MONITORING GROSS PRIMARY PRODUCTION USING THE SATELLITE DATA

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Abstract: Monitoring carbon storage in the forest is important for tracking ecosystem functionalities and climate change impacts. Estimation of GPP and study of the carbon cycle in Mongolia is essential. The main aim of this study is to develop an estimation approach for monitoring GPP (Gross Primary Production) for Mongolian forests using satellite data. GPP takes into account how much carbon dioxide (CO2) is taken in by vegetation during photosynthesis GPP and how much CO2 is given off during respiration, which is the process by which organisms use food to produce energy. The study focused on the Remote Sensing data and biomass data from ground truth measurements in 2018. Output MONGPP for 2000-2020 data were related to NDVI and LST from MODIS and agreement was 69% and 41% respectively. Thus, the estimation of carbon stocks of different climate zones would help in appropriate decision-making on carbon management in the region. This study will contribute to understanding the dynamics of carbon stocks in relation to the key factors for the sustainable management of forest carbon.

Keywords: GPP (Gross Primary Production), NDVI (Normalized Different Vegetation Index), LST (Land Surface Temperature)

1. INTRODUCTION

Forest cover is around 30% of the Earth's total surface area, and contains 19% of the Earth's overall biomass and carbon pool (Kindermann et al., 2008; FAO and UNEP 2020). Forest act as the key carbon pool for the earth and store greater biomass and soil carbon than any natural ecosystem and atmosphere (Popkin, 2019; Pugh et al., 2019; Liu et al., 2020; Favero et al., 2020; Yam et al., 2021). The carbon-sequestration capacity of forests accounts for 76–98% of the entire terrestrial ecosystem (Cheng et al., 2009) and is vital for reducing global warming caused by carbon dioxide concentration (Wang et al., 2013). Forests play an important role in storing CO2 in the global carbon balance, thereby combating adverse global climate change among other ecosystem services (Albrecht et al., 2003; Houghton et al., 2007; Heimann et al., 2008; Chave et al., 2014Liu et al., 2018).
Carbon dioxide (CO2) is one of the greenhouse gases, and its increasing concentration in the atmosphere leads to global warming and climate change. Forest are the lifeline of the world's human population, which helps to mitigate the ever-increasing atmospheric CO2 concentration. Among the most acclaimed ecosystem services provided by forests are atmospheric carbon (CO2) sequestration and its storage (Canadell and Raupach 2008). This service is of strategic importance in mitigating ongoing climate change because it acts directly in controlling global warming (Bonan 2008). Nevertheless, CO2 stocks in forest biomass decreased globally mainly because of a reduction in the global forest cover. Also, the basic elements of forest ecosystems are decreasing and degrading due to industrialization, urbanization, and human activities all over the world. Deforestation has altered the concentration of greenhouse gases in the atmosphere, thereby affecting climate and biodiversity, and becoming a threat by changing the global CO2 cycle (Harris et al. 2012). Deforestation and forest degradation typically account for 17-20% of the world's greenhouse gas (GHG) emissions (Albrecht et al., 2003; Bhishma et al., 2010; FAO, 2005; FAO, 2012; Ngo K et al., 2013). Carbon dioxide (CO2), which is partly released as a result of forest degradation, contributes to about 60% of the anthropogenic greenhouse effects and climate change (Pierzynski et al., 2005; Hendri et al., 2014). Currently, climate change is a global concern, and forests play a vital role in the regulation and mitigation of climate change by reducing CO2 concentrations in the atmosphere (Streck et al., 2006; Brack et al., 2019; Ali et al., 2020; United Nations Framework Convention on Climate Change., 2014; 2020; Burman et al., 2021). And climate change, which is now a major global challenge, is creating much evidence of irreversible environmental impacts (FAO, 2012; Pierzynski et al., 2005; FC (Forestry Commission), 2011). Forest ecosystems play an important role in global biogeochemical cycles and climate change mitigation (Lal and Lodhyal, 2015; Brienen et al., 2015; Atsbha et al., 2019). This kind of information also

contributes toward atmospheric carbon reduction targets as part of international obligations (UNFCCC 2014; Sahu et al., 2016; Mayer et al., 2020). Increasing forest carbon storage can significantly contribute to maintaining the global carbon balance and mitigating climate change (Fu, Y. 2018; Liu et al., 2020).

Forest CO2 storage is an expanding research topic that addresses local and global strategies for the reduction of emissions of CO2 into the atmosphere (Stavins et al., 2005; Sheikh et al., 2014). However, there are few studies that quantify CO2 storage in forests worldwide (Chave et al., 2014; Gibbs et al.,2007; Brown et al., 1997; Nelson et al., 199; Chave et al., 2005; Basuki et al., 2009; Navar et al., 2009; Henry et al., 2010; Beets et al., 2012), and many forests are unexplored (Jara et al., 2014; Ensslin et al., 2015). Therefore, we investigated the appropriate methodology for studying MONGPP in Mongolia using the ARIMA model.

2. STUDY AREA AND DATA

Study Area

Mongolia is a region with a continental climate, fragile nature, and semi-arid and dry climate. The study area is Bulgan province one of the northern parts of Mongolia (Figure 1). This area has a subarctic climate where the absolute temperature is +34,8 °C in summer, the absolute temperature is -45°C during winter. The average annual precipitation is 324 mm in this area. We used the ground truth measurement data for August, 2018 from the Bulgan province.

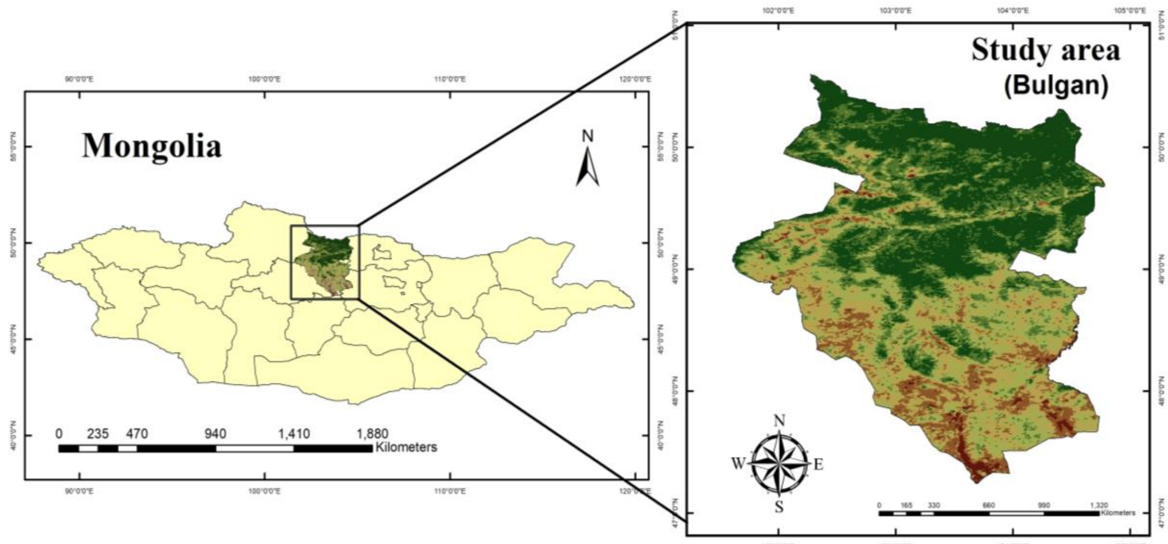


Figure 1. Location map of the Bulgan province of Mongolia.

Data

Terrestrial biological productivity, MODIS' Gross Primary Production (GPP) product, is important both practically and theoretically. Carbon cycle models are closely tied to global climate models, and regular measurements of gross and GPP are essential for both (https://modis.gsfc.nasa.gov/data). GPP estimation using the MODIS-GPP products MOD17A2HGF-006 collection 5.1 (https://lpdaac.usgs.gov/) was used in this research to evaluate MONGPP.

3. METHODOLOGY

Autoregressive (AR), Integrated (I), and Moving Average (MA) ARIMA model was applied to develop an estimation approach for MONGPP in the Mongolian forest zone. Equations 1 and 2 from the seasonal ARIMA were used to develop MONGPP model. The AR (p) model is defined as:

$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + u_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + u_t \qquad (1)$$

where φ_1, φ_2, …, φ_n illustrate the autoregressive coefficients, c is a constant, and u_t demonstrates white noise. In the autoregressive model of order p, the value of the time series at t, X_t depends upon the previous p-values and random disturbance (the stochastic part).

$$X_t = 0{,}7079 + 1.7215X_{t-1} - 0.9886X_{t-2} - 1.0831\varepsilon_{t-3} - 0.3202\varepsilon_{t-2} + 0.6237\varepsilon_{t-1} + \varepsilon_t \qquad (2)$$

where X_t is the value of GPP at time t and ε_t is the error term at time t. Equation (2) was used to create a map for MONGPP in 2020.

Multiple linear regression was used to find relationship among MONGPP, NDVI and LST.

If the joint distribution function of a random vector (X, Y) is equal to the product of its respective distribution functions for any number x, y, then the variables X and Y are said to be independent. Otherwise, they are called dependent variables. Englishman Francis Galton (1822-1911) first coined the term regression when he studied the relationship between child and parent height. If the dependent variable y examines the relationship between only one explanatory variable, it is called a simple regression. The pattern of transformation of a phenomenon can depend on many factors. If the relationship between the dependent variable y $(x_1, x_2, \ldots, x_n)$ is studied, it is called multivariate regression analysis (Makhgal et al., 2015).

A general linear regression model equation 3 was used for the analysis.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad (3)$$

Энд $y -$ Dependent variable

$\beta_0, -$ Intercept

$\beta_1, \ldots, \beta_n -$ Coefficient of regression,

$x_1, x_2, \ldots, x_n -$ Independent variable

$\varepsilon -$ Disturbance error

4. ANALYSIS

The detailed distribution of average vegetation growing season GPP for 2000–2020 is shown the Figure 2.

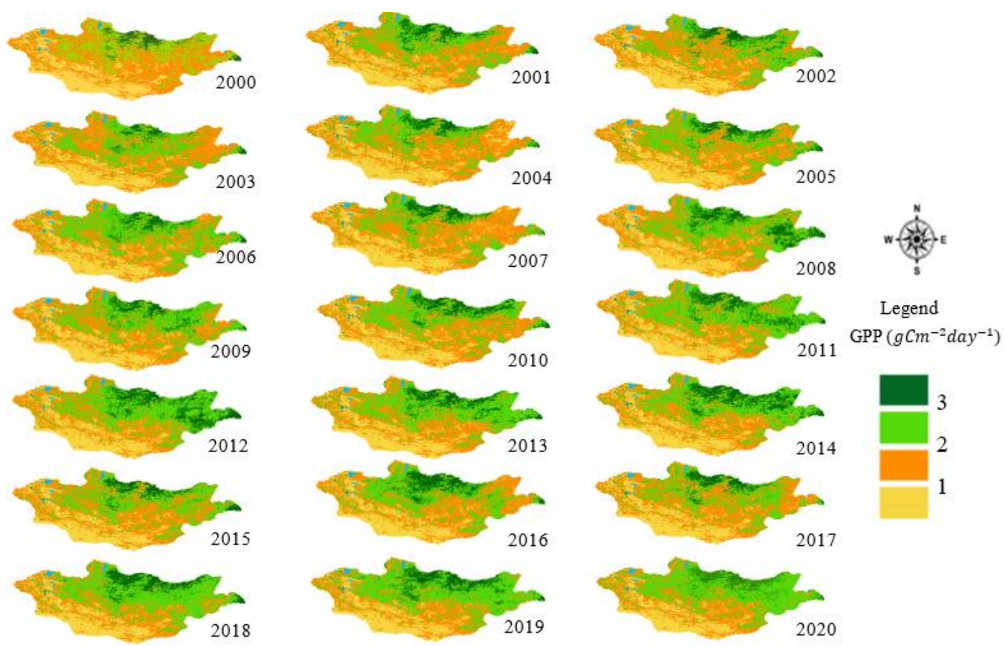


Figure 2. Spatial distribution of GPP for growing season 2000-2020.

Based on equation (2), we received MONGPP in figure 3.

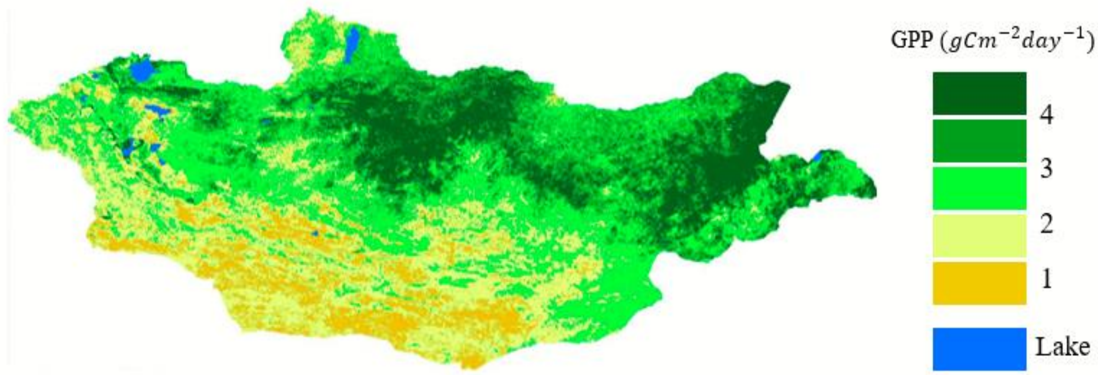


Figure 3. MONGPP for Forest zone for 2000-2020.

We collected 80 points for estimated MONGPP and GPP, then examined their relationships for forest zone (Figure 4).

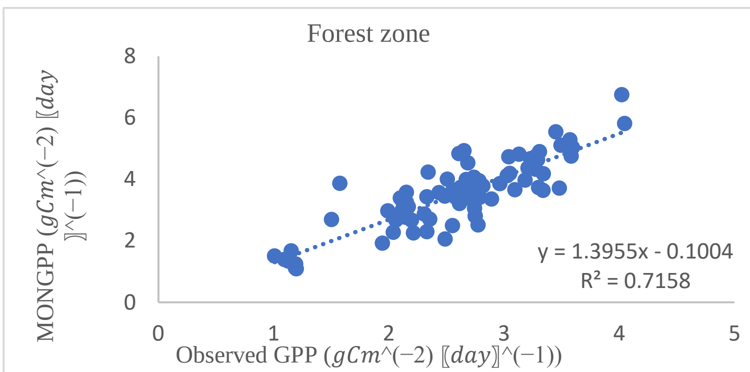
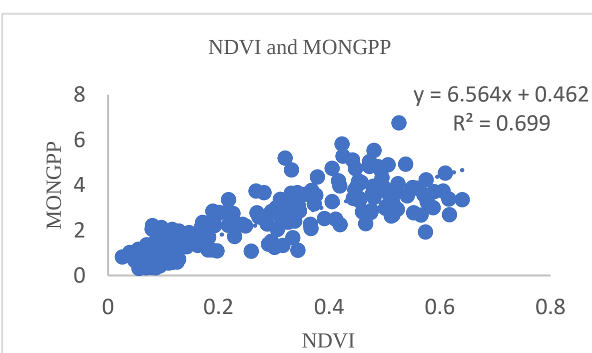


Figure 4. Correlation between the GPP and MONGPP.

There are strong positive relationships between MONGPP and GPP (r2=0.71) for forest zone. This comparison reveals that the selected approach can simulate the dynamic change of GPP in the study area. Figure 5 shows the relationship between the MONGPP, NDVI and LST for Mongolia for the 2020 year.



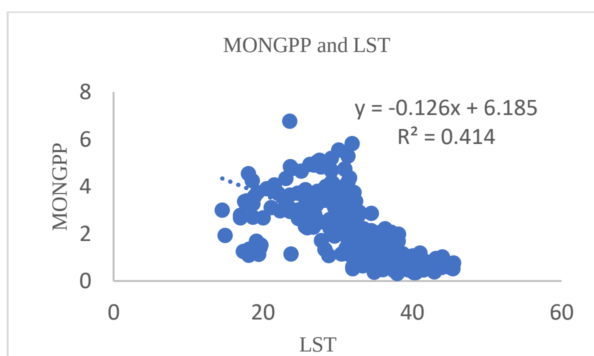


Figure 5. (a) relationship between MONGPP and NDVI, (b) relationship between MONGPP and LST.

Multiple linear regression was applied to determine relationships among NDVI, LST and MONGPP from the approach and the result was statistically significant at $p < 0.0001$ (NDVI) and $p < 0.0005$ (LST) (Table 1).

Table 1. Result of linear regression

Variable	Coefficient	Std. Error	*t*-Statistics	Prob.	R Square	Observations
Interception	-0.43461	0.219576	-1.97931	0.051356		
NDVI	4.486093	0.26372	17.01079	8.44E-28	0.7914	80
LST	0.050102	0.005398	9.282023	3.43E-14		

5. RESULT AND CONCLUSION

To monitor Gross Primary Production in Mongolia, we used MODIS GPP 1km product. Monitoring carbon storage in forest resources is important for tracking ecosystem functionalities and climate change impacts. We conclude that determining GPP for the past, present is important for Mongolia. The relationship between output MONGPP and GPP was 71% for the forest zone. Multiple linear regression analysis describes a good agreement which is 79%. In further research, we will consider general data of land cover, satellite data, and economic, statistic data for GPP estimation.

REFERENCES

1. Albrecht A, Kandji ST. Carbon sequestration in tropical agroforestry systems. Ecosyst Environ. 2003; 99: 15–27. https://doi.org/10.1016/S0167-8809(03)00138-5
2. Ali, A., Ashraf, M.I., Gulzar, S., Akmal, M., 2020. Estimation of forest carbon stocks in temperate and subtropical mountain systems of Pakistan: implications for REDD+ and climate change mitigation. Monit. Assess. 192 (3), 1–13.
3. Atsbha, T., Desta, A.B., Zewdu, T., 2019. Carbon sequestration potential of natural vegetation under grazing influence in Southern Tigray, Ethiopia: implication for climate change mitigation. Heliyon 5 (8), e02329.
4. Basuki TM, van Laake PE, Skidmore AK, Hussin YA. Allometric equations for estimating the aboveground biomass in tropical lowland Dipterocarp forests. For Ecol Manag. 2009; 257(8): 1684–1694. https://doi.org/10.1016/j.foreco.2009.01.027
5. Beets PN, Kimberley MO, Oliver GR, Pearce SH, Graham JD, Brandon A. Allometric equations for estimating C stocks in natural forest in New Zealand. For. 2012; 3 (4): 818–39. https://doi.org/10.3390/f3030818
6. Bhishma PS, Shiva SP, Ajay P, Eak BR, Sanjeeb B, Tibendra RB, et al. Forest C stock measurement: Guidelines for measuring C stocks in community-managed forests funded by NORAD. Kathmandu: ANSAB Publishing; 2010. PLOS ONE Carbon stocks of tree biomass in Kibate Forest PLOS ONE | https://doi.org/10.1371/journal.pone.0254231 July 9, 2021 12 / 15
7. Bonan GB. 2008. Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science* 320(5882): 1444-1449. DOI: 10.1126/science.1155121
8. Bracki, D., 2019, March. Forests and climate change. In: Proceedings of Background Study Prepared for the Fourteenth Session of the United Nations Forum on Forests
9. Brienen, R.J., Phillips, O.L., Feldpausch, T.R., Gloor, E., Baker, T.R., Lloyd, J., Zagt, R.J., 2015. Long-term decline of the Amazon carbon sink. Nature 519 (7543), 344–348.
10. Brown S, Gillespie JR, Lugo AE. Biomass estimation methods for tropical forests with application to forest inventory data. For Sci. 1989; 35 (4): 881–902.

11. Brown S. Estimating biomass and biomass change of tropical forests, A primer. Forestry paper 134. Rome: FAO; 1997.
12. Burman, P.K.D., Launiainen, S., Mukherjee, S., Chakraborty, S., Gogoi, N., Murkute, C., Kumar, K., 2021. Ecosystem-atmosphere carbon and water exchanges of subtropical evergreen and deciduous forests in India. For. Ecol. Manag 495, 119371.
13. Canadell JG, MR Raupach. 2008. Managing forests for climate change mitigation. *Science* 320(5882): 1456-1457. DOI: 10.1126/science.1155458
14. Chave J, Cairns MA, Andalo C, Brown C, Chambers S, Eamus JQ, et al. Tree allometry and improved estimation of C stocks and balance in tropical forests. Oecologia. 2005; 145: 87–99. https://doi.org/10.1007/s00442-005-0100-x PMID: 15971085
15. Chave J, Re´jou-Me´chain M, Bu´rquez A, Chidumayo E, Colgan MS, Delitti WBC, et al. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob Chan Biol. 2014; 20 (10): 3177–3190. https://doi.org/10.1111/gcb.12629 PMID: 24817483
16. Cheng, W.X.; Yang, C.J.; Zhou, W.C.; Liu, Y.C. Research summary of forest volume quantitative estimation based on remote sensing technology. J. Anhui Sci. 2009, 37, 7746–7750.
17. Cordeiro NG, KMG Pereira, MCNS Terra, JM Mello. 2018. Variação temporal do estoque de carbono e volume de madeira em um fragmento de cerrado *sensu stricto*. *Enciclopédia Biosfera* 15(28): 931-942. DOI: 10.18677/ EnciBio_2018B76
18. Dantas D, MCNS Terra, LOR Pinto, N Calegario, SM Maciel. 2021. Above and belowground carbon stock in a tropical forest in Brazil. *Acta Scientiarum. Agronomy* 43:e48276. DOI: 10.4025/actasciagron.v43i1.48276
19. Ensslin A, Rutten G, Pommer U, Zimmermann R, Hemp A, Fischer M. Effects of elevation and land use on the biomass of trees, shrubs and herbs at Mount Kilimanjaro. Ecosphere. 2015; 6(3): 1–45. https://doi.org/10.1890/ES14-00492.1
20. FAO (Food and Agriculture Organization). Forests and climate change working paper 10: Forest management and climate change: A literature review. Rome: FAO/UN; 2012.
21. FAO (Food and Agriculture Organization). Global forest resource assessment 2005: Progress towards Sustainable Forest Management. Rome: FAO; 2006.
22. FAO and UNEP, 2020. The State of the World's Forests 2020. Forests, biodiversity and people. Rome.
23. Favero, A., Daigneault, A., Sohngen, B., 2020. Forests: carbon sequestration, biomass energy, or both? Sci. advan. 6 (13), eaay6792.
24. FC (Forestry Commision). Forests and climate Change: UK Forestry Standard Guidelines. Edinburgh: Forestry Commission; 2011.
25. Fu, Y. Aboveground biomass estimation and uncertainties assessing on regional scale with an improved model analysis method. Hubei For. Sci. Technol. 2018, 47, 1–4+38.
26. Gibbs HK, Brown S, Niles JO, Foley JA. Monitoring and estimating forest C stocks: Making REDD a reality. Environ Res Lett. 2007; 2: 045023. https://doi.org/10.1088/17489326/2/4/045023
27. Harrell FE. Regression modeling strategies: with applications to linear models, logistic regression, and survival analysis. New York: Springer-Verlag New York, 2013.
28. Heimann M, Reichstein M. Terrestrial ecosystem carbon dynamics and climate feedbacks. Nature. 2008; 451: 289–292. https://doi.org/10.1038/nature06591 PMID: 18202646
29. Hendri J, Sumawinata B, Putro D, Baskoro T. CO2 flux from tropical land uses on Andisol in West Java, Indonesia. J Trop Soil. 2014, 19(3): 121–130.
30. Henry M, Besnard A, Asante W, Eshun J, Adu-Bredu S, Valentini R, et al. Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. For Ecol Manag. 2010; 260: 1375–1388. https://doi.org/10.1016/j.foreco.2010.07.040
31. Houghton R. Balancing the global carbon budget. Annu Rev Earth Planet Sci. 2007; 35: 313–347. https://doi.org/10.1146/annurev.earth.35.031306.140057
32. https://lpdaac.usgs.gov/

33. Jara MC, Henry M, Re´jou-Me´chain WC, Wayson C, Zapata-Cuartas M, Piotto D, et al. Guidelines for documenting and reporting tree allometric equations. Ann For Sci. 2014; 71(5). https://doi.org/10.1007/s13595-014-0415-z
34. Kindermann, G., Obersteiner, M., Sohngen, B., Sathaye, J., Andrasko, K., Rametsteiner, E., Beach, R., 2008. Global cost estimates of reducing carbon emissions through avoided deforestation. Proc. Natl. Acad. Sci 105 (30), 10302–10307.
35. Lal, B., Lodhiyal, L.S., 2015. Vegetation structure, biomass and carbon content in *Pinus roxburghii* Sarg. Dominant forests of Kumaun Himalaya. Int. J. Sci. & Tech. 10, 117–124.
36. Liu X, Trogisch S, He J-S, Niklaus PA, Bruelheide H, Tang Z, et al. Tree species richness increases ecosystem carbon storage in subtropical forests. Proc R Soc B. 2018; 285: 20181240. https://doi.org/ 10.1098/rspb.2018.1240 PMID: 30135164
37. Liu, N.; Sun, P.; Caldwell, P.V.; Harper, R.; Liu, S.; Sun, G. Trade-off between watershed water yield and ecosystem productivity along elevation gradients on a complex terrain in southwestern China. J. Hydrol. 2020, 590, 125449.
38. Liu, Z., Ciais, P., Deng, Z., et al., 2020. Near-real-time monitoring of global CO2 emissions reveals the effects of the COVID-19 pandemic. Nat. Commun. 11, 5172.
39. Makhgal ,G., Jamyansharav, B., 2015. Introduction to probability statistics
40. Mayer, M., Prescott, C.E., Abaker, W.E., Augusto, L., C´ecillon, L., Ferreira, G.W . (2020). Tamm Review: influence of forest management activities on soil organic carbon stocks: a knowledge synthesis. . For. Ecol. Manag. 466.
41. Na´var J. Allometric equations for tree species and C stocks for forests of Northwestern Mexico. For Ecol Manag. 2009; 257(2): 427–434, 2009. https://doi.org/10.1016/j.foreco.2008.09.028
42. Nelson BW, Mesquita R, Pereira JLG, de Souza SGA, Batista GT, Couto LB. Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. For Ecol Manag. 1999; 117: 149–167. https://doi.org/10.1016/S0378-1127(98)00475-7
43. Ngo K, Turner M, Muller-Landau BL, Davies SJ, Larjavaara M, Hassan NF bin N, et al. Carbon stocks in primary and secondary tropical forests in Singapore. For Ecol Manag. 2013; 296: 81 89. https://doi.org/10.1016/j.foreco.2013.02.004
44. Pierzynski GM, Sims JT, Vance GF. Soils and enviromnental quality, 3rd ed. CRC Taylor & Francis; 2005.
45. Popkin, G., 2019. How much can forest fight climate change? Nature 565 (7737), 280–283.
46. Pugh, T.A., Lindeskog, M., Smith, B., Poulter, B., Arneth, A., Haverd, V., Calle, L., 2019. Role of forest regrowth in global carbon sink dynamics. Proc. Natl. Acad. Sci. 116 (10), 4382–4387.
47. Sahu, S.C., Kumar, M., Ravindranath, N.H. (2016). Carbon stocks in natural and planted mangrove forests of Mahanadi Mangrove Wetland. East Coast of India. Curr.
48. Sheikh AQ, Skinder BM, Pandit AK, Ganai BA. Terrestrial carbon sequestration as a climate change mitigation activity. J Pollut Eff Control. 2014; 2(1).
49. Stavins RN, Richards KR. The cost of US forest-based carbon sequestration. Pew Centre on Global Climate Change; 2005.
50. Streck, C., Scholz, S.M., 2006. The role of forests in global climate change: whence we come and where we go. Inter Affar 82 (5), 861–879.
51. UNFCCC. (2014). UNFCCC detailed annual report. . http://unfccc.int/resource/docs/2014.
52. Wang, X.; Shao, G.; Chen, H.; Lewis, B.J.; Qi, G.; Yu, D.; Zhou, L.; Dai, L. An Application of Remote Sensing Data in Mapping Landscape-Level Forest Biomass for Monitoring the Effectiveness of Forest Policies in Northeastern China. Environ. Manag. 2013, 52, 612–620.
53. Yam, G., Tripathi, O.P., Das, D.N., 2021. Modelling of total soil carbon using readily available soil variables in temperate forest of Eastern Himalaya, Northeast India. Geol., Ecol. Land. 5 (3), 209–216.