Greenhouse Gas Inventory for Montgomery County's Forests and Trees, 2001-2019

World Resources Institute

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Summary

Forests and trees play a key role in mitigating climate change, yet they are often not included in local greenhouse gas (GHG) inventories or climate action plans. In 2019, Montgomery County took the first step towards understanding how local changes in land use and tree canopy from 2001-2016 contributed to the county's net GHG profile. In 2022, Montgomery County completed updates to the inventory to include estimates through 2019 and refine the data inputs to GHG flux calculations.

The original analysis in 2019 included estimates for carbon emissions and removals from forests and trees outside of forests within the community boundary. This included two inventory periods, from 2001-2011 and 2011-2016, and utilized a combination of the National Land Cover Database (NLCD), local LiDAR derived tree cover products, and Landsat imagery. This updated inventory extends the analysis to 2016-2019 and utilizes a new high-resolution tree canopy change product from the Chesapeake Bay Program (CBP).

These results contribute to local understanding of land use dynamics, how these are changing over time, and how management decisions are affecting the balance of carbon emissions and removals on lands within the community. The results of this analysis have been incorporated into ongoing community GHG reporting frameworks (see Appendix I) and can be used to inform climate action planning related to forests and trees.

Key findings:

- **Roughly one third of Montgomery County's land base is forest. Many areas outside of forests are also covered by trees, including an average of 30 percent tree canopy in developed areas.**
- **From 2001-2019, Montgomery County has reduced emissions from forests by approximately 50% by slowing conversion of forests to other non-forest land uses.**
- **Removals from forests have increased by 1.3% due to an increase in forested land.**
- **Removals from trees outside forests remained relatively stable from 2001-2019. Removals increased during the 2011-2016 period due to an increase in tree canopy but fell slightly in 2016-2019. ***
- **Between 2005 and 2020, Montgomery County reduced its overall (i.e., all sectors) emissions by 30%. When considering the impact of forests and trees, the overall net emissions reduction increases to 32%.**
- **Montgomery County's net emissions reduction could be larger if additional forest/trees were added to its land base, or if losses of forest/trees were reduced further.**

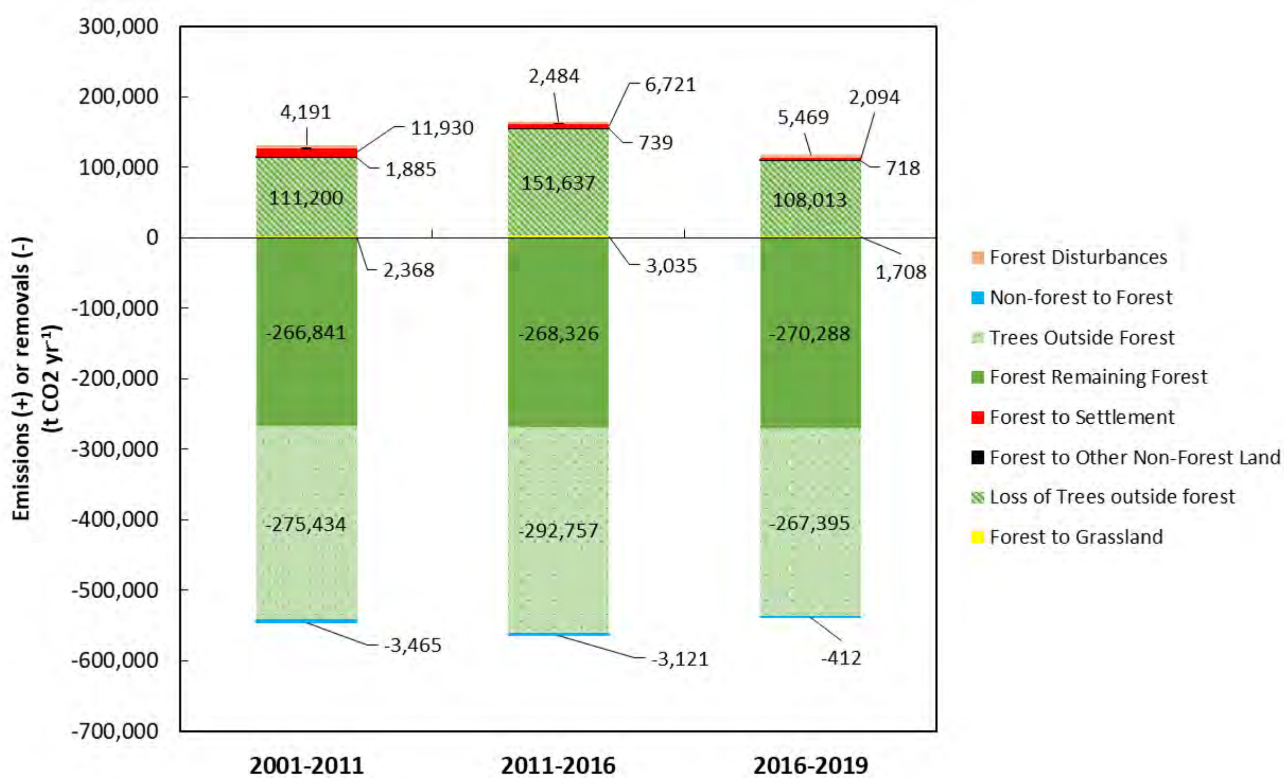
**Direct comparisons between 2001-2016 and 2016-2019 tree canopy data may be limited due to change in data sources*

*** See County's comprehensive Greenhouse Gas Inventory, including transportation, buildings, etc. in appendix.*

Net annual GHG removals from forests/trees on lands within the county decreased by about 4% from the 2001-2011 period to the 2011-2016 period, largely due to an increase in emissions from loss of tree canopy during the 2011-2016 period. Reducing losses of forests and tree canopy during the 2016-2019 period returned net annual GHG removals to 2001-2011 levels of approximately 0.42 Mt CO2 / year.

Figure 1. Montgomery County's GHGs from forests and trees for 2001-2011, 2011-2016 and 2016-2019

All values in metric tons of CO_2/year. Positive values represent a CO_2 emission, negative values represent a CO_2 removal.



The land use transition class which changed most dramatically from 2001-2019 is the non-forest to forest category. There was considerably less transition from non-forest to forest classes over the course of the inventory periods resulting in 88% less removals from reforestation. Second most significant is the forest transitioning to settlement category, with average annual emissions falling 82% from the 2001-2011 period to the 2016-2019 period.

Emissions from trees outside forests increased between the 2001-2011 period and the 2011-2016 period due to an increase in measured loss of tree canopy but fell below the 2001-2011 baseline in 2016-2019. This could indicate a reduction in tree canopy loss within the community or could partially result from the change in tree canopy data sources from iTree to CBP high-resolution data between 2011-2016 and 2016-2019.

Table 1. Montgomery County's average annual GHG emissions from forests and trees for 2001-2011, 2011-2016 and 2016-2019

All values in metric tons of CO2/year. Positive values represent a CO2 emission, and negative values represent a CO2 removal

Reporting category	2001-2011	2011-2016	2016-2019
Emissions of CO2 (metric tons) per year			
Forest → Settlement[1]	11,930	6,721	2,094
Forest → Other Land[1]	1,885	739	718
Forest → Grassland[1]	2,368	3,035	1,708
Forest → Disturbances	4,191	2,484	5,469
TOTAL FORESTS	**20,374**	**12,979**	**9,989**
Trees outside forest[2]	111,200	151,637	108,013
TOTAL ALL LANDS	**131,574**	**164,616**	**118,002**
Removals of CO2 (metric tons) per year			
Forest → Forest[3]	-266,841	-268,326	-270,288
Non-forest → Forest[4]	-3,465	-3,121	-412
TOTAL FORESTS	**-270,306**	**-271,447**	**-270,700**
Trees outside forest[5]	-275,434	-292,757	-267,395
TOTAL ALL LANDS	**-545,740**	**-564,204**	**-538,095**
Average Annual Net flux in CO2 (metric tons) per inventory period			
TOTAL ALL LANDS	**-414,166**	**-399,588**	**-420,093**

[1] Emissions from previously stored C because of converting forest land to a non-forest use.

[2] Emissions from loss of tree cover on non-forest land.

[3] Net removals for forest remaining forest, including both removals of CO2 from growth and emissions of CO2 from normal mortality (trees that die during the natural process of self-thinning during stand development) and disturbance (larger-scale, episodic events such as wildfire or insect outbreaks).

[4] Net removals for afforestation and reforestation, average of first 20 years after conversion from non-forest.

[5] Removals from trees that remained or were added on non-forest land during the inventory period.

Data Updates

Several updates were made to data sources when updating the forest/tree inventory to 2019; to the extent possible, updates were also applied to previous inventory periods to ensure consistency over the time series.

Land Cover

The 2019 inventory update includes the addition of new land cover data for 2016-2019 and the revision of previous inventory periods 2001-2016. Since the original inventory was developed, the United States Geological Survey (USGS) released its latest year of data (2019) and also updated all prior years of NLCD data for improved consistency across time periods. These updates affected the distribution of land cover/land cover change classes within Montgomery County and resulting GHG flux estimations. To improve the accuracy and consistency of reporting, previous inventory periods were revised using the updated NLCD datasets for 2001, 2011, 2016 and 2019.

Trees Outside Forests

The original tree canopy estimates for 2001-2016 were also amended using new estimates derived from the i-Tree Canopy tool and high-resolution CBP tree canopy maps. Previously, the 2001-2011 and 2011-2016 inventories used different sources of tree canopy data because a consistent high-resolution data source spanning both periods was not available. In the original analysis, high-resolution LiDAR-derived tree canopy data acquired over Montgomery County in 2009 and 2014 was used to calculate average tree canopy and average annual tree canopy loss for 2011-2016. These calculations were then used to retrospectively project tree canopy for the previous inventory period of 2001-2011.

Although this map-based method was beneficial in providing local estimates of tree canopy and loss that could be disaggregated by land use type, using a more consistent and accurate statistical data collection method better represents changes over time in Montgomery County. Therefore, previous inventory periods were revised using tree canopy and canopy change estimates developed with the i-Tree Canopy tool. These data were collected by the Metropolitan Washington Council of Governments (MWCOG). Incorporating this new data source into Montgomery County's inventory improves comparability across inventory periods and among neighboring communities within MWCOG which are also using this methodology.

For the 2016-2019 period, tree canopy and canopy losses were estimated using the newly available high-resolution (1-m) tree canopy product from the Chesapeake Bay Program, which yielded estimates similar to the (much more manual) i-Tree canopy assessments. The high-resolution data also has the advantage of providing spatialized estimates of tree canopy across the area while i-Tree can produce only statistical estimates, i.e., a single value of tree canopy (and tree canopy loss) across the entire county. Because the CBP data has been incorporated into the LEARN tool, this will likely be the most time and cost-effective method of estimating tree canopy changes going forward. Additionally, using the CBP data helps to foster consistency with neighboring communities.

Local high-resolution tree canopy data was also available for the 2016-2019 time period and both data sources were considered for the inventory. An accuracy assessment (see Tree Canopy Assessment section) was conducted to conclude that the CBP data over Montgomery County was more accurate and suitable to represent stable and changing tree canopy over time than the Montgomery County-specific lidar-derived tree canopy maps.

Data Inputs

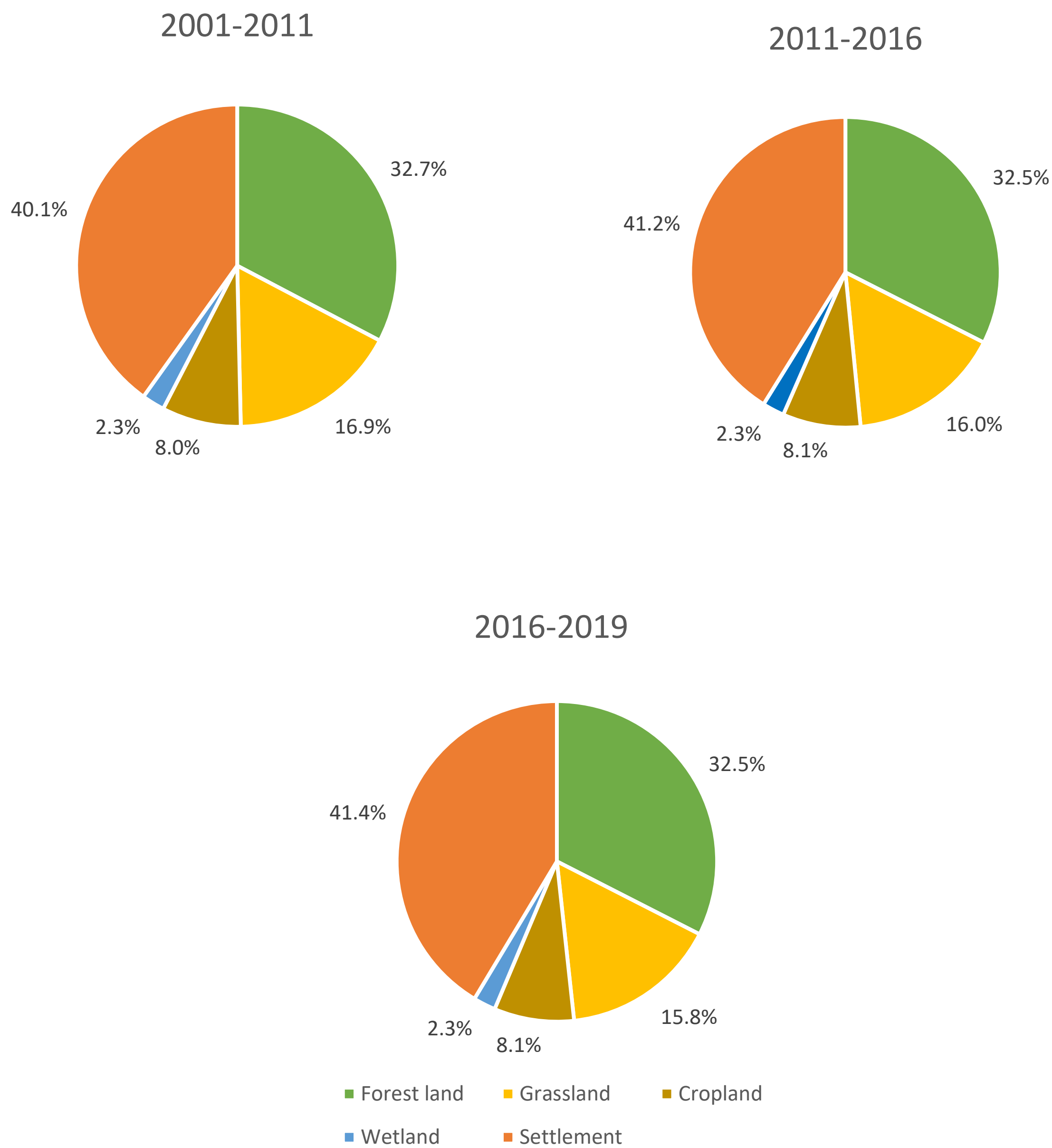
Data sets used as inputs into the carbon emission and removal calculations are described below.

Land Cover

GHG inventories for lands are reported in six “land use” categories which were defined by data on land cover—forest land, grassland, cropland, wetland, settlement, and other land (barren, snow, ice). To monitor land use change in Montgomery County, NLCD datasets for 2001, 2011, 2016 and 2019 were reclassified to these six categories and combined to calculate changes in each category over time. The breakdown of land use for each period is shown in Figure 2.

The overall distribution of land use classes has remained relatively stable from 2001-2019. In the most recent time period, the land in Montgomery County was about 41% settlement and 33% forests. Grasslands, croplands and wetlands make up a smaller proportion of the County’s land at about 16%, 8% and 2% respectively. Total hectares (ha) for each land use class in each period are also summarized in Table 2. Figure 3 shows a visualization of expanded NLCD land cover classes in 2019.

Figure 2: Land cover in Montgomery County 2001-2019



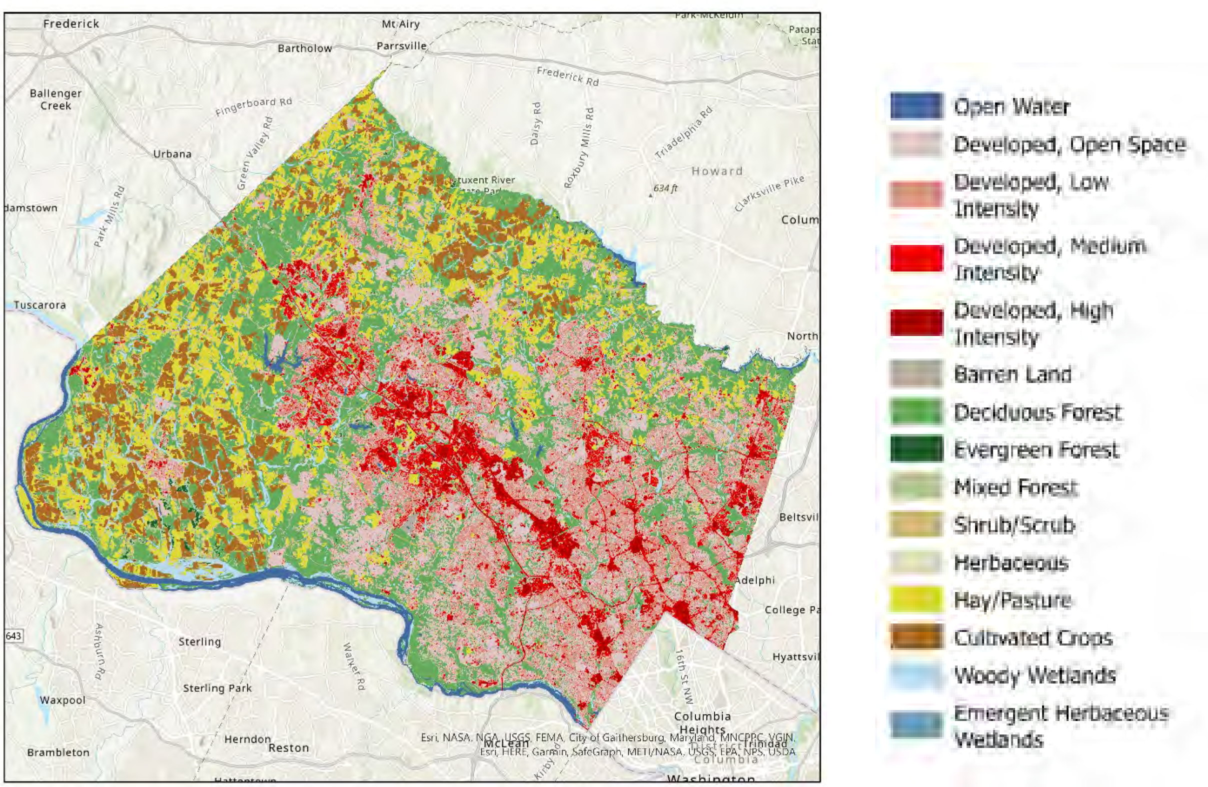
Source: National Land Cover Database (USGS, 2021)

Table 2: Land cover in Montgomery County (in hectares)

	2001-2011	2011-2016	2016-2019
Forest land	42,874	42,577	42,592
Grassland	22,211	20,925	20,511
Cropland	10,431	10,656	10,688
Wetland	3,005	2,995	2,969
Settlement	52,587	53,968	54,365
Other land	189	175	171

Source: National Land Cover Database (USGS, 2021)

Figure 3. Land cover in Montgomery County from the National Land Cover Database (2019)



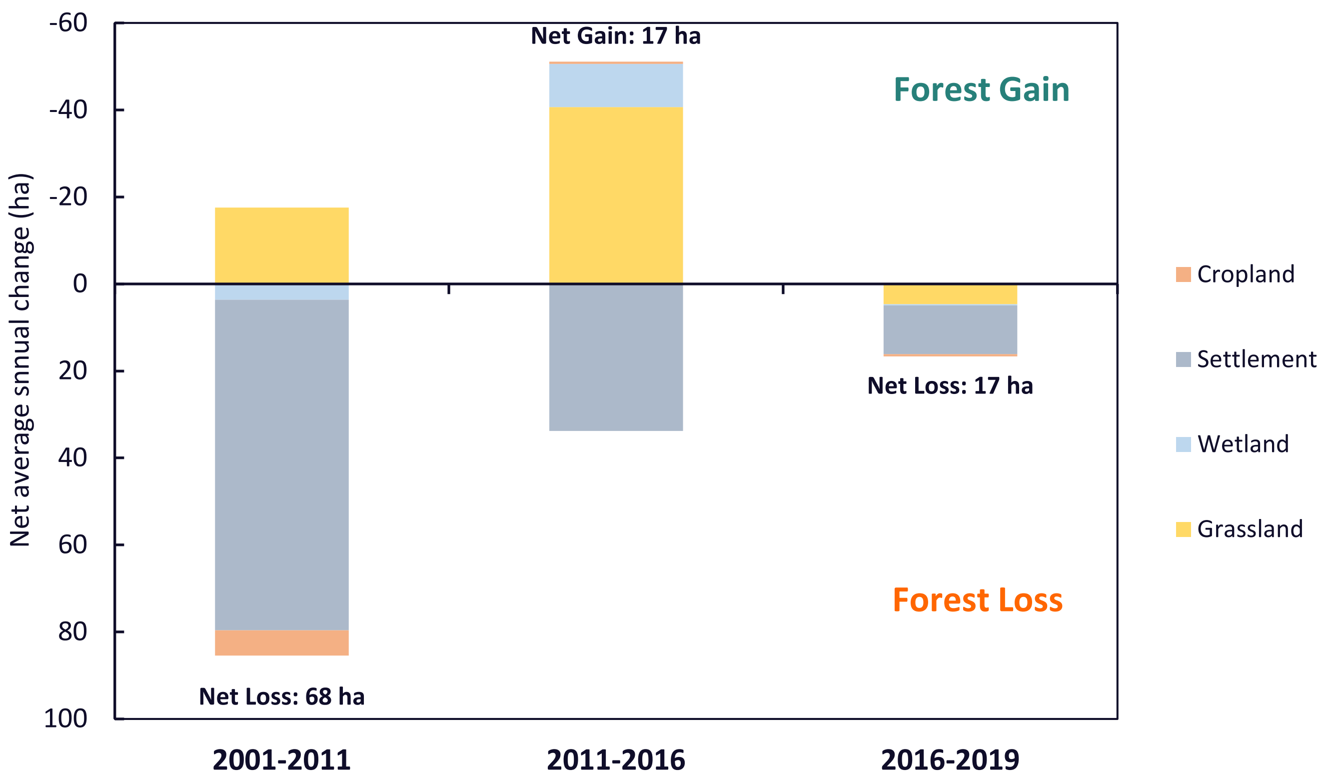
Source: National Land Cover Database (USGS, 2021)

Forest Cover Change

Generating GHG estimates requires data not just on areas of land use, but also data on how land use has changed over time. Average annual net changes in forest land to other land use types are summarized in Figure 4, where a negative number indicates a gain in forest and a positive number indicates a forest loss. Over the first period (2001-2011), the county lost around 68 hectares of forest land per year, largely conversion to Settlement (i.e., developed areas). More recently, in the period 2011-2016, there was a net gain of forest area of around 17 ha per year. In the most recent period from 2016-2019, there was a net loss of 17 ha of forest per year. The largest forest conversions occurred in the forest to settlement class where the average annual net change was 76 ha / year in 2001-2011. There was also a significant conversion of grassland to forest land from 2011 to 2016 (41 ha / year). Overall, the net change in forest land from 2001-2019 is a loss of about 1%, or 282 hectares (Table 2).

Figure 4. Average annual net change of forests to other land use types (in hectares / year)

Note: Negative number = net gain of forests. Positive number = net loss of forests.



Source: National Land Cover Database (USGS, 2021)

Forest Disturbances

In order to fully understand the GHG profile of a community's land, it is important to look not only at land use changes but also disturbances which occur within a land use class. For the purposes of this inventory, we monitor disturbances which occur in forest lands remaining forest lands throughout the inventory period. Three general categories of disturbance are analyzed: high severity fire, tree mortality from insect / disease, and harvest / other.

The disturbance dataset is produced using a hierarchical model which assigns only one disturbance type to a given pixel in the order listed above. Areas of high severity fire are delineated using the Monitoring Trends in Burn Severity Database (2022) and tree mortality due to insect or diseases are delineated using the United States Forest Service Aerial Detection Surveys (2022). Areas which fall into one of these categories are masked from the Hansen Tree Cover Loss Dataset (2013) and all other pixels of loss are assumed to fall in the harvest or "other" category. "Other" is assumed to be most likely related to weather events.

Emissions from disturbances make up only about 3% of all emissions from land use from 2001-2019 in Montgomery County. Montgomery County had no disturbances from high severity fire or insect / disease which were picked up within the forest remaining forest land use. Average annual disturbance from harvest / other was highest in 2016-2019 at around 19 ha / year, and lowest in 2011-2016 at around 9 ha / year.

Trees Outside Forests

In many communities, trees on non-forest lands may contribute significantly to emissions and removals from land use. Trees outside forests in Montgomery County were analyzed using two different methodologies to provide the best available estimate of tree canopy and tree canopy changes across the 2001-2019 period. The 2001-2011 and 2011-2016 periods utilize results from the iTree Canopy tool which provides statistical estimates of tree canopy and tree canopy loss using manual visual interpretation of satellite imagery. The 2016-2019 period uses the CBP high-resolution (1-m) tree canopy datasets for 2013-2018. For this reason, disaggregation of tree canopy and tree canopy loss by land use class is only available for 2016-2019.

Average tree cover over the inventory period and average annual loss of tree cover are visualized in Figure 6. Tree canopy increased from the 2001-2011 to 2011-2016 periods by about 6% but decreased in 2016-2019 by about 3% relative to a 2001-2011 baseline. However, due to the implementation of new high-resolution data in 2016-2019, it is possible that this does not represent an actual decrease in tree canopy. Average annual tree canopy loss was greatest in the 2011-2016 period at about 400 ha / year. Average annual loss decreased by 30% from 2011-2016 to around 286 ha / year in 2016-2019.

Figure 5. NLCD forest land (2019) overlaid with CBP trees outside forest change (2013-2018)

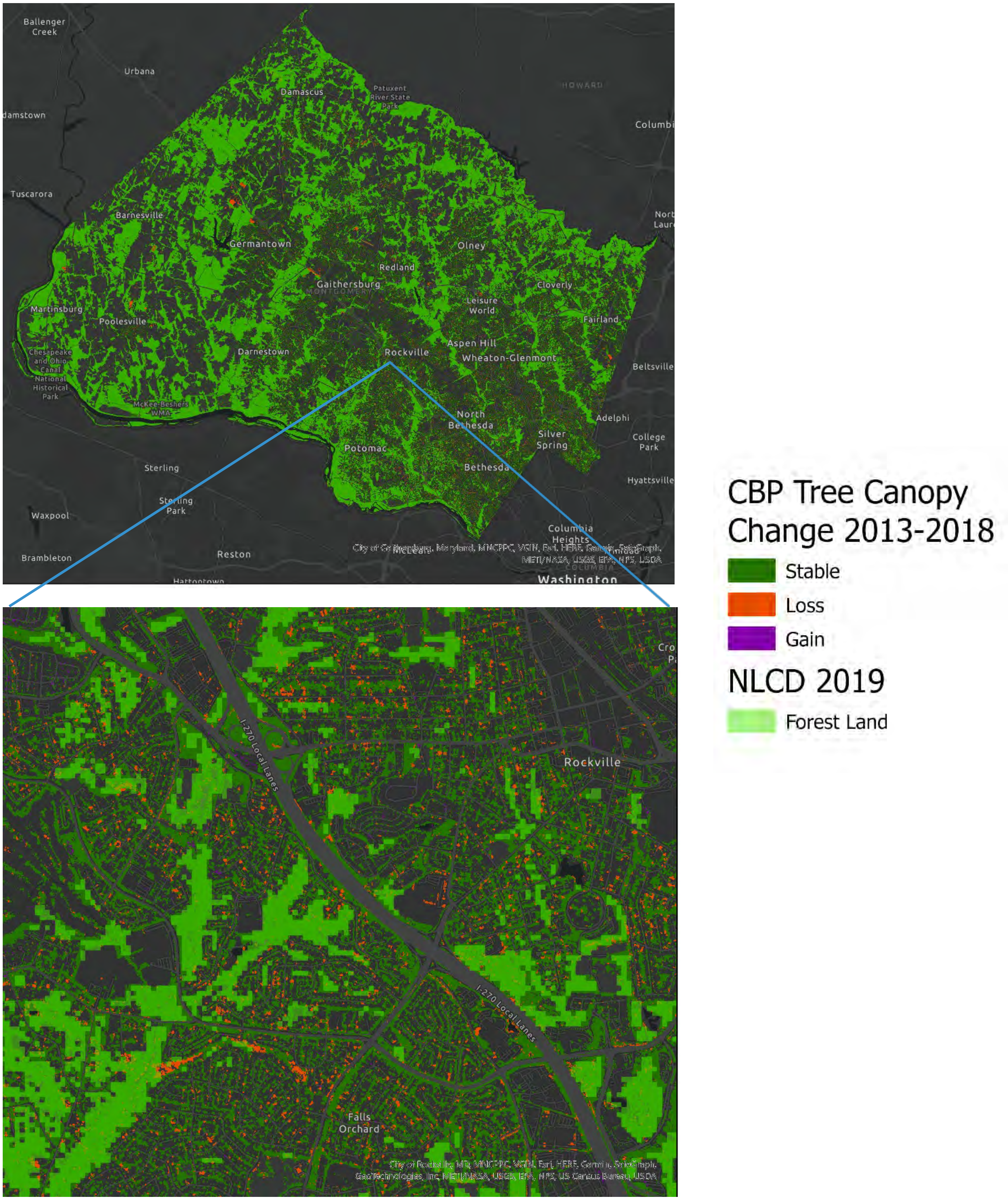
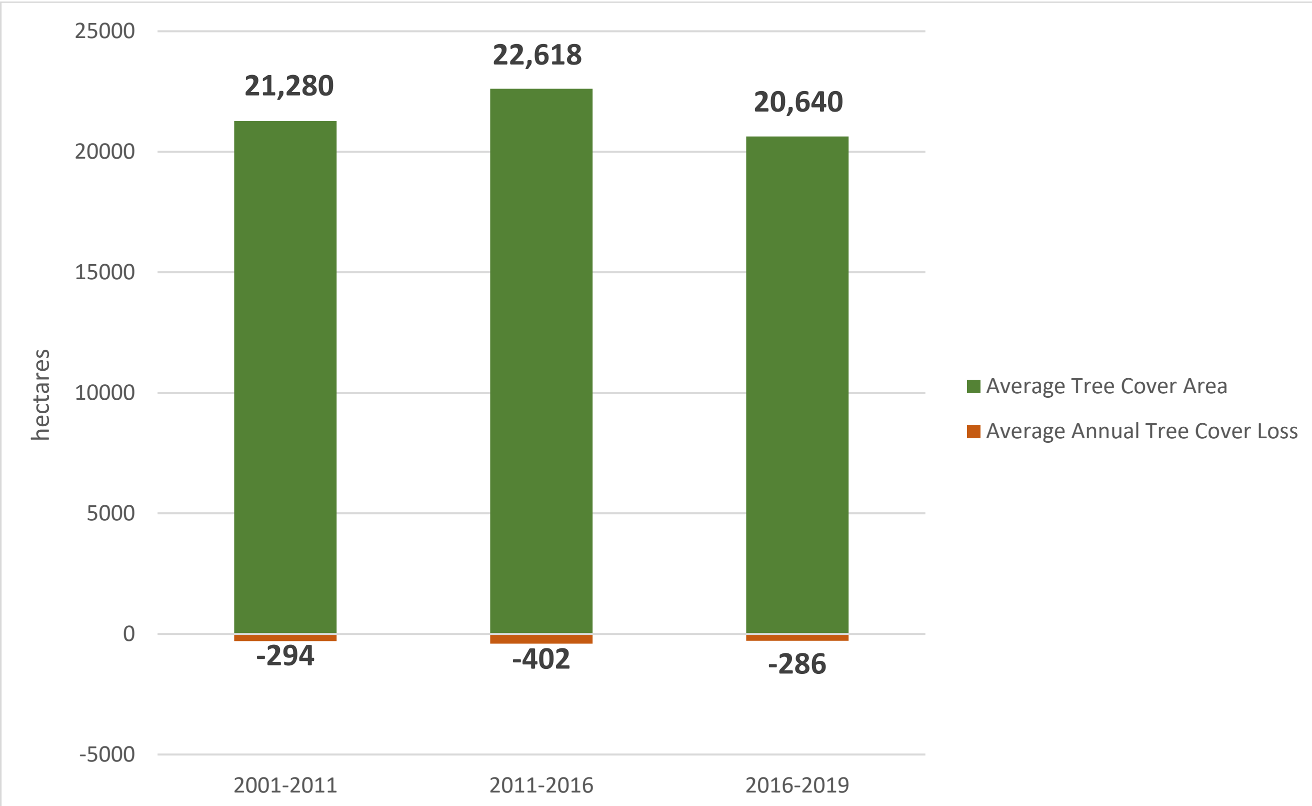


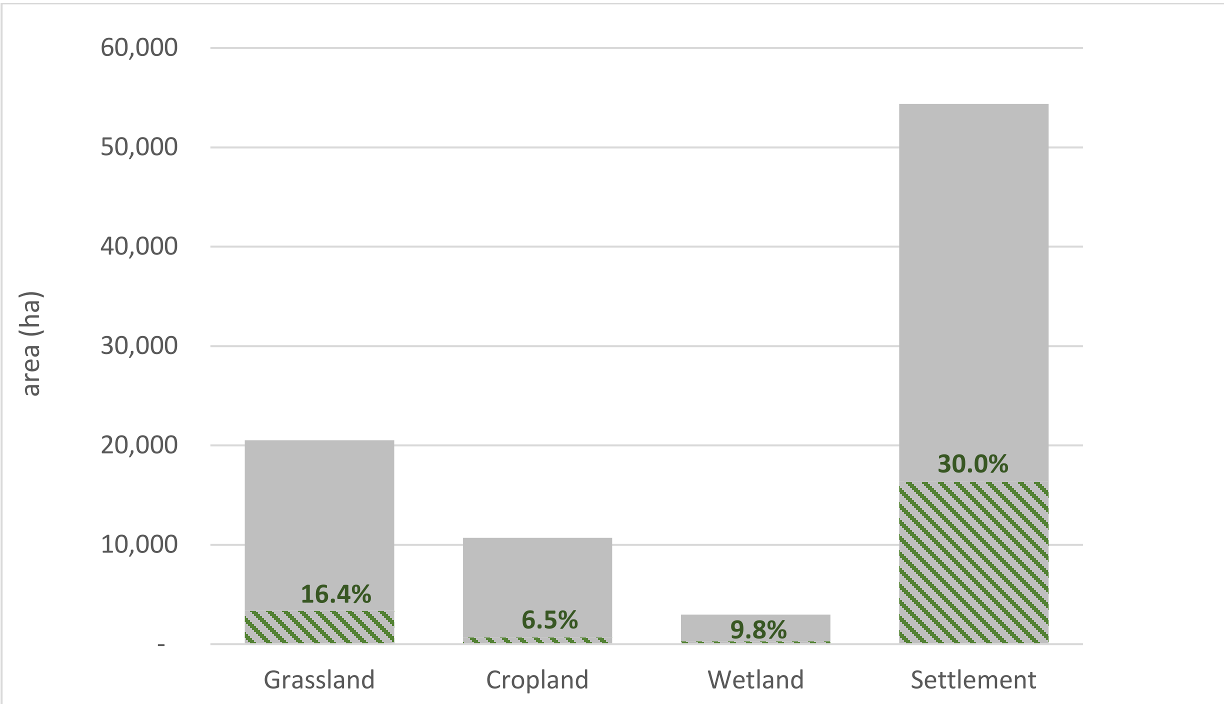
Figure 6. Average tree canopy (ha) and average annual tree canopy loss (ha / year) outside forests for each inventory period



More detailed information on 2016-2019 trees outside forests is presented in Figures 7 and 8. Figure 7 shows the total area for each non-forest land use class as well as the percent of that area which is covered by tree canopy. The settlement class has the highest percent tree canopy coverage at around 30%. Grasslands have the second highest tree canopy coverage at around 16%. Wetlands and croplands have lower percent tree canopy coverage at around 10% and 7%, respectively. This may present an opportunity for additional tree canopy coverage in the form of agroforestry or riparian buffers, for example.

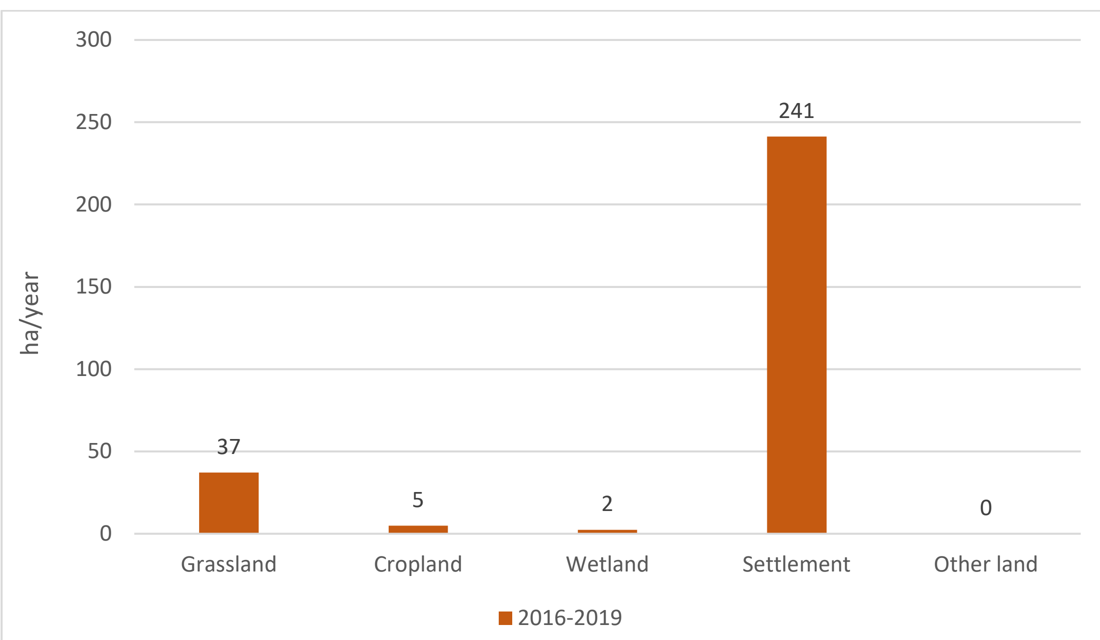
Figure 8 presents a breakdown of average annual tree cover loss in 2016-2019 by non-forest land use class. From these estimates, the largest area of loss was in the settlement class at around 240 ha / year. This is not surprising given that the settlement class has the largest area of tree canopy and is the most likely to experience additional development. Grasslands, croplands and wetlands combined had an estimated average annual loss of about 44 ha / year.

Figure 7. Average tree canopy (ha) and % tree cover disaggregated by land use categories in Montgomery County for the period 2016-2019



Source: CBP (2022)

Figure 8. Annual tree canopy loss disaggregated by land use categories in Montgomery County for the period 2016-2019 (ha / year)

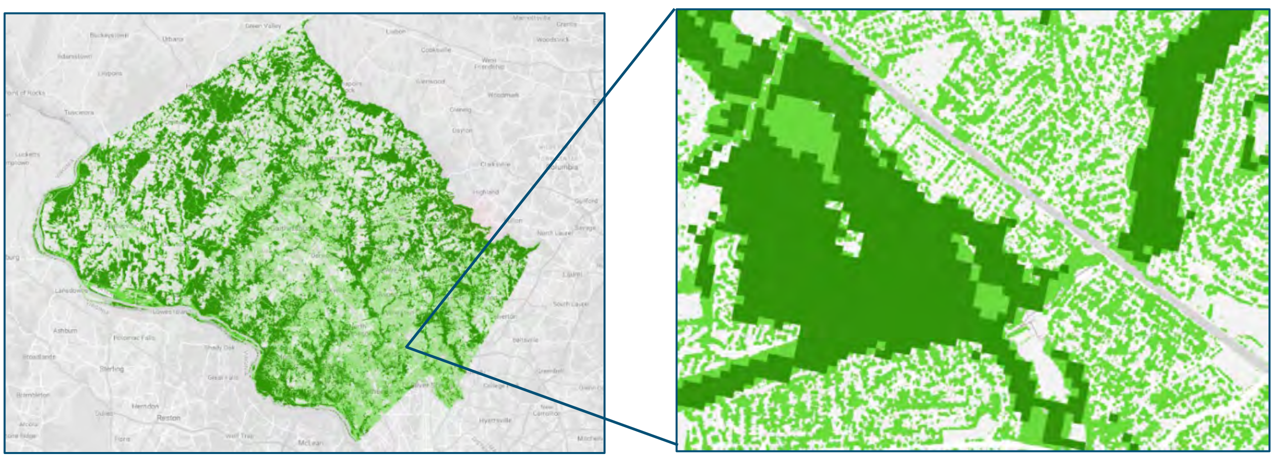


Source: CBP (2022)

Tree Canopy Data Source Assessment

As improved sources of tree canopy data become available, communities may be faced with more decisions on which data sources to use in ongoing monitoring. There are several considerations that may factor into these decisions, including data accuracy, resolution, temporal availability, and consistency with past or future inventories. Different tree canopy data sources can result in significant differences in results (see Figure 8 for a visual comparison between 30-meter NLCD Tree Canopy and 1-meter local data).

Figure 8. NLCD defined tree canopy (dark green) and LiDAR tree canopy cover (light green).



Tables 3 and 4 provide some context into how decisions were made around data sources for Montgomery County. Here you can see the data availability for many of the inputs that go into the inventory compared to the GHG inventory years for other sectors. It is often helpful to visualize data availability when making decisions on data inputs.

Table 3. Timeline of data availability for Montgomery County inventories

Dataset	Year																			
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GHG Inventory for Other Sectors					1							2			3			4		
NLCD Land Cover																				
NLCD Tree Canopy																				
Montgomery County LiDAR Derived Tree Canopy																				
Chesapeake Bay Program Tree Canopy																				

Table 4. Descriptions of available tree canopy datasets for Montgomery County inventories

Dataset	Resolution	Data Provider	Data Format
NLCD Tree Canopy	30-meter	U.S. Geological Survey	Percent tree canpoy cover per 30 meter pixel
Montgomery County LiDAR Derived Tree Canopy	1-meter	University of Vermont and Montgomery County	Binary (tree canopy or no tree canopy)
Chesapeake Bay Program Tree Canopy	1-meter	Chesapeake Bay Program	Binary (tree canopy or no tree canopy)

Previous inventory periods incorporated a combination of tree canopy data derived from high-resolution local LiDAR acquisitions and an interpolation method using Landsat imagery. In June 2022, the CBP released new high-resolution (1-meter) tree canopy data for the entire Chesapeake Bay Watershed for 2013 and 2018. A visual accuracy assessment was performed to compare the Montgomery County LiDAR tree canopy data with the new Chesapeake Conservancy Data.

Figure 9. 2018 Tree Canopy Cover from Montgomery County LiDAR and CBP

Initial visual inspection showed notable differences among the two high-resolution datasets (Figure 9). To achieve a better understanding of these differences, 50 random points were generated for each of four classes of tree canopy coverage for each of the datasets: no tree canopy, stable tree canopy, tree canopy gain, and tree canopy loss. These points were evaluated using historical imagery in Google Earth Pro, and a validation label was assigned to each point. These labelled points were spatially joined to the two tree canopy datasets to compare the classification to the validation.

Results of this analysis are presented in confusion matrices (see Tables 12-14). Table 12 shows what each cell within the confusion matrix indicates. The diagonal outlined boxes indicate areas where both the dataset and the validation agreed on the classification. Cells outside of these outlined boxes indicate areas of confusion. For example, a cell labeled Gain > None indicates that where the data source classified an area as gain, the validation label classified this same area as no tree canopy.

Table 12. Confusion Matrix Template

Data Source		Validation			
		None	Stable	Loss	Gain
Classification	None	None > None	None > Stable	None > Loss	None > Gain
	Stable	Stable > None	Stable > Stable	Stable > Loss	Stable > Gain
	Loss	Loss > None	Loss > Stable	Loss > Loss	Loss > Gain
	Gain	Gain > None	Gain > Stable	Gain > Loss	Gain > Gain

There was greater confusion between the Montgomery County LiDAR derived tree canopy and the validation than seen with the CBP Data. It appears that the 2014 and 2018 Montgomery County datasets may be less consistent with each other, and the resulting change analysis may therefore over classify areas of gain and loss (see greater areas of confusion highlighted in orange in Tables 13 and 14. The CBP data was more accurate for this time period and is also more likely to support regional and temporal consistency into the future. For these reasons, this dataset was selected to represent tree canopy for the 2016-2019 period.

Table 13. Confusion Matrix Results for Montgomery County LiDAR Tree Canopy Assessment

Montgomery County Local LiDAR		Validation			
		None	Stable	Loss	Gain
Classification	None	50	0	0	0
	Stable	0	50	0	0
	Loss	30	3	17	0
	Gain	14	25	0	11

Table 14. Confusion Matrix Results for CBP Tree Canopy Assessment

Chesapeake Bay High-Res		Validation			
		None	Stable	Loss	Gain
Classification	None	50	0	0	0
	Stable	1	49	0	0
	Loss	5	10	35	0
	Gain	6	7	0	37

These results were further assessed using measures of omission error, commission error, and overall accuracy (See Tables 15 and 16). In this assessment, an omission error for a particular class indicates the rate at which actual areas for that class were omitted from the dataset. On the contrary, a commission error indicates where an area was incorrectly included in a class.

In Table 15 you can see that the Montgomery County dataset has high commission errors for loss and gain, meaning that the change dataset more often classified these areas when they did not exist according to visual interpretation. The overall accuracy of the change dataset produced by 2009 and 2014 Montgomery County datasets was estimated at 94%. In Table 16, we see that commission and omission errors for gain and loss were much lower in the CBP change dataset. The overall accuracy of this dataset was estimated at 99%.

Based on the results of this accuracy assessment, it was determined that the CBP dataset more accurately represented tree canopy and tree canopy loss for the 2016-2019 period. This dataset also has the advantage of being incorporated into the LEARN tool, which will allow Montgomery County to run automated analysis on future versions of the dataset. Moreover, using this dataset helps to foster consistency with other communities in the region and lends credibility to findings on tree canopy. Figure 10 compares average tree canopy (ha) and average tree canopy loss (ha / year) results from local Montgomery County LiDAR derived data, the CBP data, and the i-Tree estimates calculated by MWCOG. The differences in these datasets reinforce the need for careful assessment when making decisions on data inputs for GHG inventories.

Table 15. Accuracy Assessment Results for Montgomery County LiDAR Tree Canopy Assessment

Accuracy Results					
Stratum Name	**Stratum N**	**Omission error %**	**SE of OE%**	**Commission error %**	**SE of CE %**
None	50	10.44	1.26	0.00	0.00
Stable	50	2.10	0.77	0.00	0.00
Loss	50	0.00	0.00	66.00	10.06
Gain	50	0.00	0.00	78.00	12.93

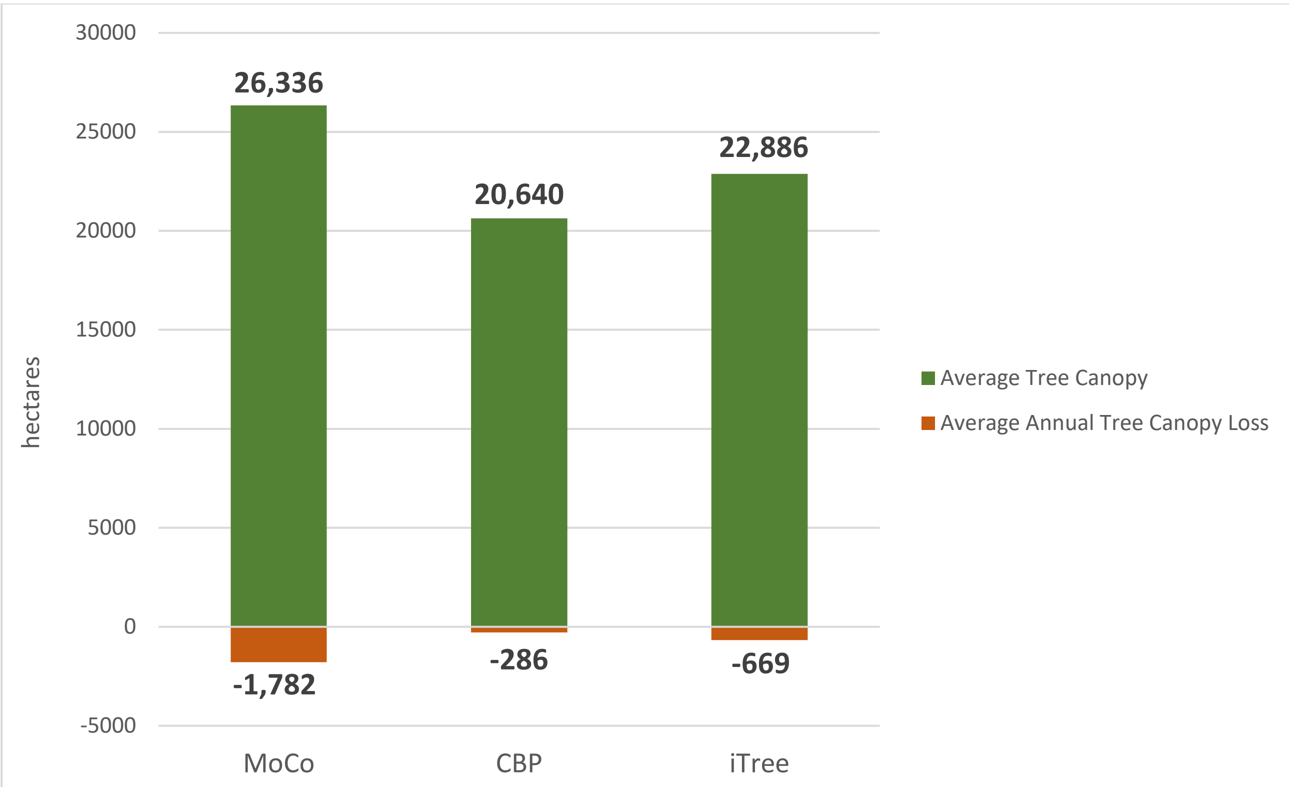
Overall accuracy	**93.6739**

Table 16. Accuracy Assessment Results for CBP LiDAR Tree Canopy Assessment

Accuracy Results					
Stratum Name	**Stratum N**	**Omission error %**	**SE of OE%**	**Commission error %**	**SE of CE%**
None	50	1.90	1.68	0.00	0.00
Stable	50	0.88	0.25	2.00	1.98
Loss	50	0.00	0.00	30.00	12.14
Gain	50	0.00	0.00	26.00	11.11

Overall accuracy	**98.5604**

Figure 10. Comparison of average tree canopy (ha) and average annual tree canopy loss (ha / year) for local Montgomery County data (2013-2018), CBP data (2013-2018) and i-Tree estimates (2016-2019) for NLCD period 2016-2019



Caveats

Information presented here represents a snapshot in time of the net GHG balance of forests and trees in Montgomery County and many of the factors contributing to that balance. The estimates can help identify where policies may be designed to reduce net GHG emissions. For example, a decrease in the conversion of forest to settlement over the three inventory periods led to emission reductions, which could be reduced further to improve the future GHG balance, as could preserving tree canopy in settlement areas.

We note that forest emissions from harvesting and carbon stored in harvested wood products were not estimated due to a lack of data about how much forest area, if any, was harvested during the inventory period. Likewise, we could not determine if any trees removed during conversion of forest land to non-forest, or any trees removed during maintenance of trees outside forests, were used for wood products. When trees are cut and put into long-term uses, such as buildings or furniture, this can reduce the immediate emissions from loss of trees. Because of lack of data, this inventory currently uses a simplifying assumption that a loss of forest or trees results in immediate emissions to the atmosphere (rather than delayed emissions in the case of various use cases from long-term storage to shorter decay timelines if sent to landfills). If data were available, the delayed emissions could be considered in the calculations.

In general, it is important to consider that these estimates represent a relatively short period of time compared with the long-term consequences of policy decisions and land management actions. For example, a forest converted to settlement represents a permanent loss of removal capacity. Over the long term, maintaining forests will sustain a higher rate of carbon removal, depending on age-related growth rates and occurrence of disturbances.

There are significant uncertainties in the estimates. Although not quantified here, typical greenhouse gas inventories of forests using similar approaches, including the national GHG inventory, report uncertainties in the net GHG balance that can be as high as ±45% (with 95% confidence). In the results presented here, the most uncertain estimates involve emissions from land-use change which are based on well-documented remote-sensing products, but relatively few field observations from a statistical sampling of county forests. While uncertainties can be high, the estimates can still provide useful information on the relative magnitude and importance of such GHGs; subsequent analyses can also provide information on the directionality of emissions and removals from land management.

Finally, it is recommended that additional analyses be done using models that project impacts of alternatives over coming decades. Such models are available and have been used in other studies at county scale. The

GHG inventory presented here is only the first step to providing science-based information to support policy decisions. To more fully explore the prospective impacts of alternate policies, projection models should be used to compare long-term results among the alternatives which typically include a “business as usual” (i.e. no change in policy) alternative.

Acknowledgements

This GHG inventory was compiled by a team of experts in close collaboration with representatives of several agencies in Montgomery County. It is part of an ongoing effort to enable communities to include the land sector in their GHG inventories. The work was linked to the development of guidance for communities to measure the GHGs from forests and trees that is now available in ICLEI-USA's US Community Scale Protocol for Accounting and Reporting of Greenhouse Gas Emissions (http://icleiusa.org/ghg-protocols/).

This work was sponsored by the Climate and Land Use Alliance and the Doris Duke Charitable Foundation. The team of experts represents the World Resources Institute, the Climate and Land Use Alliance, and the Woodwell Climate Research Center.

For additional information, please contact Douglas Weisburger in Montgomery County's Department of Environmental Protection (Douglas.Weisburger@montgomerycountymd.gov).

Appendix I: Comprehensive GHG Inventory Report

Spreadsheet with tables and graphs, produced by MWCOG on behalf of Montgomery County in December 2022, that provide data on the 2005, 2012, 2015, 2018, and 2020 GHG emissions inventories:

https://www.montgomerycountymd.gov/climate/Resources/Files/climate/ghg/ghg-inventory-data-summary.xlsx