ANALYSIS OF FOREST COVER CHANGES AND FOREST GREENHOUSE GAS EMISSIONS IN THE PHILIPPINES FROM 2011-2020 USING SATELLITE-DERIVED PRODUCTS

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ABSTRACT: Timely and spatially-consistent forest cover change information provide invaluable insights for stakeholders and policymakers in making appropriate interventions and responses in the field. In this context, freely available forest cover products derived from earth observation satellite data through the Landsat platform enable researchers to have an annual to decadal forest cover trend for the first two decades of the 21st century (Hansen et al., 2013). In this paper, we analyze annual forest cover loss and forest greenhouse gas (GHG) emission trends in the Philippines from 2011-2020 and group the findings with respect to the Philippines' 81 provinces. Results showed that Agusan del Sur (30,416.06 ha), Palawan (30,286.50 ha), and Zamboanga del Norte (10,165.96 ha) are the top three with regard to total forest loss. By comparing the provinces across similar scales, proportional forest losses were computed which showed that Zamboanga del Norte lost 13.31% of its year 2010 base forest cover, followed by Agusan del Sur (8.92%) and Tawi-tawi (8.55%, total loss = 3,373.10 ha). Ifugao (0.82, $p < 0.05$), Maguindanao (r = 0. 80, $p < 0.05$) and Mountain Province ($r = 0.78$, $p < 0.05$) exhibited significant and increasing forest loss trends. In terms of forest GHG emissions, Agusan del Sur (25.6 Mt of CO_2e), Palawan (22.3 Mt of CO_2e), and Davao Oriental (8.7 Mt CO_2e) topped the list while linear and increasing forest emission trends were observed for Mountain Province ($r = 0.82$, $p < 0.05$), Maguindanao (0.83, $p < 0.05$) and Ifugao (0.79, $p < 0.05$). This study may contribute to country-wide monitoring of forest cover change that can aid in identifying and prioritizing areas for intervention, possibly down to the municipal level. Therefore, forest-related programs on addressing and halting deforestation need to be re-evaluated in such provinces.

1. INTRODUCTION

Deforestation continues in the 21st century despite global commitments to address and reduce its rate if not halt it completely (Hansen et al., 2013; Austin et al., 2017; Lewis et al., 2015; Harris et al., 2017). Among the causes, crop commodity production for export is deemed as one of its major drivers along with forestry operations, shifting agriculture, and wildfires (Curtis et al., 2018). To address these issues, global commitments and programs were initiated like the United Nations Strategic Plan for Forests 2017–2030 and its Global Forest Goals (UN Forum on Forests, 2017), and the Reducing Emissions from Deforestation and Forest Degradation and enhancing forest carbon stocks in developing countries or REDD+ (Angelsen, 2009). Based on the recent UN-FAO (2020) Forest Resource Assessment, global forest loss rate declined from 5.2 Mha/year in 2000-2010 to 4.7 Mha/year in 2010-2020 as a result of deforestation extent reduction, but the commodity driven deforestation has not declined since 2001 (Curtis et al., 2018). On the other hand, REDD+ achieved generally mixed and partly contradicting results due to its early phase of implementation (Arts, et al., 2019), low carbon price on international markets, low capacity of countries joining the program and the resulting red tape (Leblois, 2017; Simonet et al., 2014).

The availability of data from Earth Observation (EO) satellites resulted in a new set of remote sensing products and tools that are specifically used for forest dynamics monitoring (Hansen et al., 2013; Achard et al., 2010). In the Philippines, this set of data has been utilized by various researchers to monitor and assess provincial annual forest cover changes (Fallarcuna and Perez, 2016), the National Greening Program (NGP) of the government (Perez et al., 2020), forest change patterns in protected areas (Apan et al., 2012), and inter-annual deforestation hotspot mapping (Araza, et al., 2020). In this paper, the Philippines' forest cover change from 2011-2020 are analyzed and provinces are identified with the most significant forest losses and trend patterns using the updated global forest change data of Hansen et al. (2013). In addition, forest greenhouse gas (GHG) emissions (Harris et al., 2021) were also computed in relation to aforementioned forest change data to estimate forest GHG emissions resulting from complete forest stand-replacement.

2. DATA AND METHODS

Building on the published global forest change data of Hansen et al. (2013), an updated and improved global annual forest loss layer is available for the years 2011-2020 due to increased data acquisitions (see Table 1). However, caution must be taken in using the data as there might be inconsistencies resulting from different Landsat sensor technologies, algorithm applied, and forest extent definitions (Tropek et al., 2014; Bellot et al., 2017), especially when comparing the annual forest loss trends between the 2000s and 2010s (Roddy, 2021). A tree canopy cover percentage is used as well to serve as a 2010 baseline tree cover (GLAD, 2013). Meanwhile, forest GHG emissions (Harris et al., 2021) are downloaded from Global Forest Watch (GFW, 2021), a web application for near-real time forest monitoring and a repository of forest and other forestry related scientific datasets (WRI, 2014). Lastly, official and countrywide 2010 forest cover classes from the Philippines' mapping agency (NAMRIA, 2010) and provincial boundaries (GADM, n.d.) were utilized to delineate an acceptable forest extent and assigned the results per provincial administrative jurisdiction (See Table 2 for input data visualization).

Table 1. Input data used in this study.

Layer Name	Description and publication source	Web Repository
lossyear	Annual forest losses with values indicating the year of loss (encoded as 1-20) as a result of stand-replacement disturbance or change from forest to non-forest condition in 2001-2020 (raster 30 m). (Hansen et al., 2013)	https://developers.google.com/earth-engine/datasets/catalog/UMD_hansen_global_forest_change_2020_v1_8
forest GHG emission	Estimated forest GHG emissions (aboveground, belowground, dead wood, litter, soil) and greenhouse gases (CO_2, CH_4, N_2O) resulting from stand-replacing forest disturbances. Expressed in metric tons of CO_2e/ha and tons of CO_2e/pixel (raster format, 30 m). (Harris et al., 2021)	https://data.globalforestwatch.org/datasets/forest-greenhouse-gas-emissions/
treecover2010	Tree canopy cover expressed in percentage values (1-100%) for 2010 (raster format, 30 m). (GLAD, 2013)	https://glad.umd.edu/Potapov/TCC_2010/
forest2010	Forest cover vector for year 2010 (forest classes: closed, open and mangrove, classed are aggregated) (NAMRIA, 2010)	https://www.geoportal.gov.ph/
ph_prov	Vector polygon boundaries of Philippine provinces (GADM, undated)	https://gadm.org/maps/PHL.html

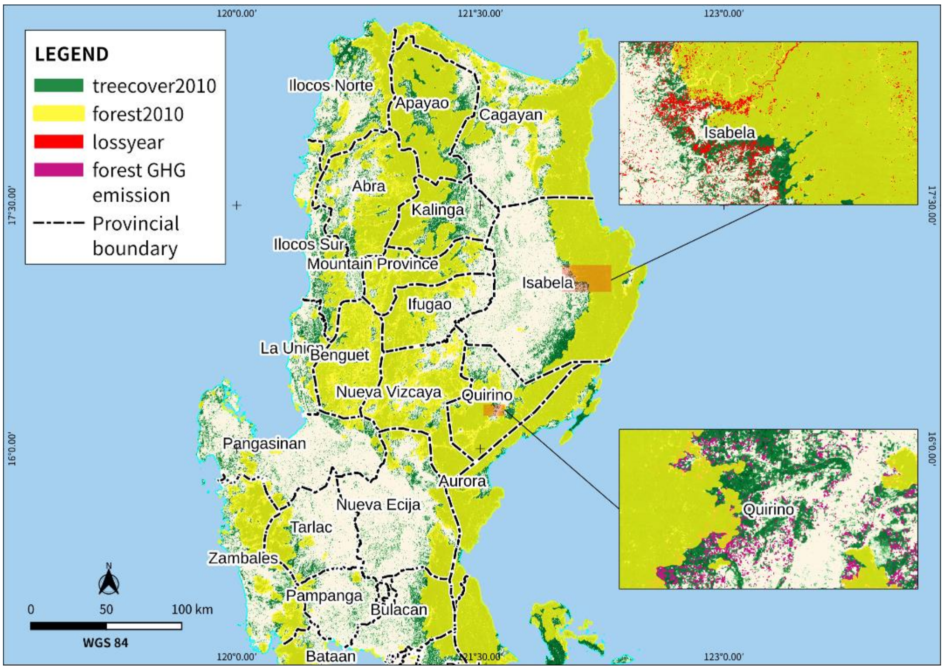

Figure 1. Input data presented in map form. (Northern Luzon, Philippines)

The first step involved the clipping of *treecover2010* using the extent of *forest2010* polygons to properly delineate and define 2010 forest boundaries and exclude tree cover pixels outside the contiguous and major forest areas. Next, *treecover2010* pixel values ranging from 80-100% were extracted as these percentage values represent up to 90% of all pixels inside the *forest2010* polygons. According to Tang et al. (2019), this tree cover threshold mainly represents broadleaf evergreen forests. This ensured that only forests with high density canopy cover were included in the analysis, eliminating the low density forests that might represent saplings, shrubs and trees in early stages of growth and regeneration. Following this, the annual forest loss and GHG estimation were estimated using the *lossyea*r and *forestGHG* layers respectively. Annual forest losses were computed by subtracting 2011-2020 *lossyear* from the earlier computed 2010 baseline forest cover, while annual *forest GHG emissions* were calculated by overlaying them to *lossyear* (Harris et al., 2021). Top provinces were then ranked by total, proportional annual forest loss and total annual forest emission and presented graphically. Lastly, Pearson correlation analysis was performed for annual forest loss and forest GHG emission graphs to determine whether the increase or decrease of the linear trends against the 2011-2020 time period were significant (Austin et al., 2017; Hansen et al., 2013; Pereira et al., 2018; Zarin et al., 2016). Pre-processing steps using GDAL and QGIS were carried out to input layers before the main analysis was implemented via Google Earth Engine.

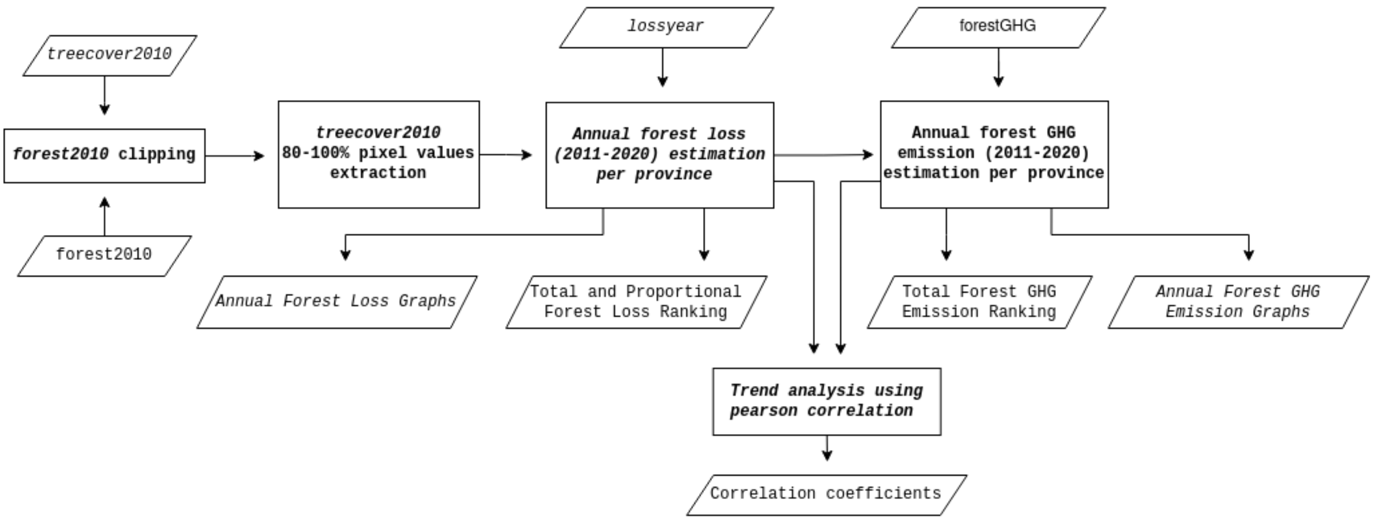

Figure 2. Flowchart of the study.

3. RESULTS AND DISCUSSIONS

3.1 Countrywide Annual Forest Loss Estimation

The Philippines experienced a mean annual forest loss of 17,248.87 ha from the period of 2011-2020 (Figure 3). Years 2016 (28,154.49 ha), 2017 (27,846.60) and 2014 (20,740.39 ha) had the highest values of loss while 2011 (5,901.75 ha), 2012 (10,075.51) and 2013 (15,061.30 ha) had the lowest ones. Compared to previous decadal analyses, the forest loss annual increment (slope of the trendline) from 2011-2020 is 1,083.66 ha compared to 261.29 ha of 2001-2012 (Fallarcuna and Perez, 2016). This can be attributed to improvements in the forest loss detection as explained by Roddy (2021) and in the Hansen et al. (2013) data repository, which are the consequences algorithm implementation enhancements and additional images acquired by Landsat 8. Nevertheless, the enactment of Executive Order 23, series of 2011 that declared a logging moratorium on natural and residual forests and created an anti-illegal logging task force had minimal effect because of the continued increase in forest loss trend from 2011-2016. Moreover, 2016, which showed the greatest forest loss, was an election year. This can be related to the findings of Burgess et al. (2012) where the conduct of elections was linked to deforestation cycles as forest loss increases were observed prior to election year based on Indonesia's experience. Insights from the ground show that this phenomenon also occurs in the Philippines to finance election campaigns (Inoguchi et al., 2005; Mallari, 2018; Chavez, 2020).

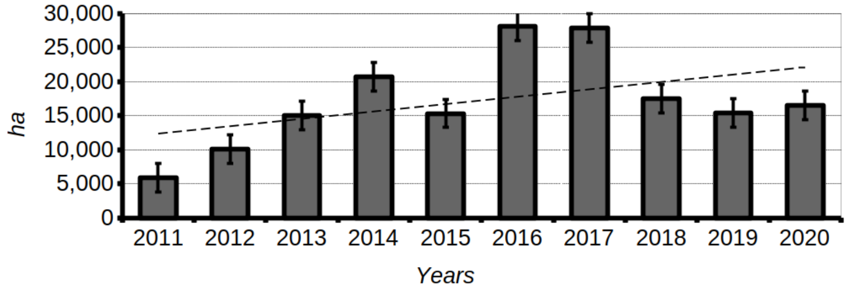

Figure 3. Philippines' annual forest loss 2011-2020 (slope = 1,083.66 ha, mean = 17, 247.87, *r* = 0.47 not significant, error bars expressed as standard error, **SE**).

3.2 Provincial Annual Forest Loss Estimation

The ten provinces that experienced the highest total loss from 2011-2020 are listed in Table 2. Except for Zamboanga del Norte (ZdN), they all belong to the top 20 provinces with the highest forest cover in 2010 (NAMRIA, 2010) and it can be expected that they will also have the greatest forest losses that occurred in that period. ZdN (total forest loss = 10,165.96 ha) is the only province in this list with forest area under 100,000 hectares, but still ranked third on the list. It is also interesting to note that six out of the ten provinces in Table 2 are located in Mindanao. The presence of negative slope (forest loss annual increment) for Davao Oriental, Eastern Samar, and Davao de Oro illustrates a unique forest loss pattern. Based on the annual forest loss graphs (see Figure 4), the three provinces had an increasing forest loss in the first three to four years and suddenly fell in later years. In contrast, Agusan del Sur (AdS), Palawan, ZdN and Surigao del Sur (SdS) have forest losses consistently increasing up to 2016 or 2017, matching the earlier observation of rising forest losses prior to the conduct of elections. Finally, Cagayan and Isabela registered distinct forest loss peaks in 2016 and 2017, respectively while Lanao del Sur (2016-2017), Eastern Samar (2013-2014) and Davao de Oro (2013-2014) had two consecutive forest loss peaks.

Table 2. Top ten provinces ranked according to total forest loss (ha).

Province	2010 baseline forest cover (ha)	Total loss (2011-2020) (ha)	Slope (forest loss annual increment) (ha)
1. Agusan del Sur	340,833.06	30,416.06	179.58
2. Palawan	624,446.29	30,286.50	334.51
3. Zamboanga del Norte	76,356.89	10,165.96	11.51
4. Davao Oriental	171,984.82	9,976.14	-100.09
5. Surigao del Sur	182,650.01	8,694.78	70.65
6. Cagayan	314,034.58	5,609.59	79.04
7. Lanao del Sur	148,650.19	4,325.13	63.22
8. Eastern Samar	176,267.54	4,228.38	-11.46
9. Isabela	349,217.95	4,212.23	48.45
10. Davao de Oro	110,846.02	4,174.05	-2.97

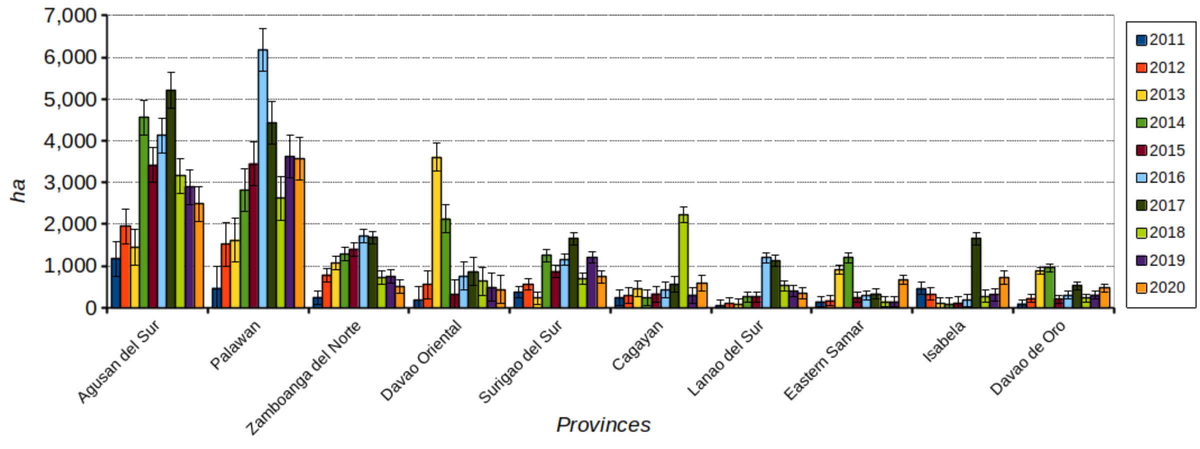

Figure 4. Annual losses (2011-2020) of top ten provinces by total forest loss.

Proportional forest change was then performed in order to gauge the amount of forest reduction of provinces relative to their starting forest cover in 2010. Using this type of analysis, nine out of the ten provinces that made the list are situated in Mindanao (Table 3) since it has substantial industrial tree plantations areas (Serrano, 2005) as well as 70% of the country's Integrated Forest Management Agreement (IFMA) tenure areas (FMB, 2019). IFMA is a forest land tenure instrument where industrial scale tree harvesting is legally permitted by the government. Moreover, 90% of total wood production (e.g plywood, veneer and lumber) came from Mindanao (Mangahas, 2010). ZdN registered the most forest cover percentage loss of 13.31% followed by AdS (8.92%) and Tawi-Tawi (8.55%). In line with this, there were reports that logging companies based in ZdN were suspended and blamed for flash floods and landslides in December 2017 caused by widespread and commercial scale logging (Mendez, 2018). AdS had the highest log production output, the most wood processing plants (e.g. sawmills) as of 2019, and possessed the most number of tree farms and forest plantations in CARAGA region (FMB, 2019).

It is interesting to note that most of the provinces from the table below are the same places experiencing high proportional forest change from the earlier decade (2000-2012) (Fallarcuna and Perez, 2016). For example, it is confirmed that the municipalities of Siocon, ZdN and Bunawan, AdS are classified as intensifying hotpots of forest loss by Harris et al. (2017) as visualized in the GFW website. Therefore, these provinces are areas of concern in monitoring deforestation in the coming years.

Table 3. Top ten provinces by proportional change.

Province	**2010 baseline forest cover (ha)**	**Total loss (2011-2020) (ha)**	**Proportional Change (Total loss/baseline forest cover, %)**	**Slope (forest loss annual increment) (ha)**
1. Zamboanga del Norte	76,356.89	10,165.96	13.31%	11.51
2. Agusan del Sur	340,833.06	30,416.06	8.92%	179.58
3. Tawi-Tawi*	39,473.06	3,373.10	8.55%	43.21
4. Zamboanga Sibugay*	29,353.21	2,201.36	7.50%	18.11
5. Davao Oriental	171,984.82	9,976.14	5.80%	-100.09
6. Maguindanao*	32,617.17	1,697.67	5.20%	24.84
7. Palawan	624,446.29	30,286.50	4.85%	334.51
8. Basilan*	19,453.43	938.01	4.82%	-8.16
9. Surigao del Sur	182,650.01	8,694.78	4.76%	70.65
10. Davao del Norte*	47,862.60	1,956.90	4.09%	26.33

*provinces absent from Table 2

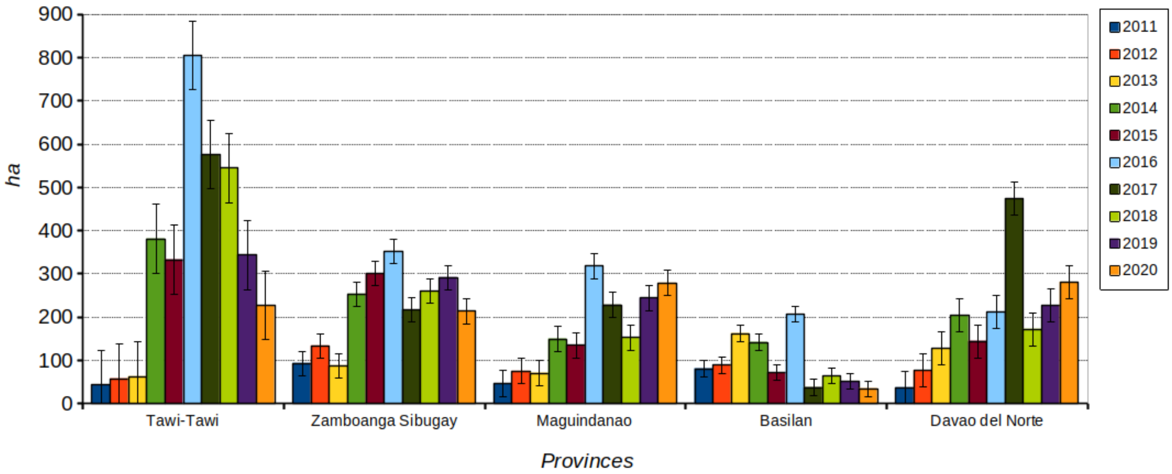

Figure 5. Annual forest loss (2011-2020) of provinces by proportional change not present in Table 2.

3.3 Provincial Annual Forest GHG Emissions Estimation

Table 4 shows the difference in values of forest GHG emissions when expressed in tons of CO_2 equivalent per hectare (*t of CO_2e/ha*) and tons of CO_2 equivalent as expressed per pixel *(t of CO_2e)*. The first unit is useful in representing the data visually as it pertains to density of emission per hectare whereas the second unit is used for computing the total emission for a particular area of interest. Results reveal that the province with the most forest GHG emissions is AdS (25.6 Mt of CO_2) followed by Palawan (22.3 Mt of CO_2e). These results should be interpreted carefully as the counterpart forest carbon removals (carbon sequestered) are not included in the computation. Thus, the forest emissions in Table 4 represent gross forest emission values instead of net values. In addition, there could also be an underestimate of forest emissions since high tree cover percentage (80-100%) pixels are the only ones included in defining the baseline forest extent of 2010. This also holds true for forest loss estimates as previously discussed. Forest GHG emissions are similar in pattern to forest losses (see Figures 4 and 6) which is expected as forest emissions are assigned and isolated using the forest *lossyear* data, as shown in the negative slopes of forest emissions in Davao Oriental, Eastern Samar, and Davao de Oro. Forest GHG emission to forest loss ratios are also shown to indicate how much forest GHG emissions are generated for every hectare of forest loss. These ratios vary in every province and it may demonstrate that vast and contiguous forest tracts have slightly lower carbon stock biomass compared to small ones (e.g. Cagayan, Isabela and Isabela are located in relatively bigger and continuous forested mountain ranges compared to other provinces in Table 4). Annually, the national average per province amounts to approximately 732.06 t of CO_2e for every hectare of forest loss in the 2011-2020 period. Biliran had the highest ratio (1049.34), followed by Surigao del Sur (866.82) and Surigao del Norte (861.00). Batanes had the least (76.31) GHG emission to forest loss ratio.

Table 4. Top ten provinces by forest gross GHG emissions.

Province	**Total (2011-2020) (t of CO_2e / ha)**	**Slope (forest GHG emission annual increment) (t of CO_2e/ha)**	**Total (2011-2020) (t of CO_2e)**	**Slope (forest GHG emission annual increment) t of CO_2e)**	**GHG Emission/Forest Loss Ratio**
1. Agusan del Sur	336,443,383.70	1,994,383.57	25,616,925.90	151,836.30	847.37
2. Palawan	293,849,054.90	3,244,021.75	22,297,297.18	246,378.20	744.012
3. Davao Oriental	113,600,717.57	-1,215,392.44	8,664,615.43	-92,676.91	857.51
4. Zamboanga del Norte	112,976,740.26	86,390.18	8,617,115.52	6,561.82	845.59
5. Surigao del Sur	98,720,105.63	822,487.24	7,505,243.71	62,520.50	866.82
6. Cagayan	56,714,667.10	842,054.48	4,151,192.57	61,619.38	728.76
7. Isabela	46,426,890.56	544,422.37	3,480,039.34	40,065.36	786.88
8. Eastern Samar	45,827,906.65	-120,818.59	3,457,972.20	-9,187.35	820.10
9. Davao de Oro	45,626,538.70	-65,229.65	3,456,556.84	-4,976.85	831.94
10. Lanao del Sur	45,361,179.41	662,975.27	3,416,639.84	50,539.41	800.78

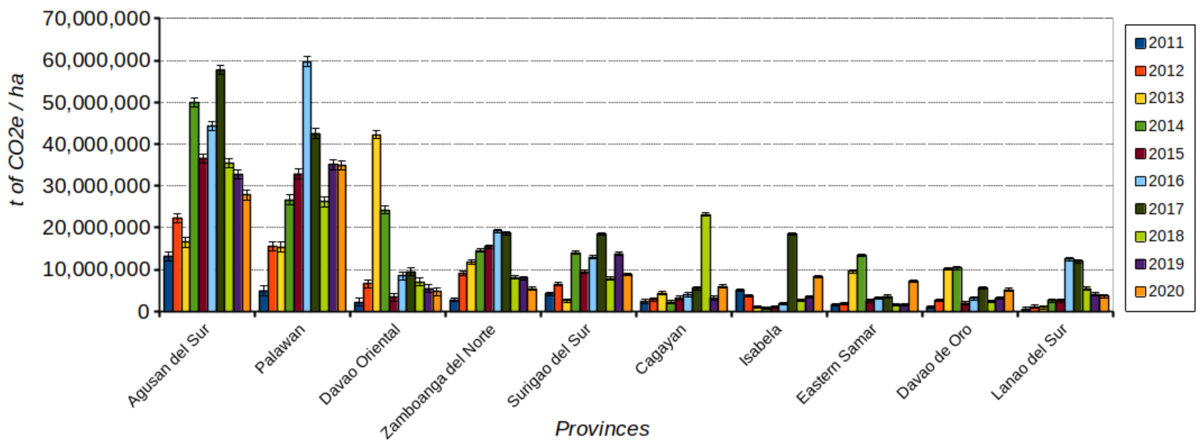

Figure 6. Annual greenhouse gas emissions of top ten provinces by total forest GHG (error bars expressed as standard deviation, σ).

3.4 Trend Analysis of Forest Loss and Forest GHG Emission

Trend values for forest loss and forest GHG emissions exhibit quite similar characteristics. Among the identified provinces from earlier tables and figures, only Maguindanao (r_{fl} = 0.80, r_{ghge} = 0.82) and Davao Oriental (r_{fl} = 0.66,

r_{ghge} = 0.67) have positive and increasing linear trends in both forest loss and forest emission categories, respectively. Interestingly, Cordillera provinces like Ifugao (r_{fl} = 0.82, r_{ghge} = 0.79) and Mountain Province (r_{fl} = 0.78, r_{ghge} = 0.83) also show an increasing linear trend. In contrast, Aurora (r_{fl} = -0.66, r_{ghge} = - 0.68) and Pampanga (r_{fl} = - 0.79, r_{ghge} = - 0.81) have a decreasing trend in forest loss and forest emission. It is important to note that Aurora was the 8th province with the most forest cover while Pampanga had the least forest cover in 2010 (FMB, 2010).

Table 5. Pearson correlation coefficients (r) for annual forest loss and forest GHG emission ($p < 0.05$).

Forest Loss				**Forest GHG Emission**			
Provinces	***r***	**Total Loss (ha)**	**Slope (forest loss annual increment) (ha)**	**Provinces**	***r***	**Total GHG Ems (t of CO2e/ha)**	**Slope (forest GHG emission annual increment) (ha)**
Ifugao	0.82	1,147.72	15.83	Mountain Province	0.83	5,306,920.29	850.68
Maguindanao	0.80	1,697.67	24.84	Maguindanao	0.82	16,396,524.61	19,288.85
Mountain Province	0.78	565.95	1.24	Ifugao	0.79	10,623,179.81	10,311.85
Samar	0.67	2,310.43	36.46	Samar	0.68	25,218,865.85	30,041.08
Sarangani	0.66	600.85	5.71	Davao Oriental	0.67	113,600,717.57	-92,676.91
Davao Oriental	0.66	9,976.14	-100.09	Sarangani	0.64	6,230,650.56	4,510.46
Sulu	0.64	276.274	5.05	Palawan	0.63	293,849,054.90	246,378.20
Aurora	-0.66	1,566.35	-13.11	Sulu	0.63	2,613,394.24	3,915.21
Pampanga	-0.79	45.40	-0.93	Aurora	-0.68	16,344,600.60	-142,023.19
				Pampanga	-0.81	394,079.92	-9,863.81

Selected significant annual forest loss and forest GHG emission graphs are presented below to illustrate their trend similarity.

Annual Forest Loss Annual Forest GHG Emissions

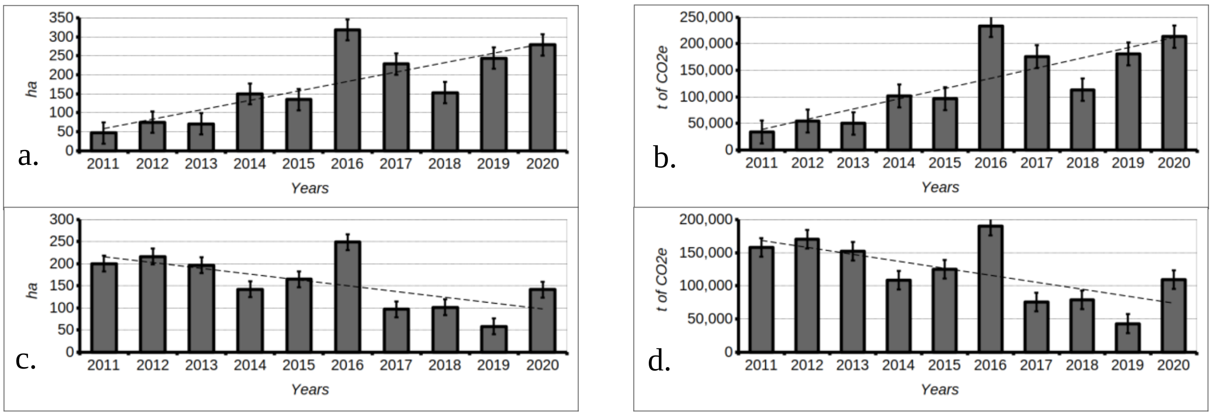

Figure 7. Forest GHG emission of Maguindanao (a,b), Aurora (c,d).

4. CONCLUSION AND RECOMMENDATION

In this study, we analyzed Philippine provinces in connection with annual forest loss and forest GHG emissions from 2011-2020. Most of the provinces which made the list in terms of total and proportional forest loss and gross forest GHG emission came from Mindanao. Several of them showed an increasing pattern of forest loss up to the first half of 2010-2020 and then dip suddenly in the subsequent years (e.g. AdS and Palawan). Correlation results illustrate a significant increasing linear trend for the provinces that are mainly absent in forest loss and forest GHG emission results listing. Subnational analysis of forest change dynamics could be useful in identifying and prioritizing provinces that need attention and immediate intervention for effective forest management and to address deforestation drivers and its causes. Data generated and results presented in this study need to be carefully evaluated and confirmed through field validation surveys (e.g. forest C stock estimation) and probability based statistical methods to find out the acceptable forest cover change extent and emission figures. Finally, in-depth studies that untangle and fully explain the complex relationships and mechanisms of deforestation drivers in the country are needed to avoid the simplistic blame game that mainly targets the most vulnerable sectors in the uplands - the poor and landless farmers - as agents of forest denudation.

5. CODE AVAILABILITY

Google Earth Engine and R script are available for access:
https://github.com/brentfallarcuna/Phil_ForestLossEmissions_11-20

LITERATURE CITED

Achard, F., Stibig, H. J., Eva, H. D., Lindquist, E. J., Bouvet, A., Arino, O., & Mayaux, P., 2010. Estimating tropical deforestation from Earth observation data. Carbon Management, 1(2), pp. 271–287.

Angelsen, A., 2009. Introduction. In: Realising REDD+: National Strategy and Policy Options, edited by Angelsen A., Center for International Forestry Research (CIFOR), Bogor, Indonesia pp. 1-9.

Apan, A., Suarez, L. A., Maraseni, T., & Castillo, J. A., 2017. The rate, extent and spatial predictors of forest loss (2000–2012) in the terrestrial protected areas of the Philippines. Applied Geography, 81, pp. 32–42.

Araza, A. B., Castillo, G. B., Buduan, E. D., Hein, L., Herold, M., Reiche, J., Gou, Y., Villaluz, M. G. Q., & Razal, R. A., 2021. Intra-Annual Identification of Local Deforestation Hotspots in the Philippines Using Earth Observation Products. Forests, 12(8), 1008.

Arts, B., Ingram, V., & Brockhaus, M., 2019. The Performance of REDD+: From Global Governance to Local Practices. Forests, 10(10), 837.

Austin, K. G., González-Roglich, M., Schaffer-Smith, D., Schwantes, A. M., & Swenson, J. J., 2017. Trends in size of tropical deforestation events signal increasing dominance of industrial-scale drivers. Environmental Research Letters, 12(5), 054009.

Bellot, F., Bertram, M., Navratil, P., Siegert, F., & Dotzauer, H., 2017. “The high-resolution global map of 21st - century forest cover change from the University of Maryland (‘Hansen Map’) is hugely overestimating deforestation in Indonesia” [Press release]. Forests and Climate Change Programme (FORCLIME), Indonesian Ministry of Environment and Forestry (MoEF) and the German Ministry for Economic Cooperation and Development (BMZ), Jakarta, Indonesia. https://forclime.org/documents/press_release/FORCLIME_Overestimation%20of%20Deforestation.pdf

Burgess, R., Hansen, M., Olken, B. A., Potapov, P., & Sieber, S., 2012. The Political Economy of Deforestation in the Tropics, The Quarterly Journal of Economics, 127(4), pp. 1707–1754.

Chavez, C., 2020. DILG chief says small-time illegal loggers continue to operate. Manila Bulletin. https://mb.com.ph/2020/11/23/dilg-chief-says-small-time-illegal-loggers-continue-to-operate/

Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., & Hansen, M. C., 2018. Classifying drivers of global forest loss. Science, 361(6407), pp. 1108–1111.

Fallarcuna, B. & Perez, G. P., 2016. Forest Cover Dynamics in the Philippines from LandSAT-Derived Global Forest Cover Dataset (2000-2012). Journal of the Philippine Geosciences and Remote Sensing Society, 2, pp. 4-17.

Forest Management Bureau (FMB), 2010. Forest Cover. https://forestry.denr.gov.ph/index.php/statistics/forest-cover

Forest Management Bureau (FMB), 2019. 2010 and 2019 Forestry Statistics. Department of Environment and Natural Resources, Quezon City, Philippines.

General Administrative Area (GADM), n.d. Provincial Boundary of the Philippines. https://gadm.org/maps/PHL.html

Global Forest Watch (GFW), 2021. Global Forest Watch Open Data Portal [Forest greenhouse gas emissions from stand-replacing disturbances at 30 x 30 m resolution]. Harris, N.L., D.A. Gibbs, A. Baccini, R.A. Birdsey, S. de Bruin, M. Farina, L. Fatoyinbo, M.C. Hansen, M. Herold, R.A. Houghton, P.V. Potapov, D. Requena Suarez, R.M. Roman-Cuesta, S.S. Saatchi, C.M. Slay, S.A. Turubanova, A. Tyukavina. 2021. Global maps of twenty-first century forest carbon fluxes. Nature Climate Change.

Global Land Analysis and Discovery (GLAD)., 2013. Global 2010 Tree Cover (30 m) | GLAD [Global 2010 tree cover percentage at 30 x 30 m resolution]. Global Land Analysis and Discovery, Department of Geographical Sciences, University of Maryland. https://glad.umd.edu/dataset/global-2010-tree-cover-30-m

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G., 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science, 342(6160), pp. 850–853.

Harris, N. L., Gibbs, D. A., Baccini, A., Birdsey, R. A., de Bruin, S., Farina, M., Fatoyinbo, L., Hansen, M. C., Herold, M., Houghton, R. A., Potapov, P. V., Suarez, D. R., Roman-Cuesta, R. M., Saatchi, S. S., Slay, C. M., Turubanova, S. A., & Tyukavina, A. 2021. Global maps of twenty-first century forest carbon fluxes. Nature Climate Change, 11(3), pp. 234–240.

Harris, N. L., Goldman, E., Gabris, C., Nordling, J., Minnemeyer, S., Ansari, S., Lippmann, M., Bennett, L., Raad, M., Hansen, M., & Potapov, P. (2017). Using spatial statistics to identify emerging hot spots of forest loss. Environmental Research Letters, 12(2), 024012.

Leblois, A., 2018. Remote-sensing evidence about national deforestation rates in developing countries: what can be learned from the last decade. Reference Module in Earth Systems and Environmental Sciences, Elsevier Reference Collection System, pp. 1-32.

Lewis, S. L., Edwards, D. P., & Galbraith, D., 2015. Increasing human dominance of tropical forests. Science, 349(6250), 827–832.

Mallari, D. T., Jr., 2019. Polls, illegal logging surge linked. Philippine Daily Inquirer. https://newsinfo.inquirer.net/1086831/polls-illegal-logging-surge-linked

Mangahas, J., 2010. Making A Difference in Mindanao. Asian Development Bank. https://www.adb.org/publications/making-difference-mindanao

Mendez, C. (2018, January 10). President Duterte shuts down logging firms. Philstar.Com. https://www.philstar.com/headlines/2018/01/10/1776385/president-duterte-shuts-down-logging-firms

National Mapping and Resources Information Authority (NAMRIA), 2010. Philippine Land Cover Data of 2010. National Mapping and Resources Information Authority, Department of Environment and Natural Resources, Taguig City, Philippines.

Pereira, O., Ferreira, L., Pinto, F., & Baumgarten, L., 2018. Assessing Pasture Degradation in the Brazilian Cerrado Based on the Analysis of MODIS NDVI Time-Series. Remote Sensing, 10(11), 1761.

Perez, G. J., Comiso, J. C., Aragones, L. V., Merida, H. C., & Ong, P. S., 2020. Reforestation and Deforestation in Northern Luzon, Philippines: Critical Issues as Observed from Space. Forests, 11(10), 1071.

Roddy, M., 2021. How Tree Cover Loss Data Has Changed Over Time | GFW Blog. Global Forest Watch Content. https://www.globalforestwatch.org/blog/data-and-research/tree-cover-loss-satellite-data-trend-analysis/

Serrano, I. R., 2005. Nature Exploitation and Protection in Mindanao. In: Social Watch Philippines 2005 Report: Race for Survival Hurdles on the road to meeting the MDGs in 2015. Social Watch Philippines, Quezon City, Philippines, pp. 89-91.

Tang, H., Armston, J., Hancock, S., Marselis, S., Goetz, S., & Dubayah, R., 2019. Characterizing global forest canopy cover distribution using spaceborne lidar. Remote Sensing of Environment, 231, 111262.

Tropek, R., Sedláček, O., Beck, J., Keil, P., Musilova, Z., Imova, I., & Storch, D., 2014. Comment on "High-resolution global maps of 21st-century forest cover change." Science, 344(6187), 981.

United Nations Food and Agriculture Organization (UN-FAO), 2020. Global Forest Resources Assessment 2020 Key Findings. Food and Agriculture Organization of the United Nations, Rome, Italy.

United Nations Forum on Forests, 2017. United Nations Strategic Plan for Forests. United Nations Department of Economic and Social Affairs. https://www.un.org/esa/forests/documents/un-strategic-plan-for-forests-2030/index.html

World Resources Institute (WRI), 2014. Forest Monitoring, Land Use & Deforestation Trends. Global Forest Watch. https://www.globalforestwatch.org/

Zarin, D. J., Harris, N. L., Baccini, A., Aksenov, D., Hansen, M. C., Azevedo‐ Ramos, C., Azevedo, T., Margono, B. A., Alencar, A. C., Gabris, C., Allegretti, A., Potapov, P., Farina, M., Walker, W. S., Shevade, V. S., Loboda, T. V., Turubanova, S., & Tyukavina, A., 2016. Can carbon emissions from tropical deforestation drop by 50% in 5 years? Global Change Biology, 22(4), 1336–1347.