall estimates of map accuracy, however, because of methodological differences these measures cannot be directly compared. For example, the reported classification accuracy for MODIS V5 (75%, Friedl et al. 2010) is 8% higher than the reported accuracy for GLOBCOVER (67%, Bicheron et al. 2008), but the significance of this difference is uncertain.

While users often rely on overall measures of map accuracy to evaluate the quality of maps, map errors are rarely equally distributed (Strahler et al. 2006). Therefore, two maps can have the same overall accuracy, but show a different spatial distribution of error. In this case, the choice of map would depend on user interest in a particular region of the map and will need to be considered in interpreting results of spatial modeling. Studies that compared global land cover maps found significant variability in class

agreement between biomes (Fritz and See 2008; Giri et al. 2005; Herold et al. 2008). Disagreement is largest for spectrally similar land cover types (e.g. mixed versus pure broadleaf and conifer forests) and spatially heterogeneous land cover. Geographic areas affected most by the disagreement among maps are the transition zones between major biome types and areas more profoundly influenced by human land-use activities. In Northern Eurasia these are regions that have historically been influenced by, and potentially will be most vulnerable to, socioeconomic and climate changes.

Despite the importance of Northern Eurasia for global change research, global maps have not been rigorously tested in this region. Frey and Smith (2007) compared field observations in Western Siberia with two land cover and two wetland databases. Agreement between the field data and the two analyzed land cover data sets, the AVHRR Global Land Cover Characterization Database and the MODIS C3 Land Cover Product, was 22% and 11%, respectively. Other comparison studies have focused only on wetlands (Krankina et al. 2008; Pflugmacher et al. 2007).

Cross comparisons between global land cover maps help identify areas of potential high map uncertainty (Herold et al. 2008; See and Fritz 2006), but independent validation studies are needed to reveal the sources of disagreement and provide local and regional scale estimates of classification accuracy. There are several challenges associated with this task:

- The collection of reference data is costly for large areas, particularly for remote regions such as Northern Eurasia. Consequently, it is crucial to design and implement validation methods that are not tailored to a single map product, i.e. a

single classification system and spatial resolution, but that can accommodate a range of current and potentially future land cover maps.

- Reference data is often collected at high spatial resolution and needs to be aggregated to the resolution of the coarse-scale map. The process of aggregation, however, can introduce biases towards dominant land cover types ("low resolution bias", Boschetti et al. 2004; Latifovic and Olthof 2004).

- Accuracy estimates depend on the choice of sampling unit (e.g. pixels or pixel-blocks), which often differ from the spatial unit of the map (Foody 2002). Commonly, a single analysis unit is used in assessments although land cover maps are used on a variety of spatial scales (including the pixel-scale).

- Maps differ with respect to class definitions and thematic detail they provide. This affects estimates of overall map accuracy (Latifovic and Olthof 2004), and therefore makes cross-comparison of accuracy estimates difficult.

The objective of this study was to evaluate accuracy measures and procedures for validating four major global land cover datasets over the region of Northern Eurasia using maps created from higher resolution satellite data (Landsat). This study is part of a broader effort to validate and improve land cover and land-cover change products for Northern Eurasia using a network of local test sites distributed throughout the region (http://www.fsl.orst.edu/nelda).

2 Methods

For the purpose of this analysis we defined the region of Northern Eurasia to extend from 42°–74° N latitude; and we included Scandinavia, the Baltic countries, Belarus, Moldova and the Ukraine (Figure 1). Reference sites were selected to cover a range of geographic and climatic gradients in locations where high quality reference data and local expertise were available. Our reference data consists of land cover maps for each site compiled from Landsat scenes and a combination of ground data and expert knowledge. Using Landsat-based maps allowed for detailed exploration of the distribution of land cover and error structure associated with selected landscape types. A similar approach has been used to validate MODIS Land Cover maps for selected biome types in North and South America (Cohen et al. 2006; Cohen et al. 2003; Latifovic and Olthof 2004). While random probability sampling is more desirable (Strahler et al. 2006), validation studies are often constrained by availability of reference data. Opportunistic selection of validation sites precludes a probability-based statistical assessment of the global maps overall, but permits different measures of map accuracy to be examined across a wide range of conditions within Northern Eurasia.

2.1 Global land cover data sources

The GLC-2000 effort was lead by the Joint Research Center of the European Commission in partnership with more than 30 institutions (Bartholome and Belward 2005). The GLC-2000 map is based on Satellite Pour l'Observation de la Terre (SPOT) VEGETATION data acquired daily between November 1999 and December 2000. The map uses a 22-class legend based on UN FAO's hierarchical Land Cover Classification

System (LCCS, DiGregorio 2005). We downloaded the global data set (v1.1) from (http://www-gvm.jrc.it/glc2000/; last accessed 20 January 2008) in geographic coordinates, and projected it to an equal area projection (Lambert Azimuthal EA).

GLOBCOVER is the successor to GLC-2000, and as such also builds on an international network of partners. GLOBCOVER was developed using an annual mosaic of Envisat's Medium Resolution Imaging Spectrometer (MERIS) data from December 2004 to June 2006. With 300 m spatial resolution, GLOBCOVER represents the highest spatial resolution global land cover dataset currently available. The map distinguishes between 22 classes that are compatible with the Land Cover Classification System (LCCS). We downloaded GLOBCOVER v2.2 from the European Space Agency GLOBCOVER Project (http://ionia1.esrin.esa.int, last accessed 12 December 2008).

The MODIS Land Cover Product is developed by scientists from Boston University for NASA's Earth Observing System (EOS) MODIS land science team (Friedl et al. 2002). The MODIS Land Cover Product provides global land cover in five different classifications, and is produced for each year since 2001. The MODIS land science team periodically reprocesses MODIS reflectance and data products, including the yearly MODIS Land Cover Product. For this study we analyzed MODIS Land Cover Collection 4 data from 2001 and Collection 5 data from 2005 using the classification of the International Geosphere-Biosphere Programme (IGBP) classification system, hereafter referred to as MODIS V4 and MODIS V5, respectively. We obtained the data from the NASA Warehouse Inventory Search Tool (https://wist.echo.nasa.gov, last accessed 25 January 2010).

2.2 Differences between global land cover classifications

The global land cover classifications analyzed in this study are generally similar, but there are differences between maps that make a direct and uniform comparison challenging (Table 1). For example GLC-2000 differentiates between evergreen and deciduous shrub types, whereas MODIS IGBP does not distinguish between shrub leaf types, but does distinguish between open and closed shrub cover. Further, GLC-2000 and GLOBCOVER distinguish between non-vegetated, bare land cover and sparse vegetation with less than 10-20% and less than 15% vegetation cover, respectively. In comparison, MODIS IGBP combines these land cover types into a single class: barren and sparsely vegetated areas with less than 10% vegetation or snow cover. Maps also show various degrees of thematic detail within tree life form classes. Generally, tree life form types are characterized by leaf type (needleleaf, broadleaf, and mixed) and seasonal phenology (evergreen and deciduous). However, each map contains classes that cannot be unambiguously assigned to either of the two, e.g. the “Burnt Tree Cover”, “Regularly Flooded Tree Cover”, and “Mosaic Tree Cover” classes in GLC-2000, the “Open Needleleaved Deciduous or Evergreen Forest” class in GLOBCOVER, and the open tree vegetation cover classes in MODIS IGBP (“Woody Savannas” and “Savannas”). The common denominator to each of the global classification systems examined here are the dominant life form types, e.g. tree, shrub, herbaceous vegetation and non-vegetated land cover such as barren, snow and ice, and water.

To minimize ambiguities in comparison of accuracy statistics among global land cover datasets, map legends need to be converted to a common classification. For this paper, we generalized map legends to six classes on the basis of the dominant life form types (LFT)

205 in each map (Table 1). Croplands were labeled as herbaceous vegetation and classes that
206 include mixtures of LFT types were labeled as "mosaic". This level of generalization
207 avoids most of the ambiguities described above, albeit at the cost of thematic detail. An
208 alternative approach to bridging the differences among legends relies on "fuzzy logic"
209 (See and Fritz 2006) in contrast to "crisp logic" chosen for this study. We opted for crisp
210 comparison in an effort to maintain objectivity by avoiding judging the severity of class
211 disagreement.

212 2.3 Test sites

213 To assess the coarse resolution maps we selected six test sites across wide latitudinal,
214 longitudinal, and climatic gradients of Northern Eurasia (Table 2, Fig. 1). Mean annual
215 temperature ranges from -5 °C at the Komi site to +6 °C at the Carpathian site and
216 precipitation ranges from <400 mm per year in Chita to about 1000 mm in the
217 Carpathians. While all sites have mild summers, the average winter temperature declines
218 from west to east as the climate becomes increasingly continental. The terrain is flat at
219 the St. Petersburg, Komi and Vasyugan site and mountainous with significant elevation
220 gradients at the remaining three sites.

221 All sites are located within the forest belt that stretches across Northern Eurasia and
222 vegetation cover in all sites includes a significant proportion of forest (tree-dominated
223 land cover). Shrub cover is present in all sites as well, but its role tends to be small. The
224 sites represent different ecoregions including temperate forest (Carpathians), southern
225 taiga or boreal forest (St. Petersburg and Vasyugan), northern taiga (Komi), and montane
226 boreal (Priangarie and Chita) (Alexeyev and Birdsey 1998). The sites also reflect the

diversity of vegetation disturbance regimes in Northern Eurasia, including forest fires (Chita), insect outbreaks (Priangarie), timber harvest (Carpathians and St. Petersburg), and changes in agricultural land use (all sites except Komi). Wetlands occupy large areas at three test sites (St. Petersburg, Komi, and Vasyugan). Excessive moisture at these sites leads to accumulation of peat, reduced density of tree cover and greater shrubs and herbaceous vegetation cover.

Detailed land cover maps for each test site were developed based on Landsat imagery combined with local expert knowledge and ground data. Results of several completed and ongoing projects that mapped land cover and examined various types of land-cover, land-use change, and vegetation disturbance were also used (e.g., Heikkinen et al. 2004; Kharuk et al. 2004; Kharuk et al. 2003; Krankina et al. 2004a; Krankina et al. 2004b; Kuemmerle et al. 2007; Kuemmerle et al. 2008). The Landsat classification approaches varied by site and included supervised (e.g. decision trees) and unsupervised classifications. All site legends followed the Land Cover Classification System (LCCS, Di Gregorio 2005) and included between 11 and 17 classes. These were recoded into the following dominant life form classes: tree, shrub, herbaceous vegetation, and barren or sparse vegetation (Table 3). The LCCS classification defines "tree dominated" cover as land with greater than 15% tree cover, where trees are any woody vegetation taller than 5 m or trees taller than 3 m. Similarly, shrub and herbaceous dominated vegetation types have a minimum of 15% plant cover, respectively. The dominant life form is defined hierarchically by the height of the canopy layer, which ranges from trees to shrubs to herbaceous plants. Lands with less than 15% vegetation cover are labeled as "bare land and sparse vegetation".

Map accuracy at test sites was assessed using forest inventory data and ground observations from research projects. Where ground observations proved insufficient, additional reference data were collected through manual interpretation of aerial photos and high-resolution imagery in Google Earth. The overall accuracy of Landsat-derived maps for dominant life forms exceeded 92% for Carpathians, St. Petersburg, Vasyugan, and Priangarie sites; it was somewhat lower for Chita and Komi sites (87% and 80%, respectively) (Table 3). For the purpose of this study the Landsat-based classifications are considered "ground truth".

2.4 Comparison and assessment of global maps

To assess the accuracy of the four global maps we explored the distribution of global land cover at the regional (Northern Eurasia), local (test sites), and pixel/pixel-block scale (within test sites). Comparisons of total map and reference class proportions are effective to assess global land cover maps at the test site scale (Cohen et al. 2006), but a more rigorous approach was required to evaluate the spatial agreement for coarse resolution pixels and pixel-blocks. Error or confusion matrices are commonly used for reporting the accuracy of thematic maps (Foody 2002). Several measures can be derived from these matrices such as the error of omission (exclusion) and commission (inclusion), and overall agreement and kappa (Cohen 1960). Like overall agreement, kappa ranges from 0 to 1, but its interpretation is less transparent. In general, kappa estimates between 0.6-0.8 are interpreted as good to very good, and between 0.4-0.6 as fair to moderate (Czaplewski 1994).

271 Reference data for validating global map products are often acquired at higher spatial
272 resolution, but conventional error matrices require the reference data to match the spatial
273 resolution of the map to be validated. As a consequence, when maps with differing spatial
274 resolutions are compared, the map with the higher spatial resolution is often aggregated
275 to the coarser resolution by assigning the dominant class to the aggregated pixel
276 (Stehman and Czaplewski 1998; Turner et al. 2000). The disadvantage of this approach is
277 that it assumes a level of homogeneity in the landscape, which rarely is the case, and as a
278 result sub-dominant and rare classes are often under-represented. The extent of this low
279 resolution bias depends on the patchiness of land cover. For example, in a study that
280 assessed the representation of wetlands in global and continental land cover maps in the
281 St. Petersburg region, we found that 50% of the wetland area would be omitted if 30 m
282 reference pixels were aggregated to 1 km pixels using the dominant class rule (Krankina
283 et al. 2008).

284 The sub-fractional error matrix introduced by Latifovic and Olthof (2004) provides a
285 method to summarize reference class proportions within coarse map pixels and therefore
286 avoids spatial aggregation of the reference data. The sub-fractional error matrix is
287 populated by counting the number of pixels of a reference class within a coarser
288 resolution pixel (Figure 2a). Thus, instead of labeling a coarse resolution pixel either
289 100% correct or 100% incorrect, the "correctness" of that pixel is rated on a continuous
290 scale based on the pixel fraction occupied by the "correct" reference class. Standard
291 accuracy measures calculated from conventional error matrices can also be computed
292 from the sub-fractional error matrices. For example, omission error is the fraction of
293 reference pixels that occupy coarse resolution pixels of other classes. Similarly,

294 commission error is the total sub-pixel fraction of coarse resolution pixels occupied by
295 reference pixels of other classes. Because coarse resolution pixels usually contain a
296 mixture of cover classes, total agreement scores obtained by this approach are generally
297 less than 1 even if the classification were perfect.

298 Classification accuracy can also be expected to decrease with increased fine-scale
299 heterogeneity in land cover types (Herold et al. 2008). To measure map accuracy
300 independent of coarse resolution bias and landscape heterogeneity, we calculated
301 accuracy statistics for "pure" pixels. Pure pixels contain at least 95% of a single land
302 cover class in the reference data.

303 Mosaic classes of global land cover classifications contain mixtures of vegetation types,
304 e.g. croplands, forests, shrub land, and grasslands that only occur at the coarse resolution
305 scale. This is problematic in accuracy assessment, because it is not clear when a pixel
306 should be labeled as mosaic and when it should be labeled according to the dominant
307 vegetation type. For example, an area with 30% tree cover could be classified either as
308 mosaic or forest. To account for this ambiguity we assume that mosaic pixels can contain
309 any combination of tree, shrub and herbaceous vegetation types. Thus, total agreement
310 for mosaic pixels was determined from the combined area of tree, shrub and herbaceous
311 reference pixels. Similarly, when we calculated omission errors for these three classes,
312 the area mapped as mosaic was added to tree, shrub, and herbaceous LFT, respectively,
313 effectively decreasing the omission error. This approach yields a conservative assessment
314 of map error as it reduces the uncertainty resulting from mosaics, but it potentially

315 inflates the map accuracy measures in proportion to the area classified by global maps as
316 mosaic or mixed vegetation.

317 Errors in spatial registration of individual coarse-resolution pixels also introduce
318 uncertainty when linking a coarse-resolution pixel to a set of fine resolution pixels on a
319 reference map. To account for potential misregistration errors, we estimated map
320 accuracies for different sizes of sampling units: ranging from individual coarse resolution
321 pixels to blocks ranging in size from 2 x 2 to 10 x 10 coarse resolution pixels. The sub-
322 fractional error method has previously only been used with sampling units of individual
323 pixels (Latifovic and Olthof 2004). However, the method can also be applied to pixel
324 blocks. For the purpose of demonstration it is convenient to describe the fractional error
325 matrix using terminology from set theory, where the set boundaries are defined by the
326 sampling unit and the set elements are the map pixels (Figure 2b). Because we are
327 interested in sub-pixel fractions of land cover, the coarse map must be resampled to the
328 spatial resolution of the reference data. The class agreement of a reference sample *X* and
329 a global map sample *X'* is then the intersection between the two sets, and the overall class
330 agreement is the sum of intersections across all samples:

331 $$Y_{i,i} = \sum_{m=1}^{M} \sum_{n=1}^{N} X_{m,n} \cap X'_{m,n} \qquad \text{Eq. 1)}$$

332 where *i* denotes the row and column (diagonal) of error matrix *Y*, and *m* and *n* denote the
333 row and column of the accuracy samples, respectively. Note that because the sampling
334 unit is greater than the map unit, non-diagonal elements do not have a unique solution.

335 The calculation of agreement, omission and commission for pixel blocks is similar to that
336 of individual pixels.

337 # 3 Results

338 ## 3.1 Comparison of land cover distributions for Northern Eurasia

339 There are significant differences among global maps with respect to spatial distribution
340 and relative frequency of vegetation types in Northern Eurasia. Estimates of the tree
341 dominated land area are relatively similar for the entire region, ranging from 35%
342 (MODIS V4) to 42% (GLC-2000) (Figure 3). However, differences in tree cover are not
343 equally distributed but concentrated mainly in northern Siberia and the Far East. For
344 example, tree cover in GLC-2000 and GLOBCOVER is significantly higher in the
345 transition zone between boreal forest and shrub tundra compared to MODIS V4 and
346 MODIS V5 (Figure 4).

347 MODIS maps a significant proportion of the northern taiga and the tundra as shrub
348 dominated vegetation. Based on MODIS V4 and V5, shrub land cover types make up
349 about one quarter of the entire Northern Eurasia region (27% and 21%, respectively).
350 This is about three times the total shrub dominated land area mapped by GLC-2000 (7%).
351 Interestingly, GLOBCOVER classifies less than 0.1% of Northern Eurasia as shrub lands,
352 but maps a significantly greater proportion of the region as sparse vegetation and barren
353 land (31%) when compared to GLC-2000 (23%), and MODIS V4 (6%) and V5 (4%).
354 The difference is most pronounced in the taiga-tundra ecotone and in the transition from
355 steppe/grasslands to non-vegetated areas in the south, where herbaceous vegetation cover

356 is significantly greater with MODIS. However, GLOBCOCVER maps about 22% of the
357 region as vegetation mosaics, which partly explains its low proportion of herbaceous and
358 shrub dominated vegetation classes. The proportion of mosaic pixels is significantly
359 lower in GLC-2000 (9%), MODIS V4 (1%), and MODIS V5 (6%).

360 3.2 Comparison of global land cover at test sites

361 3.2.1 Distribution of global land cover at test sites

362 Comparison of the four global land cover datasets with the Landsat-based reference maps
363 (Figure 5) revealed general patterns of agreement and disagreement at the site level. To
364 quantify the representation of global land cover at this scale, we compared the relative
365 proportions of dominant life form types (LFT) at each site without regard of their within-
366 site spatial distribution (Figure 6a). We found the percentage of coarse resolution pixels
367 in the tree class matches most closely the percentage of reference pixels across all global
368 maps. GLOBCOVER shows the highest overall agreement in this class (88%), followed
369 by GLC-2000 (82%), MODIS V5 (80%), and MODIS V4 (78%). There is a general
370 tendency in all four coarse resolution maps to overestimate the tree class by an average of
371 10-20% (Figure 6a). The pattern of under-reporting smaller classes does not improve on
372 maps with finer resolution (GLOBCOVER and MODIS V5). The same analysis
373 performed on coarse resolution pure pixels with uniform land cover (Figure 6b) shows a
374 much improved agreement in total tree dominated area and other LFT classes for all
375 global maps, although the improvement for non-tree classes is notably smaller for
376 GLOBCOVER.

Differences in LFT class proportions between global maps and reference data are largest where tree cover is sparse. At Komi, GLC-2000 and GLOBCOVER overestimate tree cover by 30% and 26%, respectively, whereas MODIS V4 under-represents this class by 40%. The low percentage of tree cover in V4 is accompanied by a significantly higher proportion of shrub cover; 2.6 times higher than the reference data. In MODIS V5, classification of tree vegetation significantly improved and is more consistent with GLC-2000 and GLOBCOVER. Conversely, GLOBCOVER significantly overestimates barren/sparse vegetation all test sites, but shows the best agreement for inland water bodies.

3.2.2 Pixel-based agreement of global maps

Total agreement for pixel-level comparisons ranges from 0.34 at the Komi site based on GLOBCOVER to 0.87 at the Carpathian site based on MODIS V5 (Table 4). Mean total agreement from all global maps ranges from 0.46±0.09 at Komi to 0.84 ±0.02 at Priangarie. For all sites combined, total agreement for MODIS V4 and V5 was 0.67 and 0.74, respectively; and for GLOBCOVER and GLC-2000 total agreement was 0.70 and 0.73, respectively. MODIS V5 performed better than MODIS V4 on all test sites with the exception of Chita. The lower agreement at Chita may be attributable to widespread forest fires that burned about 17% of the total site area in 2002-2003, most of it tree-dominated. The time of these disturbances falls in-between the Landsat and MODIS V5 data acquisitions in 2000 and 2005, respectively. The time difference to the reference maps is the same as that for GLOBCOVER, but larger compared to GLC-2000 and MODIS V4. However, on average the disturbance rates do not exceed 0.1-0.2% per year over large areas. Thus, we expect the effect of differences in the data acquisition dates to

400 be small on all sites with the exception of Chita. Chance corrected agreement at the pixel
401 scale is fair to moderate for all maps (Kappa = 0.41-0.52).

402 The sub-pixel fractional error matrices for dominant life form types reveal more detailed
403 patterns of class confusions across test sites (Table 5). Class errors are lowest for tree
404 vegetation with omission errors (OE) between 0.05 (GLC-2000 and GLOBCOVER),
405 0.08 (MODIS V5) and 0.13 (MODIS V4), and commission errors between 0.2
406 (GLOBCOVER and MODIS V5) and 0.24 (GLC-2000). For individual test sites
407 omission of tree land cover is less than 0.2 except at Chita (evidently due to fire, MODIS
408 V5, OE=0.28) and Komi (MODIS V4, OE=0.59). Because these error estimates
409 correspond to sub-pixel proportions of land cover, omission and commission errors
410 describe the approximate boundaries of the mapped classes. For example, a 0.05
411 omission error indicates an average tree cover in non-tree pixels of 5%. Likewise, a
412 commission error of 0.2 represents the mean fraction of non-tree cover included in coarse
413 resolution tree pixels. Because global maps typically define a minimum tree cover
414 threshold for tree dominated classes between 10-20%, it is reasonable to expect an
415 average omission of up to 0.1-0.2, depending on class definition. Tree cover in this study
416 is defined at the Landsat resolution with a minimum cover threshold of 15%.

417 Shrub cover tends to be under-represented with overall omission rates between 0.54
418 (MODIS V5) and 0.82 (GLOBCOVER). However, only 40%-52% of the omitted shrub
419 cover can be attributed to coarse resolution tree pixels. If we exclude shrub cover
420 associated with these pixels, we obtain omission errors of 0.14 (MODIS V5), 0.15 (GLC-
421 2000), 0.16 (MODIS V5) and 0.39 (GLOBCOVER). Examination of the error matrices in

Table 5 reveals, that over 90% of the omitted shrub cover is mapped as barren by GLOBCOVER, and herbaceous by GLC-2000 and MODIS. Similarly, about 50% of the omitted herbaceous cover is mapped as tree or barren, respectively, in GLOBCOVER. This indicates that GLOBCOVER underestimates shrub cover and herbaceous cover while overestimating barren/sparse vegetation. Conversely, MODIS maps large areas of herbaceous tundra as open shrub land.

3.2.3 Global map agreement for homogenous land cover

To quantify the effect of landscape homogeneity on map accuracy we performed a separate accuracy assessment for pure pixels. There is a clear relationship between the number of pure pixels and map agreement between test sites (Figure 7). The Priangarie site with the highest overall agreement also has the highest percentage of pure pixels (50%-67%), whereas Komi site with the lowest map agreement shows the lowest percentage of pure pixels (3%-13%). As expected, maps with higher spatial resolution exhibit a greater number of pure pixels. The spatial resolution of GLOBCOVER is much higher than that of GLC-2000 and MODIS V4, and its percentage of pure pixels is about twice as high as these two maps at St. Petersburg, Carpathian, and Vasyugan, and 4.5 and 1.3 times as high at Komi and Priangarie, respectively. However, there is no clear relationship between number of pure pixels and total agreement within test sites and between maps indicating that factors other than spatial resolution also affected map accuracy.

The agreement of global maps is nearly perfect if only pure pixels are considered (Table 4). Except at the Komi site, total agreement for dominant life form types exceeds 0.9.

444 Kappa also indicates good and perfect agreement for pure pixels. Total agreement
445 increases for pure pixels compared with all-pixel results between 0.09 and 0.45, with a
446 higher increase at sites with heterogeneous land cover (e.g. 0.31-0.45 at Komi) and lower
447 increase at more homogeneous sites (e.g. 0.09-0.17 at Priangarie). Further, the effect is
448 greater for the 1-km resolution maps GLC-2000 (mean = 0.23 ± standard deviation =
449 0.06) and MODIS V4 (0.27 ± 0.10) than for GLOBCOVER (0.18 ± 0.08) and MODIS
450 V5 (0.19 ± 0.08).

451 3.2.4 Agreement of global maps for different sampling units

452 In previous sections we assessed the accuracy of global maps by examining the
453 agreement of individual coarse resolution pixels with reference data. To explore the
454 effect of the sampling unit on map agreement, we increased the size of the unit from a
455 single pixel to blocks of pixels (e.g. 2 x 2, 3 x 3 coarse resolution pixels).

456 On average across sites, total agreement between global maps and reference data
457 increases between 0.089 ± 0.002 (MODIS V5) and 0.136 ± 0.002 (GLC-2000) for pixel-
458 blocks of up to 10 x 10 pixels relative to the single pixel case (Figure 8). The effect is
459 slightly larger for the coarser GLC-2000 and MODIS V4. Increase in agreement is
460 strongest for 2 x 2 pixels blocks, i.e. 0.062 ± 0.037 for GLC-2000, 0.040 ± 0.015 for
461 GLOBCOVER, 0.056 ± 0.013 for MODIS V4, and 0.037 ± 0.011. The rate of
462 improvement diminishes rapidly to about 10% ± 2% of the agreement estimate when
463 block sizes of 5 x 5 pixels are reached.

4 Discussion

This study presents an approach to assess global land cover maps consistently for the region of Northern Eurasia, and to explore the effect of sampling unit, reference class assignment and landscape characteristics on accuracy statistics. Our results show that methodology and choice of sampling unit significantly influence accuracy estimates, which indicates that reported global map statistics should be compared with caution. All analyzed maps showed similar overall agreement with Landsat-based reference data. However, results of accuracy assessments at test sites and regional statistics for Northern Eurasia indicate that similarities in map agreements are mostly due to similar representations of tree dominated land cover. Though slightly overestimated, tree dominated vegetation is the most accurate land cover class in all maps, whereas there are significant differences in the representation of non-tree land cover classes.

Our results indicate that global map accuracies for Northern Eurasia are likely lower than the reported global estimates from map developers. While methodological differences make a comparison difficult, our accuracy estimates based on six test sites (Table 4) are generally in line with the published global estimates for the examined maps (Bicheron et al. 2008; Friedl et al. 2002; Friedl et al. 2010; Mayaux et al. 2006). However, given that our analysis was based on a simplified 6-class legend, we expect that comparisons based on the full classification of these maps produce lower agreements for Northern Eurasia. Further, our analysis was not limited to homogenous areas or dominant land cover classes as is often practice in global map validation.

485 Total agreement between global land cover and reference data is similar among maps
486 (0.67-0.74), although MODIS V5 and GLC-2000 produce slightly better results than
487 MODIS V4 and GLOBCOVER. Pixel-level map accuracy increases by 7% from MODIS
488 V4 to MODIS V5, and decreases by 3% between GLC-2000 and GLOBCOVER.
489 However, when sampling units of equal area are compared, e.g. 3 x 3 km then total
490 agreement of GLOBCOVER (0.80) is similar to that of GLC-2000 (0.81), and MODIS
491 V5 (0.81), and is higher than that of MODIS V4 (0.75).

492 Tree dominated land cover is the most accurately mapped class in all global datasets. The
493 accuracies for our six test sites are within the range that can be expected from thematic
494 coarse resolution maps. Commission errors of 20% for tree dominated classes are
495 common and can be explained by the coarse spatial resolution. The high agreement for
496 pure pixels corroborates this.

497 Map disagreements are concentrated in areas with sparse tree cover and mixtures of
498 herbaceous and shrub cover, predominantly found in the taiga-tundra ecotone. The
499 hierarchical nature of land cover classifications, which define vegetation types based on
500 the order of presence of trees, shrub and then herbaceous vegetation and not the land
501 cover type that occupies the majority of the area, may increase the likelihood of class
502 confusion in transition zones of vegetation types. For example, a pixel that is comprised
503 to 20% of shrub, 40% herbaceous and 40% barren is defined as (open) shrub land, but the
504 dominance of herbaceous vegetation and barren will increase the probability that that
505 pixel is misclassified as either of the two more dominant classes. Hierarchical
506 classifications that ‘weight’ vegetation types differently according to their ‘ecological

507 value' are commonsense, but nevertheless it imposes additional requirements on thematic
508 coarse resolution maps to accurately represent sup-pixel land cover proportions.
509 Approaches that directly estimate sub-pixel proportions of land cover types might
510 provide a meaningful alternative for this task (Hansen et al. 2002; Hansen et al. 2005).

511 Subdominant and rare classes that exist largely at the sub-pixel scale are difficult to
512 resolve with thematic coarse resolution maps. Despite their spectrally distinct signature,
513 inland water bodies show omission errors between 50-70%. Representation of
514 subdominant and rare classes improved for pure pixels compared to all pixels (Figure
515 6a,b), although the improvement was less significant for GLOBCOVER. While the finer
516 resolution of GLOBCOVER could be expected to improve the accuracy of small classes,
517 water was the only class more accurately mapped by GLOBCOVER. It appears with finer
518 resolution other sources of error including pixel registration, become more significant. In
519 this context, it is important to note that the GLC-2000 and GLOBCOVER maps were
520 only available in a geographic coordinate system and had to be reprojected to an equal
521 area projection prior to analysis. Thus, registration errors may have been more significant
522 for these two maps.

523 We found overall accuracies increased by 8-12% for blocks of 5 x 5 pixels compared to
524 per-pixel comparisons, and that block sizes larger than 5 x 5 did not increase the
525 accuracies significantly (Figure 8, 9). While map accuracies are usually reported for a
526 single spatial analysis unit, maps are often used at multiple spatial scales (e.g. pixels,
527 polygons, pixel blocks). Because classification errors cannot be assumed to be the same
528 across different spatial scales, this introduces additional uncertainty for map users.

529 Furthermore, errors unrelated to map classification such as spatial misregistration and
530 convolution of the sensor signal with neighboring pixels can significantly influence the
531 underlying remote sensing data (Townshend et al. 2000), which suggests that
532 measurements of land cover properties are more robust at spatial resolutions coarser than
533 the individual pixel. In fact, reported accuracy statistics of global maps are often obtained
534 from sampling units larger than current coarse resolution map products (Stehman and
535 Czaplewski 1998), and only homogeneous or dominant land cover types are generally
536 sampled (Bicheron et al. 2008; Friedl et al. 2002; Friedl et al. 2010; Mayaux et al. 2006).
537 Because pixels are the basic mapping units of most global land cover data, users may not
538 always be aware of the uncertainties associated with using these maps at the pixel scale.
539 Our analysis of the effect of sampling unit on accuracy measures (Figure 8, 9) suggests
540 that blocks of 5 x 5 pixels are a good compromise between increased overall agreement
541 and decreased spatial detail.

542 To compare accuracy measures among maps, we generalized land cover classifications
543 using dominant life form types (LFT). Although other generalizations are possible, LFTs
544 represent the most general and unambiguous common denominator of current global
545 maps. There have been growing international efforts to promote a common land cover
546 language (LCCS, Di Gregorio 2005) and to provide translations between existing legends
547 (Herold et al. 2006; Thomlinson et al. 1999). Using the LCCS system, Herold et al.
548 (2008) created a generalized legend for the IGBP, GLC-2000 and the UMD
549 classification. Their generalized legend maintains a relatively detailed land cover scheme
550 that includes 13 classes, but does not eliminate categorical ambiguities among the tree
551 life form types. Evidently, the comparability of existing global land cover maps is limited

552 as a result of the different classification systems and class definitions. Current maps use
553 different tree cover and tree height thresholds to distinguish between tree and non-tree
554 classes (10% and 2 m in MODIS IGBP, 20% and a 5-m in GLC-2000 for Northern
555 Eurasia (Bartalev et al. 2003), and 15% and 5 m in GLOBCOVER). Considering the vast
556 diversity of biomes and vegetation types on Earth, global land cover mapping efforts face
557 a difficult task. Classes representing mixtures of different land cover reflect difficulties of
558 map developers to spectrally distinguish between the underlying cover types.
559 Nevertheless, future mapping efforts should focus on standardized classification systems
560 to improve compatibility with other maps. MODIS Land Cover for Collection 6 plans to
561 use an LCCS-based classification (Friedl et al. 2010).

562 Our approach builds on earlier global map validation efforts that relied on Landsat-based
563 maps as reference data (Cohen et al. 2006; Cohen et al. 2003).The combination of higher
564 resolution reference maps and a standardized LCCS-based classification provides a
565 flexible validation framework for assessing coarse resolution maps of different spatial
566 resolutions and thematic detail. A disadvantage is the limited number of test sites and
567 their opportunistic selection precludes the conclusive assessment of coarse resolution
568 map performance across the entire region of Northern Eurasia. However, the results give
569 an indication of the differences, strengths and weaknesses of the examined maps at
570 specific locations, and the relative magnitude of different types of errors likely to be
571 found in the maps. Furthermore, the comparison of different accuracy metrics at selected
572 locations provides insights into interpretation of commonly reported global map
573 accuracies.

574 The need for standardized quantitative assessment of available land cover maps is widely
575 recognized and different aspects of this task have been studied in recent years (e.g.
576 Herold et al. 2008; Jung et al. 2006; See and Fritz 2006). Because the collection of
577 reference data requires a significant investment, it is desirable to develop standards that
578 are not limited to a particular map, but can be 're-used' and extended to accommodate
579 different classifications and spatial resolutions (Justice et al. 2000). While sampling
580 designs for map validation are well understood (Strahler et al. 2006), methods for relating
581 maps of different spatial and thematic resolution have not been studied to the same extent
582 and community consensus on the strengths and weaknesses of different approaches is still
583 evolving. Thematic map products that focus on a single class represent a simpler case
584 (e.g. Roy and Boschetti 2009), but land cover maps are inherently more complex, which
585 makes evaluations and comparisons challenging.

586 Differences among land cover maps have important implications for biogeochemical (e.g.
587 Potter et al. 2008) and habitat models (e.g. Kuemmerle et al. in press) that use these
588 products. A simple analysis that extrapolated results of biogeochemical modeling for the
589 Arctic region of Northern Eurasia (North of 60 degrees) showed that a very different
590 picture of the regional carbon (C) balance emerges when different vegetation maps are
591 used as model inputs (Krankina et al. 2010): The estimate of C stock in live vegetation
592 based on the GLC-2000 map (24 Pg C) is 40% higher than the estimate based on the
593 MODIS plant functional type (PFT) map (17 Pg C). While the estimates of the total
594 change in live vegetation C stocks are very similar for both maps (0.2 Pg yr^{-1} C sink), the
595 attribution of the projected C sink is quite different depending on the map used: based on
596 GLC-2000 map most of the C accumulation occurs in tree-dominated ecosystems while

simulations using the MODIS PFT map attribute most of the C sink to shrub vegetation. The significant role of land cover map selection on forest biomass estimates in Russian forests was also reported by Houghton et al. (2007).

Globally consistent vegetation maps with known accuracy are a fundamental requirement for global change research and sound policies to address global change. Growing recognition of the role of terrestrial ecosystems and land use in the global carbon cycle (IPCC 2007) places new demands on the accuracy of products derived from satellite observations. Methods for independent map validation have been actively studied in recent years but many issues remain unresolved, including design of map legends that lend themselves to uniform aggregation (i.e., LCCS), consensus on metrics of agreement between fine-resolution reference data and coarser global maps, and support for a globally distributed set of test sites against which all maps can be compared (Justice et al. 2000).

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Tables

Table 1. Aligning the legends of global maps: dominant life form type (LFT) and corresponding land cover classes from GLC-2000, GLOBCOVER & MODIS IGBP

Dominant LFT	GLC-2000	GLOBCOVER	MODIS IGBP
Tree	[1] Tree Cover; broadleaved; evergreen	[40] Broadleaved evergreen or semi-deciduous forest, closed to open	[1] Evergreen Needleleaf Forest
	[2] Tree Cover; broadleaved; deciduous; closed	[50] Broadleaved deciduous forest, closed	[2] Evergreen Broadleaf Forest
	[3] Tree Cover; broadleaved; deciduous; open	[60] Broadleaved deciduous forest/woodland, open	[3] Deciduous Needleleaf Forest
	[4] Tree Cover; needle-leaved; evergreen	[70] Needleleaved evergreen forest, closed	[4] Deciduous Broadleaf Forest
	[5] Tree Cover; needle-leaved; deciduous	[90] Needleleaved deciduous or evergreen forest, open	[5] Mixed Forest
	[6] Tree Cover; mixed leaf type	[100] Mixed broadleaved & needleleaved forest, closed-open	[8] Woody Savannas
	[7] Tree Cover; regularly flooded; fresh water	[160] Broadleaved forest regularly flooded, closed to open	[9] Savannas
	[8] Tree Cover; regularly flooded; saline water		
	[9] Mosaic: Tree cover; Other natural vegetation		
	[10] Tree Cover; burnt		
Shrub	[11] Shrub Cover; closed-open; evergreen	[130] Shrubland, closed to open	[6] Closed Shrublands
	[12] Shrub Cover; closed-open; deciduous		[7] Open Shrublands
Herbaceous	[13] Herbaceous Cover; closed-open	[11] Post-flooding or irrigated croplands (or aquatic)	[10] Grasslands
	[16] Cultivated and managed areas	[140] Herbaceous vegetation, closed to open	[12] Croplands
		[14] Rainfed croplands	
Barren	[14] Sparse herbaceous or sparse shrub cover vegetation cover between 1% and 10-20% vegetation cover	[150] Sparse vegetation (<15%)	[16] Barren or Sparsely Vegetated
	[22] Artificial surfaces and associated areas	[190] Artificial surfaces and associated areas	[13] Urban and Built-Up
	[19] Bare Areas	[200] Bare areas	
	[21] Snow and Ice	[220] Permanent snow and ice	[15] Snow and Ice
Mosaic	[15] Regularly flooded shrub and-or herbaceous cover	[20] Mosaic cropland (50-70%) / vegetation (grassland/ shrubland/ forest) (20-50%)	[11] Permanent Wetlands
	[17] Mosaic: Cropland; Tree Cover; Other natural vegetation	[30] Mosaic vegetation (grassland/ shrubland/ forest) (50-70%) / cropland (20-50%)	[14] Cropland-Natural Vegetation Mosaic
	[18] Mosaic: Cropland; Shrub and-or Herbaceous cover	[110] Mosaic forest or shrubland (50-70%) / grassland (20-50%)	
		[120] Mosaic grassland (50-70%) / forest or shrubland (20-50%)	
		[170] Broadleaved forest or shrubland permanently flooded, closed	
		[180] Grassland or woody vegetation on regularly flooded or waterlogged soil, closed-open	
Water	[20] Water Bodies	[210] Water bodies	[0] Water Bodies

Table 2. Test site information

Site	Location	Latitude, Longitude	Landsat Path/Row	Landsat Image Date	Mean Temperature (ºC)			Mean Annual Precipitation (mm)	Elevation asl (m)
					January	July	Annual		
CARP	Carpathians (border region of Poland, Slovakia, Ukraine)	48.87, 22.40	186/20	6-Jun-2000 21-Aug-2000 30-Sep-2000	-7	19	6	900-1200	100-2000
STPB	St. Petersburg Region (Russia)	60.09, 31.27	184/18	2-Jun-2002	-10	17	4	600-800	0-250
KOMI	Komi Republic (Russia)	66.94, 57.10	171/13	1-Jun-2000 19-Jul-2000	-19	12	-5	360-500	20-240
VASY	Vasyugan Basin, Tomsk Region, West Siberia (Russia)	57.32, 82.09	150/20	16-Sep-1999	-18	18	0	450-550	110-130
PRIA	Priangarie, Krasnoyarsk Region, East Siberia (Russia)	57.30, 95.91	141/20	18-Aug-2000	-22	18	3	400-450	100-600
CHIT	Chita Region and Buriat Republic, East Siberia (Russia)	51.69, 111.64	129/24	11-Jun-2000	-26	15	-4	380	600-1500

Table 3. Error matrix of dominant life form types for Landsat-based reference maps at test sites.

Predicted Class	Site	Observed Class: Tree	Shrub	Herb	Barren	Water	Overall Accuracy
Tree	STPB	*2176*		18			
	CARP	*466*	7	7		4	
	KOMI	*289*	22			1	
	PRIA	*851*	7	7			
	CHIT	*210*	3	3		2	
	VASY	*179*	3	2			
Shrub	STPB		*44*	6	1		
	CARP	2	*59*	19	2	2	
	KOMI	8	*39*	8	1		
	PRIA	2	*25*	13	1		
	CHIT	18	*26*	1			
	VASY	7	*45*	3			
Herbaceous	STPB	6	5	*58*	1		
	CARP	1	26	*346*	1		
	KOMI	12	1	*14*	15	3	
	PRIA	8	1	*658*			
	CHIT	2	7	*37*	8		
	VASY	1	10	*52*	1		
Barren	STPB		1	5	*380*		
	CARP		3	3	*29*	1	
	KOMI			15	*41*	1	
	PRIA		7	13	*199*		
	CHIT			3	*22*		
	VASY				*32*		
Water	STPB					*116*	
	CARP					*22*	
	KOMI	2				*34*	
	PRIA					*274*	
	CHIT					*32*	
	VASY					*24*	
Percent Correct	STPB	1.00	0.88	0.67	0.99	1.00	0.98
	CARP	0.99	0.62	0.92	0.91	0.76	0.92
	KOMI	0.93	0.63	0.38	0.72	0.87	0.8
	PRIA	0.99	0.63	0.95	1.00	1.00	0.97
	CHIT	0.91	0.72	0.84	0.73	0.94	0.87
	VASY	0.96	0.78	0.91	0.97	1.00	0.92
	All Sites	0.98	0.70	0.90	0.96	0.97	0.91

Table 4. Overall agreement between reference maps and coarse resolution land cover products and Kappa statistic for per-pixel comparisons of dominant life form types at test sites

	GLC2000		GLOBCOVER		MODIS V4		MODIS V5	
Site	Agree-ment	Kappa	Agree-ment	Kappa	Agree-ment	Kappa	Agree-ment	Kappa
				All pixels				
Carpathians	0.69	0.45	0.73	0.57	0.75	0.56	0.87	0.79
Chita	0.76	0.40	0.83	0.51	0.72	0.37	0.67	0.35
Komi	0.58	0.41	0.34	0.22	0.42	0.16	0.49	0.28
Priangarie	0.84	0.39	0.85	0.49	0.80	0.35	0.86	0.51
St. Petersburg	0.74	0.51	0.69	0.48	0.67	0.36	0.75	0.54
Vasyugan	0.74	0.34	0.72	0.39	0.68	0.17	0.77	0.45
Total across sites	0.73	0.47	0.70	0.46	0.67	0.41	0.74	0.52
				Pure pixels only				
Carpathians	0.95	0.87	0.89	0.78	0.98	0.94	0.99	0.97
Chita	0.94	0.69	0.94	0.71	0.92	0.65	0.85	0.52
Komi	0.91	0.77	0.66	0.48	0.86	0.70	0.84	0.68
Priangarie	0.98	0.68	0.94	0.62	0.97	0.54	0.98	0.82
St. Petersburg	0.97	0.91	0.91	0.78	0.96	0.88	0.96	0.89
Vasyugan	0.98	0.49	0.94	0.54	0.97	0.27	0.97	0.62
Total across sites	0.96	0.80	0.91	0.72	0.96	0.78	0.94	0.79

Table 5. Sub-pixel fractional error matrices based on dominant life form types of GLC-2000, GLOBCOVER, MODIS V4 and MODIS V5 (aggregated results with reference data from all test sites)

	Landsat land cover (km^2)						
GLC-2000	Trees	Shrubs	Herbaceous	Barren	Mosaics	Water	Commission
Trees	***88,307***	11,900	16,103	844	0	987	0.24
Shrubs	851	***4,180***	3,618	200	0	445	0.40
Herbaceous	3,570	3,277	***12,131***	1,054	0	223	0.30
Barren	160	162	867	***378***	0	60	0.77
Mosaic	***4,867***	***3,507***	***6,589***	389	0	468	-
Water	313	64	132	89	0	***1,226***	0.33
Omission	0.05	0.67	0.53	0.87	0.00	0.64	

GLOBCOVER	Trees	Shrubs	Herbaceous	Barren	Mosaics	Water	Commission
Trees	***83,479***	10,010	11,752	589	0	796	0.20
Shrubs	1	***0***	6	0	0	0	0.00
Herbaceous	608	832	***4,831***	447	0	17	0.11
Barren	3,817	8,236	11,999	***1,198***	0	754	0.95
Mosaic	***11,311***	***4,230***	***11,248***	690	0	164	-
Water	125	46	94	72	0	***1,895***	0.15
Omission	0.05	0.82	0.60	0.60	0.00	0.48	

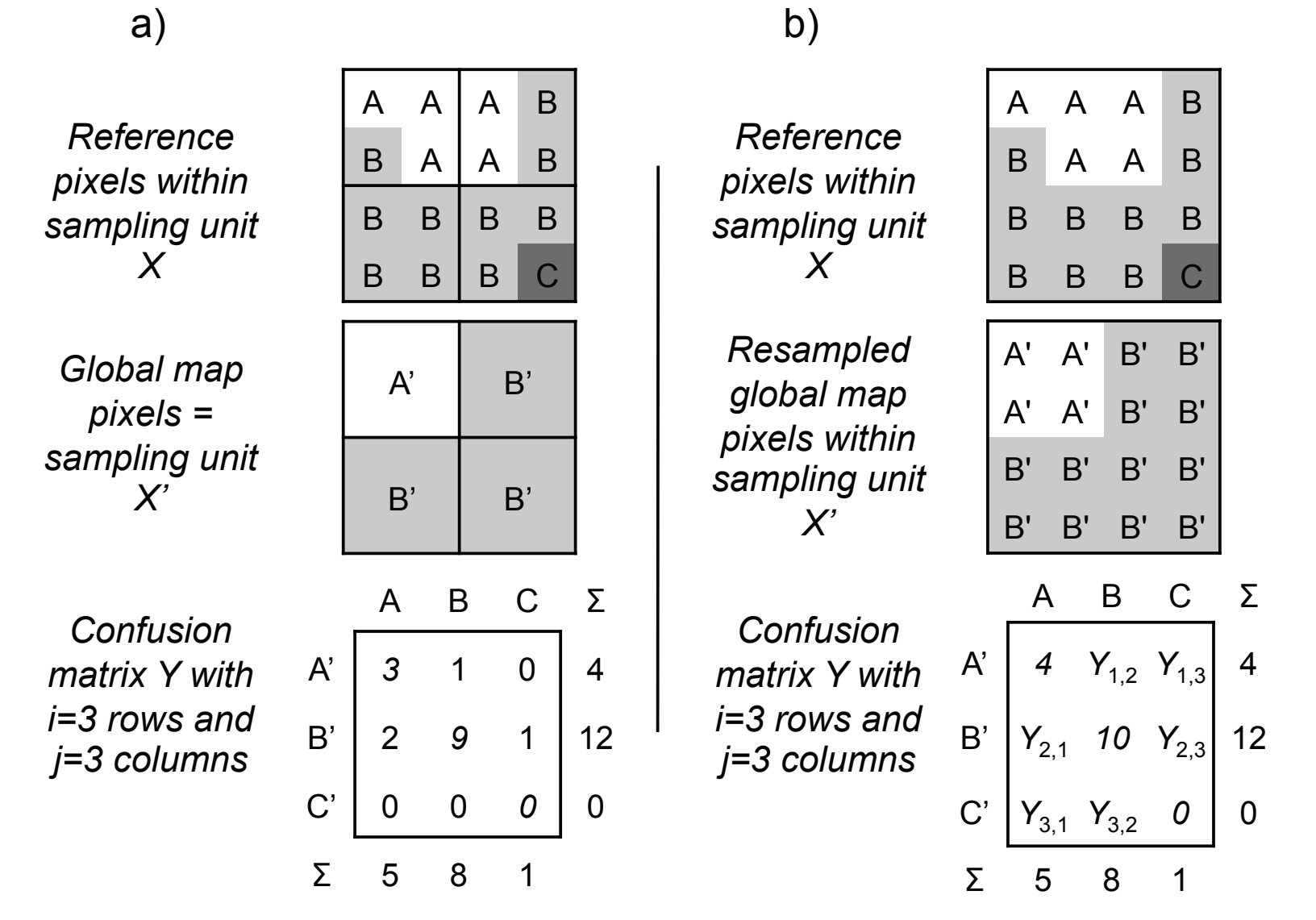
MODIS V4	Trees	Shrubs	Herbaceous	Barren	Mosaics	Water	Commission
Trees	***83,933***	9,524	12,947	827	0	710	0.22
Shrubs	7,859	***9,275***	10,657	564	0	1,210	0.67
Herbaceous	4,044	3,409	***13,733***	1,038	0	180	0.36
Barren	133	152	254	***340***	0	54	0.64
Mosaic	***1,411***	***550***	***1,557***	74	0	51	-
Water	280	115	194	105	0	***1,182***	0.37
Omission	0.13	0.57	0.61	0.88	0.00	0.65	

MODIS V5	Trees	Shrubs	Herbaceous	Barren	Mosaics	Water	Commission
Trees	***84,465***	9,207	11,100	775	0	1,209	0.20
Shrubs	2,943	***6,737***	7,354	428	0	747	0.52
Herbaceous	4,654	2,963	***12,020***	744	0	119	0.29
Barren	154	295	537	***592***	0	38	0.63
Mosaic	***6,553***	***4,043***	***8,737***	418	0	304	-
Water	20	8	14	26	0	***1,145***	0.06
Omission	0.08	0.54	0.48	0.80	0.00	0.68	

List of Figures:

Figure 1 BW (PRINT)

Figure 2 BW (PRINT)



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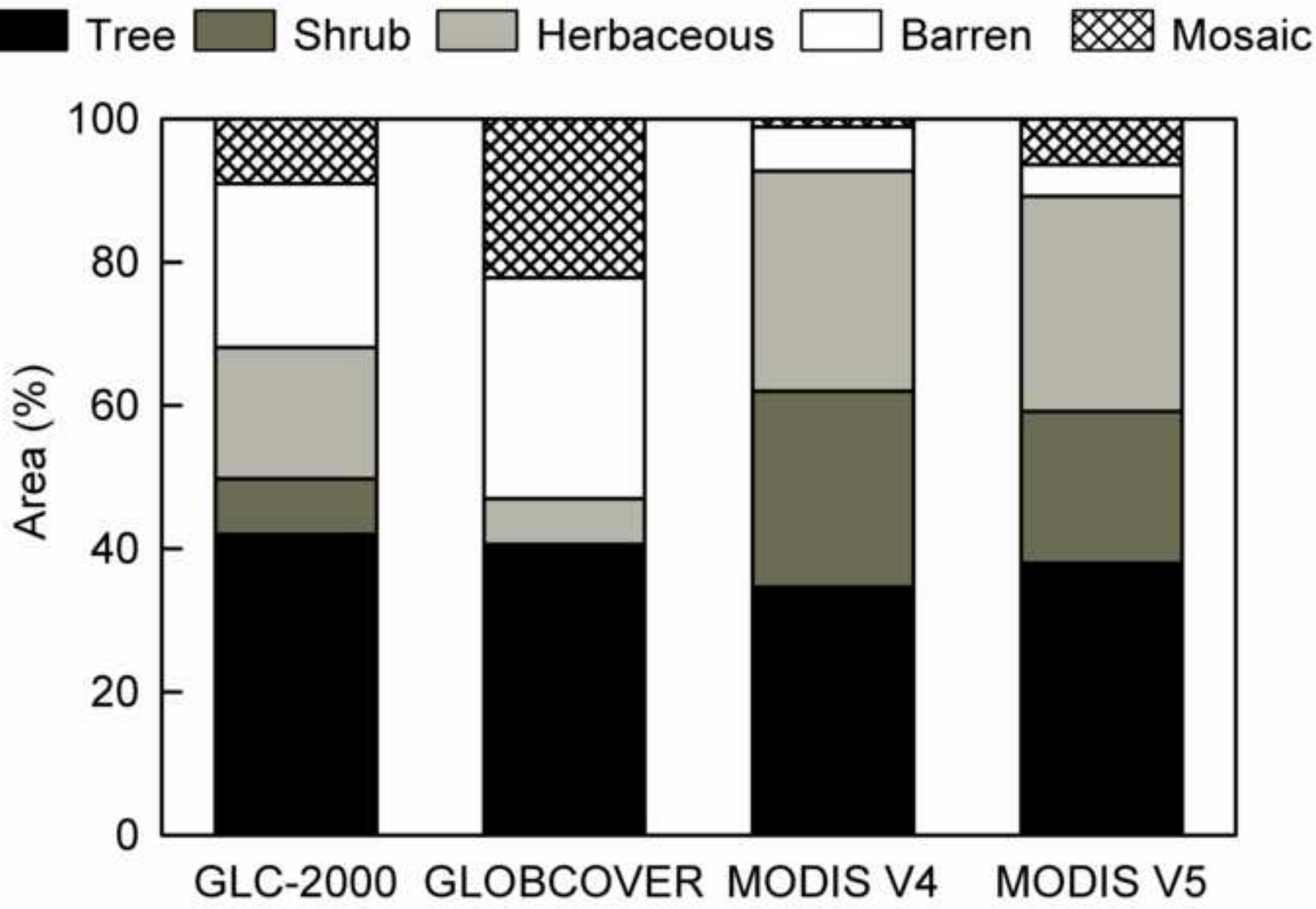

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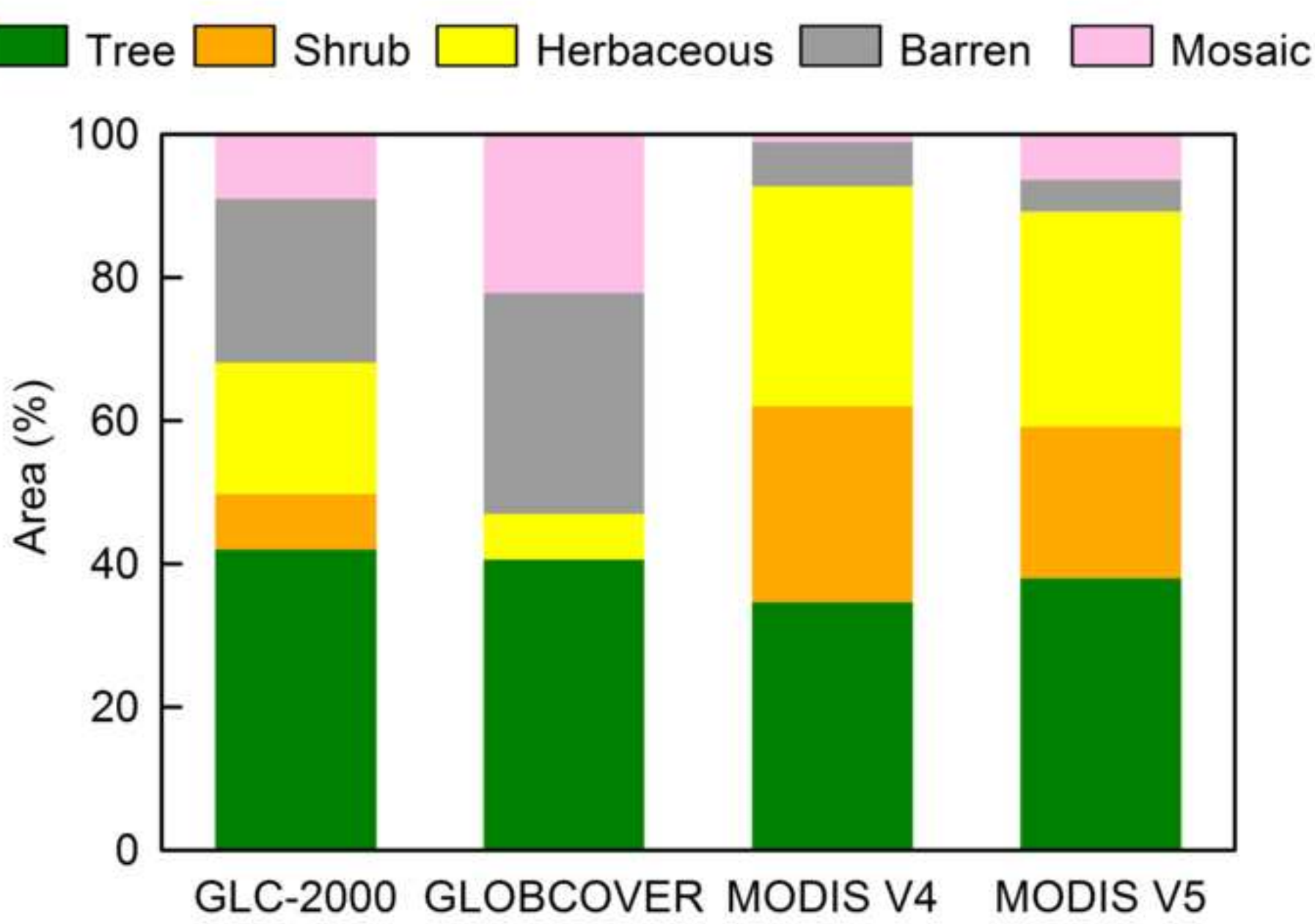

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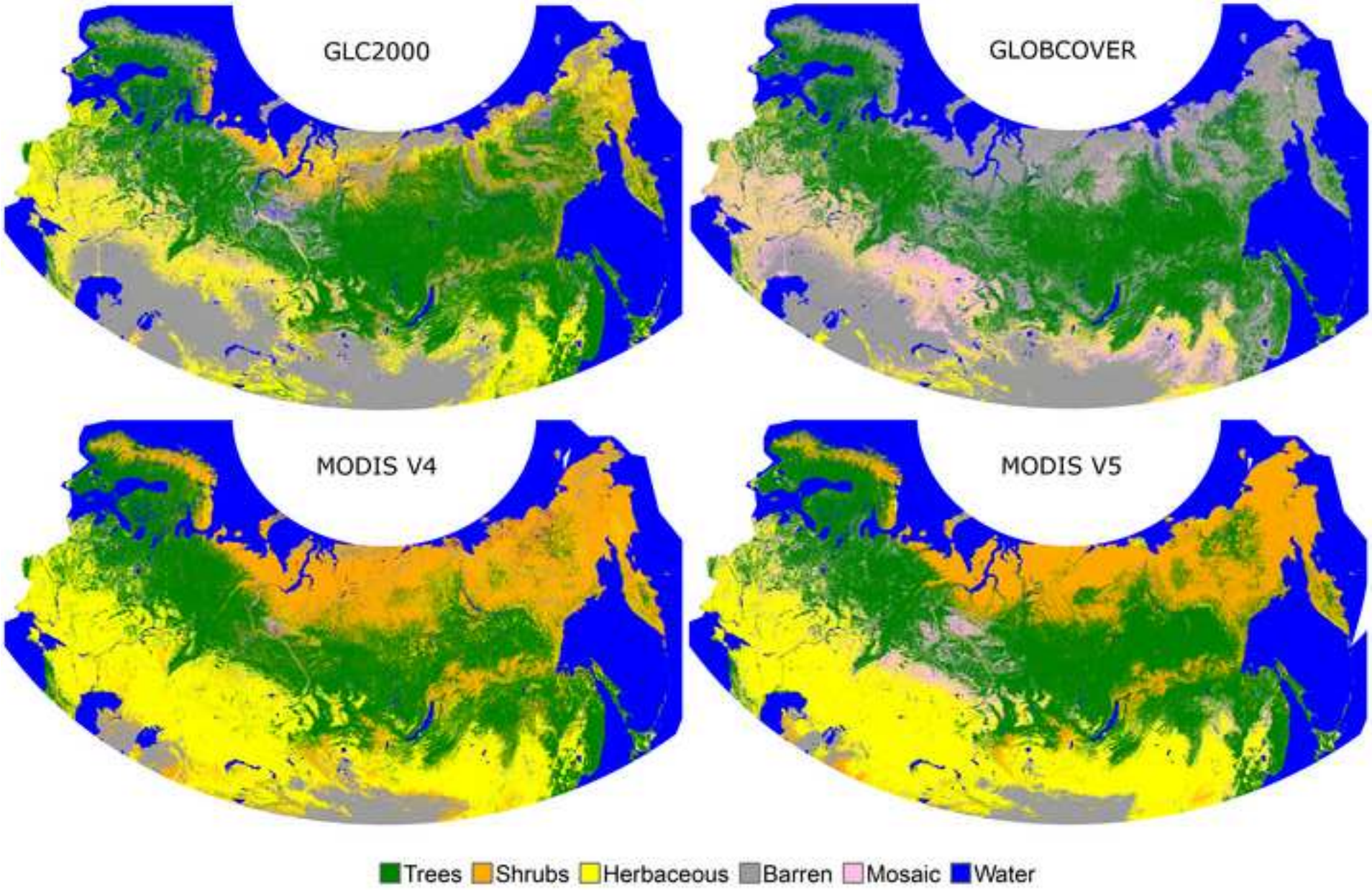

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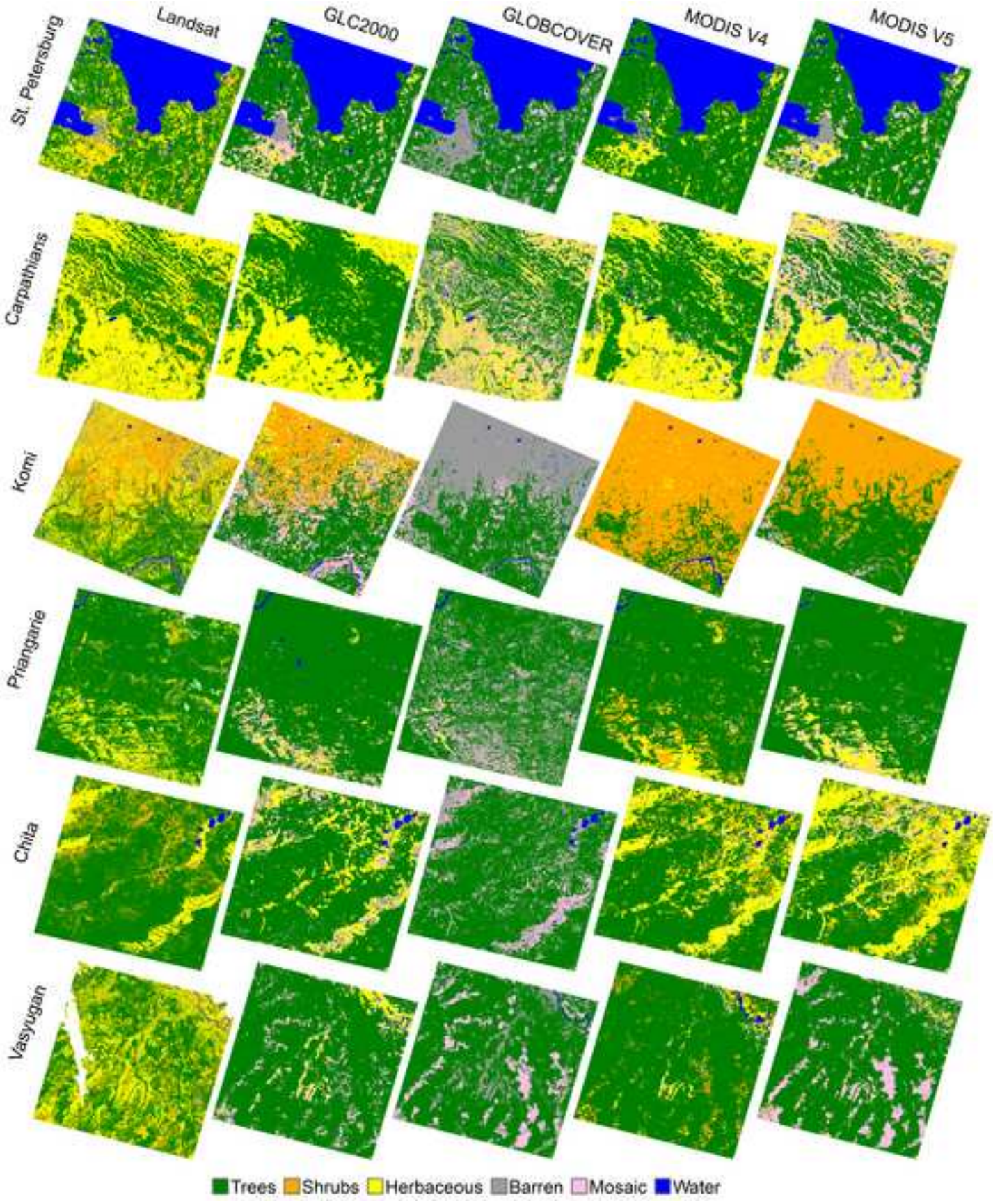

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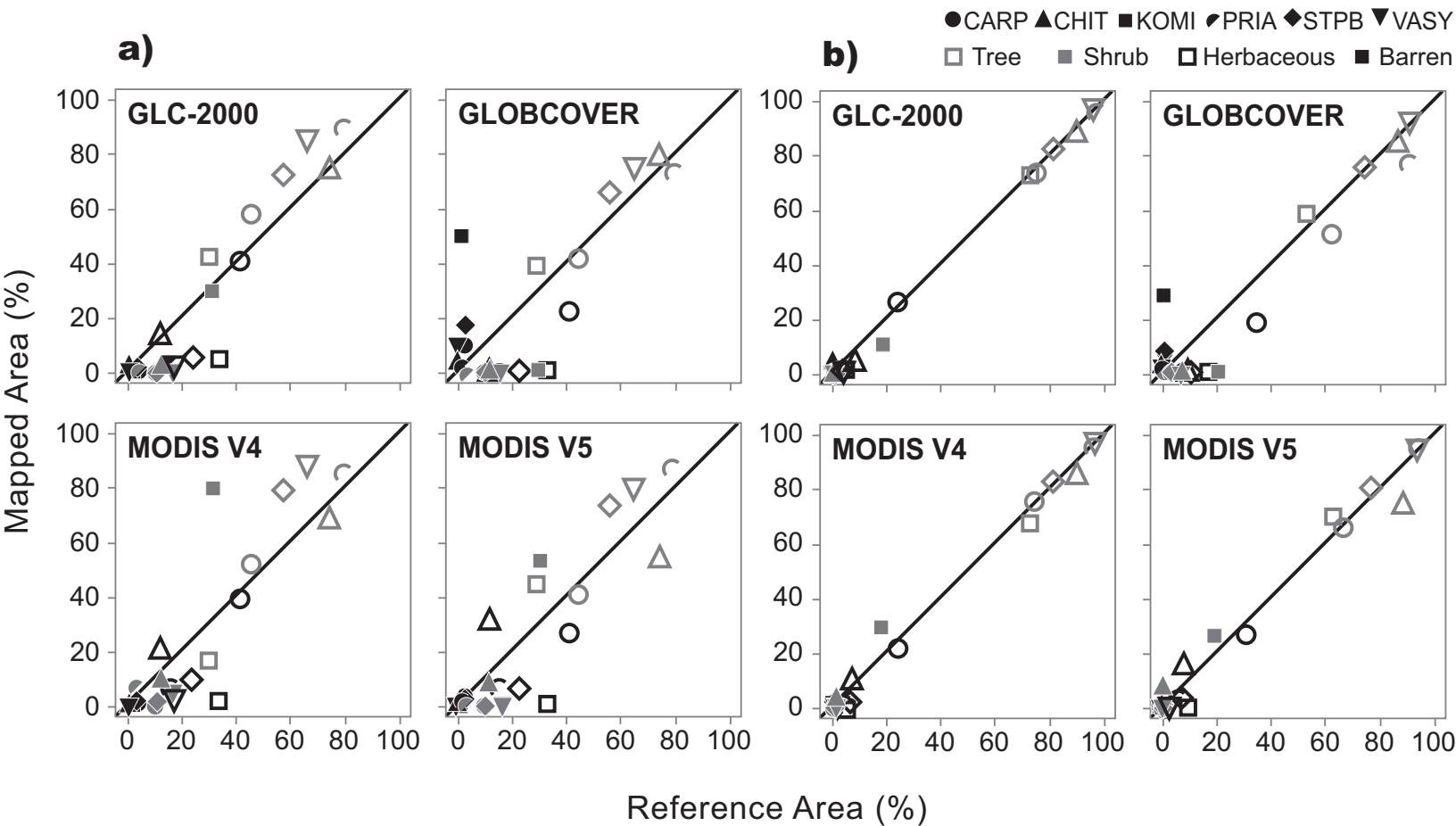

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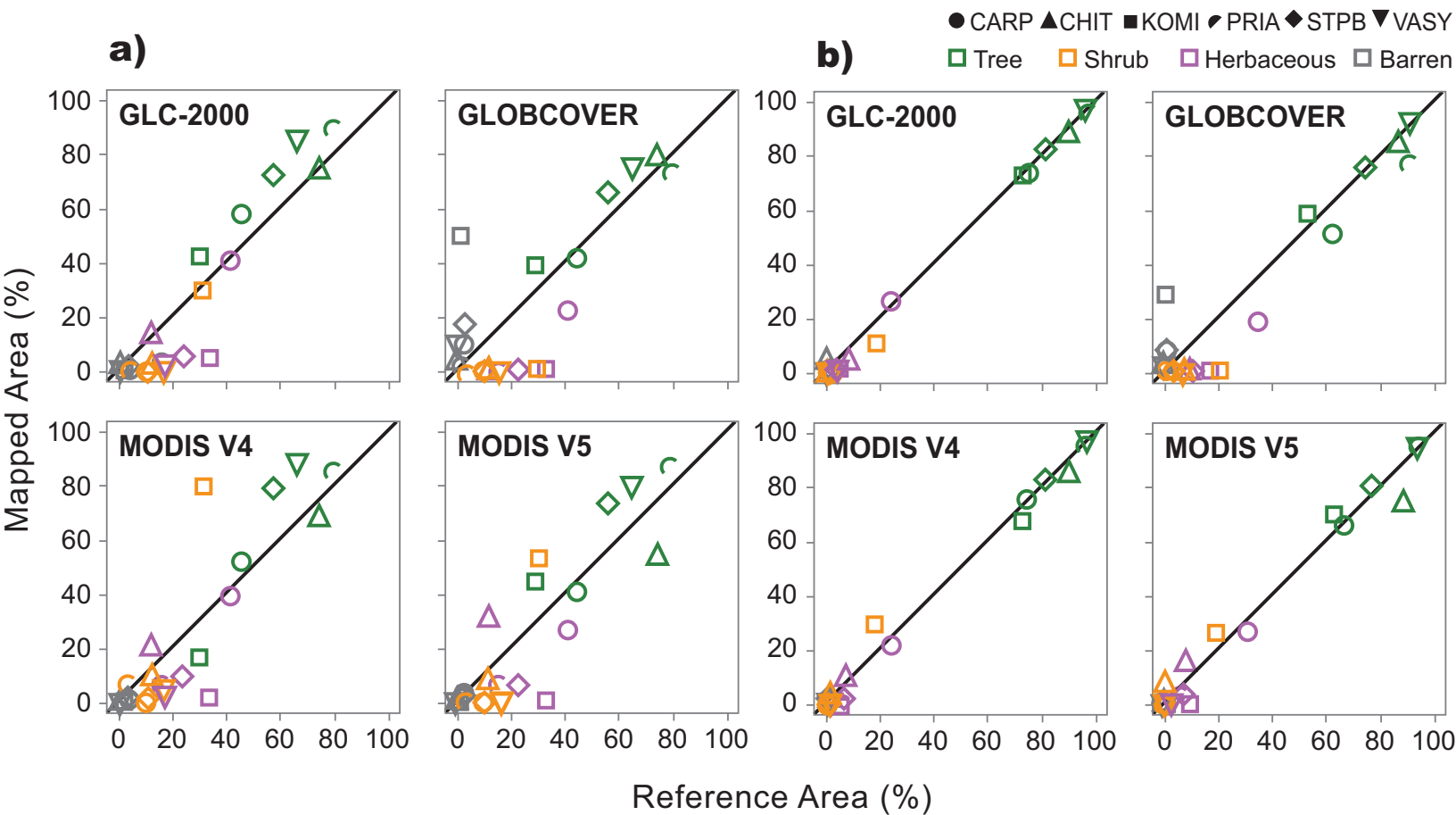

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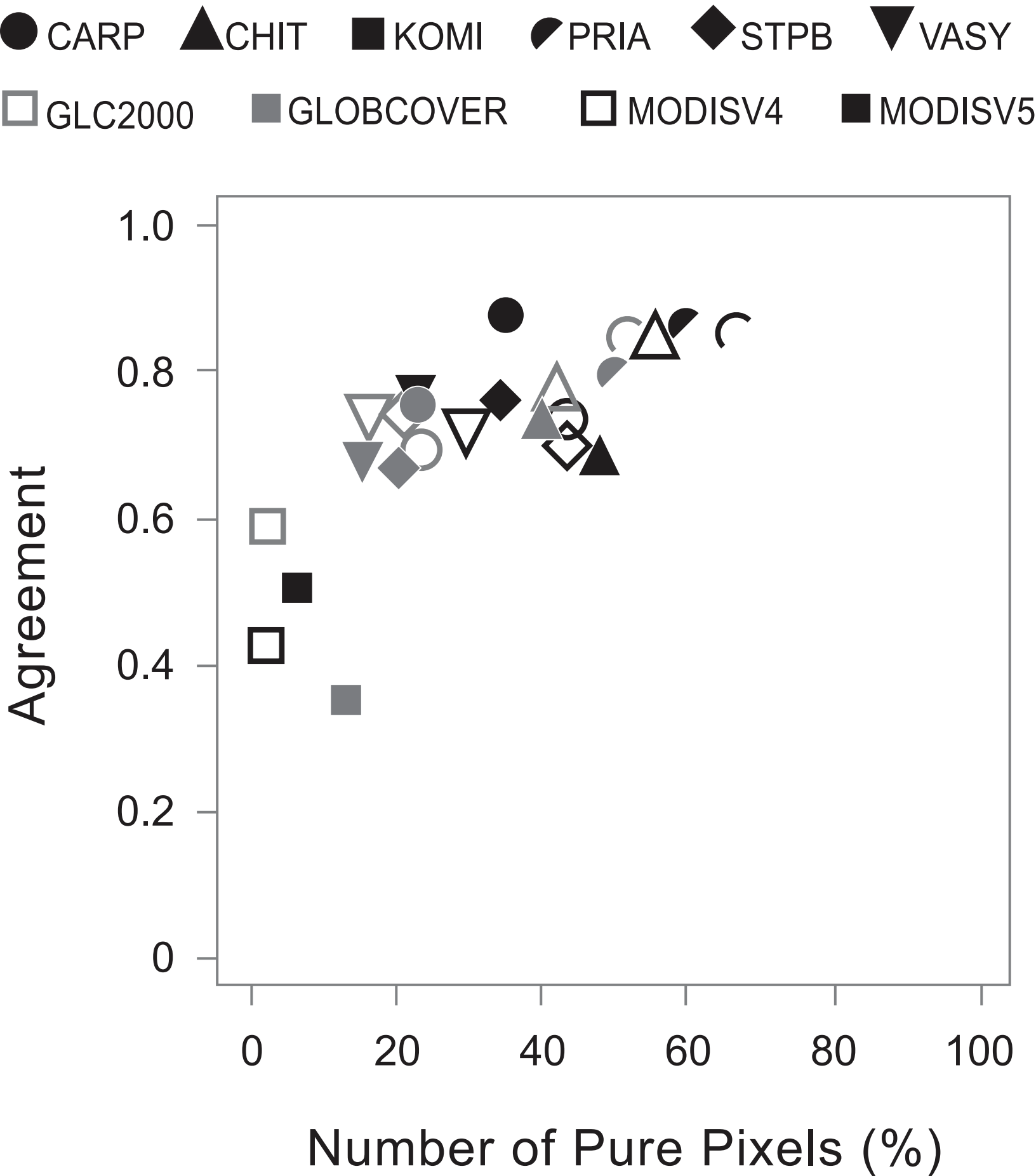

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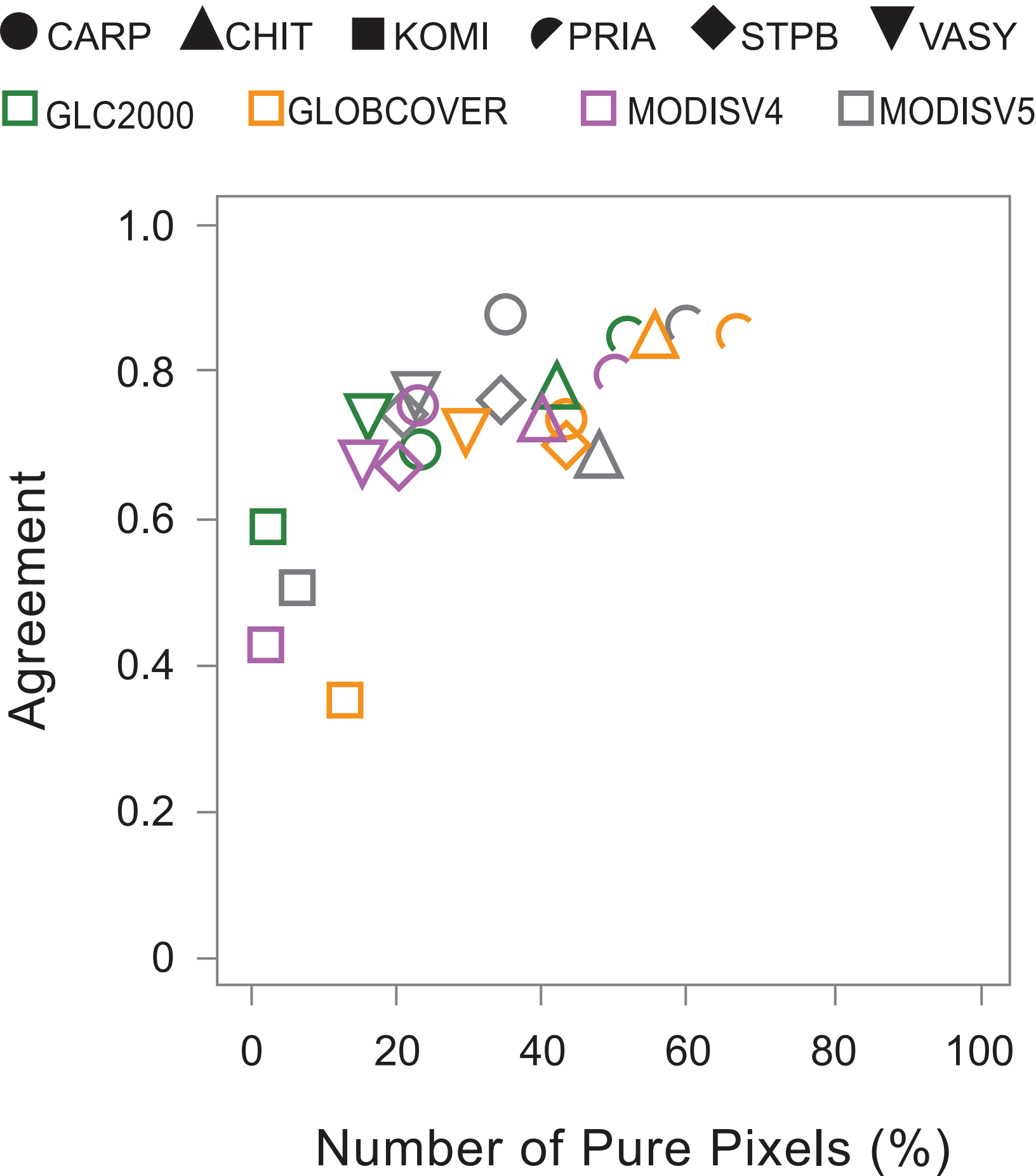

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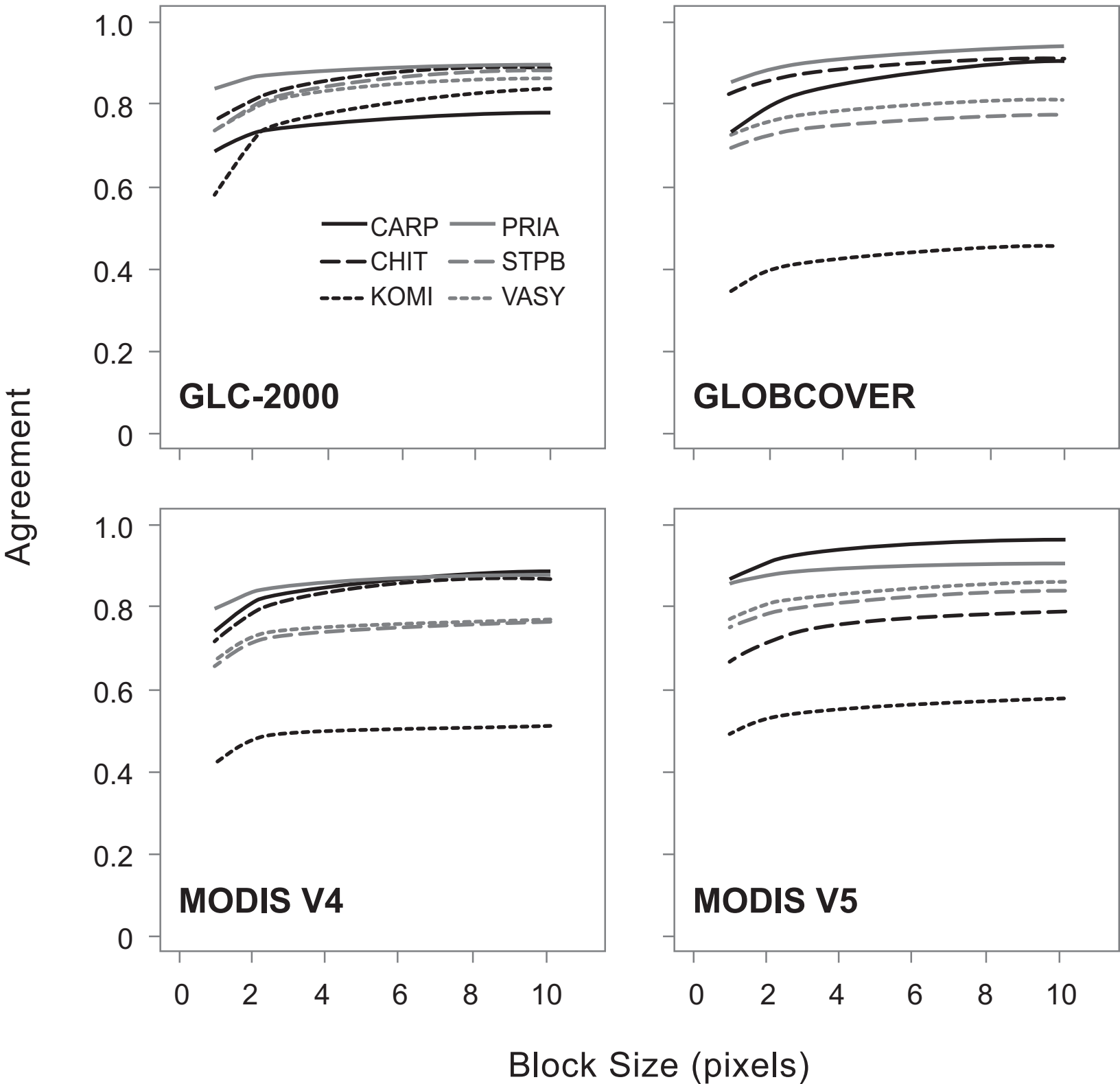

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