**Understanding the potential of reforestation as a nature-based climate solution**

**Version 1.0**

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About

The maps in this dataset were produced from existing datasets to determine the climate mitigation potential of reforestation in Southeast Asia under various constraints, namely biophysical, financial, land-use and operational constraints through to the year 2030. This was done for three main forest types: peatswamp, mangrove and terrestrial forests. All calculations were based on data dated between 2013–2019 and at a resolution of 0.01 degrees (~1 km).

*Biophysical constraints*. Biophysical constraints were firstly determined by identifying degraded forest areas: maximum threshold of 35 MgCha-1 above-ground carbon for terrestrial forests1,2, indications of clearings for peatswamp forests3,4 and changes in Landsat pixels over time for mangrove forests5 from a pantropical above-ground carbon layer6. We then focus on degraded areas that are low in biomass due to natural biophysical settings, by masking out ‘forest’ or ‘woodland’ areas that were previously identified as degraded from the Potential Natural Vegetation (PNV) map7. We also masked out current landcover areas that would preclude reforestation, such as bare ground, industrial land, large scale agriculture, water and urban areas8,9. Lastly, we estimated the climate mitigation potential of each raster cell in the biophysical constraint layer based on the different forest types and subtypes according to the PNV map and IPCC classifications3,5,7,10. This was calculated as the sum of carbon dioxide likely to be sequestered due to aboveground biomass growth and avoided business-as-usual (BAU) flux annualised to 2030 (see Table S3 for details and key references). Climate mitigation potential for areas of smallholder agriculture – defined as agricultural areas of less than 2 ha – identified within the layer nevertheless, were taken as forests and its carbon gain was calculated as the difference between croplands and natural forests11.

*Financial constraints*. Financial constraints were determined by two components: direct cost of reforestation and the opportunity cost based on revenue lost from agricultural production. Direct costs of reforestation (including planning, planting and maintenance) across Southeast Asia were specified by forest type12,13 and adjusted to each country based on relative hourly wages14 and gross domestic product per capita15. The opportunity cost based on revenue lost from agricultural production in Southeast Asia were derived from spatially explicit crop rents of the 17 most economically important crops based on production in 2017, considering only crops produced in >1% of the country’s land area16. The maximum crop rent for each cell was then identified, indicating the maximum agriculture revenue lost due to reforestation. All costs were adjusted to 2018 USD. The *low estimate* of reforestation costs was based purely on direct cost. The *moderate estimate* was based on both direct and opportunity cost from foregone agricultural rent weighted by crop development potential index17. The *high estimate* was based on the direct and full opportunity cost. We thus calculated the cost of reforestation per ton of carbon dioxide equivalent mitigated, utilising the biophysical constraints layer and omitting all areas > 100 USD MgCO2e-1 to limit reforestation to cost-effective areas 18,19,20.

*Land-use constraints*. There are two levels of land-use constraints: *more permissive* one, which only excluded reforestation on smallholder agriculture lands (any raster cell that possessed agriculture lands ≤ 2 ha) with high estimated yield17, and a *less permissive* one which excluded reforestation on all smallholder agriculture lands.

*Operational constraints*. Four operational constraints were applied to account for the practical considerations that may influence the long-term viability of reforested sites. These include proximity to seed sources (SS), protection status (PA), deforestation risk (DR) and accessibility for monitoring and management (AM). SS was determined by utilising a 2-km buffer from the nearest existing forest edge as a proxy for propagule sources21-24 to support natural regeneration. Reforestation and thus climate mitigation potential is thus constrained to areas in relative proximity to seed sources. For PA, we constrained reforestation to legally protected areas25, namely those of IUCN categories I-VI, estimating the climate mitigation potential in areas with some form of protection status. For DR, we constrained reforestation to areas with acceptable likelihood of transition to deforested areas i.e. ≥ 0.5 probability of deforestation26 (medium to high potential) from a spatially explicit layer predicting tree cover loss to 2029, estimating the climate mitigation potential in areas with acceptable deforestation risk. We also considered AM to account for the need for continued monitoring and management associated with post-planting site upkeep, thus, limiting reforestation areas to within a day’s travelling time to the nearest cities27 and estimated the climate mitigation potential for these areas.

Uncertainties across estimations of climate mitigation potential were derived from the range of values associated with the aboveground carbon gain and the BAU flux reported in our literature review (see Table S3 for details), where the minimum and maximum climate mitigation potential across each forest type were calculated for each specific study10,28 or collated across a number of studies29-31. This produced a total of 111 maps, which represented the mean, minimum and maximum climate mitigation potential of each of the constrained reforestation estimations.

Further details for this dataset are presented in Zeng et. al.

Content

This dataset contains the raster layers that were derived as described above to determine the climate mitigation potential of reforestation in Southeast Asia under various constraints, namely biophysical, financial, land-use and operational constraints through to the year 2030.

Values for the biophysical raster layer are floating points with units in tCO2eha-1yr-1. The layers for the constraints however, are masks where their values are based on the constraints applied as the following:

*Financial constraint:*

3 *High estimate*: direct and opportunity costs from foregone agricultural rent

2 *Moderate estimate*: direct and opportunity costs from foregone agricultural rent, weighted by the likelihood of agricultural development

1 *Low estimate*: only direct costs are considered (e.g. site selection, planting and maintenance)

*Land-use constraint*:

2 *Less permissive*: All smallholder agriculture land excluded

1 *More permissive*: Only high yielding smallholder agriculture land is excluded

*Operational constraint:*

1 Operational constraint for SS, PA, DR and AM.

File naming convention:

*<Constraint>\_<Description>\_<Estimate>.tif*

<Constraint> identifies the reforestation constraints i.e. biophysical, financial, landuse or operational

<Description> describes the floating point values within the dataset, where descriptions labelled ‘Climate mitigation potential’ have units of tCO2eha-1yr-1, while those labelled ‘Constraints’ are single-digit floats valued as listed above.

<Estimate> identifies range of values assessed as ‘Max’, ‘Mean’ or ‘Min’

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