An integration approach to combine land cover products for improved ecosystem modeling across the pan-arctic

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Abstract

Rapid warming across the Arctic is a main driver of observed permafrost thaw, which has significant implications for the global climate system. Land cover is a critical component of the spatial heterogeneity of the permafrost carbon climate-feedback, as vegetation structure and composition affect ecosystem carbon and nutrient turnovers, energy balance, soil environment, and ecosystem vulnerability to disturbance. An exponential increase in ecological investigations provides the necessary data for parameterization of ecosystem models for an increasing number of land cover classes in the arctic-boreal regions. However, most global land cover products do not provide classifications that match the level of detail to represent the diversity and specificity of land cover types across the pan-arctic.

We present our use of data integration using machine learning to improve validation techniques of classification systems of existing global and regional land cover products to create a hybrid map designed specifically to represent high-latitude land cover diversity in ecosystem model simulations at a 1 km spatial resolution. As a base layer we used a global land cover map and incorporated finer-resolution regional maps to capture the diversity of land cover types, in this study focused across the arctic-boreal region of North America, with the final map extending across the pan-arctic. This approach ensured comprehensive coverage while incorporating representative vegetation communities at a country level. We further show that land cover maps can be improved and tailored for use by ecosystem models at large spatial scales, while maintaining the level of detail needed to accurately represent landscape heterogeneity.

1 Introduction

Across high-latitude regions, changes in climate are altering the complex interactions between biophysical and biogeochemical processes of terrestrial ecosystems (Heimann and Reichstein 2008; Jia et al. 2019). It is critical that ecosystem models represent these complex processes and feedback to accurately forecast how these systems will respond to projected changes in climate and disturbance regimes (Fisher and Koven 2020; Heimann and Reichstein 2008). Land cover mapping of high-latitude systems is of great importance as Arctic warming results in changes in vegetation dynamics and accelerated thawing of underlying permafrost in the arctic regions (Horvath et al. 2021; Kåresdotter et al. 2021). Land cover is an important indicator of surficial changes across the pan-arctic and can have subsequent impacts on terrestrial ecosystems such as above and below-ground carbon dynamics (Poulter et al. 2015). Such impacts are the changes in albedo linked to the expansion of shrubs and the northward advancement of the treeline (Betts 2000; Miller and Smith 2012). This reduction in albedo and occurrence of arctic shrubification may further accelerate warming in these regions (Bonfils et al. 2012). Land cover information is a key input and feature for many terrestrial ecosystem models and the availability of reliable land cover data is critical for accurate estimations of carbon pools and fluxes, and permafrost dynamics (Gasser et al. 2020; Liu et al. 2023). A land cover product should thus consist of a dynamic classification scheme that allows users to tailor the products for model-specific applications at a spatial resolution which captures important vegetation community dynamics (Townsend et al. 1992).

Remotely sensed data serve as a major data source for land cover mapping, allowing monitoring across global systems (Joshi et al. 2016; Rogan and Chen 2004). There are few maps which contain a comprehensive classification of land cover across the Arctic region with one of the most comprehensive and consistent maps across the Arctic (e.g. the Circum-Arctic Vegetation Map (CAVM)), representing the area north of treeline at a 1 km spatial resolution (Raynolds et al. 2019). Because CAVM is representative of strictly the Arctic zone, its application is limited and thus not representative of land cover types within the transitional Boreal region, which falls within the main area represented in our study region.

There are multiple process-based earth system models (i.e., LPJ-GUESS, DVM-DOS-TEM, FATES), which incorporate vegetation cover to assess regional feedbacks to ecosystem structure and function across the arctic-boreal region (Euskirchen et al. 2009, 2014; Genet et al. 2018; Fisher et al. 2015; Smith et al. 2001), however many models do not often incorporate adequately detailed information on vegetation community type(s) or plant functional types represented within a given community, which may influence the accuracy of vegetation-climate feedback (Isabelle et al. 2012; Miller and Smith 2012). Thus, improved vegetation products are important for these models to project the impacts of future climate change across the arctic-boreal region. Especially important are products which contain detailed information on vegetation cover and characteristics spatially explicit to the area of interest (Miller and Smith 2012; Pearson et al. 2013; Zou et al. 2022). Modeling of permafrost is strongly linked to accurate surface data, of

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which vegetation is one of the most important as it strongly influences the soil-thermal hydrological regime (Grünberg et al. 2020; Raynolds and Walker, 2008). Thus, using the most updated sources of vegetation maps and products to drive ecosystem models is essential to provide the high accuracy level of information for the multiscale modeling needs across the high-latitude systems (Langford et al. 2019).

While there is a growing number of land cover products at both regional and global scales at varying resolutions, there is a gap for wall-to-wall land cover products, which are representative of high-latitude vegetation communities and designed specifically to meet the needs of pan-arctic ecosystem models. These products should be compatible with existing global and regional maps and be representative of the diverse land cover types within the arctic-boreal region. Here, we discuss the technique and tools we used to develop a hybrid land cover map using and leveraging existing land cover products to develop a representative map for use within ecosystem models across the arctic-boreal region.

The purpose of this paper is to assess limitations and opportunities to further improve land cover maps designed specifically to represent high-latitude terrestrial systems. We present our use of a multi-step workflow incorporating data integration, validation techniques and harmonization of classification systems of existing global and regional land cover products to create a hybrid map at a 1 km spatial resolution tailored specifically for use within a terrestrial ecosystem model, applied and tested for North America with the goal to extend across the pan-arctic region. We integrate machine learning methods to integrate and reclassify vegetation map indices to better suit our modeling needs.

2 Materials and Methods

2.1 Study Area

Our study region encompassed the Arctic-Boreal Zone (ABZ) of North America, which is characterized by spatially diverse vegetation composition and consists of northern tundra and boreal biomes (Virkkala et al. 2021). For this study, we will focus our study sites to the arctic-boreal region of Alaska and Canada. These sentinel sites were carefully selected to represent the arctic-boreal region and diverse vegetation community types. These sites provide unique land cover information for each location and provide a diverse range of vegetation community types represented within DVM-DOS-TEM (Muchoney et al. 1999). In total, we selected 17 sites across North America (Alaska, Canada; Figure 1).

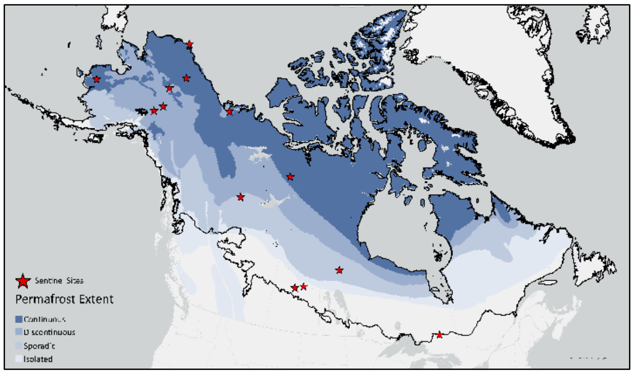

Figure 1. Our study locations shown by red stars within the Arctic Boreal extent of the study region in addition to the permafrost extent map. Modified after (Brown et al. 1997).

2.2 Methods Overview

Our goal is to form a hybrid map that merges existing land cover products to reclassify land cover indices specific to our modeling needs. Our workflow was developed to address inconsistencies across land cover datasets and produce a final harmonized pan-arctic product. Five major steps comprised the workflow (1) pre-processing and re-projecting land cover products to a 1 km grid using a majority rule approach, (2) reclassifying and combining global and regional products to a common final legend based on agreement between global and regional products, (3) finalize reclassifying remaining pixels where no condition was met using random forest machine learning algorithm in addition to input including the reclassified and harmonized products as well as ancillary data variables (i.e., fire occurrence, NDVI), (4) post classification comparison, and (5) final product compilation at 1 km resolution. The general schematic can be seen in Figure 2. This further refines the classification to the final target legend of the hybrid map for a region.

2.3 Land Cover Products

To create our hybrid land cover map, we used a global map as the base layer to provide a globally consistent land cover classification scheme. Then, we selected and integrated more region-specific land cover maps to provide a fine-scale detailed land cover classification scheme used to inform the reclassification of land cover classes to the final product (Table 1). The European Space Agency (ESA) Climate Change Initiative land cover map was selected as the global base map to be used for the creation of the composite DVM-DOS-TEM land cover map. We selected the ESA map for the year 2016 at 300 m resolution (Lamarche et al. 2017). It was used as the primary base map across the boreal region. To represent arctic vegetation community types, we incorporated the Circumpolar Arctic Vegetation Map (CAVM) which was produced in 2003 (Raynolds et al. 2019). The CAVM map includes 15 vegetation types, which we further grouped to five major land cover types based on the arctic bio climate subzones: Barrens, Graminoid tundra, Prostrate-shrub tundra, Erect-shrub tundra, and wet-sedge tundra.

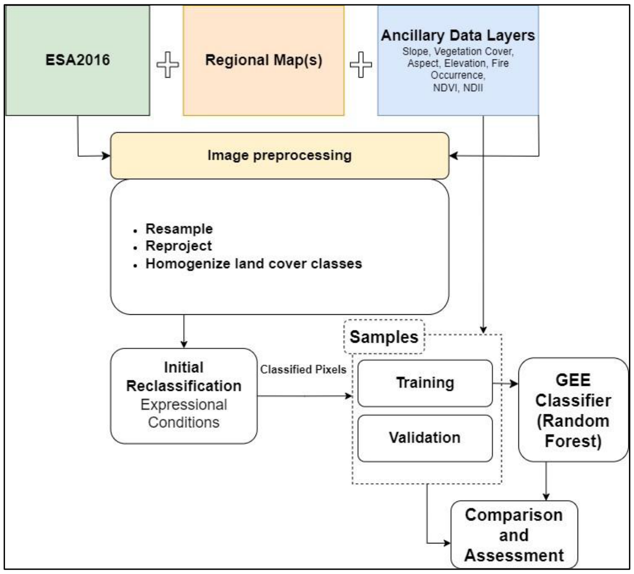

Figure 2. Flowchart of the study highlighting the major inputs, output and major steps.

We chose not to alter the circumpolar region encompassed within the CAVM map as it provides a detailed and accurate classification of arctic vegetation. We thus focused our analysis to the region below the treeline or that which excludes the CAVM extent.

2.4 Pre-Processing

Each land cover product was re-projected to a 1 km resolution using a majority-rule approach. A majority rule is used to aggregate the finer scale resolution maps into the corresponding coarser land cover map. Non-overlapping square windows, each representing one pixel in an output image, are overlaid and assigned to the class that comprises the majority in a given window. To have a one-to-one comparison of land cover classes between global and regional products, we reclassified original land cover classes to align with the classification of the global land cover map. This reclassification created a harmonized classification scheme, while maintaining the main representative land cover classes. These classes included: forest, shrubland, herbaceous/grassland, barren, and wetland. This general reclassification of land cover classes was also used to estimate the level of agreement between each regional map to the global base map.

2.5 Random Forest classification

Random Forest is one of the most widely used supervised machine learning algorithms for land cover mapping and classification because of its ability to handle noisy and multi-source datasets (Jin et al. 2018; Maxwell et al. 2019). The random forest method is an ensemble-based classifier which uses decision trees for training and prediction. In Google Earth Engine, we used the function ee.ClassifiersmileRandomForest, which is based on the random forest method. We set the hyperparameter, number of trees (ntrees), based on the value which produced the best resulting accuracy for each region. The rest of the hyperparameters were left at their default values, which is the square root of the total number of features.

To build the random forest model, we compiled a dataset with ancillary variables further detailing landscape characteristics and disturbance history to further aid in the prediction of land cover classes including fire occurrence, canopy cover, elevation, slope, and aspect, which are further detailed in (Hermosilla et al. 2022; Matasci et al. 2018). In addition, classified pixels from the initial classification based on overlap agreement between the global and regional dataset were compiled into the ancillary dataset to provide the model with training data on successfully classified land cover classes. We created a collection of samples that were then randomly split into two groups of training (80%) and testing (20%). In total between 500–1,000 samples per land cover class were collected within each region (Alaska, Canada), with the number of samples determined based on the max sample number of a given class in each region. A separate random forest model was trained for each study region (Alaska, Canada) to be region-specific to map the distribution of natural land cover by conducting a supervised classification process, integrating ancillary variables.

The first step of reclassification is based on the overlap or agreement of major land cover classification between global and regional maps. A given pixel is grouped as one of the following classes if both the global and regional map pixels agree: forest (evergreen, deciduous, mixed), shrubland, herbaceous, barren or wetland. The

Table 1. Characteristics of the land cover products used in this study.

Dataset	Spatial Resolution	Extent	Date	Reference
ESA CCI Land Cover 2016	300 m	Global	2016	Lamarche et al. 2017
Circumpolar Arctic Vegetation Map (CAVM)	1 km	Circumpolar	2022	Raynolds et al. 2019
LANDFIRE	30 m	Alaska	2016	Rollins, 2009
Alaska Vegetation and Wetland Composite (AKVWC)	30 m	Alaska	Multi-year-not explicit	Flagstad et al. 2018
Leading Tree Species	30 m	Canada	2019	Hermosilla et al, 2022
Canada Virtual Land Cover Engine (VLCE)	30 m	Canada	2016	Hermosilla et al. 2018
Wetland Map for Canada	30 m	Canada	2000-2016	Wulder et al. 2018

classification rules are further refined to then reclassify the pixels of agreements of the major land cover classes into more specific classes using various conditional statements. For example, if both the global and regional maps classify the pixel as evergreen and an overlapping ancillary regional map classifies it as a White Spruce Forest, then it gets classified as White Spruce Forest.

After this initial classification step, if a condition is not met, the pixel is left unclassified. We then incorporate our random forest model, train the model on pixels successfully classified in addition to ancillary datasets and use machine learning to classify the remaining pixels within a region. This multi-step process ensures that we are using points of agreement between maps to inform the reclassification process.

2.6 Assessment, Comparison and Testing

Model performance, which varies across regions, dictated the level of success in creating an integrated reclassified land cover map. The success or accuracy of this process was dependent on the quality of the input data and assessed based on the composition of each new land cover class for the hybrid map to the composition of its corresponding class of the regional and global maps to ensure the percentage of a given land cover type fell within the range of composition of both maps. We estimated percent coverage of each land cover class of the newly developed hybrid map for Alaska and Canada This composition estimation is straightforward yet allows us to better understand the range of accuracy of the final product.

3 RESULTS

Our workflow shows the ability to reclassify global and regional land cover maps utilizing machine learning as an additional tool to produce a final hybrid map with updated land cover classes specifically designed to meet our modeling needs. When assessing the overall agreement between global and regional land cover products, we see that across the boreal region of Alaska, the LANDFIRE and ESA showed a total 55.57% agreement in major land cover classifications, while the Canadian VLCE map and ESA showed a total of 49.68% agreement across Canada. Our assessment shows that across Alaska and Canada the land cover class with the greatest point of agreement was in classification of forest at 44% and 33% of the total area, respectively as shown in Figure 3. The greatest disagreement in land cover classification between the global ESA and regional maps occurred between wetlands and shrubland classification across both Alaska and Canada.

For each region, our combined final hybrid map (Figure 4a) was able to represent the general land cover classes for each region of focus, while maintaining and representing the fine-scale land cover classes we targeted for the final legend. Across Alaska, our final map resulted in a forest composition of 42.6% in comparison to 37.1% and 42.3% for the LANDFIRE and ESA2016 maps respectively (Figure 4b), while the final hybrid map for Canada resulted in a total forest composition of 60.6% compared to 56.8% and 71.8% for the VLCE and ESA2016 maps respectively (Figure 4c). Similarly, across Alaska shrublands represented 35.9% of the total vegetation cover, compared to 44.4% and 26.7% represented in both LANDFIRE and ESA. Total shrublands were less prominent across Canada at 12.6% within the hybrid map, compared to 15.9% and 7.6% across the VLCE and ESA maps respectively.

Since we are not creating a new land cover map, but utilizing existing land cover products, we still have to further assess the accuracy of the newly reclassified land cover scheme for each region. A method in which we do so is through comparing percent coverage of each major land cover class between the global, regional, and final hybrid map as well as using the sentinel site locations to further ground truth.

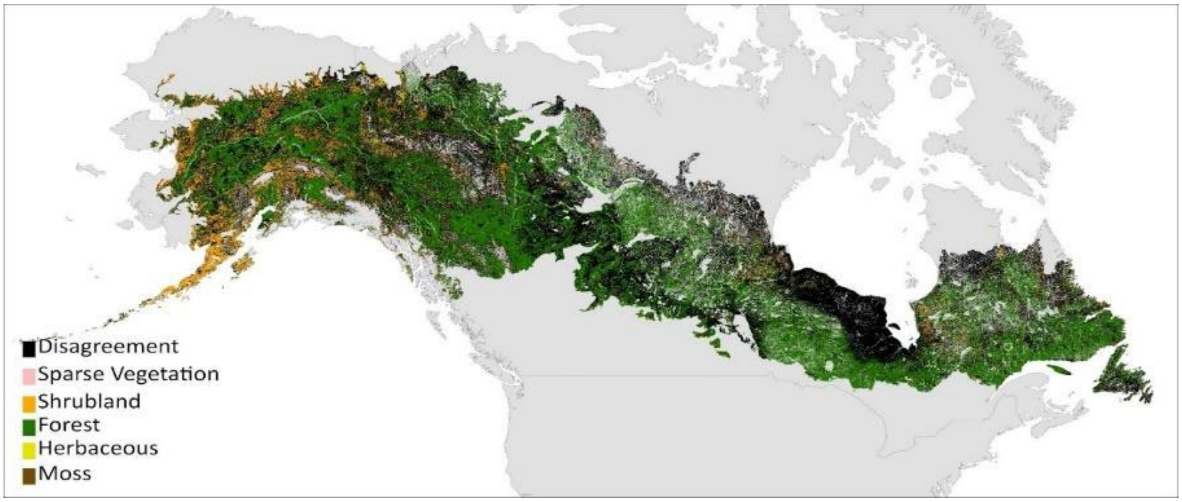

Figure 3. Agreement between the global ESA2016 map to each region-specific land cover products across Alaska and Canada highlighting the areas of classification agreement at a 1 km spatial resolution.

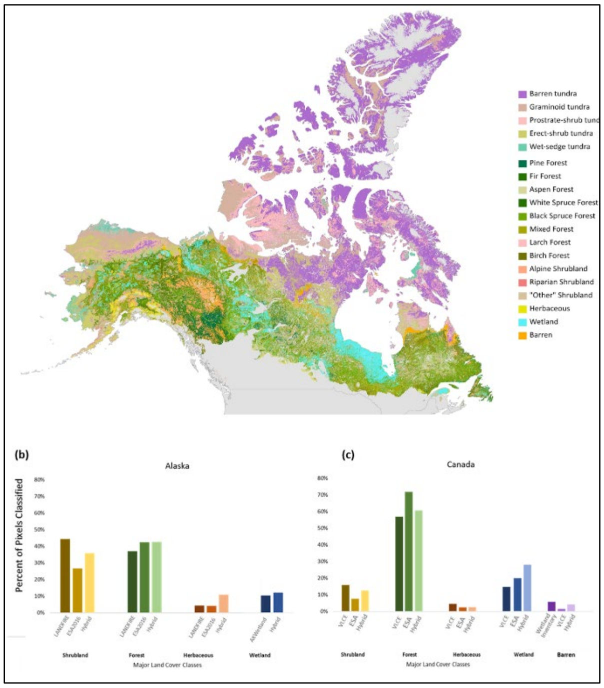

Figure 4. Final Hybrid map at 1 km resolution across the study region, in addition to the Circumpolar Arctic Vegetation Map (CAVM) across the arctic (a). Comparisons of the percent composition of each major land cover class across the major land cover products used for the study for both Alaska and Canada (b,c).

The final hybrid map is able to capture the presence of more shrubland dominant land cover types particularly in the top left quadrant of the grid.

Figure 5 shows the comparison of land cover products and their classification of an upland boreal site located outside of Fairbanks, Alaska encompassing a 10 x 10 km grid. This site is characterized by both black spruce and deciduous birch dominated forests.

4 Discussion

In this study, we present an integration approach to generate a hybrid land cover map at a 1 km spatial resolution, specifically tailored to community types parameterized within DVM-DOS-TEM. One of the primary challenges in comparing land cover products lies in the variations in resolution or detail of the land cover classes, making it difficult to ensure direct interpretation across different datasets. Our main objective is to introduce an adaptable approach that enables the combination of multiple land cover datasets with varying spatial resolutions, thematic content, and sources, resulting in a unified hybrid classification system. This method can be applied to harmonize existing global land cover datasets of moderate resolution, ultimately yielding the most accurate land cover product possible for any location worldwide.

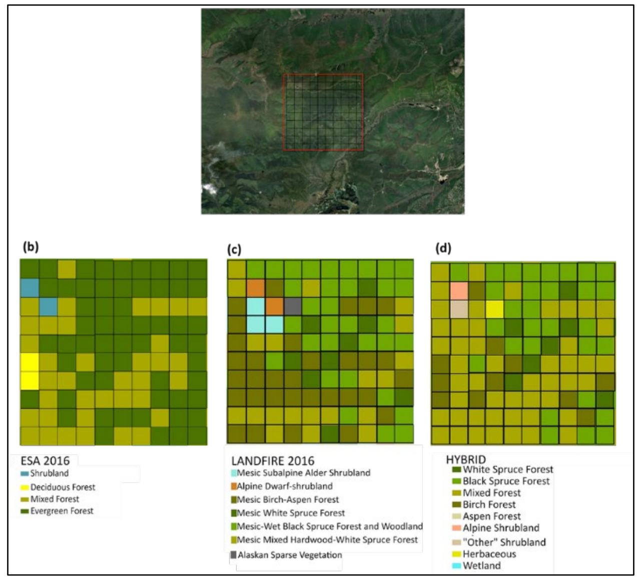

Figure 5. Comparison of land cover products: ESA2016(b), LANDFIRE2016(c), and the final hybrid map (d) classification of a 10 x10 km grid encompassing one of the boreal study sites located near Fairbanks, AK.

Throughout the study, we utilized a random forest model, incorporating four ancillary variables primarily related to topography and disturbance, as additional predictors to improve the accuracy of the hybrid map. Our results demonstrated that the hybrid map exhibited reasonable accuracy across regions when compared to both the global and corresponding regional maps, although slight variations were observed due to differences in model hyperparameters. We compile the most relevant and detailed regional land cover maps that encompassed our study region and included the target land cover classes required for reclassifying our final hybrid map. Utilizing existing global and regional products, our approach successfully generated a hybrid land cover map through a merging scheme that emphasized areas of agreement between the two types of maps. This ensured that the final product effectively represented the target classes and fell within the composition range of each class derived from both global and regional sources, capturing the general composition of land cover while accommodating new target classifications tailored to our modeling needs.

Our approach is reproducible and can be applied to other study regions at both regional and global levels. Additionally, it is versatile enough to be customized for various purposes, including modeling, allowing users to tailor land cover classes according to their specific requirements. Moreover, its adaptability permits the integration of new or updated regional and global products, facilitating ongoing revisions and improvements to the final hybrid product and allowing for the incorporation of more detailed land cover classifications.

We build our approach upon existing agreements across validated and tested land cover products rather than introducing a new product. This emphasis on existing agreements ensures the reliability and credibility of the final hybrid map. To accurately represent the diverse vegetation communities of the circumpolar arctic-boreal region, integrating multiple land cover maps derived from remotely sensed products is essential, particularly when the final product serves multiple applications in ecosystem modeling. Employing a multi-step approach, which includes a machine learning model, ensures the accurate representation and composition of the hybrid map concerning the original land cover products used in its creation. As new or updated regional and global products become available, our approach remains flexible enough to incorporate these data, leading to continuous refinement and enhancement of the final product and providing more detailed land cover classifications as needed.

To further improve our workflow, we can focus on exploring and utilizing additional ancillary datasets such as NDVI and NDII, which we have integrated into our revised workflow to enhance the precision of our findings. By incorporating these datasets, we aim to address issues such as unequal or unrepresentative sampling rates and scaling discrepancies, which may introduce biases in our results. Leveraging recently developed databases for the validation of global land cover products (e.g., Friedl et al. 2010; Pérez-Hoyos et al. 2012) could prove instrumental in overcoming these limitations and further improving the reliability of our presented outcomes. In summary, our study showcases a robust and adaptable methodology for generating a comprehensive hybrid land cover map, addressing the challenges posed by varying land cover datasets and offering valuable insights for ecosystem modeling and other applications.

5 Conclusions

Our study underscores the significance of accurate land cover mapping in high-latitude regions, where climate-induced changes are reshaping ecosystem dynamics. The integration of diverse land cover datasets using a multi-step approach and machine learning techniques has resulted in the creation of a versatile hybrid land cover map tailored to the specific needs of ecosystem models across the arctic-boreal region. Our final hybrid map not only integrates existing global and regional land cover products but also introduces refinements to better represent the unique vegetation communities in the study area. By leveraging agreements between validated land cover products, our approach ensures the reliability and credibility of the final map, enhancing its utility for diverse applications, particularly in ecosystem modeling.

While our methodology demonstrates its effectiveness in generating accurate land cover maps, future efforts should focus on incorporating additional validation datasets to further refine and enhance the precision of our findings. These datasets can help address potential biases and scaling issues, ultimately bolstering the reliability of our results. Our future product will include validation sites across Eurasia. In summary, our study offers a robust and adaptable framework for producing comprehensive land cover maps, addressing the complexities of varying datasets, and providing valuable insights for high-latitude ecosystem modeling and other related endeavors.

6 Acknowledgements

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7 References

Betts, R.A. 2000. ‘Offset of the potential carbon sink from boreal forestation by decreases in surface albedo’, *Nature*, 408(6809), pp. 187–190. doi:10.1038/35041545.

Brown, J., Ferrians, O.J., Heginbottom, J.A., and Melnikov, E.S. 1997. Circum-Arctic map of permafrost and ground-ice conditions. Available at: https://doi.org/10.3133/cp45.

Euskirchen, E.S., Edgar, C.W., Turetsky, M.R., Waldrop, M.P., and Harden, J.W. 2014. ‘Differential response of carbon fluxes to climate in three peatland ecosystems that vary in the presence and stability of permafrost’, *Journal of Geophysical Research: Biogeosciences* 119(8), pp. 1576–1595. doi:10.1002/2014JG002683.

Euskirchen, E.S., McGuire, A.D., Chapin III, F.S., Yi, S., and Thompson, C.C. 2009. ‘Changes in vegetation in northern Alaska under scenarios of climate change, 2003–2100: implications for climate feedbacks’, *Ecological Applications* 19(4), pp. 1022–1043. doi:10.1890/08-0806.1.

Fisher, R.A. and Koven, C.D. 2020. ‘Perspectives on the Future of Land Surface Models and the Challenges of Representing Complex Terrestrial Systems’, *Journal of Advances in Modeling Earth Systems* 12(4), e2018MS001453. doi:10.1029/2018MS001453.

Fisher, R.A., Muszala, S., Verteinstein, M., Lawrence, P., Xu, C., McDowell, N.G., Knox, R.G., Koven, C., Holm, J., Rogers, B.M., Spessa, A., Lawrence, D., and Bonan, G. 2015. ‘Taking off the training wheels: the properties of a dynamic vegetation model without climate envelopes, CLM4.5(ED)’, *Geoscientific Model Development*, 8(11), pp. 3593–3619. doi:10.5194/gmd-8-3593-2015.

Flagstad, L., Steer, M.A., Boucher, T., Aisu, M., and Lema, P. 2018. ‘Wetlands across Alaska: Statewide wetland map and Assessment of rare wetland ecosystems’, *Alaska Natural Heritage Program, Alaska Center for Conservation Science*, University of Alaska Anchorage.

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., and Huang, X. 2010. ‘MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets’, *Remote Sensing of Environment* 114(1), pp. 168–182. doi:10.1016/j.rse.2009.08.016.

Gasser, T., Crepin, L., Quilcaille, Y., Houghton, R.A., Ciais, P., and Obersteiner, M. 2020. 'Historical CO_2 emissions from land use and land cover change and their uncertainty', *Biogeosciences* 17(15), pp. 4075–4101. doi:10.5194/bg-17-4075-2020.

Genet, H., He, Y., Lyu, Z., McGuire, A.D., Zhuang, Q., Clein, J., et al. 2018. 'The role of driving factors in historical and projected carbon dynamics of upland ecosystems in Alaska', *Ecological Applications* 28(1), pp. 5–27. doi:10.1002/eap.1641.

Grünberg, I., Wilcox, E.J., Zwieback, S., Marsh, P., and Boike, J. 2020. 'Linking tundra vegetation, snow, soil temperature, and permafrost', *Biogeosciences* 17(16), pp. 4261–4279. doi:10.5194/bg-17-4261-2020.

Heimann, M. and Reichstein, M. 2008. 'Terrestrial ecosystem carbon dynamics and climate feedbacks', *Nature* 451(7176), pp. 289–292. doi:10.1038/nature06591.

Hermosilla, T., Bastyr, A., Coops, N.C., White, J.C., and Wulder, M.A. 2022. 'Mapping the presence and distribution of tree species in Canada's forested ecosystems', *Remote Sensing of the Environment* 282, 113276. doi:10.1016/j.rse.2022.113276.

Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., and Hobart, G.W. 2018. 'Disturbance-Informed Annual Land Cover Classification Maps of Canada's Forested Ecosystems for a 29-Year Landsat Time Series', *Canadian Journal of Remote Sensing* 44(1), pp. 67–87.doi:10.1080/07038992.2018.1437719.

Horvath, P., Tang, H., Halvorsen, R., Stordal, F., Tallaksen, L.M., Berntsen, T.K., and Bryn, A. 2021. 'Improving the representation of high-latitude vegetation distribution in dynamic global vegetation models', *Biogeosciences* 18(1), pp. 95–112. Copernicus GmbH. Doi:10.5194/bg-18-95-2021.

Isabelle, B., Pauline, P., Sylvain, A., Roland, D., Luc, G., Sébastien, L., Sandra, L., Jérémie, V.E., Pascal, V., and Wilfried, T. 2012. 'Improving plant functional groups for dynamic models of biodiversity: at the crossroads between functional and community ecology', *Global change biology* 18(11). doi:10.1111/j.1365-2486.2012.02783.x.

Jia, G., Shevliakova, E., Artaxo, P., Brazil, N., De Noblet-Ducoudré, F., Houghton, R., Anderegg, W., et al. 2019. 'Land-Climate interactions', in *Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*.

Jin, Y., Liu, X., Chen, Y., and Liang, X. 2018. 'Land-cover mapping using Random Forest classification and incorporating NDVI time-series and texture: a case study of central Shandong', *International Journal of Remote Sensing* 39, pp. 1–21. doi:10.1080/01431161.2018.1490976.

Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., Jepsen, M.R., Kuemmerle, T., Meyfroidt, P., Mitchard, E.T.A., Reiche, J., Ryan, C.M., and Waske, B. 2016. 'A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring', *Remote Sensing* 8(1), pp. 70. doi:10.3390/rs8010070.

Kåresdotter, E., Destouni, G., Ghajarnia, N., Hugelius, G., and Kalantari, Z. 2021. 'Mapping the Vulnerability of Arctic Wetlands to Global Warming', *Earth's Future* 9(5), e2020EF001858. doi:10.1029/2020EF001858.

Lamarche, C., Santoro, M., Bontemps, S., D'Andrimont, R., Radoux, J., Giustarini, L., Brockmann, C., Wevers, J., Defourny, P., and Arino, O. 2017. 'Compilation and Validation of SAR and Optical Data Products for a Complete and Global Map of Inland/Ocean Water Tailored to the Climate Modeling Community', *Remote Sensing* 9.

Le Quéré, C., Moriarty, R., Andrew, R.M., Canadell, J.G., Sitch, S., Korsbakken, J.I., et al. 2015. 'Global Carbon Budget 2015', *Earth System Science Data* 7(2), pp. 349–396. doi:10.5194/essd-7-349-2015.

Liu, A., Moore, J.C., and Chen, Y. 2023. 'PInc-PanTher estimates of Arctic permafrost soil carbon under the GeoMIP G6solar and G6sulfur experiments', *Earth System Dynamics* 14(1), pp. 39–53. doi:10.5194/esd-14-39-2023.

Matasci, G., Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., Hobart, G.W., and Zald, H.S.J. 2018 'Large-area mapping of Canadian boreal forest cover, height, biomass and other structural attributes using Landsat composites and lidar plots', *Remote Sensing of Environment* 209, pp. 90–106

Maxwell, A.E., Strager, M.P., Warner, T.A., Ramezan, C.A., Morgan, A.N., and Pauley, C.E. 2019. 'Large-Area, High Spatial Resolution Land Cover Mapping Using Random Forests, GEOBIA, and NAIP Orthophotography: Findings and Recommendations', *Remote Sensing* 11(12), 1409. doi:10.3390/rs11121409.

Miller, P.A. and Smith, B. 2012. 'Modelling Tundra Vegetation Response to Recent Arctic Warming', *AMBIO* 41(3), pp. 281–291. doi:10.1007/s13280-012-0306-1.

Muchoney, D., Strahler, A., Hodges, J., and LoCastro, J. 1999. 'The IGBP DISGover Confidence Sites and the System for Terrestrial Ecosystem Parameteilzation: Tools for Validating Global Land-Gover Data', *Photogrammetric Engineering & Remote Sensing* 65(9), pp. 1061–1067.

Pearson, R.G., Phillips, S.J., Loranty, M.M., Beck, P.S.A., Damoulas, T., Knight, S.J., and Goetz, S.J. 2013. 'Shifts in Arctic vegetation and associated feedbacks under climate change', *Nature Climate Change* 3(7), pp. 673–677.doi:10.1038/nclimate1858.

Pérez-Hoyos, A., García-Haro, F.J., and San-Miguel-Ayanz, J. 2012. ‘A methodology to generate a synergetic
land-cover map by fusion of different land-cover products’, *International Journal of Applied Earth Observation and Geoinformation* 19, pp. 72–87. doi:10.1016/j.jag.2012.04.011.

Raynolds, M. and Walker, D. 2008. ‘Circumpolar Relationships Between Permafrost Characteristics, NDVI, and Arctic Vegetation Types’, in *Ninth International Conference on Permafrost*. Fairbanks, Alaska, United States.

Raynolds, M.K., Walker, D.A., Balser, A., Bay, C., Campbell, M., Cherosov, M.M., et al. 2019. ‘A raster version of the Circumpolar Arctic Vegetation Map (CAVM)’, *Remote Sensing of Environment* 232, 111297. doi:10.1016/j.rse.2019.111297.

Rogan, J. and Chen, D. 2004. ‘Remote sensing technology for mapping and monitoring land-cover and land-use change’, *Progress in Planning* 61(4), pp. 301–325. doi:10.1016/S0305-9006(03)00066-7.

Rollins, M.G. 2009. ‘LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment’, *International Journal of Wildland Fire* 18(3), pp. 235–249.doi:10.1071/WF08088.

Smith, B., Prentice, I.C., and Sykes, M.T. 2001. ‘Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space’, *Global Ecology and Biogeography* 10(6), pp. 621–637. doi:10.1046/j.1466-822X.2001.t01-1-00256.x.

Townsend, A.R., Vitousek, P.M., and Holland, E.A. 1992. ‘Tropical soils could dominate the short-term carbon cycle feedbacks to increased global temperatures’, *Climatic Change* 22(4), pp. 293–303. doi:10.1007/BF00142430.

Virkkala, A.-M., Natali, S.M., Rogers, B.M., Watts, J.D., Savage, K., Connon, S.J., et al. 2022. ‘The ABCflux database: Arctic–boreal CO_2 flux observations and ancillary information aggregated to monthly time steps across terrestrial ecosystems’, *Earth System Science Data* 14(1), pp. 179–208. doi:10.5194/essd-14-179-2022.

Wulder, M.A., Coops, N.C., Roy, D.P., White, J.C., and Hermosilla, T. 2018. ‘Land cover 2.0’, *International Journal of Remote Sensing* 39(12), pp. 4254–4284.doi:10.1080/01431161.2018.1452075.

Zou, D., Zhao, L., Liu, G., Du, E., Hu, G., Li, Z., Wu, T., Wu, X., and Chen, J. 2022. ‘Vegetation Mapping in the Permafrost Region: A Case Study on the Central Qinghai-Tibet Plateau’, *Remote Sensing* 14(1), 232. doi:10.3390/rs14010232.