Supplementary Info	ormation for
An integrity asse	essment of
global forest carbon o	offset projects
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This PDF file includes:	
Supplementary Information A	
Supplementary Information B	
Supplementary Information C	
Supplementary Information D	
Supplementary Information E	
Supplementary Information F	
Tables S1 to S7	
Figs. S1 to S3	
References	
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Supplementary Information A: Additional tables and figures

Table S1 Data collection procedure for forest carbon offset projects

Program	Number of projects	Uncertified projects	Missing PDD	Missing or incomplete geoinformation ^a	Inconsistent geo info	Projects without issued credits	Out-of-scope satellite data (latitude within 51.6° N&S)	Projects with issued credits	Last issued before 2015	Projects starting after 2019	Main sample projects
ACR	169	100	2	19	1	3	2	42	0	3	39
CAR	146	42	1	20	0	48	1	34	0	0	34
CDM	67	0	0	5	0	30	0	32	9	0	23
VCS	144	22	1	50	0	8	1	62	3	1	58
CCER	100	83	7	2	2	4	0	2 (excluded)	0	0	0
GS	39	4	3	32 ^b	0	0	0	0	0	0	0
Total	665	251	14	128	3	93	4	170	12	4	154

Note: ^a Here, we exclude projects that overlap due to both missing PDDs and missing or incomplete geoinformation. ^b The boundary shapefile data for the GS crediting program are not uploaded to official websites.

32 Table S2 Robustness checks for effects of programs in 2021

	(1)	(2)
Variable	Discrepancy	Absolute discrepancy
ACR	0.322**	0.280**
	(0.147)	(0.135)
VCS	1.436***	1.880***
	(0.350)	(0.289)
CDM	2.089***	2.239***
	(0.572)	(0.521)
Constant	0.274***	0.365***
	(0.058)	(0.040)
Observations	158	158
Adjusted R-squared	0.114	0.217

Note: Heteroskedasticity-adjusted robust standard errors are in parentheses. *** p < 0.01,

^{34 **} p<0.05, * p<0.1.

Table S3 Evaluating effects of programs in 2019 by removing projects with less accurately inferred values verified before 2018

	(1)	(2)
Variable	Discrepancy	Absolute discrepancy
ACR	0.291*	0.263*
	(0.163)	(0.150)
CDM	1.396***	1.892***
	(0.365)	(0.296)
VCS	2.686***	2.793***
	(1.001)	(0.926)
Constant	0.319***	0.412***
	(0.072)	(0.057)
Observations	138	138
Adjusted R-squared	0.123	0.249

Note: Heteroskedasticity-adjusted robust standard errors are in parentheses. *** p<0.01,

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^{39 **} p<0.05, * p<0.1.

40 Table S4 Precision level and confidence interval of ex-post third-party verified

41 carbon stock densities by methodology

Methodology	Precision level	Confidence interval
ARB Compliance Offset Protocol: U.S. Forest Projects	5%	90%
AR-ACM0003	10%	90%
AR-ACM0001	10%	90%
AR-AM0005	10%	90%
AR-AM0004	10%	90%
AR-AM0014	10%	90%
AR-AM0003	10%	95%
AR-AM0002	10%	90%
AR-AM0001	10%	95%
AR-AMS0001	10%	95%
AR-AMS0007	10%	90%

43 Table S5 Evaluating effects of methodologies in 2019

	(1)	(2)
Variable	Discrepancy	Absolute discrepancy
Small-scale	1.367*	0.999
	(0.794)	(0.735)
Constant	0.619***	0.608***
	(0.111)	(0.096)
Program fixed effects	YES	YES
Tree species fixed effects	YES	YES
Observations	154	154
Adjusted R-squared	0.195	0.254

Note: Heteroskedasticity-adjusted robust standard errors are in parentheses. *** p<0.01,

^{45 **} p<0.05, * p<0.1.

Table S6 Evaluating effects of the characteristics of the host country in 2019

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Discrepancy	Discrepancy	Discrepancy	Absolute discrepancy	Absolute discrepancy	Absolute discrepancy
High- or Upper-middle	-1.503**		-0.770	-1.359***		-0.993*
	(0.582)		(0.630)	(0.501)		(0.552)
High BRDR		-2.149***	-1.802***		-1.348**	-0.900
		(0.600)	(0.663)		(0.529)	(0.581)
Constant	2.126**	2.783***	3.207***	1.971***	1.965***	2.511***
	(0.817)	(0.824)	(0.893)	(0.703)	(0.726)	(0.782)
Program fixed effects	YES	YES	YES	YES	YES	YES
Tree species fixed effects	YES	YES	YES	YES	YES	YES
Observations	154	154	154	154	154	154
Adjusted R ²	0.197	0.228	0.231	0.268	0.264	0.275

Note: Heteroskedasticity-adjusted robust standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table S7 List of forest carbon offset projects included in our main sample

Project ID	Project Name	Program	Category	Project Starting Year
1.	Round Valley Indian Tribes Improved Forest Management Project	ACR	IFM	2012
2.	Hanes Ranch Forest Carbon Project	ACR	IFM	2013
3.	Miller Forest	ACR	IFM	2013
4.	Green Assets-Brookgreen Gardens Improved Forest Management Project	ACR	IFM	2013
5.	Finite Carbon - The Forestland Group CT Lakes	ACR	IFM	2013
6.	Brush Creek	ACR	IFM	2013
7.	Blue Source- Goodman Improved Forest Management Project	ACR	IFM	2013
8.	Finite Carbon - The Forestland Group Chateaugay Woodlands IFM	ACR	IFM	2014
9.	Cumberland Forest Highlands IFM	ACR	IFM	2015
10.	Finite Carbon - Lyme Wyoming IFM	ACR	IFM	2015
11.	Finite Carbon - Colville IFM	ACR	IFM	2015
12.	Finite Carbon - Tennessee River Gorge Trust IFM	ACR	IFM	2015
13.	Finite Carbon - Cook's Branch Conservancy IFM	ACR	IFM	2015
14.	Bewley Ranches	ACR	IFM	2014
15.	Green Assets - Lukens Avoided Conversion Project	ACR	IFM	2015
16.	Green Assets - Milbury Avoided Conversion Project	ACR	IFM	2015
17.	Blue Source - Powellton Improved Forest Management Project	ACR	IFM	2015
18.	Green Assets - HMWCF-I Avoided Conversion Project	ACR	IFM	2016
19.	Green Assets - HMWCF-II Avoided Conversion Project	ACR	IFM	2016
20.	Green Diamond Resource Company Klamath East IFM	ACR	IFM	2015
21.	Green Diamond Resource Company Klamath West IFM	ACR	IFM	2014
22.	Blue Source - Allegheny Improved Forest Management Project	ACR	IFM	2015

23.	Cumberland Forest - Lonesome Pine Improved Forest Management Project	ACR	IFM	2015
24.	Blue Source - Marmet Improved Forest Management Project	ACR	IFM	2015
25.	Blue Source - Wisconsin Northern Highlands Improved Forest Management Project	ACR	IFM	2015
26.	Blue Creek	ACR	IFM	2015
27.	Finite Carbon - Massachusetts Audubon Society IFM	ACR	IFM	2015
28.	Camp Shelby Forest Carbon Project	ACR	IFM	2015
29.	Congaree River	ACR	IFM	2015
30.	Blue Source - Great Mountain Forest Improved Forest Management Project	ACR	IFM	2015
31.	Cappell Creek Improved Forest Management Project	ACR	IFM	2017
32.	Lord Ellis Improved Forest Management Project	ACR	IFM	2016
33.	Blue Source - Wilderness Lakes Improved Forest Management Project	ACR	IFM	2016
34.	Finite Carbon - MWF Ned Lake IFM	ACR	IFM	2017
35.	Finite Carbon - Meriwether IFM	ACR	IFM	2018
36.	Bluesource - Baskahegan Improved Forest Management Project	ACR	IFM	2018
37.	Forest Carbon Works Stewart Family Forest Project	ACR	IFM	2018
38.	The Nature Conservancy - Upper St. John Forest IFM Project	ACR	IFM	2018
39.	Bluesource - Edge of Appalachia Improved Forest Management Project	ACR	IFM	2018
40.	Ashford III	CAR	IFM	2014
41.	Yurok Tribe/Forest Carbon Partners CKGG Improved Forest Management Project	CAR	IFM	2012
42.	Buckeye Forest Project	CAR	IFM	2013
43.	Blue Source - Bishop Improved Forest Management Project	CAR	IFM	2012
44.	CF Ataya IFM	CAR	IFM	2015
45.	Finite Carbon - Potlatch Moro Big Pine CE IFM	CAR	IFM	2006
46.	Finite Carbon - JTO Champion Property IFM	CAR	IFM	2009
47.	Chugach Alaska Forest Carbon Project	CAR	IFM	2017
48.	Brushy Mountain	CAR	IFM	2014

49.	Garcia River Forest - ARB	CAR	IFM	2004
50.	Gualala River Forest - ARB	CAR	IFM	2003
51.	Big River / Salmon Creek Forests - ARB	CAR	IFM	2007
52.	Montesol - Forest Carbon Partners Improved Forest Management Project	CAR	IFM	2016
53.	Farm Cove Community Forest	CAR	IFM	2014
54.	Finite Carbon - Alma Land Company IFM	CAR	IFM	2015
55.	Finite Carbon - Lyme Brimstone Timberlands IFM	CAR	IFM	2007
56.	Van Eck Forest	CAR	IFM	2001
57.	Finite Carbon - Lyme Logan IFM	CAR	IFM	2015
58.	Finite Carbon - MWF Adirondacks IFM	CAR	IFM	2015
59.	Finite Carbon - Upper Hudson Woodlands ATP IFM	CAR	IFM	2015
60.	Finite Carbon - West Grand Lake IFM	CAR	IFM	2015
61.	Finite Carbon - Passamaquoddy Tribe IFM	CAR	IFM	2014
62.	Forest Carbon Partners - Berea College Improved Forest Management Project	CAR	IFM	2015
63.	Forest Carbon Partners - Gabrych Ranch Improved Forest Management Project	CAR	IFM	2014
64.	Hollow Tree	CAR	IFM	2015
65.	Forest Carbon Partners - Mescalero Apache Tribe Improved Forest Management Project	CAR	IFM	2015
66.	Forest Carbon Partners Eddie Ranch Improved Forest Management Project	CAR	IFM	2015
67.	Forest Carbon Partners Glass Ranch Improved Forest Management Project	CAR	IFM	2014
68.	Blue Source-Wolf River Improved Forest Management Project	CAR	IFM	2015
69.	Mailliard Ranch	CAR	IFM	2015
70.	Virginia Conservation Forestry Program - Clifton Farm	CAR	IFM	2015
71.	Virginia Conservation Forestry Program - Rich Mountain	CAR	IFM	2015
72.	Virginia Conservation Forestry Program - Tazewell - Elk Garden	CAR	IFM	2015
73.	Monte Rio Improved Forest Management Project	CAR	IFM	2019
74.	Facilitating Reforestation for Guangxi Watershed Management in Pearl River Basin	CDM	AR	2006

75.	Uganda Nile Basin Reforestation Project No.3	CDM	AR	2007
76.	Reforestation as Renewable Source of Wood Supplies for Industrial Use in Brazil	CDM	AR	2000
77.	Humbo Ethiopia Assisted Natural Regeneration Project	CDM	AR	2007
78.	Assisted Natural Regeneration of Degraded Lands in Albania	CDM	AR	2005
79.	Reforestation on Degraded Lands in Northwest Guangxi	CDM	AR	2008
80.	Southern Nicaragua CDM Reforestation Project	CDM	AR	2003
81.	Reforestation of Grazing Lands in Santo Domingo, Argentina	CDM	AR	2007
82.	India Himachal Pradesh Reforestation Project	CDM	AR	2006
83.	Ibi Batéké Degraded Savannah Afforestation Project for Fuelwood Production (Democratic	CDM	AR	2008
03.	Republic of Congo)			
84.	Uganda Nile Basin Reforestation Project No.5	CDM	AR	2006
85.	Improving Rural Livelihoods through Carbon Sequestration by Adopting Environment Friendly	CDM	AR	2004
86.	Kachung Forest Project Afforestation on Degraded Lands	CDM	AR	2006
87.	Commercial Reforestation on Lands Dedicated to Extensive Cattle Grazing Activities in the Region	CDM	AR	2000
07.	of Magdalena Bajo Seco			
88.	Uganda Nile Basin Reforestation Project No. 2	CDM	AR	2009
89.	Uganda Nile Basin Reforestation Project No. 1	CDM	AR	2008
90.	Uganda Nile Basin Reforestation Project No. 4	CDM	AR	2008
91.	Moldova Community Forestry Development Project.	CDM	AR	2006
92.	CDM Project for Forestry Restoration in Productive and Biological Corridors in the Eastern Plains	CDM	AR	2005
92.	of Colombia			
93.	Niger Acacia Senegal Plantation Project	CDM	AR	2006
94.	Small Scale Allahabad JFM A/R CDM Project on Degraded Lands in Allahabad Forest Division,	CDM	AR	2012
94.	Uttar Pradesh, India			
05	Small Scale Obra JFM A/R CDM Project on Degraded Lands in Obra Forest Division, Uttar	CDM	AR	2012
95.	Pradesh, India			

96.	Small Scale Jhansi JFM A/R CDM Project on Degraded Lands in Jhansi Forest Division, Uttar	CDM	AR	2012
90.	Pradesh, India			
97.	Reforestation of Degraded Grasslands in Uchindile & Mapanda, Tanzania	VCS	AR	2002
98.	Promoting Sustainable Development through Natural Rubber Tree Plantations in Guatemala	VCS	AR	2007
99.	Restoration of Degraded Areas and Reforestation in Caceres and Cravo Norte, Colombia	VCS	AR	2002
100.	TIST Program in Kenya, VCS 001	VCS	AR	2004
101.	TIST Program in Kenya, VCS 002	VCS	AR	2004
102.	TIST Program in Kenya, VCS 003	VCS	AR	2004
103.	TIST Program in Kenya, VCS 004	VCS	AR	2004
104.	TIST Program in Kenya, VCS 005	VCS	AR	2004
105.	Carbon Project in the Emas-taquari Biodiversity Corridor, Goiás and Mato Grosso do sul, Brazil	VCS	AR	2010
106.	Bukaleba Forest Project	VCS	AR	2004
107.	TIST Program in Uganda, VCS 001	VCS	AR	2003
108.	TIST Program in Uganda, VCS 002	VCS	AR	2003
109.	TIST Program in Uganda, VCS 004	VCS	AR	2003
110.	TIST Program in Uganda, VCS 003	VCS	AR	2003
111.	Guanare Forest Plantations on Degraded Grasslands under Extensive Grazing	VCS	AR	2006
112.	Forteko Afforestation on Degraded Grasslands under Extensive Grazing	VCS	AR	2007
113.	TIST Program in Uganda, VCS 005	VCS	AR	2003
114.	TIST Program in India, VCS 001	VCS	AR	2004
115.	TIST Program in Uganda, VCS 006	VCS	AR	2006
116.	TIST Program in Kenya, VCS 009	VCS	AR	2004
117.	Livelihoods' Mangrove Restoration Grouped Project in Senegal	VCS	AR	2009
118.	Araku Valley Livelihood Project	VCS	AR	2010
119.	Reforestation Project in Yingjing County, Sichuan Province	VCS	AR	2011
120.	Reforestation Project in Qinghai Province 2012	VCS	AR	2012

121.	India Sundarbans Mangrove Restoration	VCS	AR	2010
122.	ECO ₂ Rubber Forests Guatemala	VCS	AR	2011
123.	Agroforestry and Forest Restoration for Ecological Connectivity, Poverty Reduction and	VCS	AR	2013
	Biodiversity Conservation in Cerro San Gil, Caribbean Guatemala			
124.	Mitigation of GHG: Rubber based Agro-forestry System for Sustainable Development and Poverty	VCS	AR	2008
	Reduction in Pakkading, Bolikhamsay Province, Lao PDR			
125.	Reforestation with Teak CO ₂ e TEAKMEX	VCS	AR	2013
126.	Qinghai Afforestation Project	VCS	AR	2014
127.	Hechu Afforestation Project in Anhui Province	VCS	AR	2014
128.	Puzhen Afforestation Project in Guizhou Province	VCS	AR	2014
129.	Xiguan Afforestation Project in Guizhou Province	VCS	AR	2014
130.	Jilin Linjiang Afforestation Project	VCS	AR	2015
131.	Hunan Northern and Northwestern Area Afforestation Project	VCS	AR	2017
132.	Guinan Afforestation Project	VCS	AR	2015
133.	Liangdu Afforestation Project	VCS	AR	2015
134.	Henan Fangcheng and Tanghe Afforestation Project	VCS	AR	2015
135.	Anhuang Afforestation Project	VCS	AR	2016
136.	TIST Program in Kenya, VCS-CCB 010	VCS	AR	2015
137.	Zhanjiang Mangrove Afforestation Project	VCS	AR	2015
138.	Afforestation in Cooperation with Local Landowners for Forestal San Pedro S.A	VCS	AR	2015
139.	Integrated Project for Reforestation and Agroforestry on Degraded Lands in Nicaragua	VCS	AR	2016
140.	Zhangye City Afforestation Project in Gansu Province	VCS	AR	2016
141.	Jilin Sanchazi Afforestation Project	VCS	AR	2016
142.	Miaoling Afforestation Project	VCS	AR	2016
143.	Huadu Afforestation Project	VCS	AR	2016
144.	Liugui Afforestation Project	VCS	AR	2016

145.	Gansu Tianshui Afforestation Project	VCS	AR	2016
146.	Reforestation of Degraded Lands in Sierra Leone	VCS	AR	2016
147.	Reforestation of Degraded Forest Reserve Areas in Ghana, West Africa	VCS	AR	2016
148.	Gansu Lanzhou Afforestation Project	VCS	AR	2016
149.	Shanxi Loufan Afforestation Project	VCS	AR	2016
150.	Generation Forest Group Project	VCS	AR	2016
151.	Afforestation of Degraded Grasslands in Caazapa and Guaira	VCS	AR	2016
152.	Afforestation of Degraded Grasslands in Vichada, Colombia	VCS	AR	2016
153.	Yunnan Qiubei Afforestation Project	VCS	AR	2017
154.	Unitan Afforestation and Reforestation of Grazing Lands Project	VCS	AR	2016

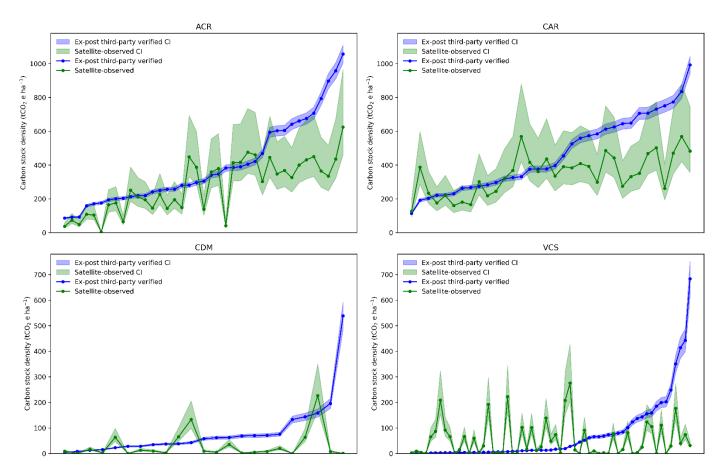


Fig. S1 Uncertainty range associated with ex-post third-party verified and satellite-observed estimates by carbon-crediting program in 2019

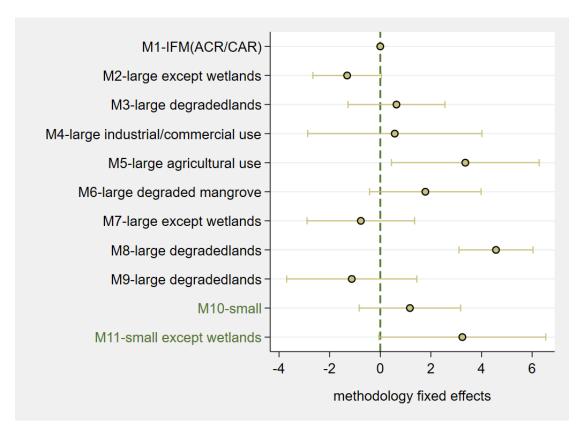


Fig. S2 Evaluating effects of methodologies in 2019

Note: The fixed effects of the most frequently applied methodology (M1) in our sample are normalized to zero. The order of the methodology effects abides by the applied number for large-scale methodology (M1-M9) in descending order first, followed by the applied number for small-scale methodology (M10 and M11) in descending order.

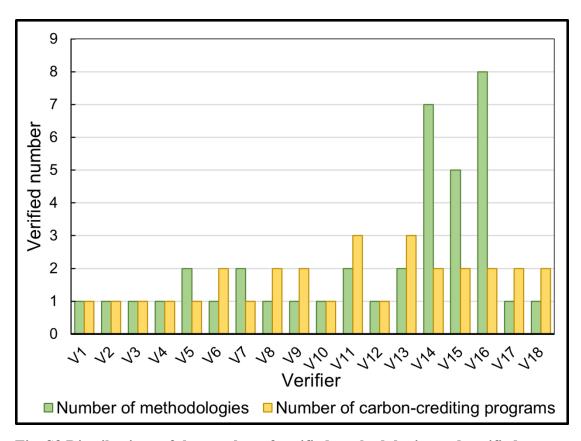


Fig. S3 Distributions of the number of verified methodologies and verified programs for each verifier

Supplementary Information B: Collection procedure for forest carbon offset projects

From the official websites of the six carbon-crediting programs covered in this analysis, we conduct a scope search with the following terms: "Agriculture Forestry and Other Land Use (AFOLU)" for VCS¹, "Afforestation and Reforestation" for CDM, CCER, and GS, "Forest Carbon" for ACR¹, and "Improved Forest Management, Conservation-based Forest Management, Forestry, and Reforestation" for CAR². Compared to AR and IFM activities, evaluating REDD activities involves more intricate baseline construction approaches^{3–7}, and directly measuring the carbon stock in the project area would be insufficient. Therefore, we leave out all the REDD activities from our analysis. We then exclude 251 projects that had not been successfully registered by December 31, 2021. This search yields 414 forest carbon offset projects from January 1, 1999, at the earliest and still ongoing by December 31, 2021, as our initial sample.

The main objective of this analysis is to evaluate the integrity of carbon credits. We focus on the ex-post third-party on-site assessments of carbon stock, which are directly related to the amount of carbon credits issued. We then check the availability of public project information, especially regarding PDDs, monitoring reports, third-party verification reports, discernible project boundary maps, and ex-post carbon emission removal data, and we clean the raw dataset further to eliminate projects with missing key information. For the VCS, CDM, CCER, and GS programs, essential ex-ante information is disclosed in PDDs, and for the ACR and CAR programs, it is disclosed in offset project listing forms. PDDs prepared by project developers include detailed planning information, including estimations of GHG emission removal or carbon stocks

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¹Under the AFOLU category of VCS, some projects are not forest carbon offset projects, e.g., "Adjusted Water Management in Rice Cultivation in Jiashan County", "Mangrove Restoration Project with Sine Saloum and Casamance communities, Senegal", and "Regenerating Soil Life with Waste Management". We thus manually review all the projects and remove those that do not meet the criteria to ensure our sample are all forest carbon offset projects.

occurring in the selected carbon pools under the project scenario and the annual ex-ante GHG emissions reduction tables over the entire crediting period, and demonstrate compliance with the requirements of a forest carbon-crediting program. Similarly, the offset project listing form describes the project activity, satisfies eligibility requirements, identifies GHG emission sources or sinks, and defines methodologies for GHG quantification. It also documents specific information required for registering an offset project with ACR or CAR^{8,9}. A discernible project boundary map should include information about the project location, border, and area with shape files containing geographical coordinates or discernible geolocation map figures. The achieved emissions reductions or removals are regularly monitored by project developers following the plan outlined in the PDDs, which is stated in the monitoring reports under the VCS, CDM, CCER, and GS programs. Similarly, the offset project data reports (OPDRs) under the ACR and CAR programs provide documentation required by the regulation and applicable compliance offset protocols prepared by project developers for each reporting period. After that, an accredited third-party verifier is engaged to independently assess the monitoring data on-site and confirm the amount of emissions reductions or removals achieved, which determines the issuance of carbon credits that can be issued. These verified carbon removal data are disclosed in the verification reports under the VCS, CDM, CCER, and GS programs or verification statements under the ACR and CAR programs.

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First, we exclude 14 projects without accessible project design documents (PDDs), also known as offset project listing forms. Subsequently, we remove 131 projects without discernible project boundary maps or inconsistent boundary maps from the provided PDDs². The boundary shapefile data for the GS crediting program are not uploaded to official websites. At this stage, the GS program is eliminated for further analysis because no project remains with complete PDDs and discernible project boundary maps.

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² Inconsistent boundary maps mean that the actual project boundaries outlined according to the geographical coordinates do not correspond to the project-located county provided in PDDs.

Furthermore, we eliminate 93 projects without issued carbon credits that lack ex-post carbon stock information. Finally, 4 projects outside the accessible zone of satellite data are removed, for which the latitude is between 51.6° N and S^{10–12}, leaving 172 projects. At this stage, the CCER program is eliminated due to the insufficient sample size (2 projects). We further scrutinize the verification reports and screen out projects disclosing carbon removal verification as near to the year 2019 as possible, allowing us to extract and confidently infer the ex-post aboveground biomass carbon stocks in both 2019 and 2021. This process discards 12 projects that released verification reports prior to 2015, resulting in a final sample of 154 projects for comparative analysis in 2019. The detailed collection procedure for forest carbon offset projects is displayed in Table S1. The full list of forest carbon offset projects included is provided in Table S7.

Supplementary Information C: Project boundary delineation process

We complete project boundary delineation by either delineating the boundary following detailed geolocation map figures or manually delineating the boundary based on geographical coordinates and cartographic information. Supplementary Information F demonstrates the pairwise comparisons of delineation (or manual delineation) boundaries versus ex-ante outlined boundaries in the PDDs for the estimated 154 projects. Most projects provide discernible outlined boundary maps in the PDDs under the CDM and VCS programs or offset project listing forms under the ACR and CAR programs. For some projects, discernible outlined boundaries are disclosed in monitoring reports, which are provided by project developers under the CDM and VCS programs or OPDRs under the CAR program.

For most forest carbon offset projects under VCS, ACR, and CAR (less often for projects under CDM), shape files of spatial boundaries providing detailed geolocation maps are available. Under these circumstances, we directly delineate the boundaries to determine the project location and geographic areas according to the shapefile. If the ex-ante outlined boundary map in the PDDs matches the shape file, we refer to the boundary from the shape file to estimate the real size of the project area. We scale up or scale down the scope of the outlined boundary to match the ex-ante claimed size when the size of the actual delineation area according to the shape file differs from the ex-ante claimed size. For some projects under the VCS program when the shapefiles present the coarse boundary, we manually delineate the complex boundaries of dispersed sites to match the geo-coordinates and areas provided in PDDs as much as possible. Additionally, for certain projects under the VCS program where PDDs outline the project boundary on a broader scale, we manually adjust the delineation area to match the total project area presented in PDDs.

Most projects under the CDM program lack discernible geolocation maps and provide only geographical coordinates or delimitations. We follow the complete geo-referenced information to manually delineate each discrete area of the project boundary. For projects with incomplete geo-referenced coordinates, we confirm the project location by cross-referencing the surrounding roads and counties against the geolocation on Google Maps and delineating the project boundary to match the project area image disclosed in the PDDs. After making refined adjustments, we ensure that the manual delineations for all project geographic locations, boundaries, and estimated areas are congruent with the ex-ante descriptions and geographical coordinates presented in the PDDs.

Supplementary Information D: Procedure for forest carbon stocks estimated by satellites

While the forest carbon stock consists of aboveground and belowground components, only the aboveground portion can be explicitly estimated using remote sensing methods¹³⁻¹⁵. For example, by combining aerial imagery and deep learning, Mugabowindekwe et al. (2023) mapped the aboveground carbon stock for each overstory tree at the national scale in Rwanda. Such a method can estimate the aboveground biomass by obtaining plane information on trees in farmland and savannas; however, its feasibility and accuracy in forest areas remain uncertain. In this study, we integrate the space-borne light detection and ranging (LiDAR) data from the Global Ecosystem Dynamics Investigation (GEDI) mission with satellite remote sensing images to assess aboveground carbon stocks in selected worldwide forest carbon offset projects. The GEDI utilizes an active LiDAR remote sensing technique capable of penetrating dense forest canopies and capturing vertical forest structure 17,18, thereby offering more accurate aboveground biomass estimates¹⁴. However, GEDI data are spatially discrete, prompting the need for integrating wall-to-wall satellite remote sensing imagery and creating comprehensive aboveground biomass maps at the resolution of 30 metres^{19,20}.

GEDI data collection and processing

The GEDI mission, launched in December 2018 and mounted on the International Space Station, is designed to measure the vertical structure of temperate and tropical forests between 51.6° N and S^{10–12}. The GEDI can generate full-waveform LiDAR data with a footprint diameter of 25 metres by emitting laser pulses at a wavelength of 1,064 nm¹⁰. The GEDI team processes these waveforms to estimate vegetation height metrics (relative height (RH) metrics), predict aboveground biomass density (AGBD) as a function of RH metrics for each footprint, and produce the GEDI Level 4A (L4A) footprint-level AGBD product^{21–23}. In this study, the GEDI L4A AGBD product is used to assess the aboveground biomass of forest carbon offset projects in our sample.

To ensure high-quality GEDI data, we rely on the sensitivity metric and quality flag provided with L4A data. Our selection criteria involve choosing data with a beam sensitivity of ≥ 0.95 and a quality flag value of 1^{24-26} . Furthermore, we exclusively utilize data collected at night and during the leaf-on season to eliminate the influence of solar background noise and leaf phenology interference²⁷.

Sentinel data

We utilize Sentinel-1 and Sentinel-2 datasets available on the Google Earth Engine (GEE) platform to extract feature parameters for AGBD mapping. The Sentinel-1 mission comprises a constellation of two polar-orbiting satellites that perform C-band synthetic aperture radar (SAR) imaging, allowing them to acquire imagery regardless of weather conditions²⁸. The Sentinel-1 data used in our study are from the Level-1 Ground Range Detected (GRD) product. Given that horizontal-horizontal polarized Sentinel-1 SAR imagery does not cover the entire globe, we employ only vertical-vertical-polarized and vertical-horizontal-polarized imagery. Sentinel-2 is a polar-orbiting, multispectral, high-resolution imaging mission for land monitoring²⁹. We utilize the atmospherically corrected L2A product with 12 bands ranging from visible and near-infrared to shortwave infrared. To mitigate the effects of cloud cover and atmospheric interference, we initially apply a cloud masking algorithm from the Open Earth Engine Library (OEEL) in the GEE and resample both the Sentinel-1 and Sentinel-2 data to a 30-metre resolution for consistency.

Ancillary data

We utilize near-global-scale Shuttle Radar Topography Mission (SRTM) digital elevation data³⁰, void-filled with open-source data, to compute the terrain elevation, slope, and aspect at an approximately 30-metre resolution. Additionally, we extract two climate feature parameters, mean annual temperature (MAT) and mean annual precipitation (MAP), from the climate data product WorldClim 2.1 and resample these datasets to a 30-metre resolution³¹. Forest areas are determined by employing the

223 GlobelLand30 V2020 land cover product, a 30-metre resolution dataset developed by

224 China's National Geomatics Centre.

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Estimation of the aboveground carbon stocks of the forest carbon offset project

Forest distribution within forest carbon offset projects tends to be fragmented, and GEDI data can be sparse and discontinuous within these areas. This scarcity makes it challenging to rely solely on GEDI L4A AGBD products for an accurate estimation of aboveground carbon stocks. To address this issue, we integrate GEDI L4A data with satellite remote sensing imagery to estimate the aboveground carbon stock of each forest carbon offset project through a four-step process. (a) We identify GEDI footprintscale AGBD samples located within forested areas of each offset project by using the GlobalLand30 data product. To avoid the potential overfitting bias, we set the minimum sample size for training as 10,000, which is sufficiently large according to the literature^{32,33}. When the available GEDI samples within the forested areas of the carbon offset project are limited or sparse (less than 30% of projects), we use a neighbourhood expansion approach to increase the sample size to 10,000. Specifically, we select GEDI samples from buffer zones around the project area—these are regions adjacent to the project boundaries that are still part of the same forested landscape. By using a spatially extended range, we can draw on additional GEDI footprints with similar ecological characteristics, helping to increase the sample density. (b) We develop a random forest model to extend estimates beyond GEDI footprints by correlating GEDI AGBD estimates with covariate stacks from Sentinel data, the SRTM Digital Elevation Model (DEM) data, and climate data. (c) An AGBD map is generated for each forest carbon offset project by applying the AGBD estimation model to the satellite remote sensing imagery. (d) The aboveground biomass for each carbon offset project is calculated using the AGBD map and forest area data derived from the GlobalLand30 product. The aboveground biomass of the forest is then converted to carbon stocks by multiplying by the carbon fraction, which refers to the mass of carbon present in various forms within a unit volume of biomass.

Validation of forest carbon stock densities estimated by satellite remote sensing

Although previous studies have justified the applicability of airborne LiDAR in assessing carbon stocks for forest offset projects^{34–36}, to further validate our satellite remote sensing method for assessing carbon stocks of offset projects, we compare carbon stock densities derived from satellite remote sensing to those from airborne LiDAR. The airborne LiDAR data for validation in China are from our self-collected UAV LiDAR data in Chongqing area, which are obtained using the Riegl VUX-1 system, with a flight strip overlap greater than 60%. The scanner frequency was 400 kHz, with an average point density of 150 pts/m² and elevation accuracy better than 0.1 metres. Except for the validation in China, the airborne LiDAR data in other regions are adopted from the Oak Ridge National Laboratory Distributed Active Archive Centre (ORNL DAAC)^{37–41}. In total, 24 sample forest areas are selected for validation to cover as many continents and forest types as possible, given complete airborne LiDAR data. The 24 sample sites are located in the United States, Brazil, Mozambique, Gabon, Indonesia, and China. We compute the coefficient of determination to support the validation of our satellite remote sensing method (R²: 0.94).

Supplementary Information E: Uncertainty associated with ex-post third-party verified and satellite-observed estimates

Ex-post third-party verified and satellite-observed aboveground biomass carbon stock estimates stem from various information that may lead to uncertainty. We calculate the claimed credits' uncertainty range between the lower and upper bound of each project based on the precision level with the confidence interval determined by the respective methodologies shown in Table S4.

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Correspondingly, given our adoption of airborne LiDAR technology to validate satellite-observed aboveground biomass carbon stocks, the real error in satellite remote sensing estimation (X) can be assessed via two major facets: the measurement uncertainty inherent in airborne LiDAR (Y) and the satellite remote sensing error relative to airborne LiDAR (Z). Here, we use the validation sample of 24 forest areas to estimate the average relative error of satellite remote sensing at the project level. The uncertainty of airborne LiDAR in evaluating forest carbon stocks in the plot area is set as 10% with a 90% confidence interval⁴². If we assume the actual carbon stock densities generated by each project is C_0 . The observations derived from the airborne LiDAR and satellite remote sensing are C_a and C_s . Let X and Y be two independent variables obeying the asymptotically normal assumption shown in equation (1) and (2). We define Z = X/Y and the distribution of the ratio of two independent normals as equation (3)⁴³. σ_y^2 of airborne LiDAR and σ_z^2 of the validation sample can be calculated based on our assumption. Assuming C_a and C_s are unbiased estimation in the context ($\mu_x = \mu_y = 1$), the uncertainty range of satellite remote sensing estimation can be obtained as $[0.74C_s, 1.54C_s]$, and the calculation process is shown in the inequality (4).

$$X = \frac{c_s}{c_0}, \ X \sim N(\mu_x, \sigma_x^2)$$
 (1)

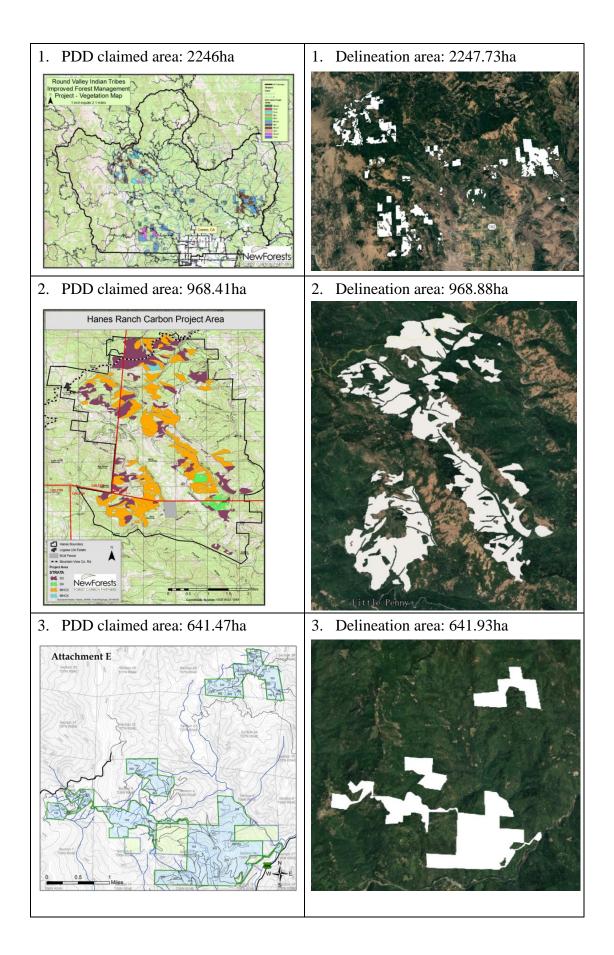
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$$Y = \frac{c_a}{c_0}, Y \sim N(\mu_y, \sigma_y^2)$$
 (2)

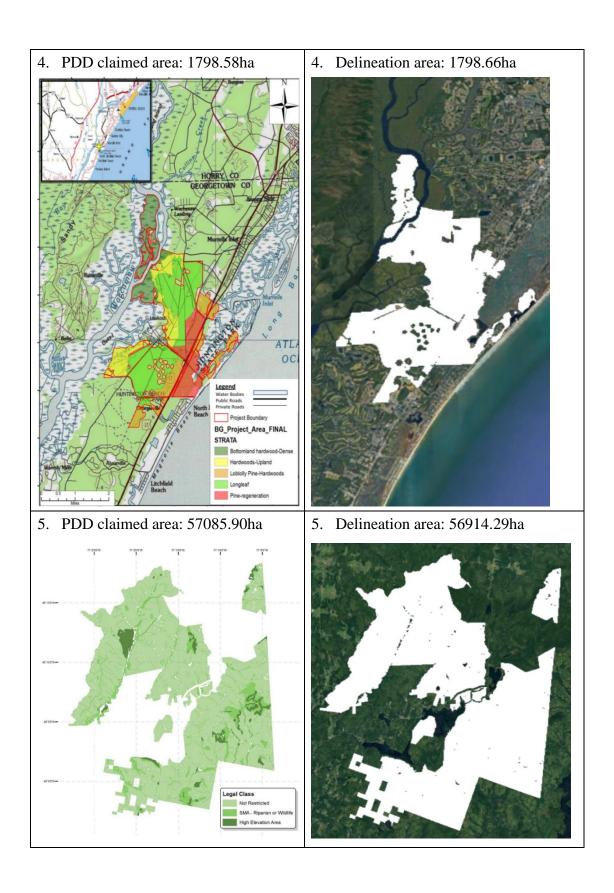
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$$Z = \frac{X}{Y} = \frac{c_S}{c_a}, \ Z \sim N(\mu_z, \sigma_z^2), \ where \ \mu_z = \frac{\mu_x}{\mu_y} \ and \ \sigma_z^2 = \sigma_y^2 (\frac{\sigma_x^2}{\sigma_y^2} + \frac{\mu_x^2}{\mu_y^2})$$
 (3)

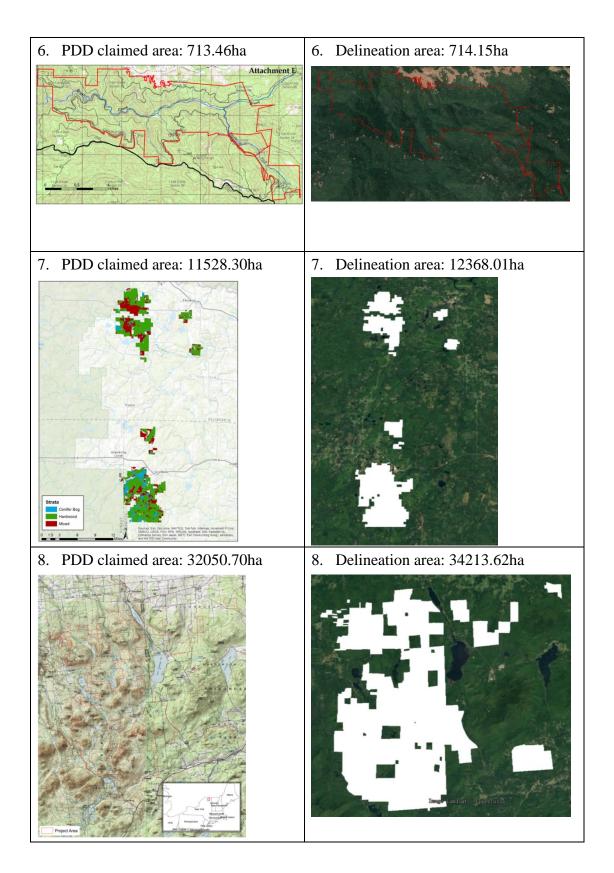
$$-Z\alpha_{/2} \cdot \sigma_x \le \frac{c_s}{c_0} - \mu_x \le Z\alpha_{/2} \cdot \sigma_x \implies \frac{c_s}{1 + Z\alpha_{/2} \cdot \sigma_x} \le C_0 \le \frac{c_s}{1 - Z\alpha_{/2} \cdot \sigma_x} \tag{4}$$

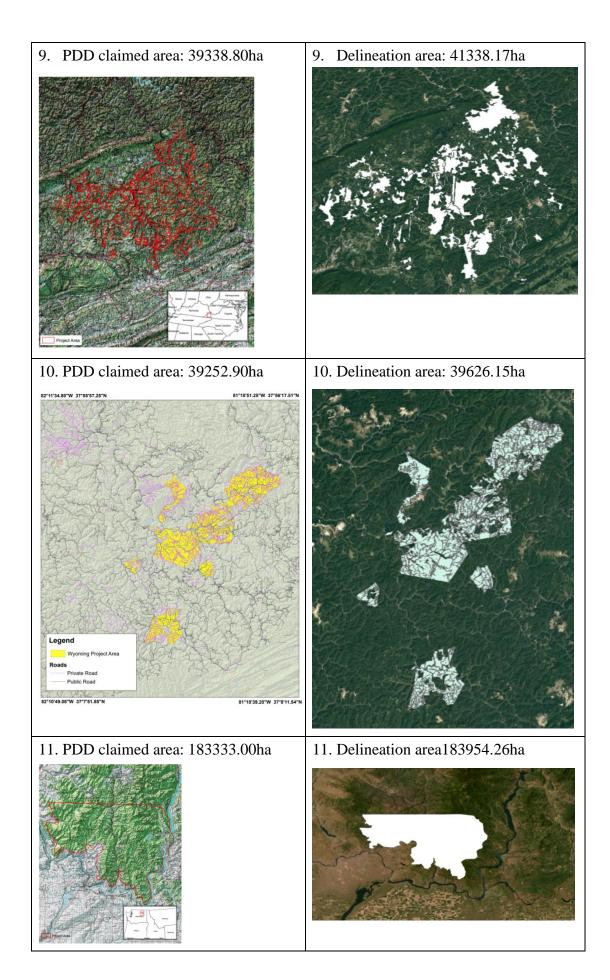
Supplementary Information F: The pairwise comparisons of delineation border versus ex-ante outlined boundary for the estimated 154 projects

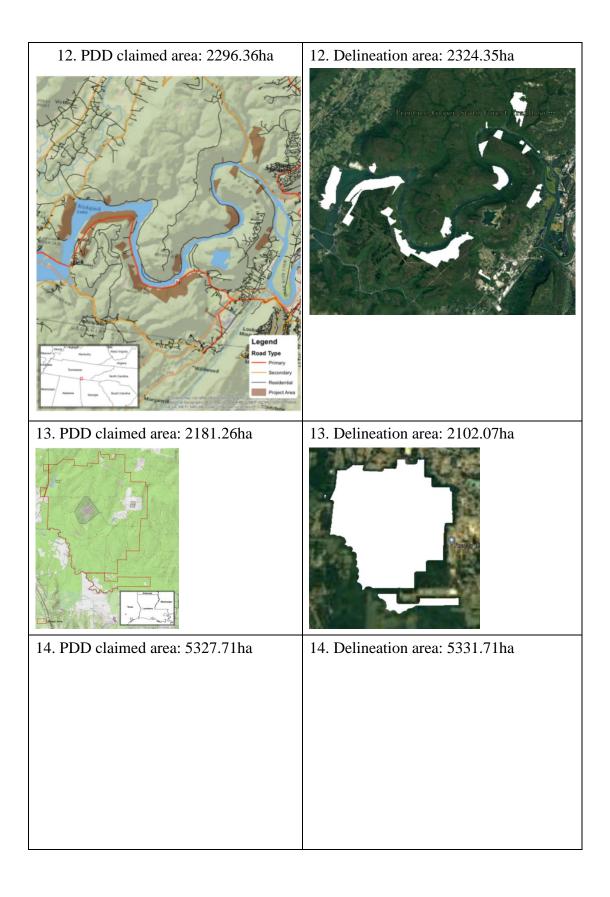
 Note: The left column shows boundaries provided by PDDs, and the right column shows the delineated boundaries according to discernible geolocation map figures. If the shapefile that provides detailed geolocations for the project boundary is available, we directly delineate the boundary based on the shapefile. Otherwise, we manually delineate the project boundary based on geographical coordinates and cartographic information based on PDDs.

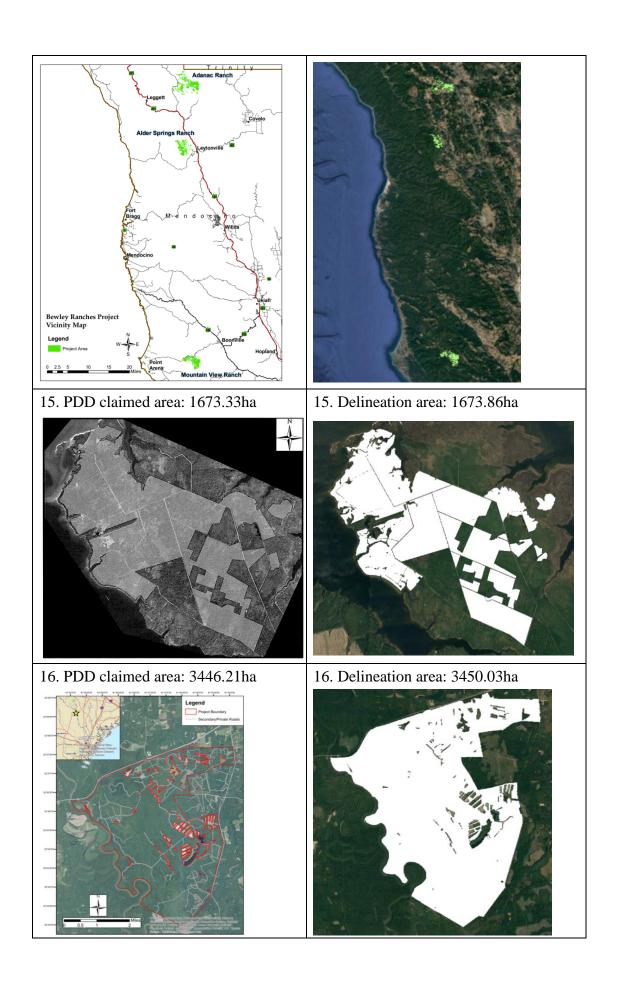


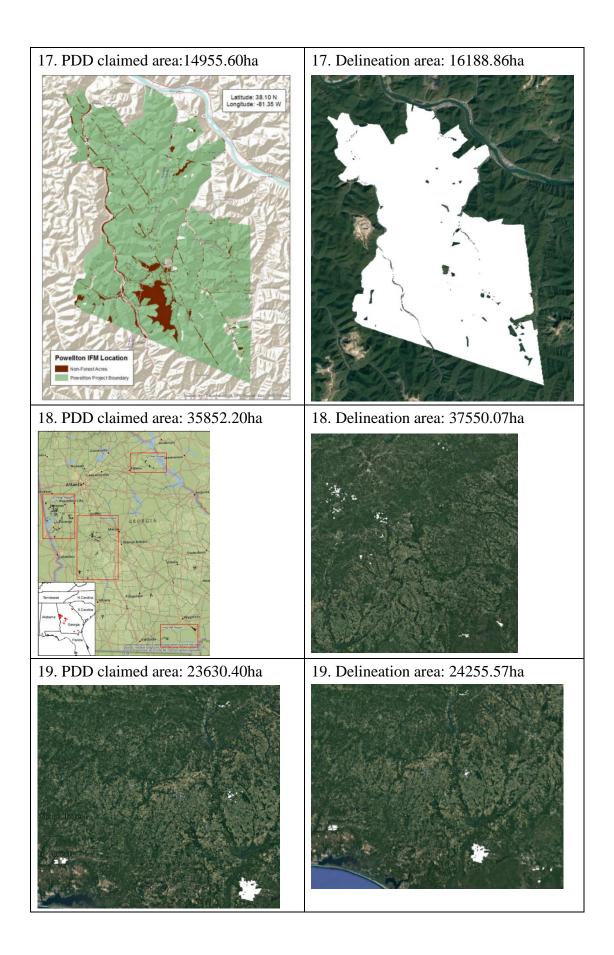


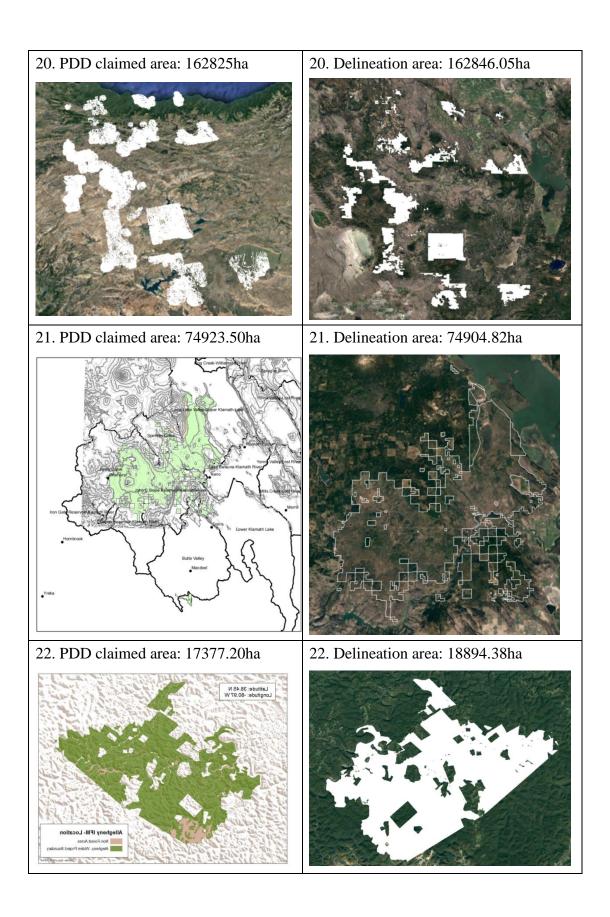


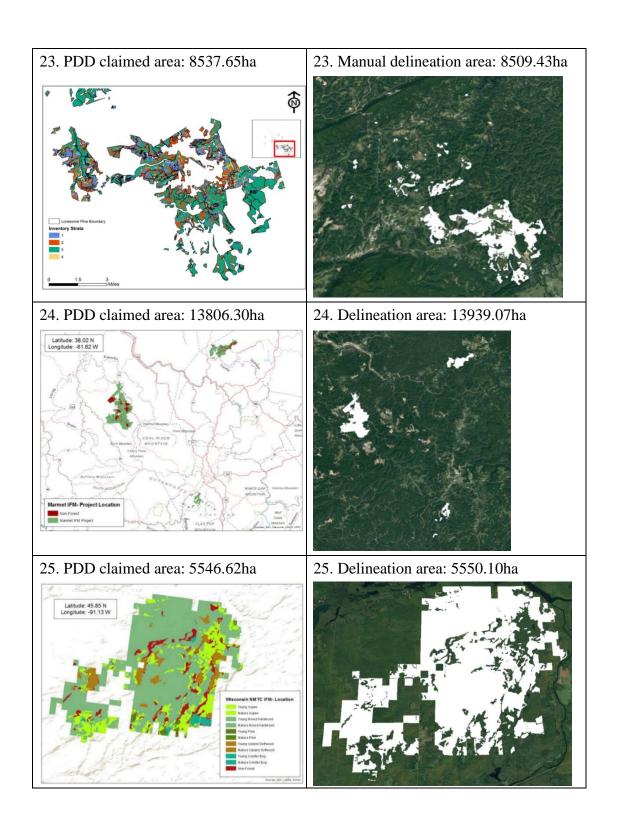


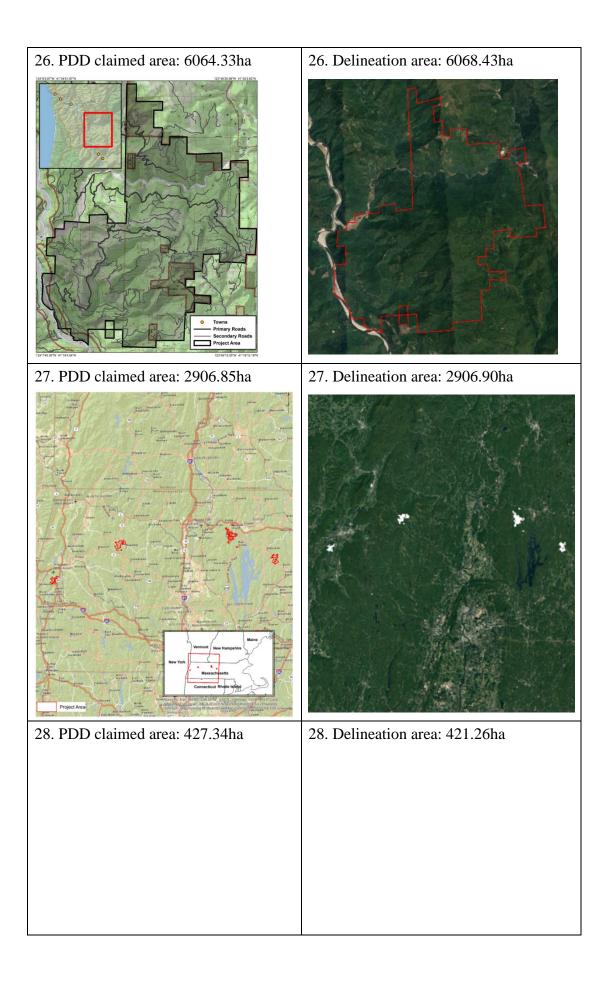


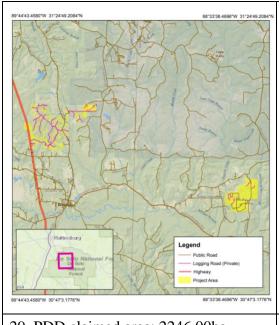






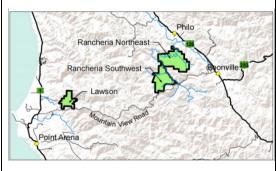








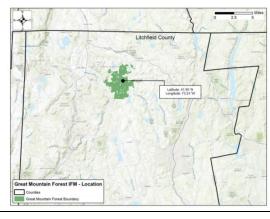
29. PDD claimed area: 2246.00ha



29. Delineation area: 2248.35ha

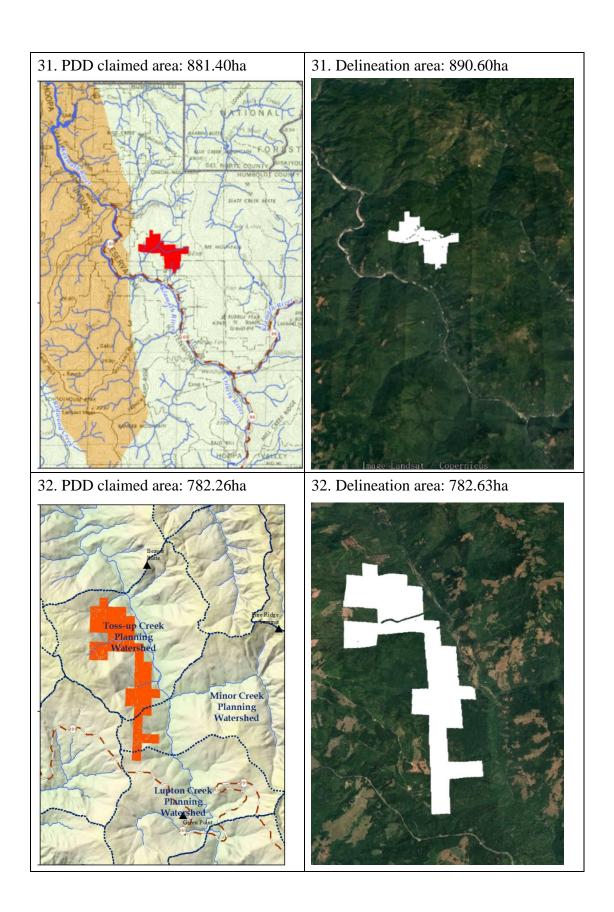


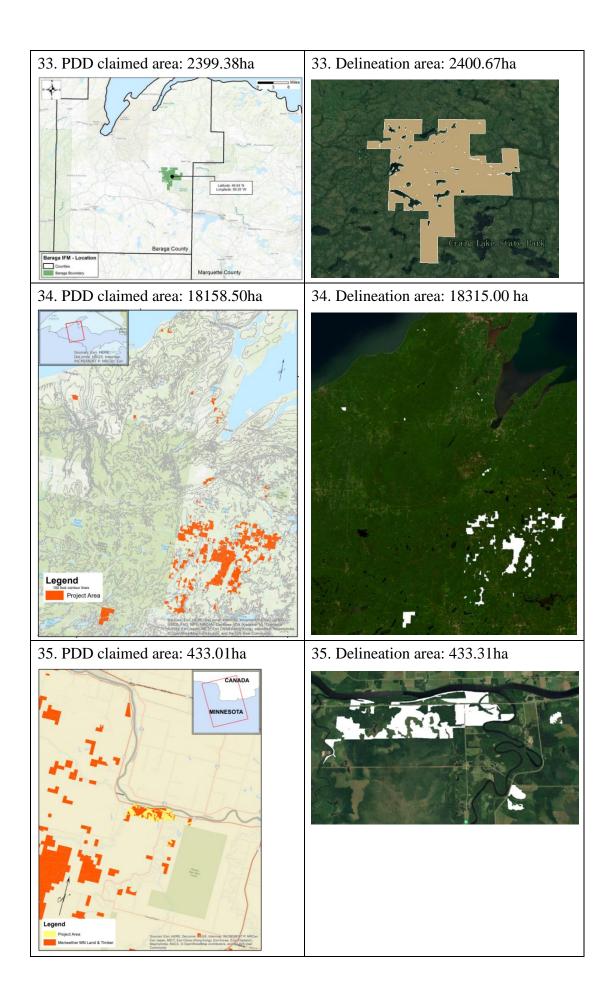
30. PDD claimed area: 2387.00ha

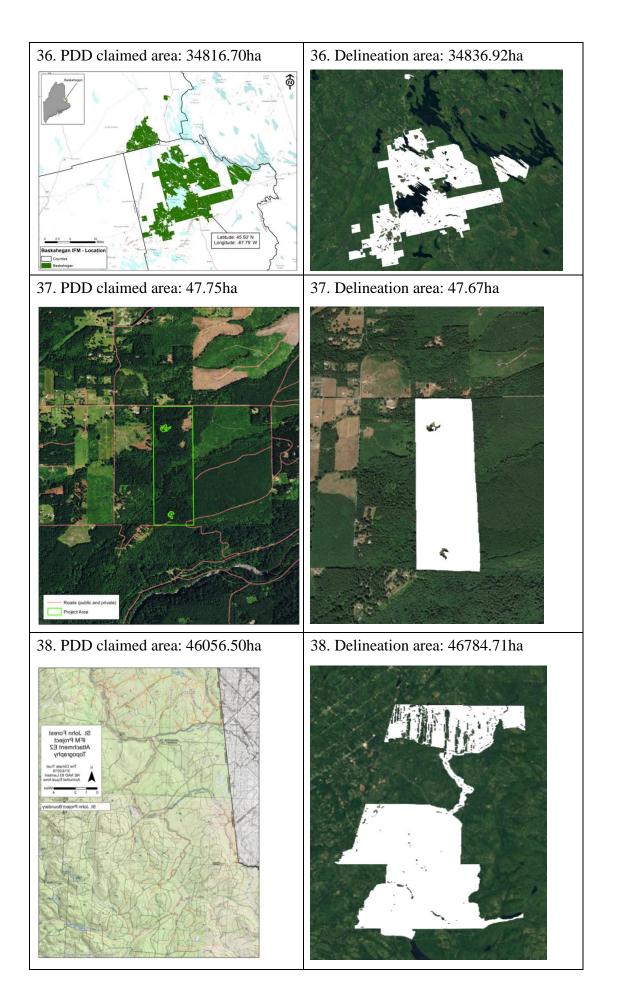


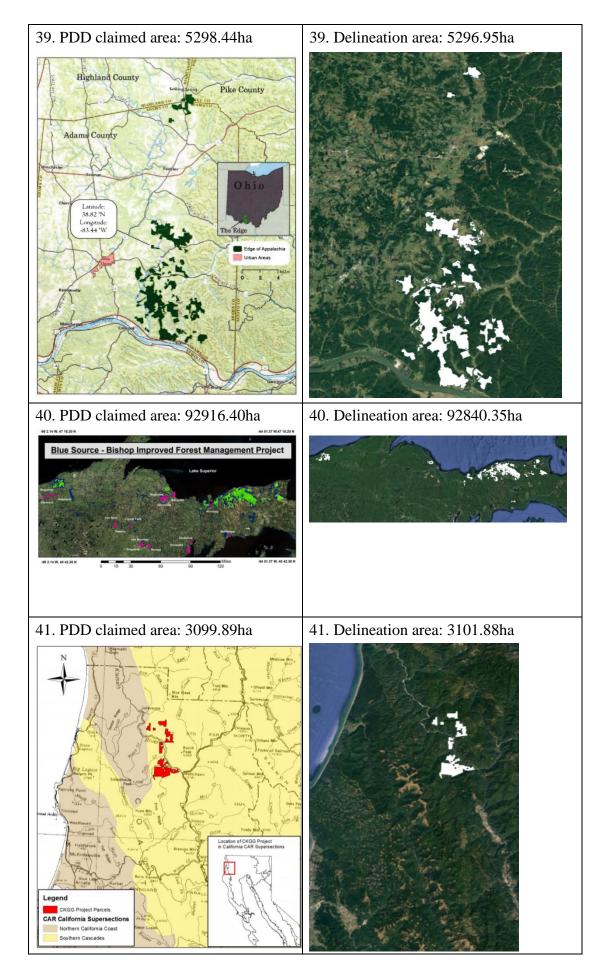
30. Delineation area: 2533.56ha

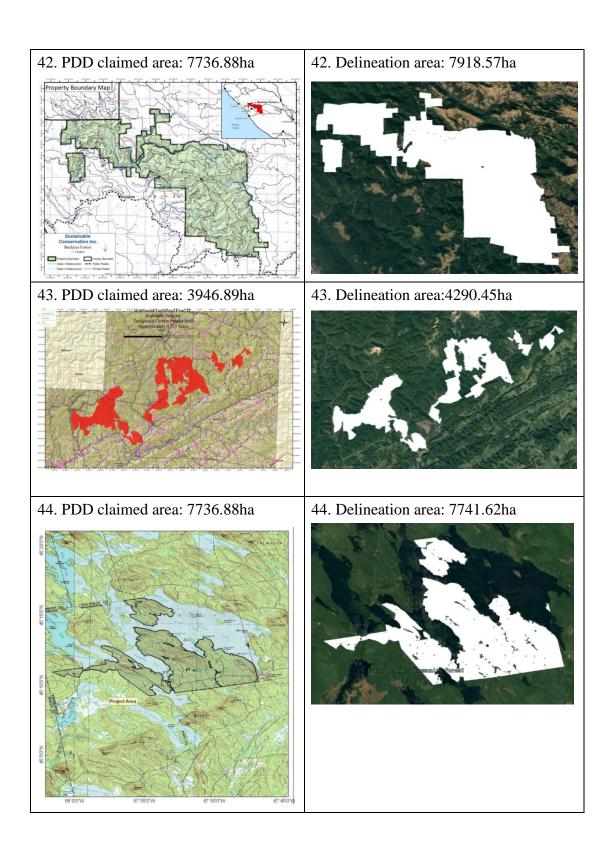


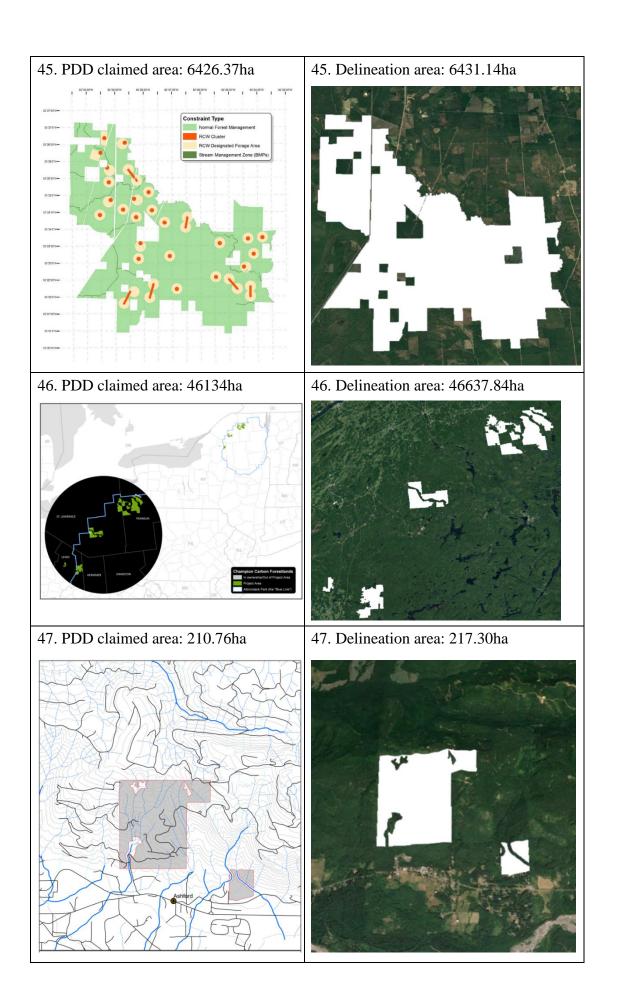


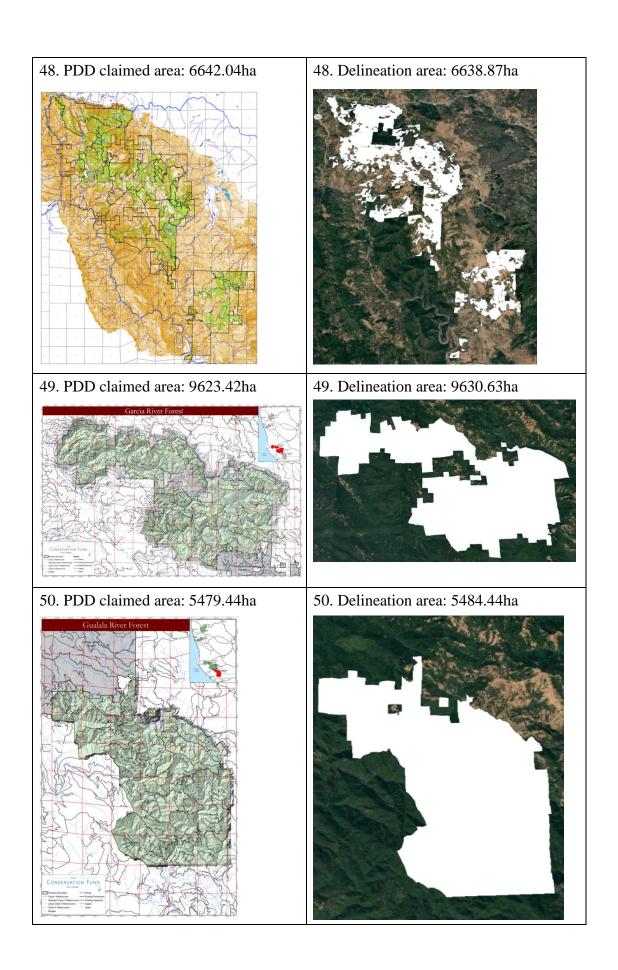


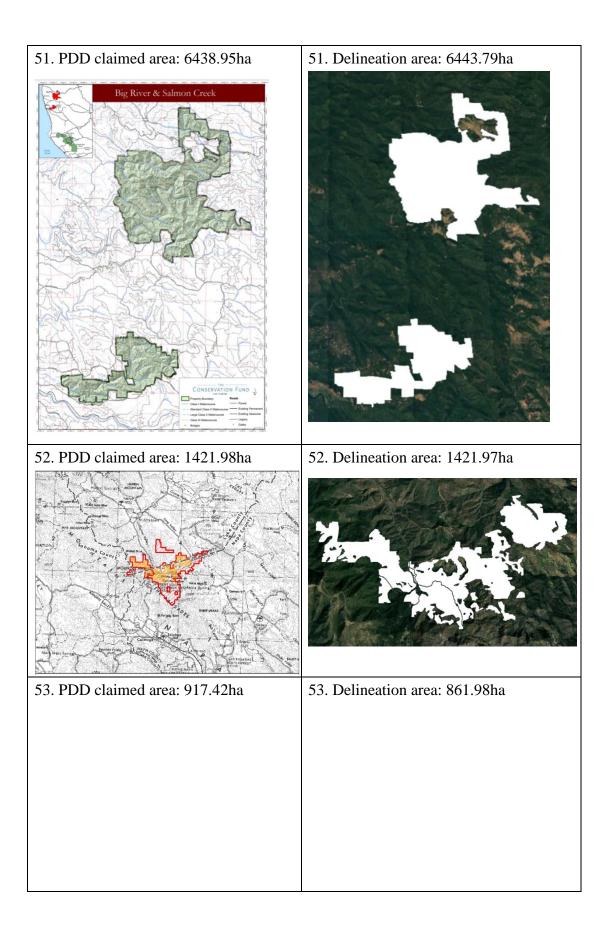


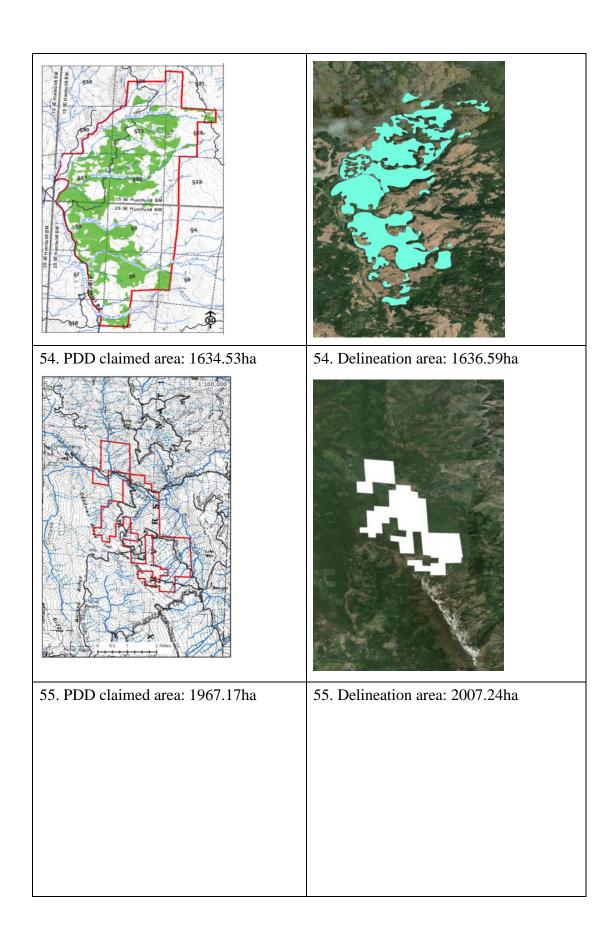


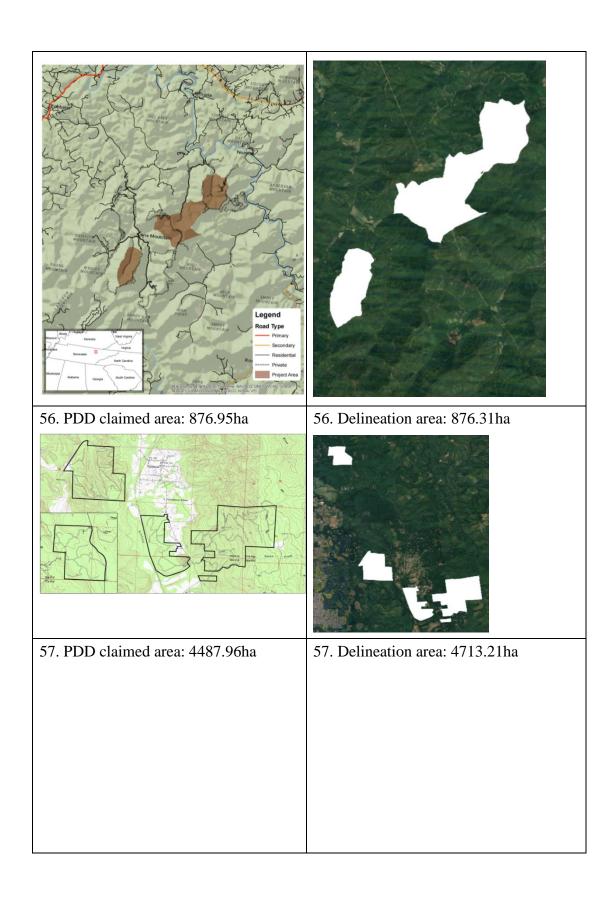


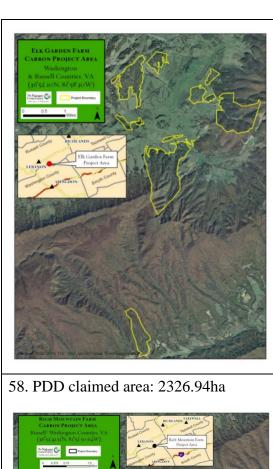




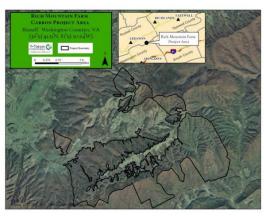




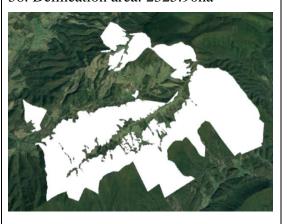




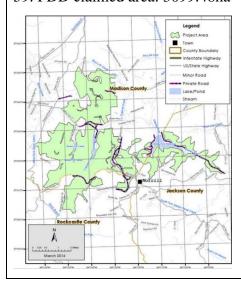




58. Delineation area: 2325.90ha

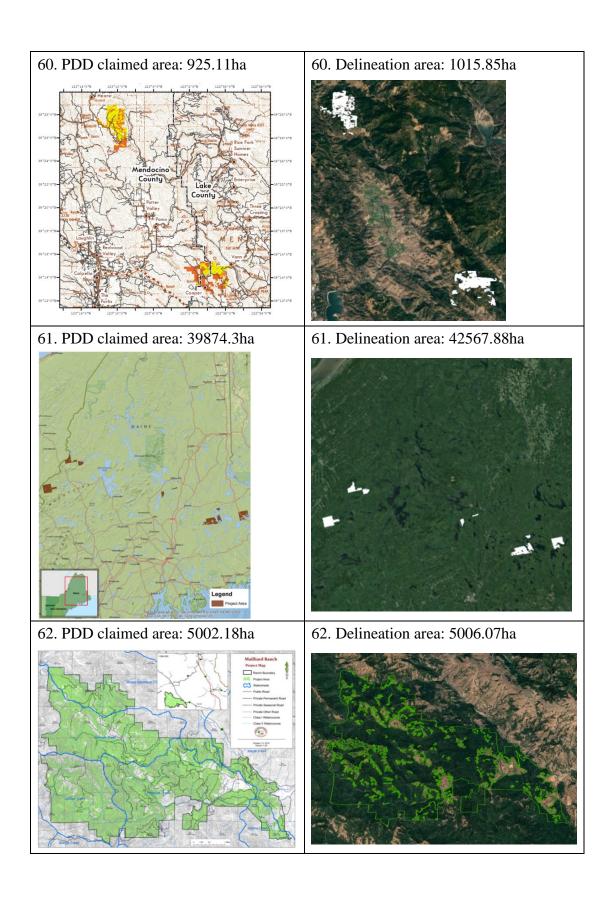


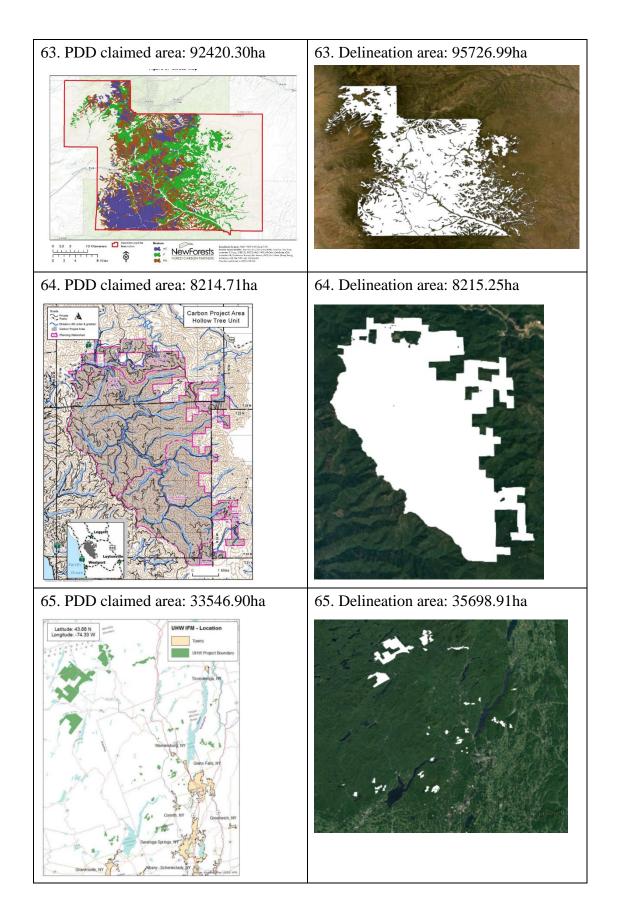
59. PDD claimed area: 3099.48ha

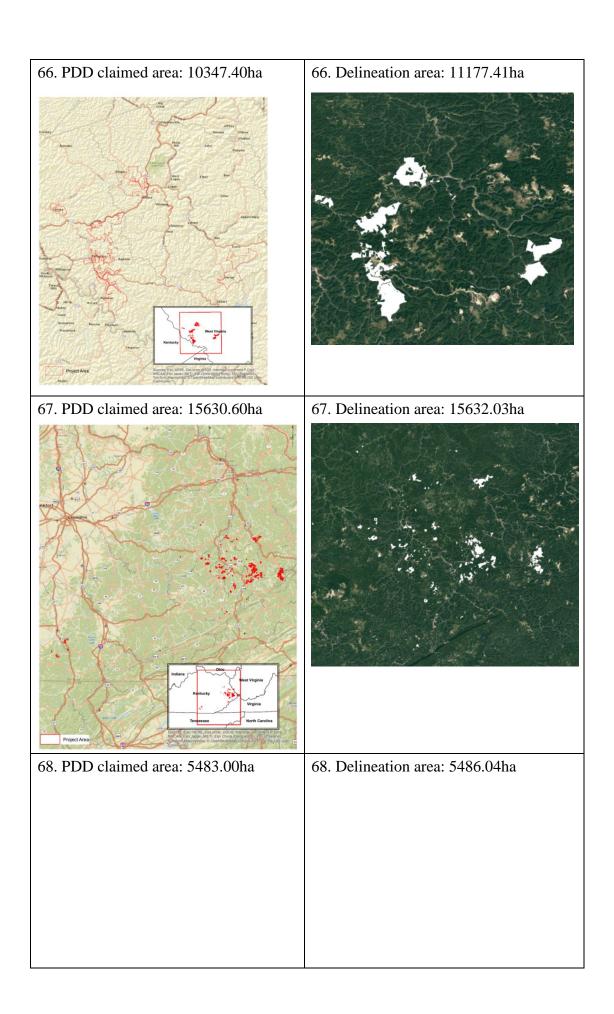


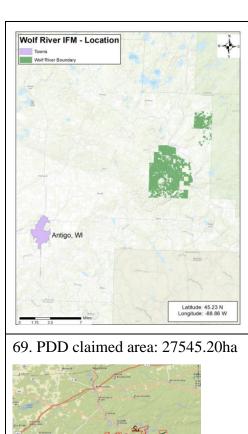
59. Delineation area: 3099.97ha



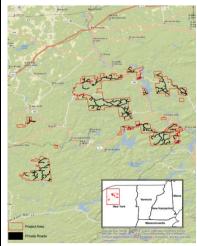








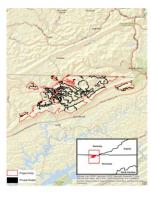




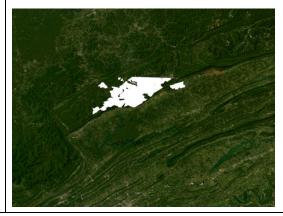
69. Delineation area:28278.99ha

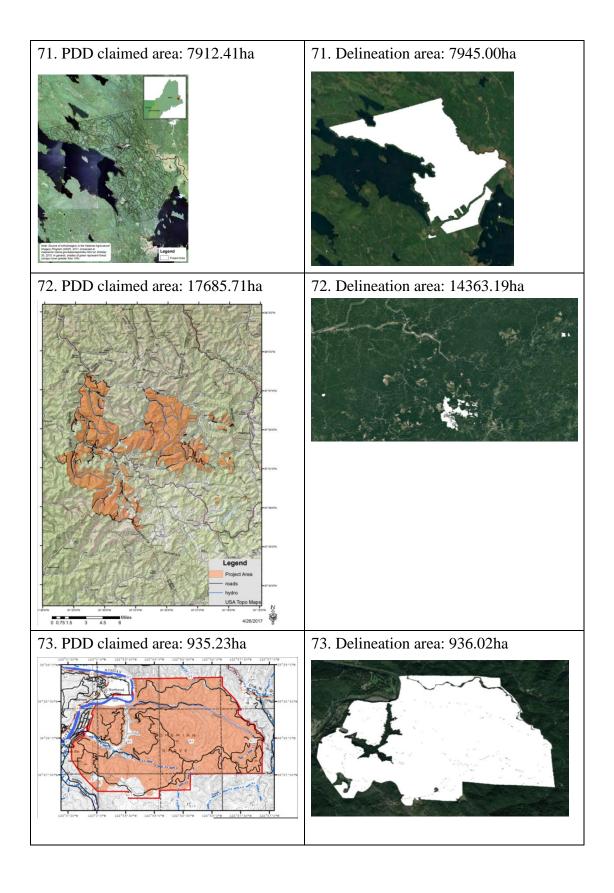


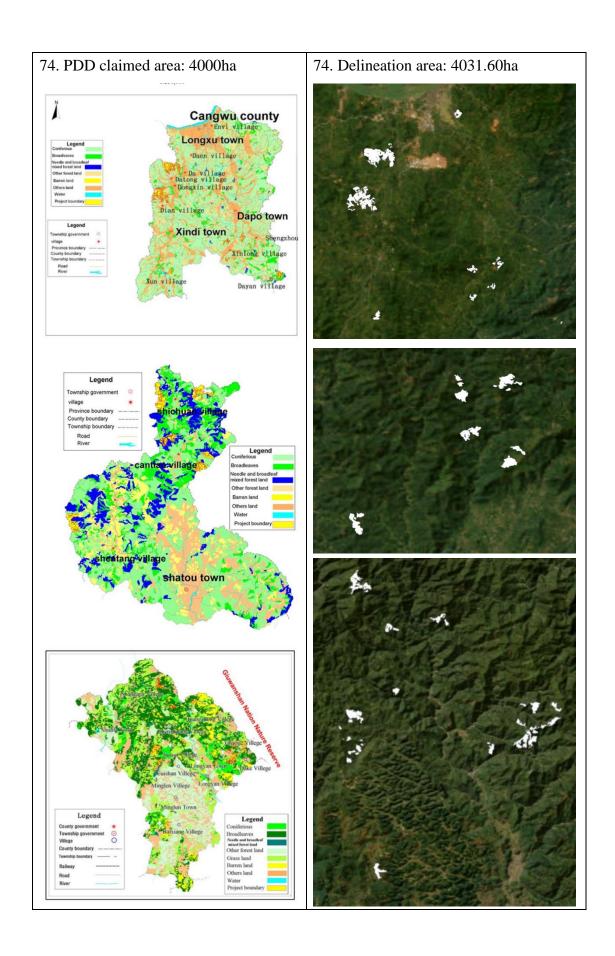
70. PDD claimed area: 32944.7ha

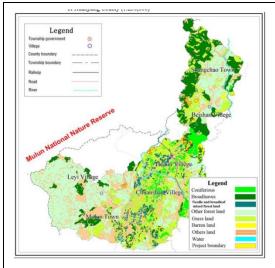


70. Delineation area: 32443.57ha









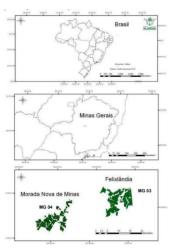


75. PDD claimed area: 341.9ha

75. Manual delineation area: 340.79 ha

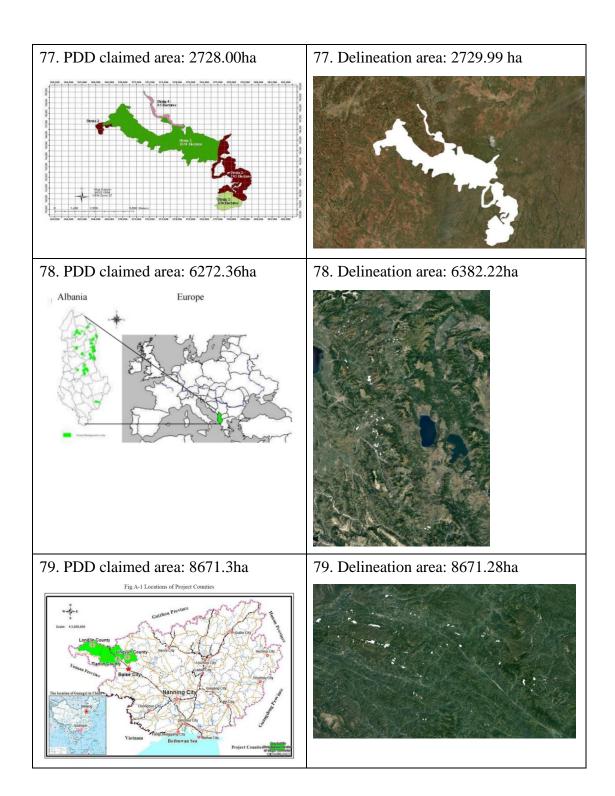


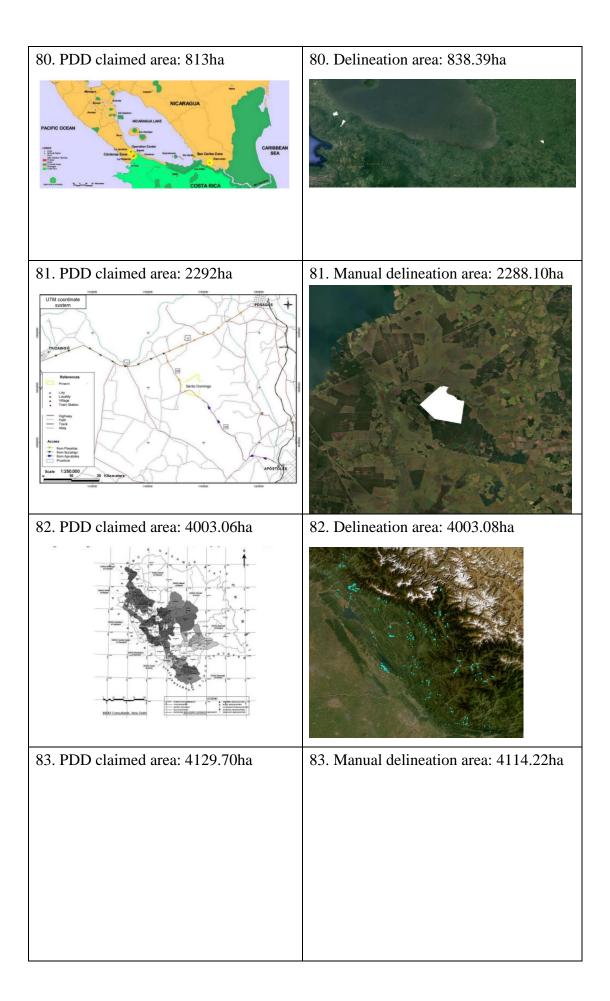
76. PDD claimed area: 11711.4ha

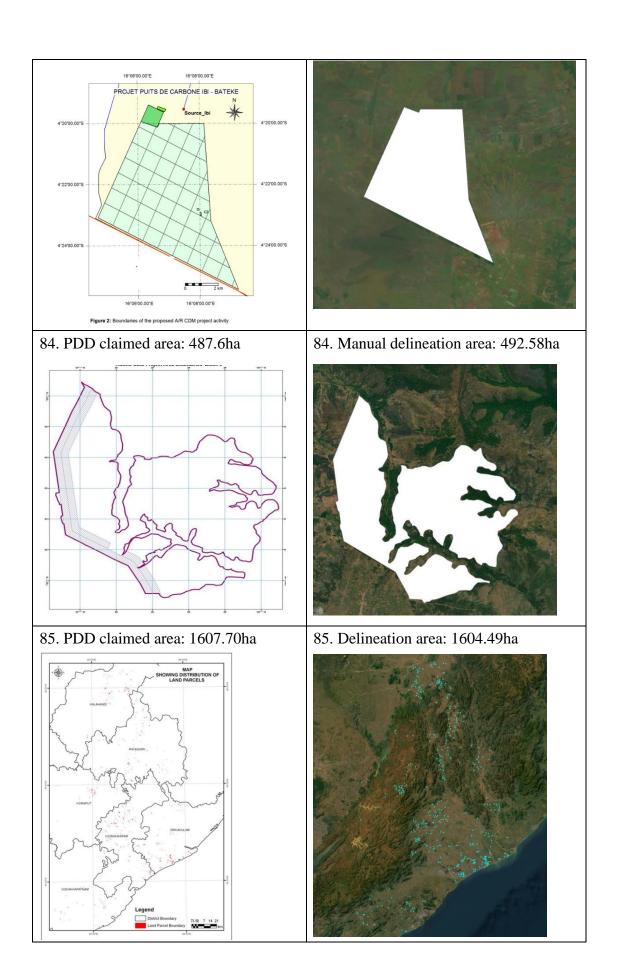


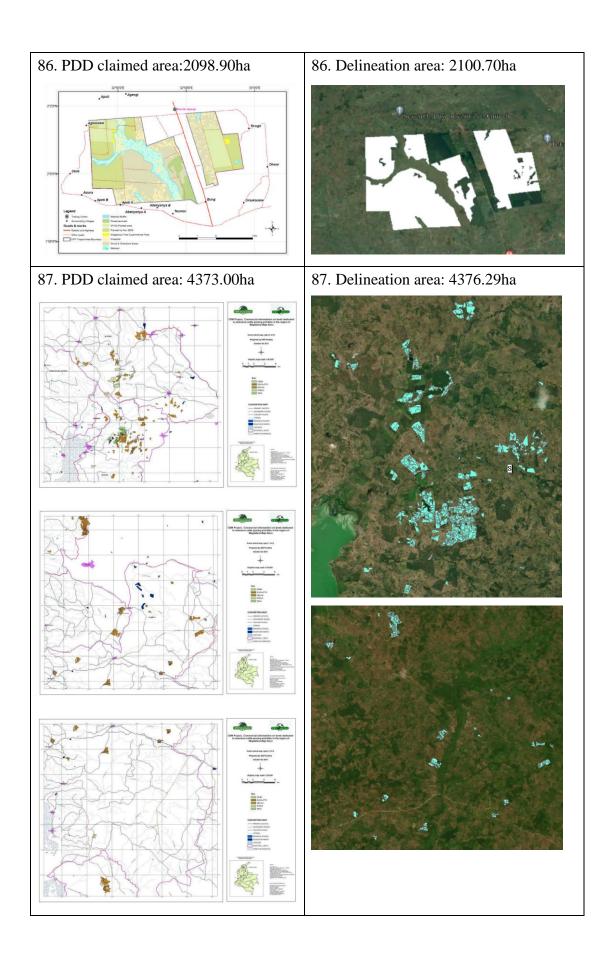
76. Delineation area: 11744.89ha



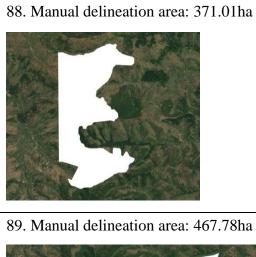


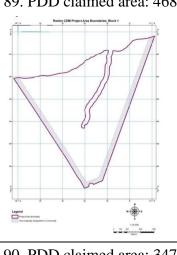




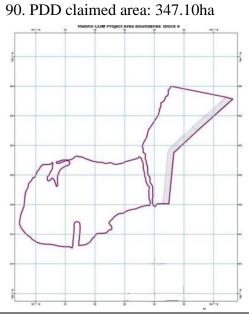


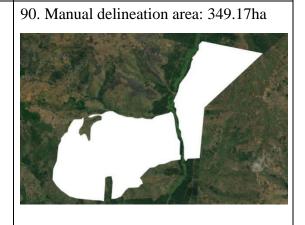
88. PDD claimed area: 370ha 89. PDD claimed area: 468ha

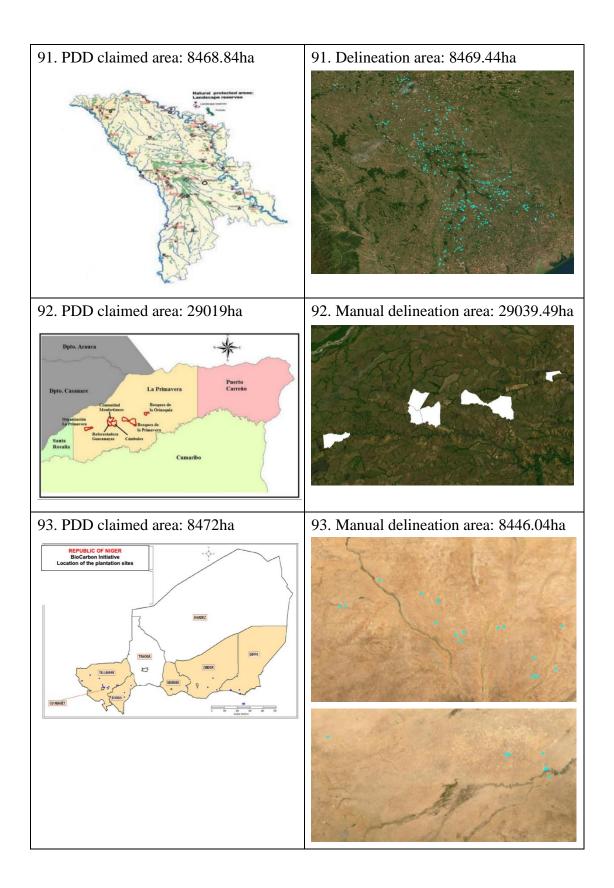


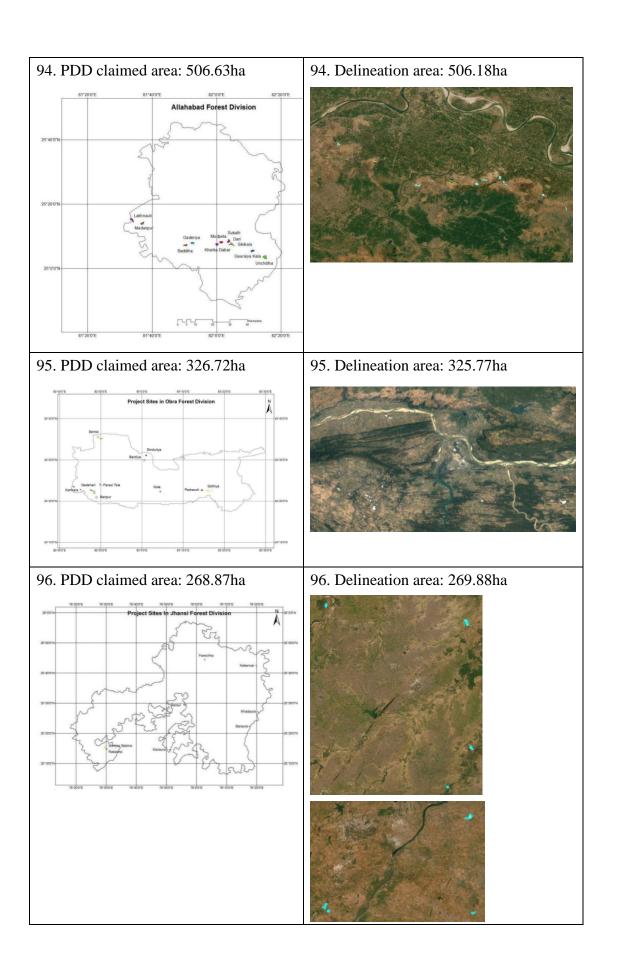


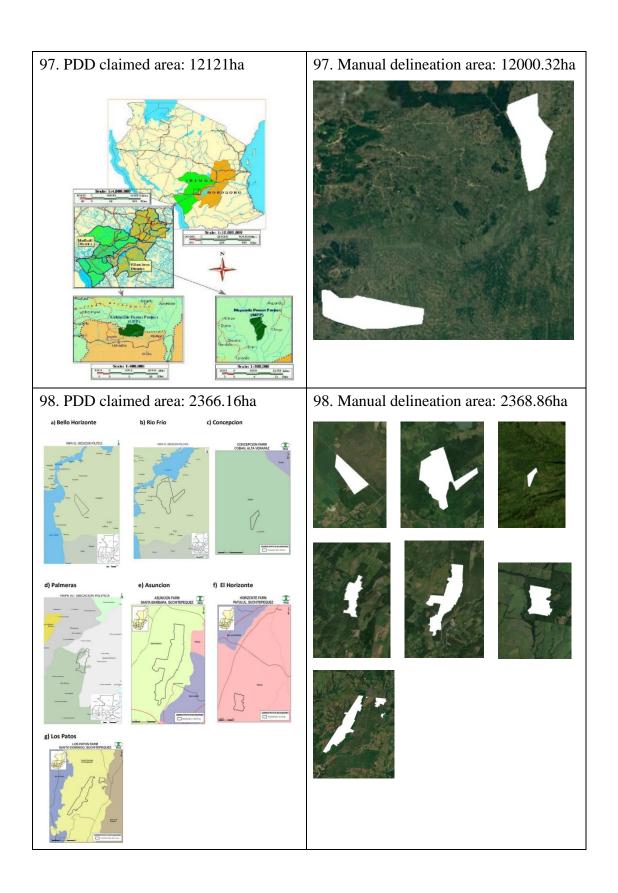


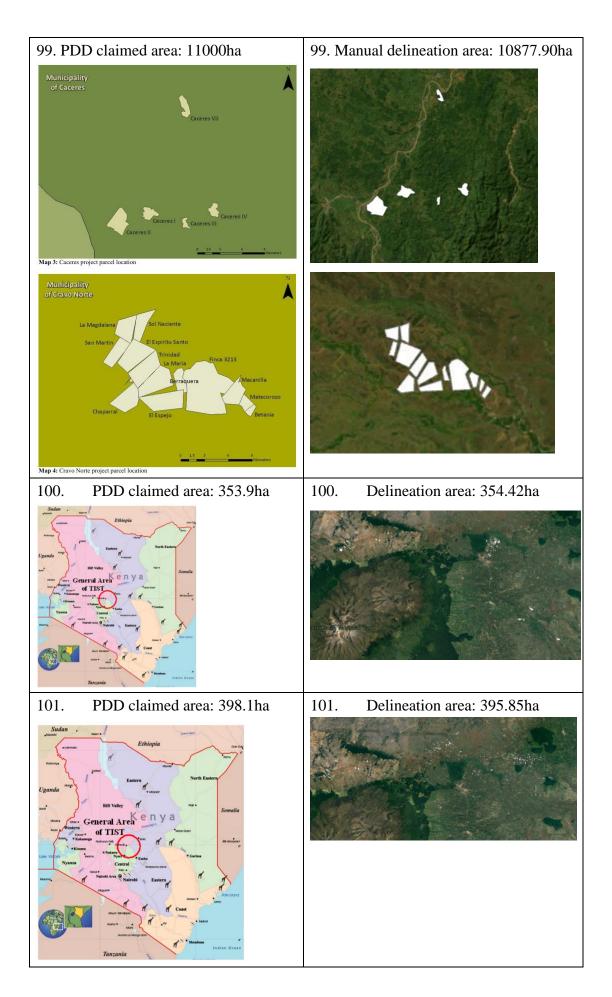


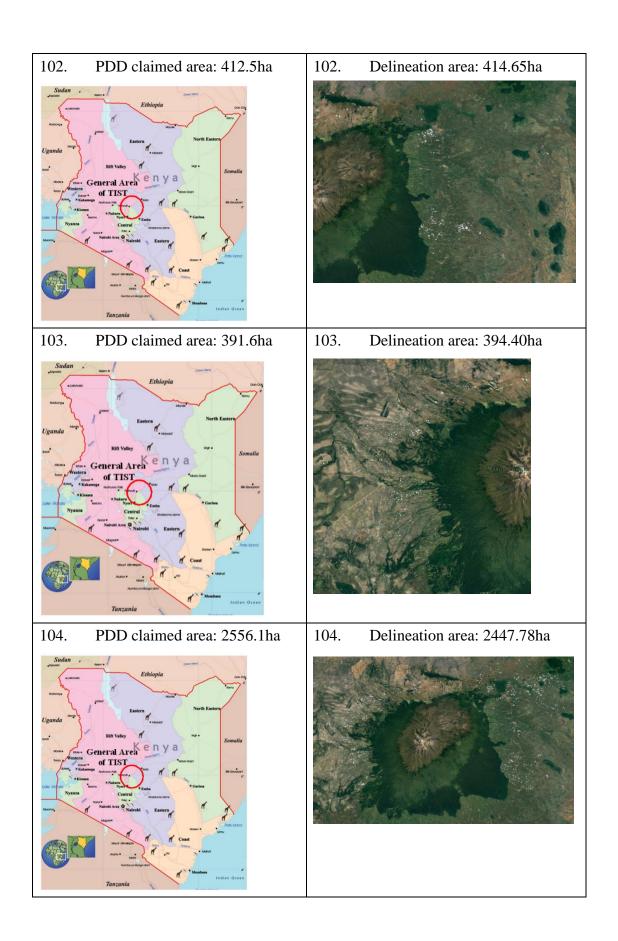




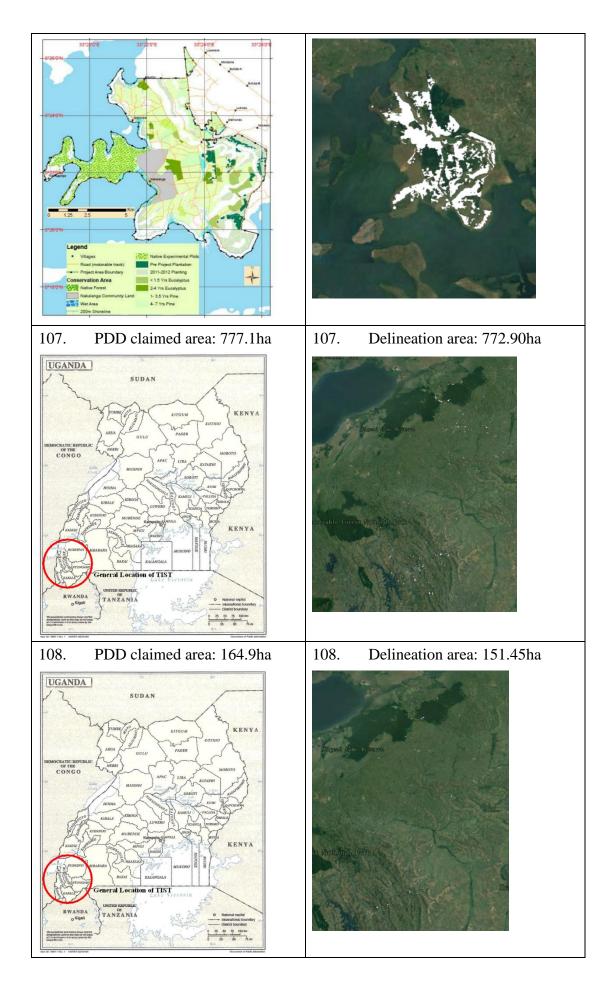


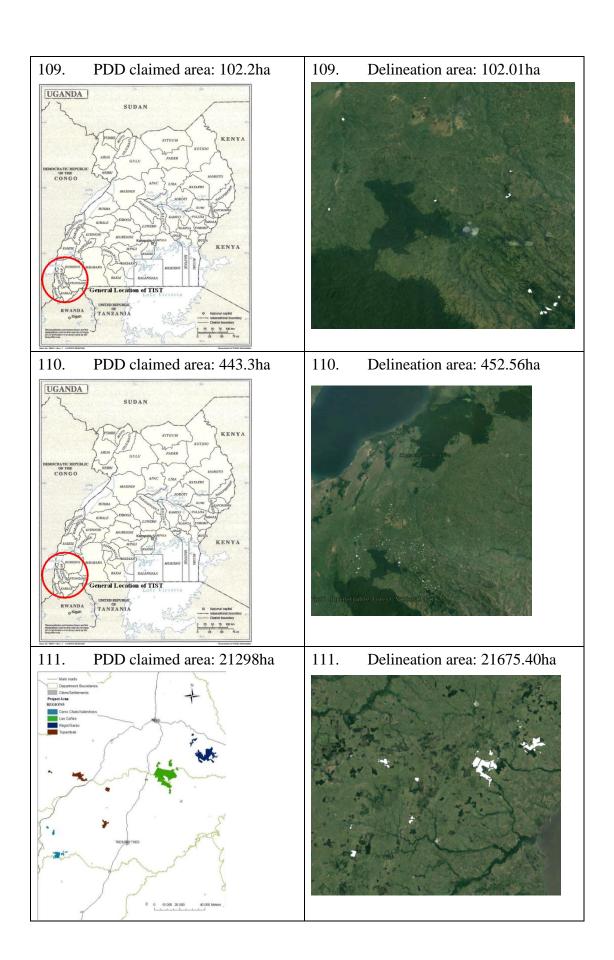


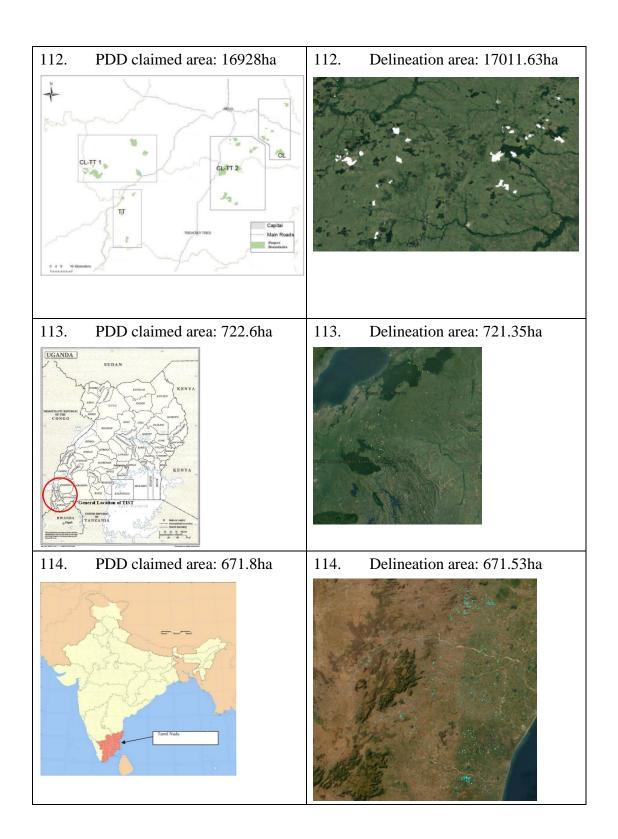


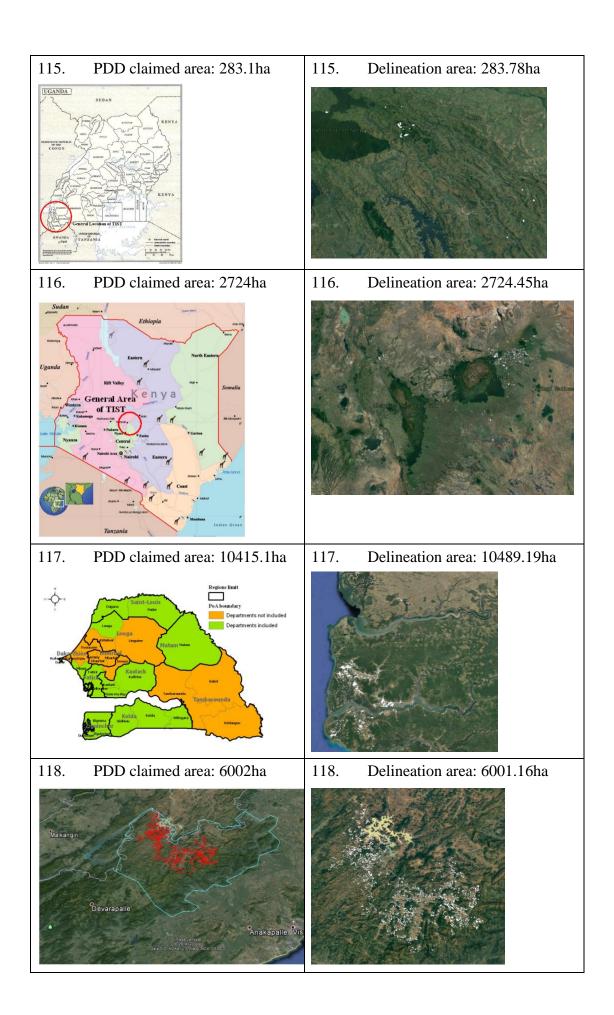


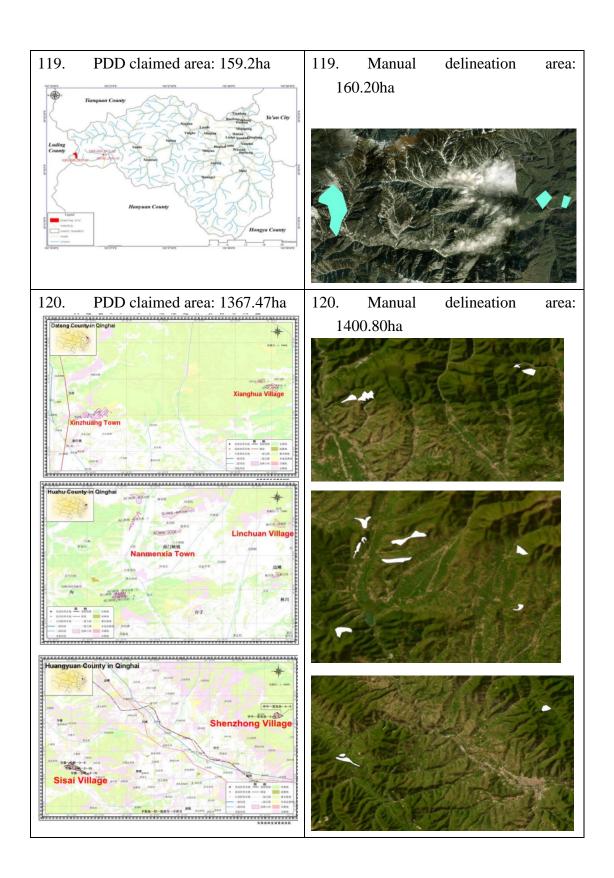


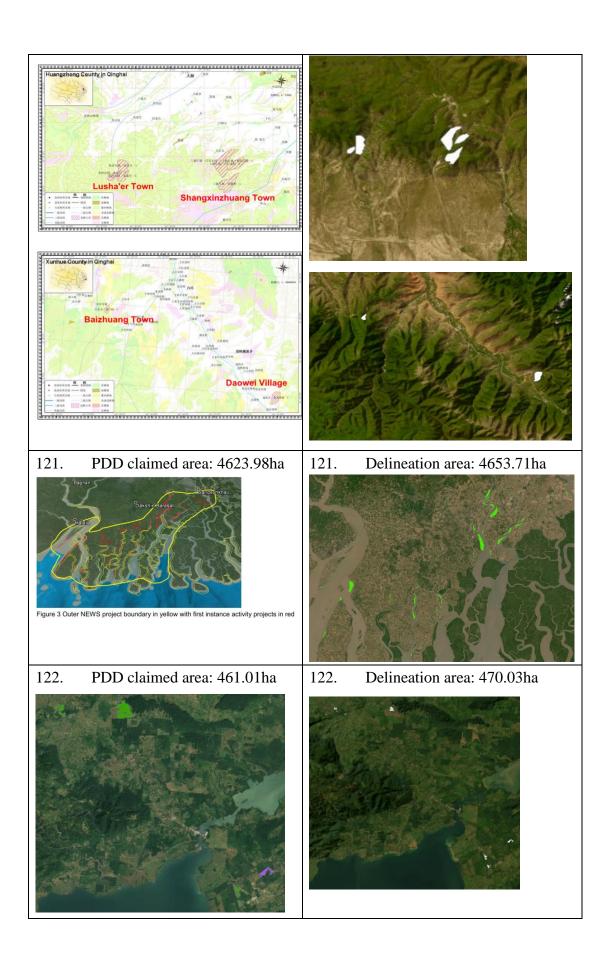


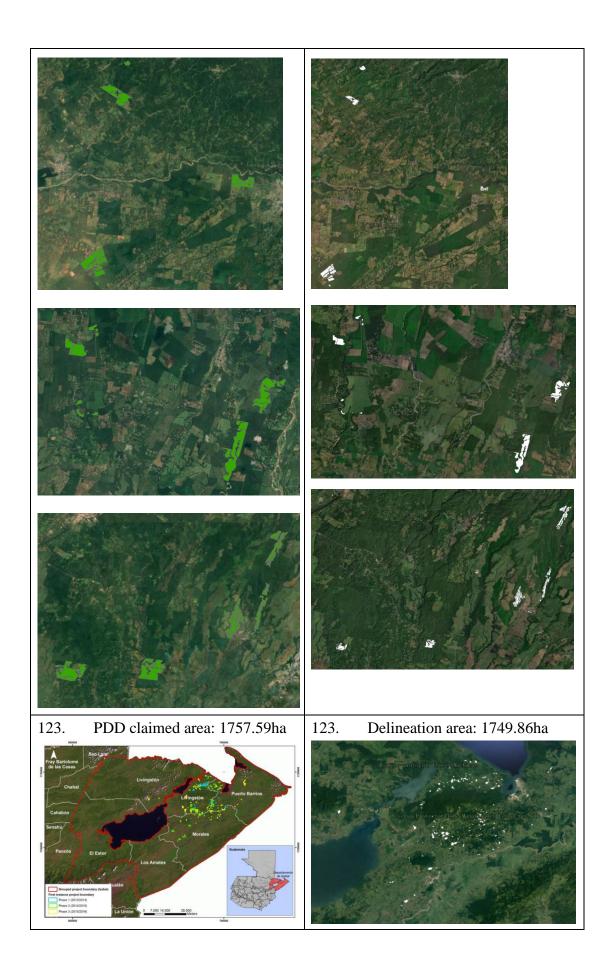


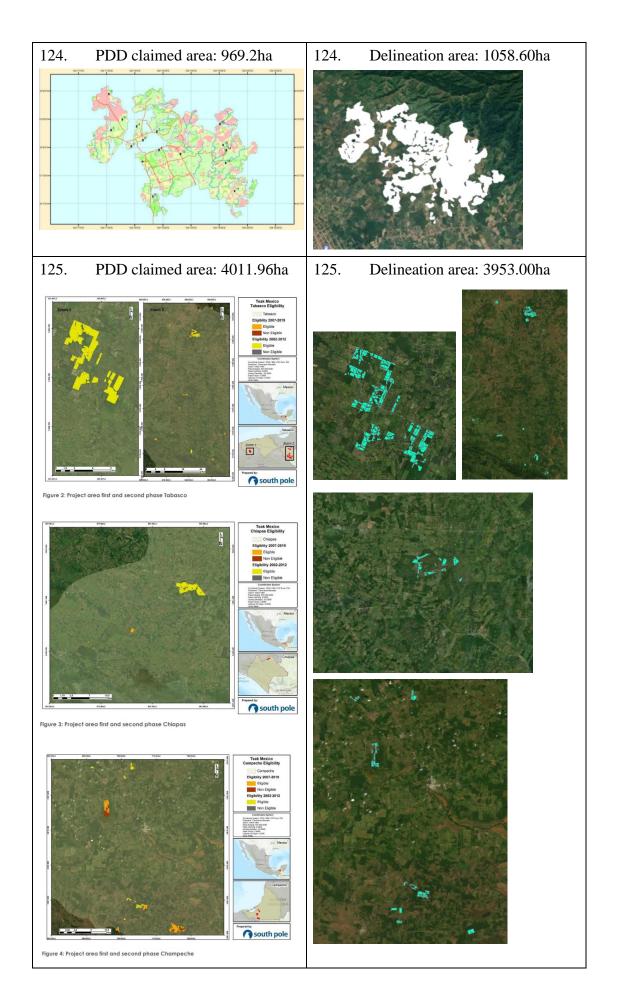


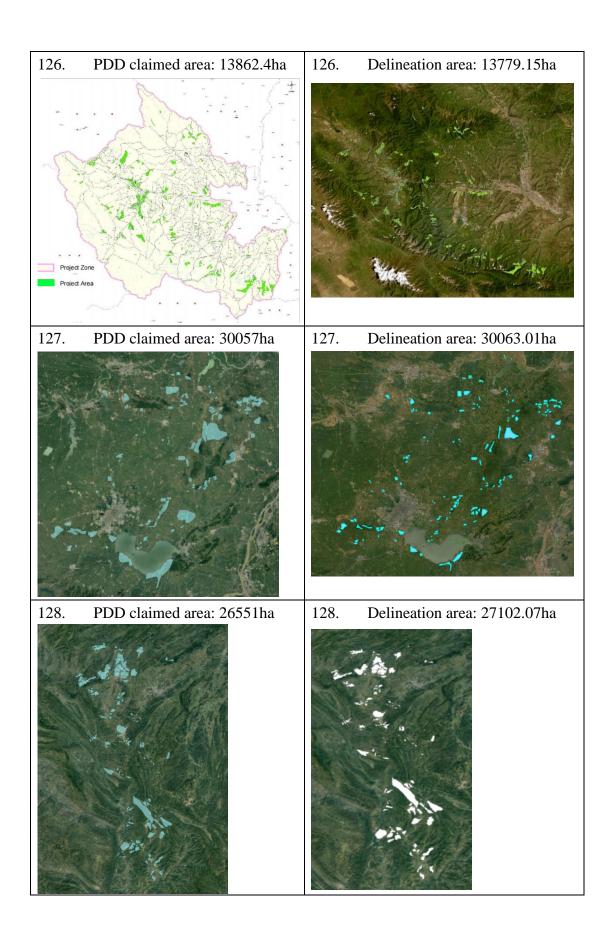


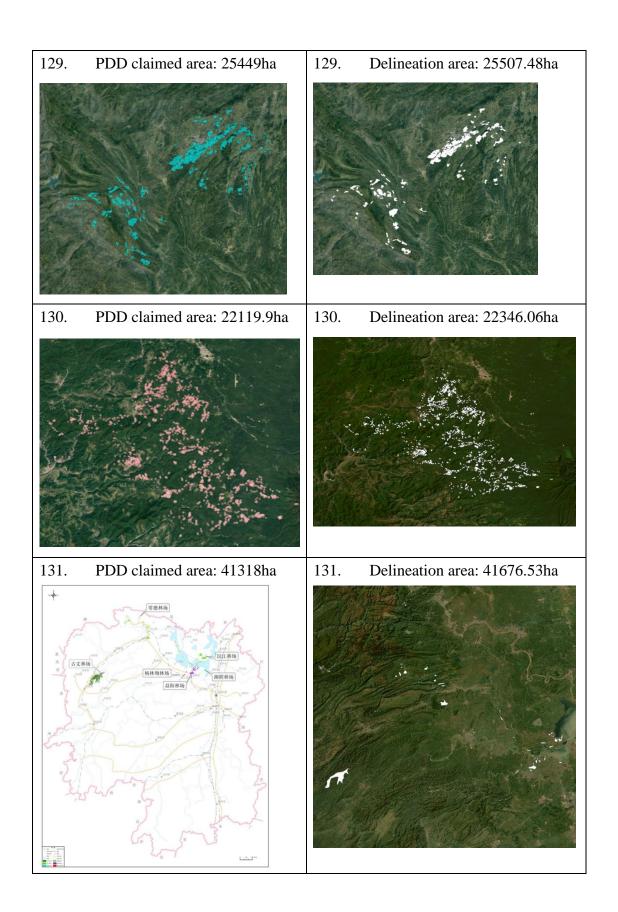


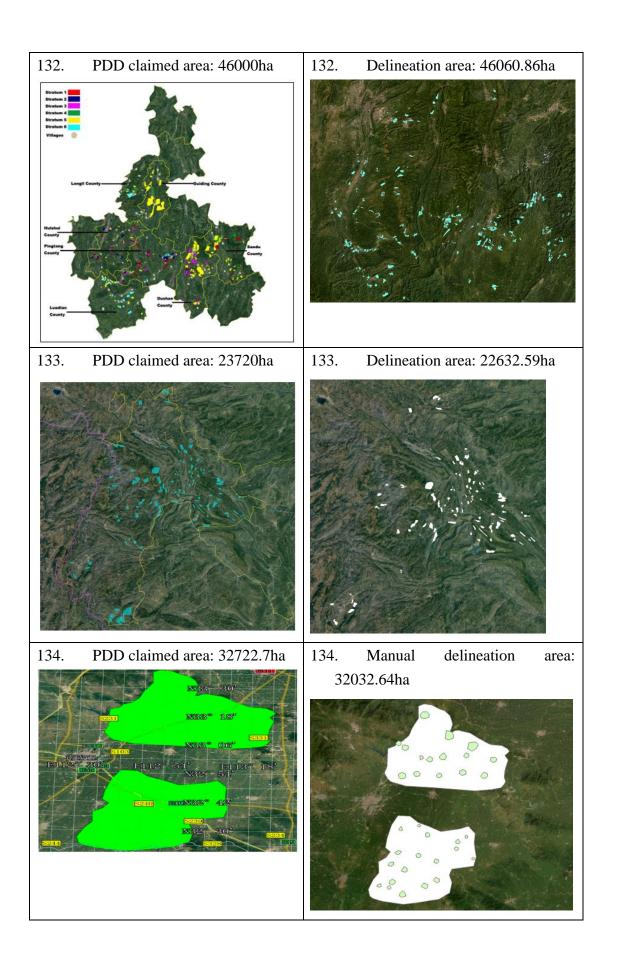


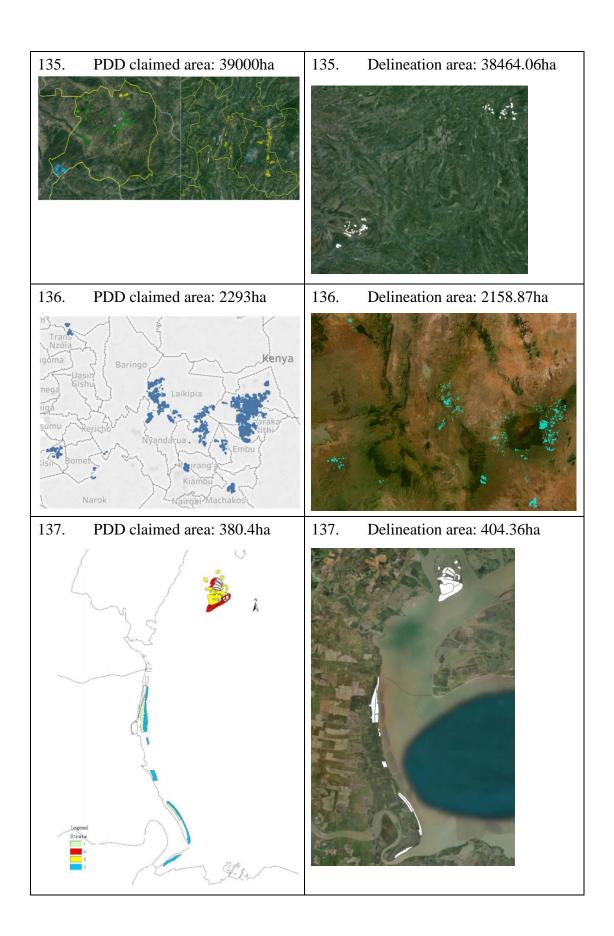


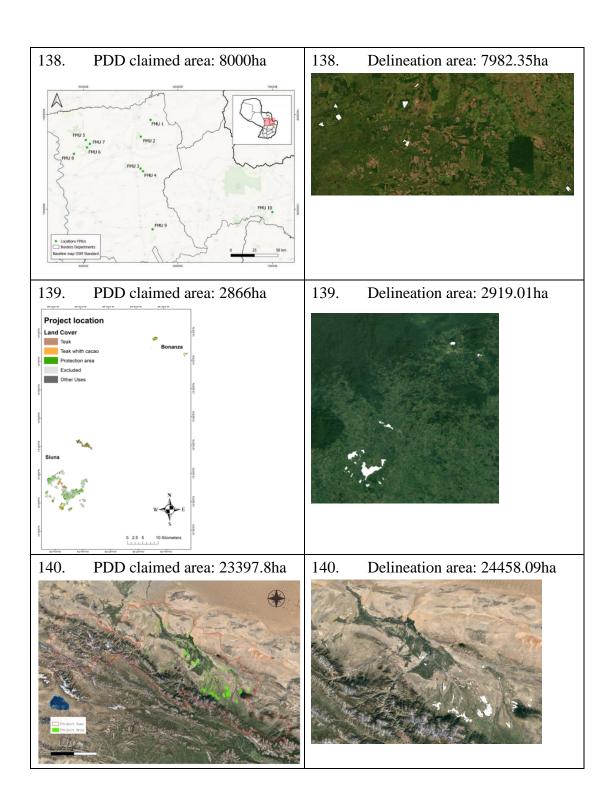


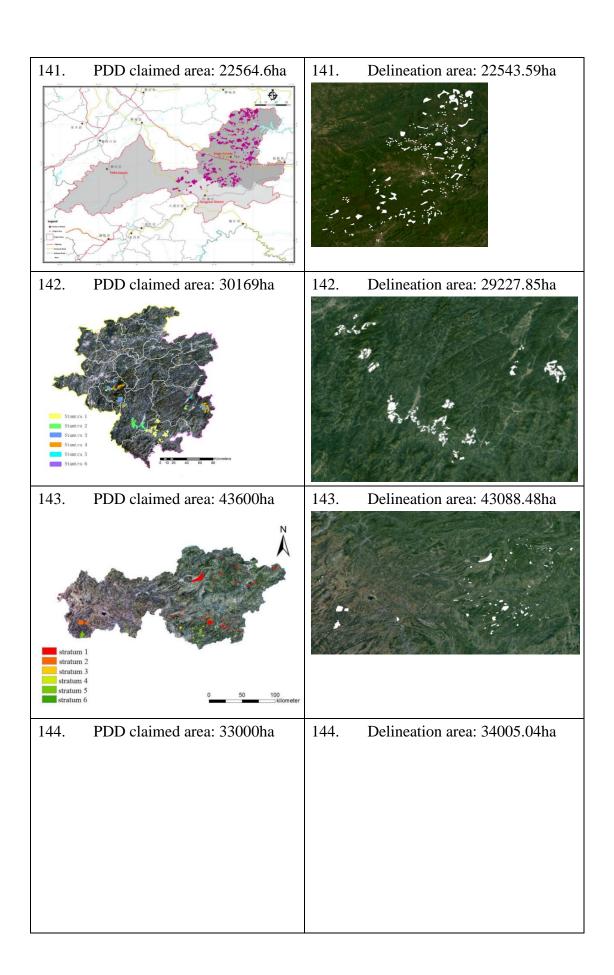


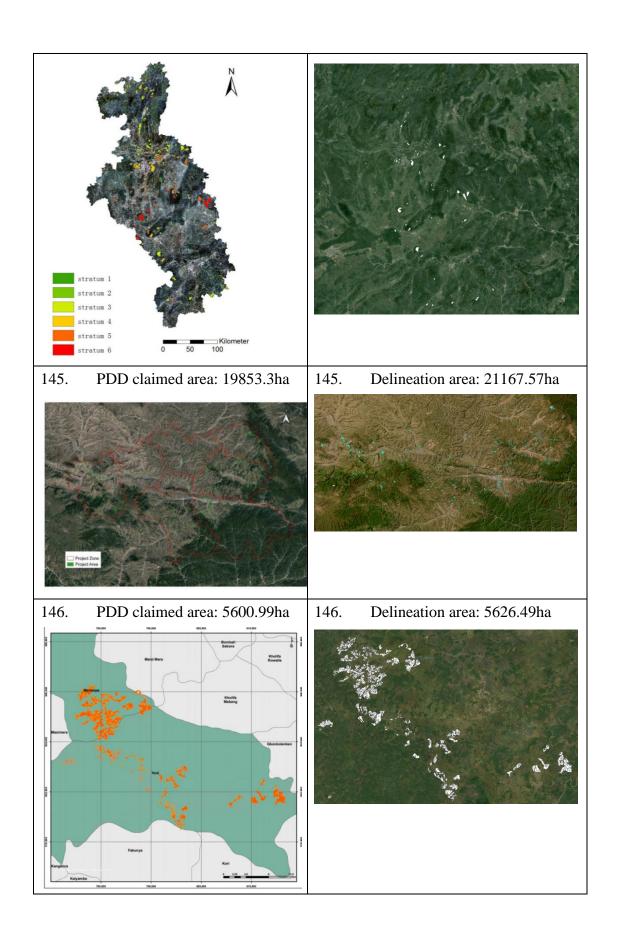


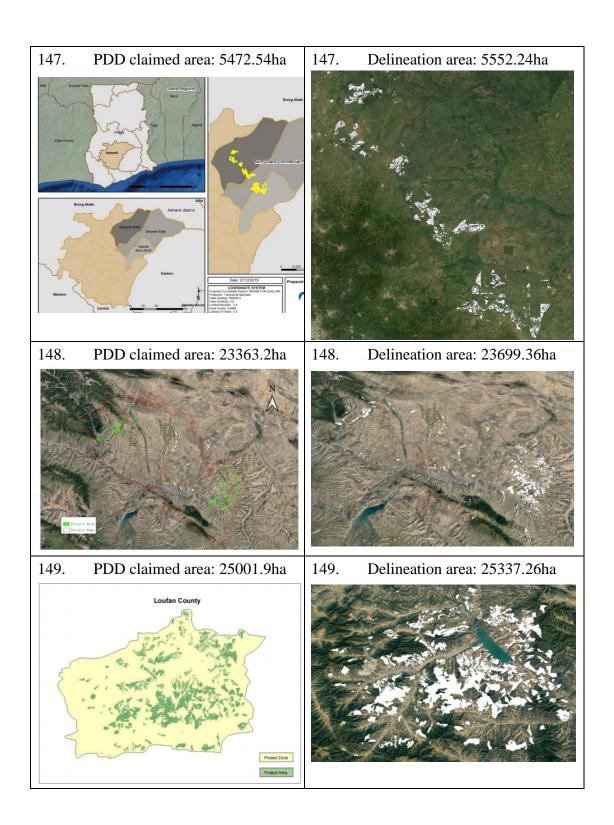


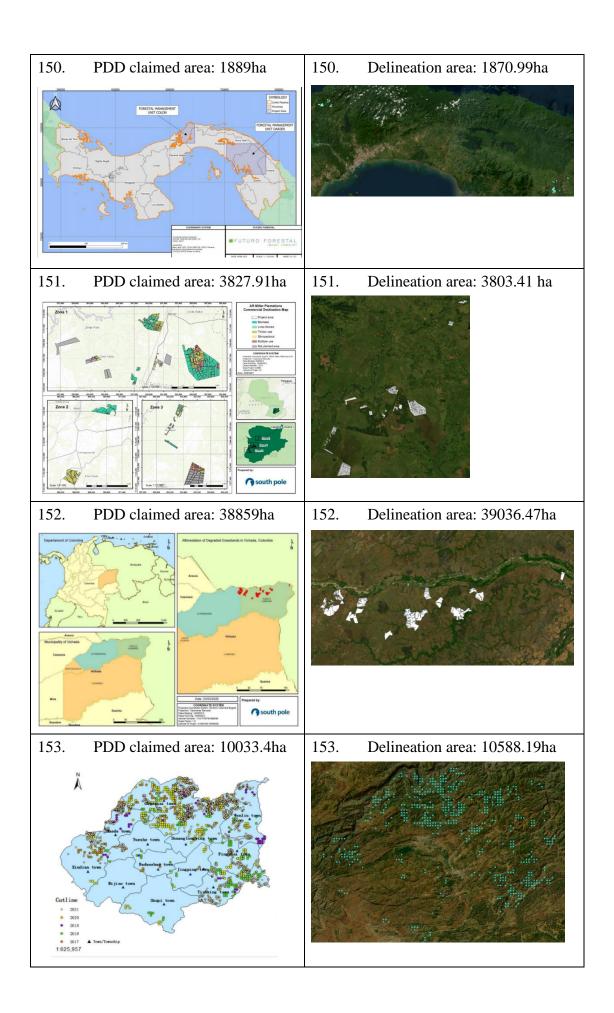


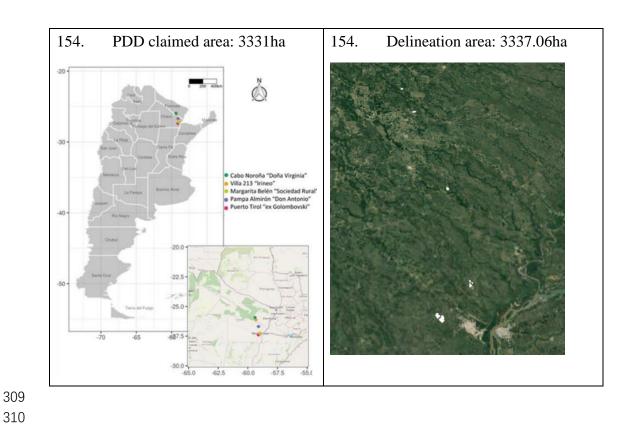












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422