Appendix to Evaluating the Role of ARPA and Anti-Deforestation Policies for Supplying Hydropower, Avoiding Carbon Emissions, and Economic Returns in the Brazilian Amazon

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A. Measuring the hydropower production of the GOV scenario versus the BAU scenario

A.1. Introduction

The InVEST Hydropower model's power production subroutine converts the annual inflow volume to each dam, adjusted for consumption, to a per-second rate. Because of difficulties in obtaining data on each dam's physical characteristics (especially for future dams) we use previously published estimates for turbine efficiency and water in the reservoir available to generate energy (Tallis et al. 2011). For current dams dam height is obtained from ANEEL and future dams is calculated as the difference between upstream and downstream reservoir elevation as a best approximation of usable head. Each of the dams considered wither uses or will use reservoirs to provide a more dependable source of power by smoothing seasonal changes in water flow (ANEEL 2012; personal communication with Zachery Hurwitz, International Rivers). The water yield and potential energy production estimates provided here serve as useful first steps in evaluating how and where changes in a catchment may affect hydropower production. We estimate the annual gross value of hydropower production at \$0.09 per KWH in 2000 US\$ based on 2009 industry electricity prices in Brazil (International Energy Agency 2010).

A. 2. Modified InVEST Hydropower Production Model with THMB water yield

Please refer to Tallis et al. 2011 for details on the InVEST Hydropower Production model and Coe et al. 2009 for details on the IBIS-THMB and CCM3/IBIS-THMB water yield models. Inputs for InVEST Hydropower Production model are presented below.

InVEST estimates the annual average quantity and value of hydropower produced by reservoirs, and identifies how much water yield or value each part of the landscape contributes annually to hydropower production. The model has three components: water yield, water consumption, and hydropower valuation.

A.3. Water yield

We use two estimates of water yield taken from Coe et al. 2009. The first excludes climate feedbacks to precipitation (hereafter referred to as "static climate.") The second considers the combined effect of local evapotranspiration and regional precipitation, as well as feedbacks from deforestation on water flow (hereafter referred to as "dynamic climate"). In the static case, we use outputs from the land surface model IBIS (Kucharik et al., 2000) and the river transport model THMB (Coe et al. 2007) to create annual and seasonal maps of water yield across the basin in 2050. In the dynamic case, we use outputs from the fully coupled CCM3/IBIS global climate and land surface model (Delire et al. 2002, 2004) and THMB to create annual and seasonal maps of water yield across the basin as of 2050.

A.4. Water consumption

InVEST requires several input tables. First it requires a table of LULC classes, showing consumptive water use for each LULC type. Consumptive water use is that part of water used that is incorporated into products or crops, consumed by humans or livestock, or otherwise removed from the watershed water balance.

Table 1. Average water demand in the Amazon basin circa 2000

Liters / person / day	**m^3/ person / yr**	**Source**
187	65.7	http://www.data360.org/dsg.aspx?Data_Set_Group_Id=757
143	52.2	wikipedia unsourced
	270 - 395	http://chartsbin.com/view/1455
149	54.75	http://www.environmental-expert.com/Files%5C5302%5Carticles%5C9780%5CAssessingtherelevanceofintervening.pdf
	1381	http://www.waterfootprintnetwork.org/Reports/Hoekstra_and_Chapagain_2007.pdf
	359	http://www.ielts-exam.net/IELTS-Writing-Samples/IELTS_Sample_Writing_Academic_Task_1_1.pdf
Average (low)	57.55	
Average (medium)	341.33	

Below we detail the steps we took to create the InVEST water demand table for the CTL scenario.

1. We combined the current watersheds and enhanced 2000 LULC map. For each grid cell the enhanced LULC map indicates:
    a. forest (= 2), deforest (= 1), or other (= 3) according to the raster "LULC2000";
    b. whether or not the cell is in a current ARPA (= 1 in the "in_ARPA" field in map "ARPA_1_2.shp");
    c. whether or not the cell is an urban cell according to the urban extent grid map (= 2 in value field from raster *urbextent* from Columbia University - CIESIN);
    d. proportion of grid cell in cropland in 2000[1] (= 1 if 0.00; = 2 if 0.01-0.30; or =3 if 0.31 – 1.00); and
    e. proportion of grid cell in pasture in 2000[2] (0.00; 0.01-0.30; or 0.31 – 1.00)
2. For each unique combination of (a)-(e) we generate a LULC code. We have 195 unique combinations of (a)-(e) on the 2000 landscape (the raster file is called *amazon2000_p*).
3. Next we took the projected 2000 population map (the raster file is called *popin00_p*), which gives people per grid cell where a grid cell is 4875 meters squared, and converted this to people per hectare (the raster file is called *popin00_ph*). In other words, we divided the raster map *popin00_p* by ((4875 x 4875) / 10000) = 2,376 hectares.
4. We then overlaid amazon2000_p on the per hectare 2000 population map (the raster is called *popin00_ph*) and performed a zonal statistic analysis across LULC. The zonal

[1] Taken from "Agricultural Lands in the Year 2000 (M3-Cropland and M3-Pasture Data)" from http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html.
[2] Taken from "Agricultural Lands in the Year 2000 (M3-Cropland and M3-Pasture Data)" from http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html).

statistic procedure gives us the average number of people per hectare for each LULC type. Then we multiply the average people per hectare for each LULC type by the hectares of a grid cell in *amazon2000_p* (105.88 hectares) to get people in each LULC type on the *amazon2000_p* map.

5. Then we multiply the number of people in each LULC type by annual water use per person (cubic meters per year per person) in Brazil circa 2000 to get cubic meters withdrawn per year in each LULC type (we have low and high estimates). The low estimate of water use per person per year is 57.55 cubic meters and the high estimate is 341.33. All of the data is in *popdatacomb1.xls*.
6. Finally, the water consumption results by LULC code for low and high consumption rates are placed in the MS Access database tables *waterdemand2000low* and *waterdemand2000high*. The data is given in Table 2 below as well.

Table 2. Water demand table for CTL

LULC code	People per grid	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
1	0.62	35.90	212.90
2	0.63	36.20	214.68
3	0.63	36.20	214.68
4	0.63	36.20	214.69
5	0.68	38.94	230.95
6	0.67	38.50	228.36
7	0.75	43.18	256.12
8	0.75	43.04	255.27
9	0.23	13.27	78.73
10	0.63	36.19	214.67
11	0.00	0.00	0.00
12	0.51	29.33	173.96
13	0.23	13.43	79.66
14	0.63	36.19	214.66
15	0.00	0.00	0.00
16	0.65	37.26	220.99
17	0.52	29.75	176.43
18	0.00	0.00	0.00
19	0.41	23.36	138.52
20	0.23	13.28	78.78
21	0.55	31.61	187.49
22	0.25	14.43	85.58
23	0.38	21.97	130.28
24	0.00	0.00	0.00
25	0.30	17.19	101.98
26	0.00	0.00	0.00
27	10.53	605.81	3593.09
28	12.28	706.85	4192.33
29	11.46	659.37	3910.73
30	3.64	209.36	1241.73
31	1.78	102.42	607.43
32	2.21	127.45	755.92
33	11.62	668.59	3965.41

LULC code	People per grid	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
34	15.90	914.87	5426.12
35	20.60	1185.34	7030.27
36	4.00	230.45	1366.78
37	6.79	391.01	2319.06
38	2.01	115.43	684.60
39	4.67	269.00	1595.43
40	8.61	495.28	2937.49
41	8.53	490.70	2910.32
42	4.25	244.84	1452.14
43	3.20	184.40	1093.67
44	1.66	95.62	567.13
45	4.63	266.26	1579.21
46	7.75	446.19	2646.37
47	0.47	26.91	159.62
48	0.46	26.58	157.64
49	51.20	2946.70	17476.95
50	15.66	901.12	5344.59
51	22.34	1285.47	7624.13
52	6.20	356.60	2115.01
53	10.73	617.25	3660.93
54	4.53	260.76	1546.56
55	12.82	737.53	4374.33
56	7.80	448.94	2662.68
57	9.03	519.80	3082.95
58	0.00	0.00	0.00
59	10.04	578.08	3428.59
60	85.37	4913.22	29140.39
61	0.00	0.00	0.00
62	0.00	0.00	0.00
63	4.98	286.72	1700.52
64	11.49	661.12	3921.10
65	10.72	617.03	3659.59
66	10.72	617.00	3659.44
67	0.00	0.00	0.00
68	10.44	600.84	3563.57
69	0.00	0.00	0.00
70	0.00	0.00	0.00
71	5.53	318.01	1886.11
72	2.51	144.39	856.40
73	2.76	158.91	942.52
74	0.00	0.00	0.00
75	3.48	200.02	1186.30
76	8.88	511.09	3031.27
77	6.41	369.12	2189.24
78	3.48	200.22	1187.48
79	1.97	113.57	673.59
80	0.92	53.19	315.48
81	0.00	0.00	0.00

LULC code	People per grid	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
82	3.04	175.13	1038.69
83	2.05	118.00	699.89
84	9.39	540.23	3204.13
85	4.77	274.76	1629.59
86	4.92	282.97	1678.30
87	28.35	1631.54	9676.71
88	16.61	955.92	5669.56
89	5.68	326.87	1938.66
90	11.85	681.94	4044.63
91	0.00	0.00	0.00
92	0.00	0.00	0.00
93	1.34	77.08	457.18
94	3.66	210.39	1247.83
95	4.22	242.82	1440.15
96	2.98	171.24	1015.65
97	1.86	106.82	633.54
98	4.46	256.86	1523.45
99	6.93	399.00	2366.45
100	1.60	92.06	546.04
101	8.11	466.88	2769.06
102	0.00	0.00	0.00
103	0.00	0.00	0.00
104	0.00	0.00	0.00
105	0.00	0.00	0.00
106	0.54	31.10	184.48
107	0.00	0.00	0.00
108	0.00	0.00	0.00
109	6.81	392.03	2325.15
110	11.08	637.67	3782.03
111	0.00	0.00	0.00
112	6.40	368.28	2184.27
113	8.93	513.83	3047.56
114	15.84	911.67	5407.11
115	0.00	0.00	0.00
116	0.00	0.00	0.00
117	0.00	0.00	0.00
118	0.00	0.00	0.00
119	2.33	134.20	795.91
120	2.50	144.05	854.39
121	0.00	0.00	0.00
122	20.07	1155.17	6851.31
123	1.14	65.59	389.02
124	1.59	91.37	541.91
125	2.92	168.09	996.96
126	1.34	77.02	456.82
127	100.84	5803.44	34420.32
128	0.95	54.51	323.27
129	0.79	45.71	271.13

LULC code	People per grid	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
130	0.65	37.30	221.21
131	0.65	37.29	221.15
132	0.00	0.00	0.00
133	0.65	37.30	221.21
134	0.65	37.30	221.22
135	6.68	384.42	2279.98
136	6.25	359.50	2132.23
137	1.32	76.04	451.02
138	1.76	101.56	602.33
139	0.00	0.00	0.00
140	1.26	72.66	430.94
141	2.37	136.58	810.06
142	1.61	92.89	550.95
143	0.00	0.00	0.00
144	1.61	92.78	550.29
145	2.68	154.37	915.56
146	6.69	384.99	2283.38
147	2.08	119.89	711.05
148	1.33	76.81	455.54
149	1.47	84.85	503.23
150	4.10	235.68	1397.84
151	4.60	264.70	1569.95
152	2.27	130.73	775.36
153	0.52	29.95	177.64
154	9.53	548.20	3251.39
155	0.00	0.00	0.00
156	2.58	148.72	882.09
157	2.69	154.74	917.74
158	3.79	218.34	1294.96
159	1.74	100.08	593.58
160	1.88	107.93	640.11
161	4.04	232.70	1380.16
162	3.44	198.11	1175.02
163	11.80	679.01	4027.24
164	7.47	429.82	2549.27
165	10.51	605.02	3588.41
166	6.19	356.02	2111.59
167	0.80	46.14	273.68
168	7.65	440.22	2610.97
169	1.83	105.55	626.03
170	0.00	0.00	0.00
171	2.14	123.39	731.81
172	0.00	0.00	0.00
173	0.00	0.00	0.00
174	25.04	1440.85	8545.70
175	17.21	990.53	5874.84
176	1.73	99.61	590.79
177	1.83	105.27	624.34

LULC code	People per grid	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
178	0.00	0.00	0.00
179	1.24	71.25	422.61
180	1.85	106.59	632.16
181	2.04	117.50	696.92
182	3.73	214.65	1273.11
183	1.56	89.79	532.53
184	4.07	233.99	1387.79
185	0.00	0.00	0.00
186	0.00	0.00	0.00
187	1.83	105.09	623.27
188	4.56	262.61	1557.57
189	4.79	275.57	1634.43
190	25.73	1480.74	8782.27
191	0.00	0.00	0.00
192	21.65	1246.03	7390.23
193	0.00	0.00	0.00
194	0.00	0.00	0.00
195	27.98	1610.03	9549.10

Below we detail the steps we took to create the InVEST water demand table for the BAU scenario.

1. We combined the “all” watersheds and enhanced business as usual 2050 LULC map. This raster is named *amznbau2050_p*. For each grid cell the enhanced business as usual 2050 LULC map indicates,
    a. Watershed ID
    b. forest (= 2), deforest (= 1), or other (= 3) according to the raster “bau2050lulc” (this raster is based on the raster “BAU_2050” from Coe’s group); and
    c. whether or not the cell is in a current or future ARPA (= 1 or = 2 in the “in_ARPA” field in map “ARPA_1_2.shp”).
2. For each unique combination of (a)-(c) we have a LULC code. We have 192 unique combinations of (a)-(c) on the BAU2050 landscape (the raster is called *amznbau2050_p*).
3. Next we took the projected 2050 population map (the raster is called *popin50_p*), which gives people per grid cell where a grid cell is 4875 meters squared, and converted this to people per hectare (this raster is called *popin50_ph*).
7. We then overlaid *amznbau2050_p* on the 2050 population map (this raster is called *popin50_ph*) and performed a zonal statistics analysis across LULC. The zonal statatic analysis gives us the average number of people per hectare for each LULC type. Then we multiply the average people per hectare for each LULC type by the size of a grid cell on *amznbau2050_p* in hectares ((11105 x 11105) / 10000 = 12,333) to get people in each LULC type on the *amznbau2050_p* map.
8. Then we multiply the average number of people in each *amznbau2050_p* LULC type by annual water use per person (cubic meters per year per person) in Brazil circa 2000 to get cubic meters withdrawn per year in each LULC type (we have low and high estimates). The low estimate of water use per person per year is 57.55 cubic meters

and the high estimate is 341.33. All of the data is in *popdatacomb2050BAU.xlsx*.

9. Finally, the water consumption results by LULC code for low and high consumption rates are placed in the MS Access database tables are *waterdemandBAU2050low* and *waterdemandBAU2050high*. The data is given in Table 3 below as well.

Table 3. Water demand table for BAU

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
1	24565	145693
2	18634	110520
3	19983	118521
4	37663	223382
5	44030	261143
6	43636	258808
7	35394	209924
8	38088	225900
9	15881	94192
10	15427	91497
11	29067	172397
12	43293	256773
13	22111	131143
14	56687	336210
15	55304	328012
16	47158	279693
17	40679	241266
18	55464	328957
19	40694	241356
20	63977	379451
21	38887	230638
22	43447	257686
23	40693	241352
24	38287	227083
25	40691	241340
26	32292	191525
27	63953	379307
28	63964	379371
29	63956	379324
30	14945	88636
31	6615	39232
32	32350	191866
33	98313	583098
34	163497	969705
35	35266	209162
36	23582	139865
37	24802	147102
38	12989	77038
39	287205	1703418
40	270006	1601413
41	5924	35136
42	6740	39977

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
43	7789	46194
44	5909	35044
45	340088	2017066
46	36482	216378
47	15083	89458
48	8896	52765
49	259365	1538297
50	71543	424321
51	72122	427756
52	45704	271069
53	21995	130453
54	72103	427647
55	26837	159169
56	15571	92352
57	236838	1404689
58	72074	427474
59	175779	1042545
60	13223	78428
61	8887	52707
62	14358	85158
63	312543	1853696
64	8883	52684
65	7223	42842
66	312458	1853191
67	167396	992829
68	147084	872355
69	8881	52674
70	8880	52665
71	8879	52663
72	10129	60072
73	103478	613732
74	105048	623044
75	39082	231798
76	0	0
77	496780	2946413
78	33624	199426
79	8875	52637
80	29137	172811
81	36470	216301
82	24685	146410
83	96178	570431
84	38450	228045
85	38507	228386
86	26653	158081
87	26056	154542
88	7770	46083
89	32200	190976
90	8855	52522

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
91	8857	52529
92	5579	33086
93	23530	139558
94	7976	47305
95	21448	127210
96	88730	526259
97	47110	279411
98	77430	459241
99	42012	249176
100	40852	242293
101	36735	217876
102	1020	6052
103	89942	533445
104	1020	6048
105	1020	6051
106	166310	986388
107	5144	30509
108	1020	6049
109	175944	1043526
110	186511	1106200
111	102697	609098
112	80757	478971
113	165147	979492
114	123987	735368
115	25619	151950
116	16760	99405
117	79100	469142
118	40531	240392
119	6393	37916
120	169477	1005172
121	20177	119669
122	304084	1803529
123	111569	661715
124	44194	262115
125	158380	939353
126	15909	94354
127	58539	347197
128	553289	3281568
129	5459	32376
130	64102	380189
131	94127	558270
132	4298	25490
133	60879	361077
134	22533	133641
135	27678	164159
136	80624	478180
137	25037	148493
138	169110	1002995

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
139	83179	493335
140	32441	192408
141	51482	305339
142	25392	150599
143	35761	212096
144	10114	59984
145	17769	105389
146	29429	174544
147	11221	66552
148	38859	230472
149	17406	103235
150	7828	46426
151	52799	313155
152	328897	1950692
153	120901	717068
154	68465	406070
155	37286	221142
156	164575	976099
157	77459	459409
158	6118	36289
159	6819	40443
160	8587	50929
161	33840	200708
162	37821	224315
163	41658	247074
164	32178	190850
165	59997	355841
166	36852	218569
167	95687	567518
168	34842	206650
169	29134	172796
170	36274	215141
171	2717	16112
172	57635	341832
173	54010	320334
174	57703	342237
175	34802	206410
176	86364	512224
177	24899	147677
178	2714	16097
179	21049	124842
180	25264	149840
181	41374	245388
182	7010	41576
183	24250	143827
184	154687	917454
185	45827	271799
186	15309	90796

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
187	120826	716622
188	20603	122198
189	0	0
190	24307	144167
191	49615	294268
192	50374	298769

Below we detail the steps we took to create the InVEST water demand table for the GOV scenario.

1. We combined the "all" watersheds and enhanced government 2050 LULC map. This map is named *amzngov2050_p*. For each grid cell the enhanced business as usual 2050 LULC map indicates,
    a. Watershed ID
    b. forest (= 2), deforest (= 1), or other (= 3) according to the raster "gov2050lulc" (this raster is based on the raster "BAU_2050" from Coe's group); and
    c. whether or not the cell is in a current or future ARPA (= 1 or = 2 in the "in_ARPA" field in map "ARPA_1_2.shp").
2. For each unique combination of (a)-(c) we have a LULC code. We have 195 unique combinations of (a)-(c) on the GOV landscape (the raster is called *amzngov2050_p*).
3. Next we took the projected 2050 population map (the raster is called popin50_p), which gives people per grid cell where a grid cell is 4875 meters squared, and converted this to people per hectare (the raster is called *popin50_ph*).
4. We then overlaid *amzngov2050_p* on the 2050 population map (the raster is called *popin50_ph*) and performed a zonal statistical analysis across LULC. The zonal statistical analysis gives us the average number of people per hectare for each LULC type. Then we multiply the average people per hectare for each LULC type by the hectares in a grid cell on *amzngov2050_p* ((11105 x 11105) / 10000 = 12,333) to get people in each LULC type on the *amzngov2050_p* map.
5. Then we multiply the average number of people in each *amzngov2050_p* LULC type by annual water use per person (cubic meters per year per person) in Brazil circa 2000 to get cubic meters withdrawn per year in each LULC type (we have low and high estimates). The low estimate of water use per person per year is 57.55 cubic meters and the high estimate is 341.33. All of the data is in *popdatacomb2050GOV.xlsx*.
6. Finally, the water consumption results by LULC code for low and high consumption rates are placed in the MS Access database tables are *waterdemandGOV2050low* and *waterdemandGOV2050high*. The data is given in Table 4 below as well

Table 4. Water demand table for GOV

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
1	23652	140269
2	19983	118511
3	20585	122079
4	43877	260213

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
5	35394	209905
6	38088	225879
7	30725	182212
8	42518	252151
9	30755	182393
10	55304	327981
11	47157	279667
12	40679	241247
13	40346	239271
14	40694	241334
15	63977	379416
16	42349	251153
17	40259	238758
18	40693	241332
19	35324	209488
20	40691	241318
21	33887	200966
22	63953	379272
23	63958	379300
24	14944	88628
25	6615	39229
26	63951	379261
27	32349	191848
28	105628	626426
29	163497	969616
30	53352	316402
31	16621	98569
32	23657	140298
33	57241	339466
34	287204	1703261
35	247583	1468289
36	6539	38780
37	7862	46627
38	336252	1994142
39	5909	35040
40	29230	173350
41	8888	52708
42	8896	52760
43	263161	1560675
44	72103	427607
45	10571	62693
46	190978	1132596
47	70504	418122
48	55652	330046
49	27736	164487
50	16928	100392
51	26836	159153
52	236836	1404556

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
53	72074	427435
54	40483	240083
55	30584	181379
56	8887	52702
57	11095	65797
58	312502	1853294
59	8883	52680
60	8884	52684
61	8882	52677
62	172146	1020910
63	150244	891019
64	8879	52660
65	8879	52658
66	11295	66984
67	9420	55865
68	105438	625298
69	105048	622987
70	39079	231758
71	0	0
72	83876	497427
73	327766	1943815
74	29444	174619
75	31907	189225
76	29136	172794
77	41152	244052
78	102158	605847
79	38449	228024
80	49498	293545
81	38507	228365
82	29003	172002
83	26643	158007
84	31646	187679
85	6480	38432
86	8856	52520
87	22890	135751
88	7976	47300
89	96897	574647
90	47110	279385
91	83405	494632
92	42012	249153
93	41776	247755
94	38593	228876
95	64227	380898
96	1020	6051
97	1020	6049
98	166309	986297
99	5144	30506
100	1020	6049

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
101	160337	950880
102	187922	1114471
103	98905	586555
104	132049	783114
105	165147	979402
106	169287	1003955
107	96495	572265
108	128072	759533
109	93082	552022
110	25619	151936
111	17663	104751
112	34474	204446
113	137270	814077
114	79099	469099
115	45965	272596
116	13148	77975
117	6393	37913
118	198312	1176091
119	39586	234767
120	20177	119658
121	80502	477416
122	353050	2093764
123	44194	262091
124	158315	938888
125	15908	94345
126	553287	3281266
127	5459	32373
128	64533	382713
129	4298	25488
130	51528	305588
131	18807	111533
132	28012	166127
133	27509	163144
134	80623	478136
135	25037	148480
136	23835	141356
137	26338	156195
138	51482	305311
139	31068	184248
140	10114	59979
141	23504	139390
142	17651	104681
143	38859	230451
144	62976	373481
145	17406	103225
146	7828	46422
147	52810	313189
148	353701	2097619

LULC Code	Water Consumption Low (m^3 per year per grid cell)	Water Consumption High (m^3 per year per grid cell)
149	123341	731474
150	120901	717002
151	68435	405854
152	54812	325061
153	35487	210454
154	164575	976010
155	77458	459367
156	6118	36285
157	6819	40439
158	8587	50924
159	36080	213970
160	37820	224294
161	43305	256821
162	25630	151997
163	59996	355808
164	36852	218549
165	95932	568923
166	19894	117981
167	29134	172780
168	42316	250957
169	36274	215121
170	2717	16111
171	61633	365515
172	41292	244884
173	2717	16111
174	57703	342206
175	34802	206391
176	86363	512177
177	47837	283698
178	22043	130723
179	2714	16095
180	21049	124831
181	26327	156134
182	25264	149826
183	57230	339400
184	7010	41572
185	24250	143813
186	154687	917370
187	24230	143693
188	15309	90787
189	56625	335814
190	120826	716556
191	20603	122187
192	0	0
193	24307	144154
194	49615	294241
195	50374	298742

A.5. Creation of UHE hydropower dam watersheds

We obtained UHE dam locations from ANEEL 2012. To create the dam watersheds we used Arc Hydro Tools 2.0 (http://blogs.esri.com/esri/arcgis/2011/10/12/arc-hydro-tools-version-2-0-are-now-available/) for manual watershed delineation with ArcGIS 10.0 w/ Spatial Analyst Extension. All operations were performed in WGS 1984 geographic projection with a resolution of 0.0833 Degrees ≈ 10 km. We created dam watersheds for current (Operação) then with all planned dams (Construção, Inventariado, Operação, Outorg, PB com Registro, VB Aprovado, VB com Aceite, VB com Registro). We calculated flow accumulation with Arc Hydro Tools 2.0default parameters. UHE dam points from ANEEL 2012 were manually aligned to nearby gird cells with a flow accumulation > 0. For the UHE dams Cachoeira Caracol, Cachoeira do Meio, Cachoeira Fortaleza, and Cachoeira São José we merged these dams into 1 point renamed Cachoeira_4 because they are all located within the same single raster cell. See table 5 and figure 1 for the list of all UHE dam watersheds

Table 5. All UHE dam location or pour points with original and modified X,Y coordinates.

UHE Name	Estagio	Old X	Mod X	Old Y	Mod Y
Água Limpa	VB com Aceite	-53.37	-53.33	-15.37	-15.17
Araguainha	Inventariado	-53.02	-53.00	-16.89	-16.92
Araguanã	Inventariado	-48.65	-48.67	-6.62	-6.67
Arraias	Inventariado	-47.45	-47.42	-12.43	-12.42
Balbina	Operação	-59.47	-59.42	-1.92	-1.92
Bambu I	Inventariado	-52.61	-52.58	0.79	0.75
Barra do Claro	Inventariado	-56.58	-56.50	-13.41	-13.33
Barra do Palma	Inventariado	-47.80	-47.75	-12.61	-12.50
Belo Monte	Construção	-51.78	-51.75	-3.13	-3.17
Berimbau	VB com Registro	-55.18	-55.17	-1.33	-1.33
Brejão	VB com Registro	-46.95	-46.92	-10.16	-10.17
Cachoeira do Caí	VB com Registro	-56.47	-56.33	-5.08	-4.92
Cachoeira dos Patos	VB com Registro	-5.92	-55.67	-5.92	-5.92
Cachoeira Santo Antônio	Inventariado	-65.55	-65.83	-8.60	-8.58
Cachoeira Velha	Inventariado	-46.87	-46.83	-10.24	-10.25
Cachoeira_4	Inventariado	Various	-66.17	Various	-8.83
Cachoeirão	Inventariado	-58.96	-59.00	-12.99	-13.00
Chacorão	PB com Registro	-58.32	-58.33	-6.50	-6.50
Cinta Larga	Inventariado	-58.33	-58.58	-10.96	-10.92
Colíder	Construção	-55.76	-55.83	-10.98	-11.00
Couto Magalhães	Outorga	-53.14	-53.17	-17.17	-17.17
Curuá-Una	Operação	-54.30	-54.33	-2.81	-2.75
Dardanelos	Operação	-59.46	-59.25	-10.16	-10.17
Diamantino	Inventariado	-52.89	-52.92	-16.80	-16.75
Estreito	Operação	-47.46	-47.42	-6.59	-6.58
Foz do Apiacás	VB com Aceite	-57.09	-57.08	-9.21	-9.25
Garça	PB com Registro	-57.17	-57.25	-13.17	-13.17
Guaporé	Operação	-58.96	-59.00	-15.12	-15.08
Ipueiras	VB Aprovado	-48.45	-48.50	-11.25	-11.25
Isamu Ikeda	Operação	-47.79	-47.75	-10.70	-10.67
Jamanxim	VB com Registro	-55.88	-55.67	-5.65	-5.67
Jardim de Ouro	VB com Registro	-55.77	-55.58	-6.26	-6.25

UHE Name	Estagio	Old X	Mod X	Old Y	Mod Y
Jirau	Construção	-64.73	-64.75	-9.33	-9.50
Juruena	Inventariado	-59.01	-59.08	-13.40	-13.42
Jutuarama	VB com Registro	-54.49	-54.42	-1.33	-1.33
Luís Eduardo Magalhães (Lajeado)	Operação	-48.37	-48.33	-9.76	-9.75
Magessi	VB com Registro	-55.26	-55.25	-13.58	-13.58
Marabá	VB com Registro	-49.07	-49.08	-5.32	-5.25
Mocotó	VB com Registro	-54.44	-54.33	-1.49	-1.50
Novo Acordo	Inventariado	-47.64	-47.67	-9.97	-10.00
Paiaguá	VB com Registro	-57.52	-57.50	-13.22	-13.25
Paranã	VB com Registro	-47.81	-47.83	-12.67	-12.67
Parecis	Inventariado	-57.37	-57.50	-12.84	-12.83
Paredão	VB Aprovado	-61.58	-61.58	-2.95	2.83
Pau D'Arco	VB com Registro	-47.15	-47.17	-12.38	-12.33
PCH Jatobá	VB com Registro	-56.92	-56.92	-5.20	-5.25
Peixe Angical	Operação	-48.38	-48.33	-12.24	-12.25
Perdida 1	VB com Registro	-47.42	-47.42	-9.24	-9.33
Perdida 2	VB com Registro	-47.87	-47.83	-9.35	-9.25
Pitinga	Operação	-59.60	-59.25	-0.87	-0.92
Ponte de Pedra	Operação	-57.37	-57.42	-13.58	-13.67
Rio Sono	Inventariado	-47.89	-47.92	-9.36	-9.33
Roncador	Inventariado	-57.64	-57.67	-12.27	-12.25
Rondon II	Operação	-60.70	-61.25	-12.00	-11.92
Salto Apiacás	PB com Registro	-56.98	-57.00	-10.34	-10.33
Samuel	Operação	-63.45	-63.42	-8.75	-8.75
Santa Isabel	Outorga	-48.33	-48.33	-6.13	-6.08
Santo Antônio	Construção	-63.95	-64.00	-8.80	-8.83
Santo Antônio do Jarí	Construção	-52.52	-52.50	-0.65	-0.67
Serra Quebrada	VB com Aceite	-47.47	-47.42	-5.66	-5.67
Sinop	VB com Aceite	-55.45	-55.42	-11.27	-11.25
São Luiz do Tapajós	VB com Registro	-56.79	-56.58	-4.57	-4.75
São Manoel	VB com Aceite	-57.05	-57.00	-9.19	-9.17
São Salvador	Operação	-48.24	-48.17	-12.81	-12.83
Tabajara	VB com Registro	-62.17	-62.17	-8.90	-8.83
Teles Pires	Construção	-56.78	-56.75	-9.34	-9.33
Toricoejo	VB com Registro	-53.08	-53.08	-15.25	-15.17
Torixoréu	VB com Registro	-52.62	-52.58	-16.28	-16.33
Tucuruí I e II	Operação	-49.65	-49.58	-3.83	-3.83
Tupiratins	VB com Aceite	-48.17	-48.08	-8.18	-8.17

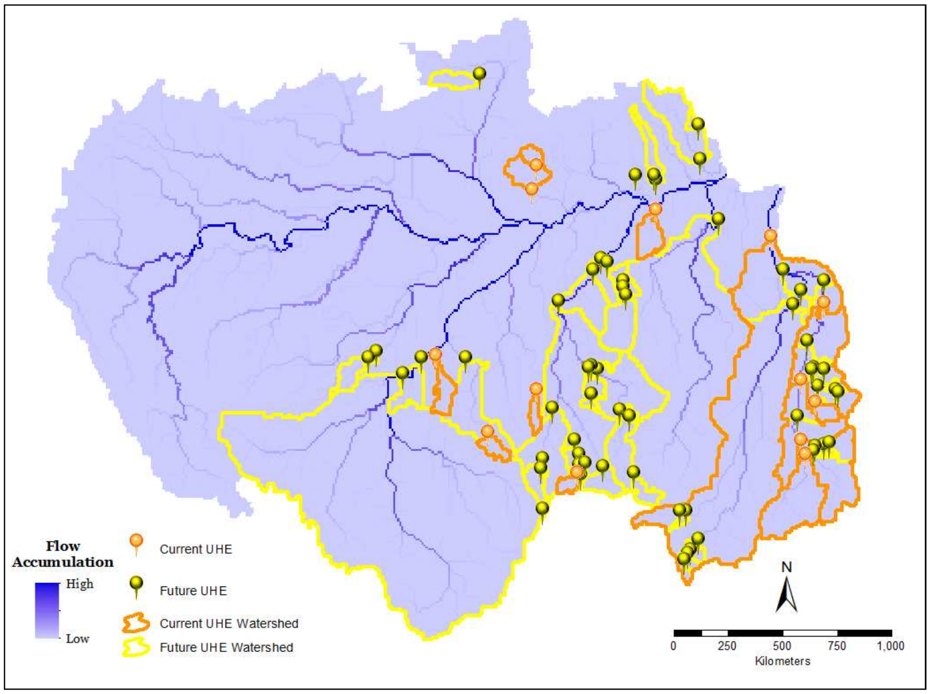


Figure 1. Flow Accumulation Raster along with Current and Future UHE derived watersheds

A.6. Table of hydropower stations with associated model parameter estimates.

We chose a constant estimate of turbine efficiency because we were unable to get dam-specific information. This estimate is a floating-point value generally from 0.70 to 0.90. Similarly we also chose a recommended constant estimate for the fraction of inflow water volume that is used to generate energy (Driss Ennaanay, personal communication). For current dams dam height is obtained from ANEEL and future dams is calculated as the difference between upstream and downstream reservoir elevation as a best approximation of usable head. We estimate the gross value of hydropower production at $0.09 per KWH (2000 US$) as given by 2009 industry electricity prices in Brazil (International Energy Agency 2010). We chose a constant time span of 100 years for every dam; again due to lack of information. Future sensitivity analyses could be performed on these parameters. Table 6 indicates all the dam data submitted to the InVEST hydropower model

Table 6. Hydropower value data table.

Watershed ID	Name	efficiency	fraction	height	kw_price	cost	time_span	discount
1	Balbina	0.85	0.7	30	0.12	0	100	0
2	Pitinga	0.85	0.7	30	0.12	0	100	0
3	Curua-Una	0.85	0.7	35	0.12	0	100	0
4	Tucurui I e II	0.85	0.7	72	0.12	0	100	0
5	Estreito	0.85	0.7	22	0.12	0	100	0
6	Luis Eduardo Magalhaes (Lajeado)	0.85	0.7	92	0.12	0	100	0
7	Isamu Ikeda	0.85	0.7	17.5	0.12	0	100	0
8	Peixe Angical	0.85	0.7	24.3	0.12	0	100	0

Watershed ID	Name	efficiency	fraction	height	kw_price	cost	time_span	discount
9	Sao Salvador	0.85	0.7	34.6	0.12	0	100	0
10	Samuel	0.85	0.7	30	0.12	0	100	0
11	Dardanelos	0.85	0.7	95	0.12	0	100	0
12	Rondon II	0.85	0.7	30	0.12	0	100	0
13	Santo Antðnio do Jari	0.85	0.7	27.1	0.12	0	100	0
14	Mocoto	0.85	0.7	75	0.12	0	100	0
15	Jutuarama	0.85	0.7	60	0.12	0	100	0
16	Paredao	0.85	0.7	0	0.12	0	100	0
17	Belo Monte	0.85	0.7	92.4	0.12	0	100	0
18	PCH Jatoba	0.85	0.7	16	0.12	0	100	0
19	Jamanxim	0.85	0.7	57.5	0.12	0	100	0
20	Cachoeira dos Patos	0.85	0.7	33	0.12	0	100	0
21	Jardim de Ouro	0.85	0.7	14	0.12	0	100	0
22	Maraba	0.85	0.7	21	0.12	0	100	0
23	Santa Isabel	0.85	0.7	30	0.12	0	100	0
24	Araguana	0.85	0.7	25	0.12	0	100	0
25	Serra Quebrada	0.85	0.7	29	0.12	0	100	0
26	Tupiratins	0.85	0.7	18	0.12	0	100	0
27	Novo Acordo	0.85	0.7	37.9	0.12	0	100	0
28	Brejao	0.85	0.7	32	0.12	0	100	0
29	Cachoeira Velha	0.85	0.7	30	0.12	0	100	0
30	Teles Pires	0.85	0.7	59	0.12	0	100	0
31	Colider	0.85	0.7	19.38	0.12	0	100	0
32	Sinop	0.85	0.7	50	0.12	0	100	0
33	Ipueiras	0.85	0.7	21.36	0.12	0	100	0
34	Arraias	0.85	0.7	28	0.12	0	100	0
35	Pau D'Arco	0.85	0.7	25	0.12	0	100	0
36	Cachoeirao	0.85	0.7	40.5	0.12	0	100	0
37	Juruena	0.85	0.7	35.5	0.12	0	100	0
38	Roncador	0.85	0.7	20	0.12	0	100	0
39	Parecis	0.85	0.7	18	0.12	0	100	0
40	Paiagua	0.85	0.7	30.5	0.12	0	100	0
41	Barra do Claro	0.85	0.7	18	0.12	0	100	0
42	Magessi	0.85	0.7	17	0.12	0	100	0
43	Toricoejo	0.85	0.7	21.2	0.12	0	100	0
44	Agua limpa	0.85	0.7	107	0.12	0	100	0
45	Torixoreu	0.85	0.7	108	0.12	0	100	0
46	Diamantino	0.85	0.7	25	0.12	0	100	0
47	Araguainha	0.85	0.7	35	0.12	0	100	0
48	Sao Luiz do Tapajos	0.85	0.7	35.8	0.12	0	100	0
49	Tabajara	0.85	0.7	26.43	0.12	0	100	0
50	Santo Antðnio	0.85	0.7	13	0.12	0	100	0
51	Jirau	0.85	0.7	15.77	0.12	0	100	0
52	Cachoeira Santo Antðnio	0.85	0.7	17.8	0.12	0	100	0
53	Cachoeira_4	0.85	0.7	30	0.12	0	100	0
54	Sao Manoel	0.85	0.7	24.4	0.12	0	100	0
55	Foz do Apiacas	0.85	0.7	44.8	0.12	0	100	0
56	Cinta Larga	0.85	0.7	15	0.12	0	100	0

Watershed ID	Name	efficiency	fraction	height	kw_price	cost	time_span	discount
57	Guapore	0.85	0.7	35.5	0.12	0	100	0
58	Ponte de Pedra	0.85	0.7	59.5	0.12	0	100	0
59	Garca	0.85	0.7	20	0.12	0	100	0
60	Salto Apiacas	0.85	0.7	26.5	0.12	0	100	0
61	Cachoeira do Cai	0.85	0.7	34.5	0.12	0	100	0
62	Chacorao	0.85	0.7	24.1	0.12	0	100	0
63	Salto Apiacfls	0.85	0.7	26.5	0.12	0	100	0
64	Couto Magalhaes	0.85	0.7	150	0.12	0	100	0
65	Barra do Palma	0.85	0.7	24	0.12	0	100	0
66	Parana	0.85	0.7	24	0.12	0	100	0
67	Perdida 2	0.85	0.7	26	0.12	0	100	0
68	Rio Sono	0.85	0.7	21.4	0.12	0	100	0
69	Perdida 1	0.85	0.7	26	0.12	0	100	0
70	Bambu I	0.85	0.7	30	0.12	0	100	0
71	Berimbau	0.85	0.7	45	0.12	0	100	0

B. Measuring the carbon emissions of the GOV scenario versus the BAU scenario

B.1. Introduction

We use the InVEST carbon model (Tallis et al. 2011) to estimate maps of above ground and below biomass carbon stock in 2000 (CTL), maps of above ground and below biomass carbon stock in 2050, and maps of 2000 to 2050 change in above ground and below ground biomass carbon stock for the basin.

To make these maps we have to estimate the biomass carbon or aboveground biomass stock associated with each land use type found in the basin. If the data is aboveground biomass carbon we assume carbon is 50 percent of dry biomass (Saatchi 2011) and belowground carbon (roots) is 25 percent of aboveground carbon (live trees, stumps, branches, and twigs) (Cairns et al. 1997). We calculate three sets of biomass carbon by land use type: one from a global map of biomass carbon stored in above and belowground living vegetation created using the International Panel on Climate Change (IPCC) Good Practice Guidance for reporting national greenhouse gas inventories (Ruesch and Gibbs 2008); a second from a remote sensing of forest structural parameters and environmental variables, and more than 500 plot measurements of forest biomass distributed over the Amazon basin (Saatchi et al. 2007; 2009); and a third from a global tropical forest map of national level aboveground biomass based on field measurements, LiDAR observations and imagery recorded from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Baccini et al. 2012).

B.2. Estimating carbon biomass carbon based on Ruesch and Gibbs (2008)

1. We downloaded the “New IPCC Tier-1 Global Biomass Carbon Map for the Year 2000” map from http://cdiac.ornl.gov/epubs/ndp/global_carbon/carbon_documentation.html.
    a. Specifically, we downloaded the c_1km grid which reports above and belowground biomass carbon in 0.01 Mg of carbon /ha units at a spatial resolution of 1 km.
    b. We call this map *cutcarbonmap.*

2. Next we combined the *lulc2000* map with the current ARPAs map (= 1 in field "in_ARPA" in the "ARPA_1_2.shp"). We call this map *lu2000curarpa*. This map has 6 LULC types:
    a. 1 → other and not in current ARPA
    b. 2 → forest and not in current ARPA
    c. 3 → deforest and not in current ARPA
    d. 4 → other and in current ARPA
    e. 5 → forest and in current ARPA
    f. 6 → deforest and in current ARPA
3. Next we performed a zonal statistics with *lu2000curarpa* as the mask and *cutcarbonmap* as the value raster.
    a. After dividing mean data by 100 to convert the mapped values from 0.01 Mg of carbon /ha to Mg of carbon /ha units we get the following data,

Table B.1. Carbon lookup table based on Ruesch and Gibbs (2008) for InVEST Carbon Model

LULC Code	Grid cell count	Mean Mg of C ha^{-1}
1	1,649,474	66.46
2	4,345,832	179.88
3	564,977	87.31
4	25,788	127.12
5	265,338	190.74
6	1,435	159.59

4. The mean field in the table became our biomass carbon look up table for the InVEST Carbon molde. On average, forested ARPA area had the highest biomass carbon stock (191 Mg of C ha^{-1}). Conversely, other cover not in an ARPA had the lowest biomass carbon stock, on average (66 Mg of C ha^{-1})
5. We than projected the *lu2000curarpa* map to *l2000curarp_p* at a spatial resolution of 1,028.98 by 1,028.98 meters.
6. We then ran the InVEST carbon model with *l2000curarp_p* and the table above. The resulting map is called *cur*. See Tallis et al. (2011) for details on carbon model.
    a. We did not use the actual 2000 map because we want a baseline that uses the same average values by LULC as the future maps.
7. We then made four 2050 LULC maps and 4 corresponding carbon maps.
    a. We combined *gov2050lulc* and the current and future ARPA map. The projected version of this map is called *go2050arpa_p*. This map has 6 LULC types:
        i. 1 → other and not in current or future ARPA
        ii. 2 → forest and not in current or future ARPA
        iii. 3 → deforest and in current or future ARPA
        iv. 4 → other and in current or future ARPA
        v. 5 → forest and in current or future ARPA
        vi. 6 → deforest and in current or future ARPA

This map was assigned carbon values according to the table above where land in future ARPA was give the same carbon value as land in current ARPA.

    i. The InVEST carbon interpretation of this map is *gov_all_arpa*.

b. We combine of *bau2050lulc* and the current and future ARPA map. The projected version of this map is called *b2050arpa_p*. This map has 6 LULC types:
    i. 1 → other and not in current or future ARPA
    ii. 2 → forest and not in current or future ARPA
    iii. 3 → deforest and in current or future ARPA
    iv. 4 → other and in current or future ARPA
    v. 5 → forest and in current or future ARPA
    vi. 6 → deforest and in current or future ARPA

    This map was assigned carbon values according to the table above were land in future ARPA was give the same carbon value as land in current ARPA.

    ii. The InVEST carbon interpretation of this map is *bau_all_arpa*.

8. The we created the following sequestration maps:
    a. *gov_all_arpa – cur = s_gov_a_arpa*
    b. *bau_all_arpa – cur = s_bau_a_arpa*

Table B.2. Estimated change in biomass carbon content across the basin based on Ruesch and Gibbs (2008)

Scenario	Change in biomass carbon storage (Mg)
GOV (*s_gov_a_arpa*)	-6,708,082,000
BAUS (*s_bau_a_arpa*)	-15,027,680,000

B.3. Estimating carbon biomass carbon based on (Saatchi et al. 2007; 2009)

1. We combined the lulc2000 map with the current ARPAs map (= 1 in field "in_ARPA" in the "ARPA_1_2.shp"). We call this map *lu2000curarpa* and the projected version *lu2000curarpa_p*. This map has six LULC types:
    a. 1 → other and not in current ARPA
    b. 2 → forest and not in current ARPA
    c. 3 → deforest and not in current ARPA
    d. 4 → other and in current ARPA
    e. 5 → forest and in current ARPA
    f. 6 → deforest and in current ARPA
2. Next we combined *lu2000curarpa_p* with a raster of the WWF global ecoregion map to generate a LULC 2000 map with 192 unique LULC types. There are 47 ecoregions in the study area. This super LULC map is called *ecoregionarpa*.
3. Next we performed a zonal statistics with *ecoregionarpa* as the mask and *biomass_p* as the value raster.
    a. The result is Table 9 and the data indicates Mg of live aboveground biomass / ha in each LULC category.

Table B.3. Estimated live aboveground biomass (Mg) ha^{-1} in each LULC category based on Saatchi et al. (2007; 2009)

			Biomass (Mg) ha^{-1}						
Land use code	**Grid cell count**	**Area (m^2)**	**MIN**	**MAX**	**MEAN**	**STD**	**MAJORITY**	**MINORITY**	**MEDIAN**
1	3,059	3,238,880,000	12	325	162	76	175	87	175
2	32,637	34,556,200,000	12	400	194	60	175	12	175
3	4,411	4,670,380,000	62	375	190	58	125	375	175
4	413	437,286,000	12	325	171	71	125	62	175
5	320	338,817,000	12	400	161	94	225	400	175
6	15,780	16,707,900,000	12	400	206	114	325	400	225
7	52,853	55,961,000,000	12	400	73	108	12	400	12
8	2,353	2,491,370,000	12	400	105	97	37	400	62
9	4,114	4,355,920,000	0	400	153	102	175	0	175
10	80,517	85,251,700,000	0	400	229	77	175	0	225
11	421	445,756,000	12	400	147	103	37	400	125
12	1,124	1,190,100,000	12	400	181	124	325	375	175
13	21,131	22,373,600,000	12	400	260	69	325	400	275
14	231	244,584,000	12	325	92	109	12	225	37
15	164	173,644,000	37	325	182	63	125	37	175
16	106	112,233,000	12	400	217	77	225	12	225
17	734	777,162,000	12	400	231	75	275	12	225
18	5	5,294,020	12	375	185	129	12	12	175
19	111	117,527,000	37	375	215	72	275	37	275
20	48	50,822,600	12	275	211	81	275	37	225
21	8	8,470,430	125	275	238	65	275	125	275
22	64,192	67,966,700,000	0	400	267	81	275	12	275
23	2,830	2,996,420,000	12	400	206	111	125	87	225
24	202,003	213,882,000,000	0	400	271	76	275	12	275
25	32,761	34,687,500,000	0	400	163	117	275	400	175
26	348,389	368,876,000,000	0	400	260	73	325	0	275
27	16,468	17,436,400,000	0	400	143	114	37	0	87
28	6,321	6,692,700,000	0	400	202	92	225	12	225
29	14,646	15,507,200,000	0	400	200	102	275	400	225
30	12,099	12,810,500,000	62	325	250	72	325	62	275
31	331	350,464,000	62	325	245	78	325	62	275
32	6,181	6,544,470,000	12	400	150	115	175	400	125
33	130,935	138,634,000,000	0	400	216	73	175	0	175
34	13	13,764,500	175	325	237	68	175	275	175
35	3,615	3,827,580,000	12	325	180	67	225	12	225
36	259	274,230,000	12	400	200	91	225	12	225
37	49,312	52,211,700,000	0	400	243	79	275	0	275
38	25,055	26,528,300,000	0	400	177	115	125	0	175
39	1,145	1,212,330,000	12	325	80	90	12	325	37
40	432	457,403,000	12	325	173	72	225	12	175
41	110	116,468,000	125	325	239	66	175	125	275
42	5,098	5,397,780,000	12	400	70	84	12	400	37
43	15,086	15,973,100,000	0	400	268	74	275	12	275
44	479	507,167,000	37	275	177	66	225	175	225
45	1,295	1,371,150,000	0	400	202	111	275	0	225
46	923	977,276,000	12	275	128	111	275	175	62
47	135,836	143,824,000,000	0	400	270	80	275	0	275

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
48	17,582	18,615,900,000	0	400	212	104	275	0	225
49	1,503	1,591,380,000	0	400	170	110	275	400	175
50	15,478	16,388,200,000	0	400	219	99	125	0	225
51	206,570	218,717,000,000	0	400	213	71	175	0	225
52	14,649	15,510,400,000	0	400	85	95	12	0	37
53	28	29,646,500	87	375	219	72	275	325	225
54	1,951	2,065,730,000	0	400	185	117	275	0	225
55	23,972	25,381,600,000	0	325	110	97	12	0	62
56	6,161	6,523,290,000	12	325	45	85	12	175	12
57	6	6,352,820	37	225	96	64	62	37	62
58	38,230	40,478,100,000	12	325	184	57	225	12	225
59	9,687	10,256,600,000	12	325	98	78	37	325	62
60	208	220,231,000	12	325	77	95	12	225	37
61	132	139,762,000	12	275	63	59	37	125	37
62	34,224	36,236,500,000	0	400	237	70	275	0	275
63	19,053	20,173,400,000	0	400	162	114	275	400	175
64	1	1,058,800	62	62	62	0	62	62	62
65	2	2,117,610	87	325	206	119	87	87	87
66	126	133,409,000	37	325	132	91	62	175	87
67	7,946	8,413,260,000	0	400	234	104	275	0	275
68	1,407	1,489,740,000	12	400	177	115	275	400	175
69	4,133	4,376,040,000	0	400	150	111	275	400	125
70	5,214	5,520,600,000	0	375	152	113	275	325	175
71	145,861	154,438,000,000	12	400	287	73	325	12	325
72	3,203	3,391,350,000	0	400	257	116	325	0	275
73	433	458,462,000	12	400	236	128	325	225	275
74	7	7,411,630	375	400	379	9	375	400	375
75	3,592	3,803,220,000	0	400	203	104	275	12	225
76	30,573	32,370,800,000	37	400	285	63	325	37	275
77	76,976	81,502,500,000	12	400	259	94	325	12	275
78	167,966	177,843,000,000	0	400	203	92	125	0	225
79	22	23,293,700	125	375	227	68	225	175	225
80	14,894	15,769,800,000	0	400	136	109	37	400	125
81	64,549	68,344,700,000	0	400	83	98	12	400	37
82	3,817	4,041,450,000	0	375	101	111	12	375	37
83	2,873	3,041,940,000	0	400	76	99	12	400	37
84	1,114	1,179,510,000	12	400	205	104	275	400	225
85	553	585,519,000	0	375	186	97	275	0	175
86	789	835,396,000	12	375	109	114	12	325	37
87	179	189,526,000	12	400	170	124	275	225	175
88	57,832	61,232,800,000	0	400	155	113	275	400	125
89	10,494	11,111,100,000	0	400	263	75	275	0	275
90	96,665	102,349,000,000	0	400	92	99	12	0	37
91	967	1,023,860,000	0	400	205	94	275	0	225
92	475,528	503,491,000,000	0	400	231	80	275	0	225
93	8,087	8,562,550,000	62	400	291	62	275	62	275
94	17,623	18,659,300,000	0	400	231	119	325	0	275

			Biomass (Mg) ha^{-1}						
Land use code	**Grid cell count**	**Area (m^2)**	**MIN**	**MAX**	**MEAN**	**STD**	**MAJORITY**	**MINORITY**	**MEDIAN**
95	12,406	13,135,500,000	12	400	166	130	37	400	125
96	455	481,756,000	0	375	203	95	275	12	225
97	1,920	2,032,900,000	0	400	204	85	275	0	225
98	25	26,470,100	125	400	210	81	125	400	175
99	8,475	8,973,360,000	0	400	155	108	275	400	175
100	61,460	65,074,100,000	12	400	216	69	225	12	225
101	378	400,228,000	12	400	189	114	275	400	225
102	4,353	4,608,970,000	0	375	137	114	275	325	125
103	9	9,529,240	125	375	281	86	325	275	325
104	224,399	237,595,000,000	0	400	207	77	175	0	175
105	5,035	5,331,080,000	0	400	187	108	275	400	225
106	19,855	21,022,600,000	0	400	146	116	37	0	125
107	12,598	13,338,800,000	0	400	97	106	12	400	37
108	1,944	2,058,310,000	12	375	213	72	275	12	225
109	192	203,290,000	12	375	175	98	275	12	175
110	212,329	224,815,000,000	12	400	276	65	275	12	275
111	4,429	4,689,440,000	0	400	221	106	275	87	225
112	689	729,516,000	12	400	224	112	275	12	225
113	130	137,645,000	0	400	217	81	225	0	225
114	7,403	7,838,330,000	0	375	185	103	275	0	225
115	137,223	145,292,000,000	0	400	248	56	275	0	275
116	4,825	5,108,730,000	12	375	163	115	275	375	175
117	10,416	11,028,500,000	37	400	291	70	325	37	325
118	122	129,174,000	37	400	257	111	325	37	325
119	67	70,939,900	37	400	274	104	375	37	325
120	16	16,940,900	87	275	185	72	125	87	125
121	3	3,176,410	275	275	275	0	275	275	275
122	601,505	636,876,000,000	0	400	217	73	175	0	225
123	23,183	24,546,300,000	12	400	131	108	37	400	125
124	53,335	56,471,300,000	0	400	149	110	12	0	125
125	3,243	3,433,700,000	12	400	247	61	275	12	275
126	1,113	1,178,450,000	0	375	203	97	275	0	275
127	14	14,823,300	62	275	177	90	275	87	125
128	21	22,234,900	125	325	254	48	275	125	275
129	13,609	14,409,300,000	12	400	257	41	275	12	275
130	555	587,636,000	12	375	183	109	275	325	225
131	88,504	93,708,400,000	12	400	201	59	225	12	225
132	6,002	6,354,940,000	12	400	177	95	225	400	175
133	13,614	14,414,600,000	12	400	142	95	37	400	125
134	5,809	6,150,590,000	12	325	43	84	12	175	12
135	1,179	1,248,330,000	12	325	30	59	12	125	12
136	303	320,818,000	12	325	114	119	37	225	62
137	29,475	31,208,200,000	12	375	46	60	12	375	12
138	47,705	50,510,200,000	0	375	105	76	125	0	125
139	203,324	215,280,000,000	12	400	141	74	125	400	125
140	100,617	106,534,000,000	12	375	56	68	12	375	12
141	76,682	81,191,200,000	0	375	66	79	12	0	37

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
142	598,785	633,996,000,000	0	375	29	46	12	0	12
143	63,662	67,405,600,000	0	325	187	72	225	0	225
144	76,942	81,466,500,000	12	325	45	83	12	175	12
145	2,301	2,436,310,000	12	325	191	68	225	12	225
146	2,771	2,933,950,000	12	325	34	56	12	175	12
147	4,572	4,840,850,000	12	325	28	57	12	175	12
148	26,385	27,936,500,000	12	325	72	95	12	175	12
149	7,452	7,890,210,000	12	400	222	71	175	12	225
150	39,436	41,755,000,000	12	400	252	67	275	12	275
151	1,336	1,414,560,000	37	375	187	83	175	37	175
152	34	35,999,300	12	325	97	74	37	125	62
153	7,328	7,758,920,000	0	375	152	125	12	0	125
154	27,118	28,712,600,000	37	375	191	42	175	37	175
155	932	986,805,000	37	375	228	59	225	37	225
156	103	109,057,000	125	375	221	65	225	375	225
157	26	27,528,900	87	325	195	52	225	275	175
158	55	58,234,200	37	375	236	90	325	37	275
159	138	146,115,000	37	375	212	59	225	87	225
160	16	16,940,900	125	225	216	26	225	125	225
161	41,775	44,231,500,000	12	325	29	66	12	87	12
162	230	243,525,000	12	325	33	71	12	87	12
163	83	87,880,700	12	325	156	111	225	87	125
164	116,918	123,793,000,000	0	400	73	96	12	400	12
165	1,590	1,683,500,000	12	375	198	90	275	375	175
166	44	46,587,400	12	325	140	104	275	87	125
167	85,468	90,493,900,000	12	375	128	75	175	375	125
168	32,175	34,067,000,000	12	325	39	55	12	325	12
169	33,697	35,678,500,000	12	375	75	76	37	375	37
170	341	361,052,000	37	325	165	73	175	325	175
171	89	94,233,600	37	325	153	72	175	325	175
172	14,500	15,352,700,000	12	325	119	113	12	87	62
173	65,799	69,668,200,000	12	325	197	58	225	12	225
174	3,788	4,010,750,000	12	325	130	92	225	325	125
175	21,525	22,790,800,000	12	325	18	42	12	87	12
176	82	86,821,900	12	325	18	39	12	175	12
177	3,053	3,232,530,000	12	325	227	117	325	175	275
178	26,272	27,816,900,000	12	325	38	80	12	175	12
179	816	863,984,000	12	325	34	72	12	175	12
180	39	41,293,400	12	12	12	0	12	12	12
181	9,475	10,032,200,000	0	325	50	61	12	325	37
182	472	499,755,000	12	275	57	62	12	275	37
183	222	235,054,000	12	275	45	61	12	125	12
184	11,525	12,202,700,000	12	325	22	43	12	62	12
185	1,272	1,346,800,000	12	325	13	21	12	37	12
186	1	1,058,800	37	37	37	0	37	37	37
187	6,335	6,707,520,000	12	325	161	123	325	225	125
188	33,748	35,732,500,000	12	325	37	50	37	87	37

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
189	4,678	4,953,080,000	12	325	40	64	12	87	12
190	1,015	1,074,690,000	12	325	220	133	325	175	325
191	3,221	3,410,410,000	12	325	46	91	12	175	12
192	161	170,467,000	12	325	36	80	12	125	12

4. The "mean" field in Table 9 became our biomass look up table for the 2000 map. We ran the InVEST carbon model with the biomass storage table *base_lulc.dbf* (based on the above) and the LULC 2000 map to produce the *cur* map. This gives predicted Mg of live aboveground biomass in each cell. See Tallis et al. (2011) for details on carbon model.
5. Next we combined *go2050arpa_p* with a raster of the WWF global ecoregion map to generate a GOV map with all ARPA areas. This super LULC map is called *g_all_arpa*.
6. Next we combined *b2050arpa_p* with a raster of the WWF global ecoregion map to generate a BAU map with all ARPA areas. This super LULC map is called *b_all_arpa*.
7. Several novel LULC types were created by the 2050 maps. We made our best guess as to each novel LULC type's biomass content.
8. For each of these 2050 maps we found the appropriate carbon storage number for each LULC from the table above. The final carbon tables are called *b_all_arpa.dbf* and *g_all_arpa.dbf*.
9. We ran the InVEST carbon model with the 2050 biomass storage tables and the 2050 LULC maps to produce the *b_all_arpa.dbf* and *g_all_arpa.dbf* maps. These give predicted Mg of live aboveground biomass in each cell.
10. We then calculated change in biomass by subtracting *cur* from each of the 2050 biomass maps. These maps are called *s_gov_a_arpa* (*gov_all_arpa* less *cur*) and *s_bau_a_arpa* (*bau_all_arpa* less *cur*).

Table B.4. Estimated change in biomass carbon content across the basin (Saatchi et al. 2007; 2009)

Scenario	Change in aboveground biomass (Mg)	Change in biomass (Mg) assuming belowground is 20% of aboveground	Change in biomass carbon (Mg) assuming carbon is 50% of biomass.
GOV (*s_gov_a_arpa*)	-7,205,630,000	-8,646,756,000	-4,323,378,000
BAU (*s_bau_a_arpa*)	-15,882,300,000	-19,058,760,000	-9,529,380,000

B.4. Estimating carbon biomass carbon based on Baccini et al. (2012)

1. We combined the lulc2000 map with the current ARPAs map (= 1 in field "in_ARPA" in the "ARPA_1_2.shp"). We call this map *lu2000curarpa* and the projected version *lu2000curarpa_p*. This map has 6 LULC types:
    a. 1 → other and not in current ARPA
    b. 2 → forest and not in current ARPA
    c. 3 → deforest and not in current ARPA
    d. 4 → other and in current ARPA

   e. 5 → forest and in current ARPA
   f. 6 → deforest and in current ARPA
2. Next we combined *lu2000curarpa_p* with a raster of the WWF global ecoregion map to generate a LULC 2000 map with 192 unique LULC types. There are 47 ecoregions in the study area. This super LULC map is called *ecoregionarpa*.
3. Next we performed a zonal statistics with *ecoregionarpa* as the mask and *baccini_cut_p* as the value raster.
   a. Table 11 gives the results of this zonal statistics analysis where data is measured in Mg of aboveground biomass / ha.

Table B.5. Estimated live aboveground biomass (Mg) ha^{-1} in each LULC category based on Baccini et al. (2012)

			Biomass (Mg) ha^{-1}						
Land use code	**Grid cell count**	**Area (m^2)**	**MIN**	**MAX**	**MEAN**	**STD**	**MAJORITY**	**MINORITY**	**MEDIAN**
1	3,050	3,229,350,000	0	348	236	92	0	41	269
2	32,220	34,114,700,000	0	368	269	42	303	51	274
3	4,395	4,653,440,000	0	353	251	48	299	60	258
4	411	435,168,000	0	338	244	70	0	64	267
5	319	337,758,000	0	338	193	99	0	42	219
6	15,779	16,706,900,000	0	351	196	84	0	32	203
7	52,641	55,736,500,000	0	361	49	75	0	14	0
8	2,350	2,488,190,000	0	325	115	51	0	22	110
9	4,110	4,351,680,000	0	356	175	109	0	24	194
10	80,375	85,101,400,000	0	371	258	46	249	37	258
11	423	447,874,000	0	357	162	79	0	41	151
12	1,022	1,082,100,000	0	342	190	99	0	30	223
13	19,330	20,466,700,000	0	356	272	35	265	0	274
14	233	246,701,000	0	308	113	68	0	39	94
15	161	170,467,000	0	331	249	61	280	0	271
16	106	112,233,000	0	343	251	80	0	85	269
17	734	777,162,000	0	351	253	55	0	77	260
18	5	5,294,020	93	207	135	46	93	93	101
19	111	117,527,000	0	312	216	59	214	68	217
20	48	50,822,600	0	293	109	85	0	47	79
21	8	8,470,430	0	284	181	76	202	0	197
22	64,257	68,035,600,000	0	391	286	51	325	78	300
23	2,832	2,998,530,000	0	357	234	86	0	53	259
24	202,006	213,885,000,000	0	387	303	46	320	40	314
25	32,720	34,644,100,000	0	384	124	110	0	349	113
26	348,379	368,865,000,000	0	397	277	54	319	26	289
27	16,439	17,405,700,000	0	356	134	58	0	24	132
28	6,324	6,695,880,000	0	360	172	116	0	65	180
29	14,646	15,507,200,000	0	370	151	137	0	29	186
30	12,082	12,792,500,000	141	353	283	29	270	141	283
31	331	350,464,000	191	342	270	32	264	191	267
32	6,181	6,544,470,000	0	374	175	98	0	40	160
33	130,961	138,662,000,000	0	383	286	57	324	56	302

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
34	13	13,764,500	211	315	272	24	274	211	275
35	3,614	3,826,520,000	0	367	228	72	301	73	250
36	259	274,230,000	0	373	203	100	0	63	197
37	49,312	52,211,700,000	0	386	285	61	325	39	305
38	25,055	26,528,300,000	0	376	142	69	0	37	142
39	1,141	1,208,100,000	0	327	125	46	90	47	117
40	433	458,462,000	68	345	230	75	304	68	258
41	109	115,410,000	230	338	293	26	310	230	296
42	5,100	5,399,900,000	0	351	111	45	81	50	99
43	15,092	15,979,500,000	0	368	295	56	329	38	310
44	479	507,167,000	0	313	180	66	0	65	172
45	1,295	1,371,150,000	0	364	202	111	0	42	208
46	923	977,276,000	0	304	73	69	0	58	86
47	135,834	143,822,000,000	0	402	291	74	0	45	312
48	17,579	18,612,700,000	0	386	199	136	0	48	266
49	1,503	1,591,380,000	0	356	144	137	0	48	148
50	15,474	16,383,900,000	0	391	240	101	0	62	278
51	206,561	218,708,000,000	0	389	284	57	329	66	299
52	14,649	15,510,400,000	0	379	142	67	0	44	133
53	28	29,646,500	0	352	199	121	0	84	232
54	1,951	2,065,730,000	0	376	189	110	0	34	190
55	22,504	23,827,300,000	0	371	161	112	0	15	172
56	5,674	6,007,650,000	0	352	43	87	0	71	0
57	1	1,058,800	219	219	219	0	219	219	219
58	37,164	39,349,400,000	0	366	246	62	0	51	263
59	9,071	9,604,410,000	0	355	165	91	0	24	162
60	210	222,349,000	0	336	91	106	0	49	0
61	83	87,880,700	0	314	135	124	0	106	149
62	34,224	36,236,500,000	0	387	238	89	0	28	267
63	19,052	20,172,300,000	0	393	102	109	0	27	70
64	1	1,058,800	0	0	0	0	0	0	0
65	2	2,117,610	246	267	257	11	246	246	246
66	107	113,292,000	0	305	155	121	0	140	205
67	7,941	8,407,960,000	0	355	175	74	0	30	185
68	1,407	1,489,740,000	0	308	148	61	0	28	157
69	4,129	4,371,800,000	0	313	84	75	0	22	64
70	5,214	5,520,600,000	0	353	125	77	0	25	133
71	145,861	154,438,000,000	0	391	309	44	332	90	321
72	3,203	3,391,350,000	0	374	249	123	0	95	308
73	433	458,462,000	0	361	222	129	0	113	282
74	7	7,411,630	88	277	206	66	88	88	241
75	3,592	3,803,220,000	0	367	120	134	0	108	0
76	30,573	32,370,800,000	0	375	293	41	312	101	304
77	76,975	81,501,400,000	0	422	293	77	0	29	321
78	167,972	177,849,000,000	0	381	231	85	0	22	252
79	22	23,293,700	0	331	188	132	0	191	249
80	14,892	15,767,700,000	0	362	118	91	0	14	111

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
81	64,546	68,341,600,000	0	365	98	53	0	13	88
82	3,815	4,039,340,000	0	299	41	40	0	24	44
83	2,873	3,041,940,000	0	321	53	36	0	20	44
84	1,114	1,179,510,000	0	342	189	72	212	30	199
85	553	585,519,000	0	347	134	76	0	28	149
86	789	835,396,000	0	327	81	60	0	27	75
87	179	189,526,000	0	332	128	72	0	23	124
88	57,830	61,230,600,000	0	376	153	99	0	20	160
89	10,494	11,111,100,000	0	393	293	77	0	45	313
90	96,665	102,349,000,000	0	366	100	54	0	17	90
91	967	1,023,860,000	0	402	202	128	0	89	260
92	475,528	503,491,000,000	0	395	249	69	296	17	265
93	8,087	8,562,550,000	0	390	332	33	337	180	337
94	17,623	18,659,300,000	0	401	220	125	0	32	265
95	12,406	13,135,500,000	0	392	176	104	0	24	160
96	455	481,756,000	0	359	151	130	0	52	138
97	1,920	2,032,900,000	0	365	233	109	0	27	280
98	25	26,470,100	0	326	177	126	0	196	222
99	8,475	8,973,360,000	0	369	138	122	0	23	153
100	61,460	65,074,100,000	0	378	295	51	329	23	307
101	378	400,228,000	0	351	202	83	0	46	204
102	4,362	4,618,500,000	0	354	67	76	0	41	50
103	9	9,529,240	217	341	271	39	243	217	251
104	224,399	237,595,000,000	0	391	266	65	307	23	284
105	5,091	5,390,370,000	0	371	191	89	0	27	178
106	19,854	21,021,500,000	0	373	156	72	0	21	154
107	12,632	13,374,800,000	0	347	110	54	0	17	98
108	1,944	2,058,310,000	0	366	268	60	307	61	283
109	192	203,290,000	0	314	178	59	134	58	171
110	212,329	224,815,000,000	0	405	332	34	332	79	334
111	4,429	4,689,440,000	0	396	232	139	0	85	307
112	689	729,516,000	0	382	234	112	0	67	286
113	130	137,645,000	0	360	230	118	0	122	284
114	7,403	7,838,330,000	0	371	169	97	0	22	177
115	137,223	145,292,000,000	0	394	260	57	295	35	272
116	4,825	5,108,730,000	0	340	142	64	0	28	140
117	10,416	11,028,500,000	0	399	327	42	332	90	332
118	122	129,174,000	0	367	211	141	0	113	293
119	67	70,939,900	0	367	292	67	299	163	313
120	16	16,940,900	0	227	64	85	0	135	0
121	3	3,176,410	0	164	55	77	0	164	0
122	601,431	636,798,000,000	0	402	294	54	302	21	301
123	23,170	24,532,500,000	0	384	166	87	0	373	155
124	53,316	56,451,200,000	0	394	189	105	0	22	186
125	3,243	3,433,700,000	0	378	260	79	0	90	290
126	1,113	1,178,450,000	0	359	138	107	0	68	159
127	14	14,823,300	0	313	74	121	0	164	0

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
128	21	22,234,900	0	351	231	104	0	171	266
129	13,609	14,409,300,000	0	391	277	45	294	103	286
130	555	587,636,000	0	347	176	119	0	87	213
131	88,433	93,633,200,000	0	397	279	56	311	47	296
132	5,995	6,347,530,000	0	391	209	98	0	45	215
133	13,606	14,406,100,000	0	394	184	76	0	34	166
134	5,783	6,123,060,000	0	368	37	87	0	32	0
135	1,174	1,243,040,000	0	331	42	90	0	50	0
136	298	315,524,000	0	361	162	130	0	110	218
137	29,499	31,233,700,000	0	283	80	45	0	14	69
138	47,716	50,521,900,000	0	346	157	69	0	14	171
139	203,324	215,280,000,000	0	389	188	68	203	9	200
140	100,616	106,533,000,000	0	341	82	47	43	271	67
141	76,682	81,191,200,000	0	383	100	67	0	339	77
142	599,221	634,458,000,000	0	384	67	44	0	7	59
143	63,295	67,017,000,000	0	367	255	69	0	49	274
144	76,862	81,381,800,000	0	364	36	84	0	22	0
145	2,286	2,420,430,000	0	339	238	68	0	48	260
146	2,772	2,935,000,000	0	336	67	62	0	19	77
147	4,571	4,839,790,000	0	326	40	56	0	22	0
148	26,234	27,776,700,000	0	363	81	108	0	28	0
149	7,452	7,890,210,000	0	387	271	48	297	78	281
150	39,436	41,755,000,000	0	390	275	47	294	41	284
151	1,336	1,414,560,000	0	361	193	69	0	96	186
152	34	35,999,300	0	301	140	81	0	47	156
153	7,328	7,758,920,000	0	366	161	89	0	40	157
154	27,118	28,712,600,000	0	378	286	39	300	0	295
155	932	986,805,000	0	385	302	67	0	99	317
156	103	109,057,000	0	378	296	59	301	0	307
157	26	27,528,900	0	336	235	104	0	112	296
158	55	58,234,200	0	339	225	78	182	0	228
159	138	146,115,000	125	352	270	62	289	125	294
160	16	16,940,900	145	339	296	47	318	145	310
161	41,828	44,287,700,000	0	365	11	51	0	36	0
162	230	243,525,000	0	311	19	65	0	70	0
163	83	87,880,700	0	329	213	101	0	109	248
164	116,918	123,793,000,000	0	370	121	74	0	20	112
165	1,590	1,683,500,000	0	358	234	79	0	57	259
166	44	46,587,400	0	332	158	74	0	87	149
167	85,485	90,511,900,000	0	361	210	71	235	20	215
168	32,180	34,072,300,000	0	323	85	48	0	254	75
169	33,722	35,705,000,000	0	353	147	63	0	20	142
170	341	361,052,000	85	307	196	39	194	85	196
171	89	94,233,600	92	296	195	48	199	92	193
172	14,505	15,358,000,000	0	363	143	120	0	25	147
173	65,801	69,670,400,000	0	373	275	48	293	48	285
174	3,788	4,010,750,000	0	355	172	81	0	37	168

			Biomass (Mg) ha^{-1}						
Land use code	Grid cell count	Area (m^2)	MIN	MAX	MEAN	STD	MAJORITY	MINORITY	MEDIAN
175	21,558	22,825,700,000	0	355	4	17	0	20	0
176	82	86,821,900	0	90	3	15	0	67	0
177	3,054	3,233,590,000	0	370	224	69	0	54	232
178	26,275	27,820,100,000	0	352	58	66	0	317	43
179	816	863,984,000	0	329	68	76	0	24	47
180	39	41,293,400	0	49	4	13	0	43	0
181	9,481	10,038,500,000	0	272	125	53	0	24	118
182	472	499,755,000	0	263	149	58	0	36	158
183	222	235,054,000	0	238	87	42	82	27	82
184	11,550	12,229,200,000	0	209	69	19	75	18	71
185	1,281	1,356,330,000	0	353	18	36	0	54	0
186	1	1,058,800	254	254	254	0	254	254	254
187	6,336	6,708,580,000	0	345	168	51	176	32	169
188	33,797	35,784,400,000	0	335	131	33	126	21	127
189	4,679	4,954,140,000	0	273	105	45	0	205	111
190	1,015	1,074,690,000	0	347	203	63	167	62	181
191	3,221	3,410,410,000	0	331	83	76	0	26	69
192	161	170,467,000	0	314	111	84	0	32	103

4. The "mean" field in the table became our aboveground biomass look up table for the 2000 map. We ran the InVEST carbon model with the biomass storage table *lulc2000.dbf* (based on the above) and the LULC 2000 map to produce the *cur* map. This gives predicted Mg of live aboveground biomass in each cell as of 2000. See Tallis et al. 2011 for details on carbon model.
5. Next we combined *go2050arpa_p* with a raster of the WWF global ecoregion map to generate a GOV map with all ARPA areas. This super LULC map is called *g_all_arpa*.
6. Next we combined *b2050arpa_p* with a raster of the WWF global ecoregion map to generate a business as usual 2050 map with all ARPA areas. This super LULC map is called *b_all_arpa*.
7. Several novel LULC types were created by the 2050 maps. We made our best guess as to their biomass content.
8. For each of these 2050 maps we found the appropriate carbon storage number for each LULC from the table above. The final carbon tables are called *bau_all_arpa* and *gov_all_arpa*.
9. We ran the InVEST carbon model with the 2050 biomass storage tables and the 2050 LULC maps to produce the *bau_all_arpa* and *gov_all_arpa* maps. These give predicted Mg of live aboveground biomass in each cell.
10. We then calculated change in biomass by subtracting *cur* from each of the 2050 biomass maps. These maps are called *s_gov_a_arpa* (*gov_all_arpa* less *cur*) and *s_bau_a_arpa* (*bau_all_arpa* less *cur*).

Table B.6. Estimated change in biomass carbon content across the basin (Baccini et al. 2012)

Scenario	Change in	Change in biomass (Mg)	Change in biomass

	aboveground biomass (Mg)	assuming belowground is 20% of aboveground	carbon (Mg) assuming carbon is 50% of biomass.
GOV (s_gov_a_arpa)	-9,140,800,000	-10,968,960,000	-5,484,480,000
BAU (s_bau_a_arpa)	-20,607,600,000	-24,729,120,000	-12,364,560,000

B.5. Present value of carbon sequestration in 2050

We use an equation derived from Feng (2005) to estimate the present value of carbon sequestered in the basin from 2000 to 2050,

$$V = \int_0^T e^{-rt} p(t)x(t)dt \qquad (1)$$

where *t* = 0 is the year 2000 and *T* is the year 2050, *p*(*t*) is the cost of a ton of carbon (the value of a ton of sequestered or avoided carbon emissions) at time *t*, *x*(*t*) is the tons of carbon sequestered across the Basin at time *t*, and *r* is the per annum discount rate.

However, because we do not have the time path of avoided deforestation in the Basin (i.e., we do not know *x*(*t*)'s path over time; we only know $X(T) = \int_0^T x(t)dt$, the change in biomass carbon from 2000 to 2050) and we do not know how *p*(*t*) moves over time (we only have a current estimates of *p*, \$28.43 and \$97.76), we reduce equation (1) to,

$$V = \int_0^T e^{-rt} p \frac{X(50)}{T} dt = p \frac{X(50)}{T} \int_0^T e^{-rt} dt = p \frac{X(50)}{T} \frac{1-e^{-50r}}{r} \qquad (2)$$

where $\frac{X(50)}{T}$ is the annualized avoided emissions. The value of $\frac{1-e^{-50r}}{r}$ at *r* = 0.05, for example, is 18.3583. Note how we assume the rate of carbon sequestration is constant across time.

Finally, because the other values in this analysis are annual flow values (i.e., the potential hydropower value in 2050, the BGP in 2050) we have to estimate the portion of *V* generated in 2050. We simply divide *V* by 50 to determine the annualized avoided deforestation value in the Basin.

We calculated monetary values of the changes in carbon storage using a couple estimates of *p*. First we use the European Union trading price of \$28.43 2000 US\$ per Mg C (10.41 per Mg CO_2) from October 25, 2012.[3] We also use estimates of the social cost of carbon (Tol 2009). The social cost of carbon is the cost to society incurred by the potential climate change damages from each additional ton of carbon emitted to the atmosphere. Values for the social cost of carbon reported in the literature range from near \$0 to over \$500 per ton of carbon (Tol 2009). Here we SCC values of \$97.76 (\$26.37 per ton of CO_2) and \$152.55 (\$41.15 per ton of CO_2) in constant 2000 US \$. These are the median and 66th percentile SCC values from the median fitted distribution for social cost of carbon assuming a 1 per cent pure rate of time preference (Table 2 from Tol 2009). (Values from Table 2 of Tol 2009 are in 1995 US \$. The

[3] http://www.bloomberg.com/news/2012-10-25/options-trading-to-buy-and-sell-eu-carbon-at-8-euros-surges.html.

values used here have been inflated to 2000 US $.) The results of the carbon analysis are in Table B.7.

Table B.7. Estimated change in Mg of aboveground and belowground carbon content from baseline (CTL).

	Change in carbon from 2000 to 2050 (billions Mg)		
Scenarios	Ruesch and Gibbs (2008)	Saatchi et al. (2009)	Baccini et al. (2012)
BAU	-15.03	-9.53	-12.36
GOV	-6.71	-4.32	-5.48
	Avoided carbon emissions (GOV – BAU)		
Mg C (billions)	8.32	5.21	6.88
	Value (billions 2000 US$) using EU Market price $28.43 per Mg C		
Present value of total avoided emissions	86.84	54.34	71.82
Present value of 2050 avoided emissions	1.74	1.09	1.44
	Value (billions 2000 US$) using SCC $97.76 per Mg C		
Present value of total avoided emissions	298.62	186.87	246.95
Present value of 2050 avoided emissions	5.97	3.74	4.94
	Value (billions 2000 US$) using SCC $152.55 per Mg C		
Present value of total avoided emissions	466.01	291.82	385.35
Present value of 2050 avoided emissions	9.32	5.84	7.71

Note: All present values are expressed as of 2000. We use a 5% yr^{-1} real discount rate.

C. Measuring the economic cost of the GOV scenario versus the BAU scenario

C.I. Introduction

Gross domestic product (GDP) measures the value of a country's final marketed output. The measure has been criticized because it does not include the full value of a country's natural capital stock, its ecosystem service flows, its biodiversity, and other non-market goods. For example, the in-kind income that villagers generate for themselves by gathering non-timber forest products for direct consumption is not included in GDP measures.

Nevertheless, we can use reductions in GDP due to land conservation activities to approximate the economic opportunity cost of conservation. William Nordhaus of Yale University has spatially allocated estimates of national GDPs over one-degree gird cell maps (Nordhaus 2006). Gross cell product (GCP) in year *t* measures the contribution that a gird cell makes to its country's overall GDP in year *t*. GCP is measured in billions of purchasing power parity US dollars (2005 US$). Here we map year 2000 estimates of GCP in each grid cell in the Amazon Basin. This includes grid cells from Brazil, Ecuador, and Venezuela. Then we explain year 2000 GCP using basin maps of cropland, pasture, and urban distribution in 2000. We experiment with several model forms and land use datasets in this process. Then we select an estimated model to use in our 2050 analysis. Then we predict 2050 CGPs in the basin under both 2050 scenarios, BAU and GOV, using the respective 2050 land use maps and the estimated functions that explain GCP as a function of land use distribution. When predicting 2050 GCP we have to consider how the productivity of land use and other productive inputs will grow over time and how real prices of output will change. Finally, we estimate the "conventional" cost of conserving substantial portions of the basin's natural capital.

C. II. Data preparation

1. We downloaded the Geographically based Economic database (G-Econ) from http://gecon.yale.edu/. This Excel database gives gross cell product (GCP) and other time series data for each one-degree grid cell in the world.
2. We extracted the data for all the countries that have at least some area in the Amazon basin.
3. We then spatially digitized the G-Econ data. For each one-degree point we mapped all the data from G-Econ. This point shape file is called *GEcon*.
4. Then we converted the point shape file *GEcon* to a 1 degree cell raster, called *gridpoints*.
5. We projected *gridpoints* to *gridpoints_p* and then converted *gridpoints_p* to a shapefile called *gridpoints_p*.
6. We clipped *gridpoints_p* to the study area and then used *gridpoints_p* as a zonal map and obtained the following data for each grid cell j:
    a. Grid cell product in 2000 (Y_j) measured in billions of US dollars at the purchasing power parity exchange rate (2005 US$).
    b. Area of cropland (C_j) and pasture (P_j) circa 2000 measured in square meters (Ramankutty et al. 2008).
    c. Population (E_j) in 2000 (Balk et al. 2006, CIESIN, IFPRI, The World Bank, and CIAT 2011a).
    d. Urban area (U_j) in square meters (Balk et al. 2006, CIESIN, IFPRI, The World Bank, and CIAT 2011b).
    e. Area in forest (F_j); other (O_j); and deforest (D_j) in square meters according to the CTL map from Soares-Filho et al. (2006).[4]
    f. The grid cell's average scores on seven soil suitability metrics ($Soil1_j$ – $Soil7_j$) (Fischer et al. 2008).
    g. The distance to nearest major navigable river in kilometers ($River_j$) and distance to nearest ice-free coast point in kilometers ($Coast_j$) (Nordhaus 2006).
7. We joined this database of grid cell data to the clipped *gridpoints_p* and created the shapefiles *TotalEconData* and *TotalEconData_soil* (the second shapefile includes each grid cell's average on the seven soil suitability metrics).

C. III. Year 2000 analysis

C.III.a. 2000 land use map constructed from multiple sources

[4] From the shapefile *lulc2000_p*; described above.

GCP in cell j, given by Y_j, is explicitly explained by the amount of cropland, pasture, and urban extent in a grid cell.

$$Y_j = f(C_j, P_j, U_j) \tag{C.1}$$

where C_j, P_j, and U_j are the square kilometers of cropland, pasture, and urban area, respectively, in grid cell j in 2000. In this framework forest is the missing LULC (along with other minor uses) and is contained in the intercept term. We explicitly drop one land use from model (C.1) because $C_j + P_j + U_j + F_j$ is approximately equal across all grid cells. In other words, $\left(C_j + P_j + U_j + F_j\right)\frac{1}{A} = 1$ where A is the area of a grid cell (14,423 sq. km in our case). This means that the intercept term in the estimate of (C.1) would be a linear combination of the land-use variables if all four were included in the model. Therefore, to avoid perfect multicollinearity when estimating (C.1) we drop the extent of forest land use.

Let α be the intercept term in a linear estimate of (C.1) and β_1 be the coefficient associated with cropland (C_j). Therefore, $\hat{\alpha} = E(GDP_j | F_j = A;\ C_j + P_j + U_j = 0)$. In other words, the estimated intercept term gives expected 2000 GCP if the cell were all forest in 2000. Further, $\hat{\alpha} + \hat{\beta}_1 A = E(GDP_j | C_j = A;\ F_j + P_j + U_j = 0)$ or the estimated intercept term plus the estimated coefficient on C_j times A gives expected 2000 GCP if the cell were all cropland in 2000. We can interpret $\hat{\beta}_1$ as the expected increase in GCP for every additional square kilometer of land used for cropland in lieu of forest in the grid cell. We can interpret $\hat{\beta}_2$ and $\hat{\beta}_3$, the coefficients on pasture and urban land, similarly vis-à-vis forest land use. Figure 1 is a map of Y_j.

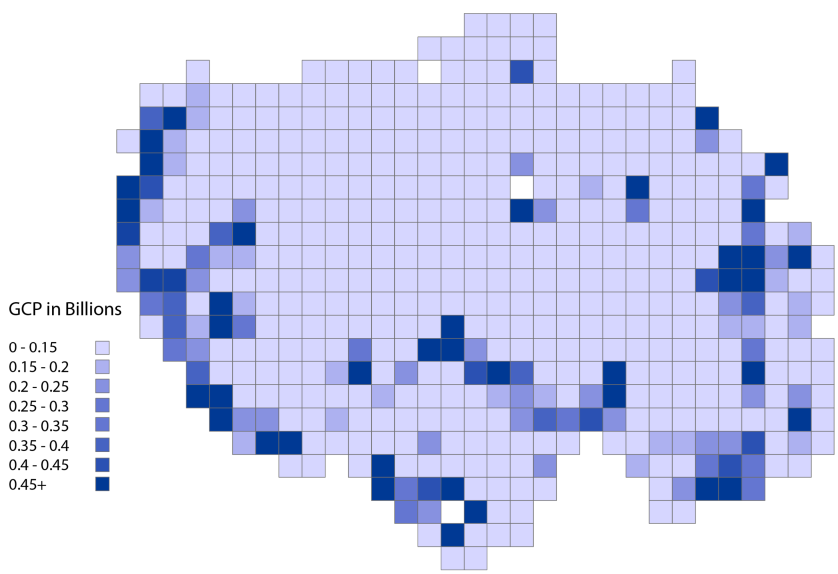


Figure X: Observed 2000 GCP in the Basin

Model (C.1) assumes land use and its associated activities explain income. Could the opposite be argued? Does GDP cause land use patterns? In other words, will our model have endogeneity issues due to reverse causality? Certainly landowners and politicians react to changes in GDP. For example, as market prices change, and GDP along with it, landowners react. Typically we assume landowners will switch land uses if the changes in prices are such that their current use is no longer net revenue-maximizing. However, this reaction may take some time after a price change for various reasons. We conjecture that land use changes in year *t* are most often a reaction to price trends that were first noticed in years $t-1$, $t-2$, $t-3$, etc. Therefore, land use in year *t* causes GDP in year *t* and not the other way around.

Further, politicians react to trends in prices and wealth measures by implementing policies to improve economic performance (or at least that is the goal, if not the result). Land use policies are one set of such tools. However, again we suspect that there is a time lag. Policies implemented in year *t* will often be a reaction to trends observed in years $t-1$, $t-2$, $t-3$, etc. Therefore, while land use pattern in year *t* is a function of land use policies these policies were caused by prior observations of GDP, not year *t*'s observation. In summary, we are fairly confident that GDP in year *t* does not cause land use pattern in year *t*.

C.III.b. Model (C.1) estimate

Because we are modeling a spatial process – the generation of income over a landscape – we may need to control for spatial autocorrelation either in the data or the error structure when estimating the models. Therefore, we estimate all GCP functions with ordinary least squares (OLS), a spatial auto regression (SAR) model, and a spatial error model (SEM). The cross-sectional spatial econometric models were written for MATLAB by J.P. Elhorst (Elhorst 2014). The spatial weight matrix **W** used in the spatial regression models is comprised of the inverse distances between gird cells where each row of **W** is normalized to sum to 1. Further, we set all pairwise distances greater than 200 kilometers equal to 0 in **W**. Pairwise distances are measured from cell centroids.

Finally, we include a variable in model (C.1) that indicates whether or not a grid cell is partially in the basin as opposed to wholly ($Partial_j$ = 1 if the cell is partially in the basin). If a grid cell is only partially in the Basin then the amount of land use in the cell does not add up to the area of the cell (i.e., $C_j + P_j + U_j + F_j < A$). If we did not flag these cells then the impact of forest on GCP would be biased upward and the impacts of urban, cropland, and pasture on GCP would be biased downwards. Estimates of model (C.1) where the dependent variable is logged are given in Table C.1.

Table C.1: Estimates of model (C.1) where Y_j is logged

Variable	OLS		SAR		SEM	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	17.26***	216.89	4.90***	7.50	17.44	83.34
Cropland	1.19E-03***	7.14	7.22E-04***	5.37	8.34E-04***	5.06
Pasture	1.07E-04***	4.16	2.92E-05	1.43	5.21E-05	1.38
Urban	2.86E-03***	5.42	1.67E-03	4.05	9.57E-04	2.24
Partial	-0.15	-0.99	-0.33	-2.82	-0.23	-1.30
ρ			0.71	18.96	0.76	20.29
Adj. R^2						
Log-likelihood						

N	519	519	519

Notes: Numbers in parentheses are t-stat values. To find standard errors divide the coefficient estimate by its t-stat value. ρ is a model's the spatial effect estimate. See Elhorst (2014) for the details on ρ is SAR and SEM models. '***' indicates statistical significance at the 99% confidence level; '**' indicates statistical significance at the 95% confidence level; and '*' indicates statistical significance at the 90% confidence level.

The statistical significance of the spatial coefficient ρ in the SAR and SEM estimates of (C.1) indicate that spatial autocorrelation is prevalent in the GCP data and the model's unobserved variables, respectively. Therefore, the SAR and SEM estimates should be prioritized over the OLS results. A summary of the expected marginal effects of cropland, pasture, and urban land use on 2000 GCP across all 3 estimation techniques are given in Table C.2.

Table C.2: Expected change in 2000 GCP from an additional square kilometer of cropland, pasture, or urban land use in lieu of a forest square kilometer (2005 US$) using estimated model (C.1)[5]

Variable	OLS	SAR	SEM
Cropland	0.120***	0.082***	0.083***
Pasture	0.011***	0.003	0.005
Urban	0.287***	0.190***	0.096**

Notes: For OLS and SEM, $\%\Delta Y = 100(e^{\beta_i} - 1)$. For SAR, $\%\Delta Y = 100(e^{\delta\beta_i} - 1)$ where the coefficient δ is equal to the mean of the diagonal elements of $(\mathbf{I} - \rho\mathbf{W})^{-1}$. This indicates the direct effect of a change in land use in *j* on Y_j only and does not include the impact of a change in land use in *j* on Y_{-j} (GCP in other grid cells). See Elhorst (2014). '***' indicates statistical significance at the 99% confidence level; '**' indicates statistical significance at the 95% confidence level; and '*' indicates statistical significance at the 90% confidence level. Significance comes from STATA code.

Finally, we can use the estimated model to "predict" 2000 GCP across all basin cells and basin GDP where basin GDP is given by the sum of all GCPs. We conduct this prediction exercise to calibrate estimated models to observed basin 2000 GDP. Specifically, we calculate the sum of expected and the 95th prediction interval estimates of GCP across all *j*. For the SAR model the predicted vector $\widehat{\mathbf{Y}}$ is given by,

$$\widehat{\mathbf{Y}} = (\mathbf{I} - \hat{\rho}\mathbf{W})^{-1}\mathbf{X}\widehat{\boldsymbol{\beta}} \qquad \text{(C.2)}^{6}$$

[5] If all partial cells were dropped from the analysis the marginal impacts are,

Variable	OLS	SAR	SEM
Cropland	0.113***	0.067***	0.061***
Pasture	0.010***	0.001	-0.002
Urban	0.222***	0.168***	0.126***

[6] See footnote 4 on page 211 in Exploring Spatial Data with GeoDa : A Workbook by Luc Anselin from 2005 (http://geodacenter.asu.edu/system/files/geodaworkbook.pdf).

where $\hat{\rho}$ is the predicted spatial coefficient in the SAR model, **X** is the matrix of observed data, and $\widehat{\boldsymbol{\beta}}$ is the vector of the SAR model's estimated coefficients. The predicted interval for cell *j* with the OLS and SEM models is given by,

$$\exp\left(\hat{Y}_j \pm t_{\alpha/2}\sqrt{\hat{\sigma}^2\big(1+\mathbf{X}_j'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}_j\big)}\right) \quad \text{(C.4)}$$

where $t_{\alpha/2}$ is the 100((1 + α)/2)th percentile of Student's t-distribution with n − 1 degrees of freedom, $\hat{\sigma}^2$ is the model's error mean square, and $\mathbf{X}_j$ is cell *j*'s observed explanatory variable vector.

The predicted interval for cell *j* with the SAR models is given by,

$$\exp\left(\hat{Y}_j + t_{\alpha/2}\sqrt{\hat{\sigma}^2\big(1+\mathbf{Z}_j(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}_j'\big)}\right) \quad \text{(C.3)}$$

where $\mathbf{Z} = (\mathbf{I} - \hat{\rho}\mathbf{W})^{-1}\mathbf{X}.$[7]

We use $t_{0.05/2} = 1.96$ to calculate the bounds on the 95th prediction interval. Table C.3 contains each model's basin 2000 GDP prediction and 95th prediction interval estimates. Table C.3 also indicates the percentile of the t-distribution under each estimation technique that sets the sum of $\hat{Y}_j$ across all *j* equal to observed basin 2000 GDP ($98.95 billion (2005 US$)).

Table C.3: Predicted and observed basin 2000 GDP (billions of 2005 US$) using estimated model (C.1)

	Predicted			Observed
	OLS	**SAR**	**SEM**	
Expected basin GDP	50.85	42.44	28.96	98.95
95th prediction interval lower bound	3.18	5.01	3.35	
95th prediction interval upper bound	822.12	359.68	251.08	
Percentile of t-distribution that matches predicted to observed	0.469	0.773	1.116	

C.III.c. 2000 land use map from Soares-Filho et al. (2006)

Model (C.1) was estimated with year 2000 land use data from several different sources. Alternatively we can explain 2000 GCP with land use data from one source (Soares-Filho et al. 2006). The advantage of this alternative estimation strategy is data consistency, the drawback is less land use classes and less precise land use definitions. The 2000 land use map in Soares-Filho et al. (2006), called *CTL*, includes three land use classes: deforest (*D*), forest (*R*), and other (*O*). Other is typically agricultural land and deforest is typically Cerrado grassland (Coe et al.

[7] Here we assume the estimated $\hat{\rho}$ is certain. Otherwise equation (C.3) would have to be adjusted to take into account $\hat{\rho}$'s variance and its effect on the prediction interval.

2009). With this dataset GCP in cell *j* is explicitly explained by the amount of other and deforested land in a grid cell,

$$Y_j = f(O_j, D_j) \tag{C.5}$$

where O_j and D_j are the square kilometers of other and deforested area, respectively, in grid cell *j* in 2000.

III.d. Model (C.5) estimate

Forest is the omitted land use class category in model (C.5). Once again, this is necessary to avoid perfect multicolinearity. Finally, we include $Partial_j$ in model (C.5) to reduce the bias that forest cover would have on GCP in partial cells and mitigate the downward bias on other and deforest cover's impact on GCP. OLS, SAR, and SEM estimates of a linear version of model (C.5) where the dependent is logged are given in Table C.4.

Table C.4: Estimates of model (C.5) where Y_j is logged

Variable	OLS		SAR		SEM	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	17.01	185.05	4.68	7.36	17.11	77.07
Other	1.21E-04	8.05	6.13E-05	4.81	1.26E-04	6.50
Deforest	3.13E-04	9.59	1.53E-04	5.61	1.98E-04	5.23
Partial	0.21	1.35	-0.13	-1.12	-0.02	-0.12
ρ			0.72	19.26	0.77	21.21
Adj. R^2						
Log-likelihood						
N	519		519		519	

Notes: Numbers in parentheses are t-stat values. To find standard errors divide the coefficient estimate by its t-stat value. ρ is a model's the spatial effect estimate. See Elhorst (2014) for the details on ρ is SAR and SEM models. '***' indicates statistical significance at the 99% confidence level; '**' indicates statistical significance at the 95% confidence level; and '*' indicates statistical significance at the 90% confidence level.

The statistical significance of the spatial coefficient ρ in the SAR and SEM estimates of (C.5) again indicate that spatial autocorrelation is prevalent in the data and the model's unobserved variables. Therefore, the OLS estimates should be ignored in this case. The expected marginal effects of land use type on GCP in 2000 in the Basin using the estimates from Table C.4 are given in Table C.5.

Table C.5. Expected change in 2000 GCP from an additional square kilometer of other or deforest land use in lieu of a forest square kilometer (2005 US$) using estimated model (C.5)[8]

[8] If all partial cells were dropped from the analysis the marginal impacts are,

Variable	OLS	SAR	SEM
Other	0.009***	0.003**	0.006**
Deforest	0.028***	0.014***	0.015***

Variable	OLS	SAR	SEM
Other	0.012***	0.007***	0.013***
Deforest	0.031***	0.017***	0.020***

Notes: For OLS and SEM, $\%\Delta Y = 100\left(e^{\beta_i} - 1\right)$. For SAR, $\%\Delta Y = 100\left(e^{\delta\beta_i} - 1\right)$ where the coefficient δ is equal to the mean of the diagonal elements of $(\mathbf{I} - \rho\mathbf{W})^{-1}$. This indicates the direct effect of a change in land use in *j* on Y_j only and does not include the impact of a change in land use in *j* on Y_{-j}.

Table C.6 contains each model's basin 2000 GDP prediction and 95th prediction interval estimates from estimates of model (C.5). Table C.6 also indicates the percentile of the Student's t-distribution under each estimation technique that sets the sum of $\widehat{Y}_j$ across all *j* equal to observed basin 2000 GDP.

Table C.6. Predicted and observed basin 2000 GDP (billions of 2005 US$) using estimated model (C.5)

	Predicted			Observed
	OLS	**SAR**	**SEM**	
Expected basin GDP	39.08	44.87	31.78	98.95
95th prediction interval lower bound	2.48	5.19	3.84	
95th prediction interval upper bound	615.81	388.00	262.98	
Percentile of t-distribution that matches predicted to observed	0.661	0.719	1.053	

C.IV. Including landscape variables in year 2000 estimates

In models (C.1) and (C.5) the marginal impact of land-use type on GCP is homogenous across the basin. However, we assume, for example, that cropland on better soil will contribute more to GCP than cropland on lesser soil, all else equal. Further, cropland near transposition infrastructure tends to be more productive in Brazil due to higher rates of investments in these fields' productivity (Mann et al. 2010). In addition, older urban areas may be marginally more productive than newer urban areas due to greater supportive infrastructure in the more established urban areas.

To explain any marginal differences in land use type contribution to GCP across space we interact our land use category variables in each grid cell with soil quality, distance to nearest major river, and distance to nearest coast point data for each grid cell. Because most economic activity in the Basin today takes place near the coast the distance to coast variable will control for any marginal effect that long-established cropland, pasture, and urban areas have on grid cell product versus more recently established areas in the basin's interior. Distance to river controls for the marginal impact that proximity to a transportation network has on land use type's contribution to GCP. Similarly, the inclusion of a soil quality variable will allow us to determine the impact better quality land has on GCP as mediated through land use type, all else equal.

We do not use climate and road networks to explain marginal differences of land use on GCP because we cannot predict their spatial patterns in the future. We plan to use our model estimates from the 2000 landscape to predict future GCP. And as of now we do not have a good idea how climate will be different at a sub-regional spatial grain by 2050. Similarly we do not know where future roads will be built.

The model that explains marginal differences in land use type's contribution to GCP using the 2000 land use map with crop, pasture, urban, and forest uses is given by,

$$\begin{aligned} Y_j = f(&C_j, C_j \times River_j, C_j \times Coast_j, C_j \times Soil_j, P_j, P_j \times River_j, \\ &P_j \times Coast_j, U_j, U_j \times River_j, U_j \times Coast_j, River_j, Coast_j, Soil_j) \end{aligned} \tag{C.6}$$

where *River*$_j$ measures the distance from gird cell *j* to the nearest major river in kilometers, *Coast*$_j$ measures the distance from gird cell *j* to the nearest coast point in kilometers, and *Soil*$_j$ gives *j*'s soil's potential to utilize fertilizer score from the World Harmonized Soil Database. The *Soil* is a categorical variable where lower *Soil* scores mean better soil. Finally, note that model (C.6) assumes the impact of forest, urban, and pasture on GCP is not mediated by soil type.

C.IV.a. Model (C.6) estimate

When we estimate a linear version of (C.6) the term $E(GDP_j|F_j = A;\ C_j + P_j + U_j = 0)$ is given by $\hat{\alpha} + \hat{\beta}_{11}River_j + \hat{\beta}_{12}Coast_j + \hat{\beta}_{13}Soil_j$ Further, $E(GDP_j|C_j = A;\ F_j + P_j + U_j = 0)$ is given by $\hat{\alpha} + \hat{\beta}_1 A + \left(\hat{\beta}_2 A + \hat{\beta}_{11}\right)River_j + \left(\hat{\beta}_3 A + \hat{\beta}_{12}\right)Coast_j + \left(\hat{\beta}_4 A + \hat{\beta}_{13}\right)Soil_j$. In this case a negative $\hat{\beta}_4$ would mean that better soil quality (lower *Soil*$_j$ means better soil) has a bigger impact on GCP when the land is used for crops than when used for forest. Finally, we can interpret $\hat{\beta}_1 + \hat{\beta}_2 River_j + \hat{\beta}_3 Coast_j + \hat{\beta}_4 Soil_j$ as the expected increase in GCP for every additional square kilometer of land used for cropland instead of forest. We can interpret the coefficients associated with pasture and urban vis-à-vis forest land use in the same way. Finally, we include *Partial*$_j$ in model (C.6) to reduce the bias forest cover would have on GCP in partial cells and mitigate the downward bias on urban, cropland, and pasture cover's impact on GCP. OLS, SAR and SEM estimates of a linear version of model (C.6) are given in Table C.7.

Table C.7. Estimates of model (C.6) where Y_j is logged

Variable	OLS		SAR		SEM	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	17.49	54.82	5.20	7.07	17.36	34.20
Cropland	3.99E-03	4.02	2.31E-03	2.89	2.62E-03	2.91
Cropland x River	-2.96E-06	-2.48	-1.71E-06	-1.79	-1.71E-06	-1.55
Cropland x Coast	9.69E-07	1.16	4.93E-07	0.74	1.22E-07	0.16
Cropland x Soil	-3.94E-04	-1.13	-1.63E-04	-0.59	-9.94E-05	-0.35
Pasture	5.14E-05	0.50	3.13E-05	0.38	1.51E-04	1.11
Pasture x River	-5.34E-08	-0.57	4.34E-08	0.58	-4.14E-08	-0.32
Pasture x Coast	6.77E-08	0.57	-5.34E-08	-0.57	-1.07E-07	-0.69
Urban	3.60E-03	2.31	1.74E-03	1.39	1.30E-03	1.03
Urban x River	-1.74E-06	-0.90	-5.59E-07	-0.36	-8.65E-07	-0.56
Urban x Coast	-2.00E-07	-0.10	9.45E-08	0.06	1.36E-07	0.09

River	8.37E-04	3.06	8.60E-05	0.39	4.14E-04	0.81
Coast	-6.88E-04	-3.20	-7.16E-05	-0.41	-1.10E-04	-0.24
Soil Category	-3.00E-02	-0.33	-6.12E-04	-0.01	-3.36E-02	-0.42
Partial	-0.44	-2.66	-0.35	-2.64	-0.25	-1.36
ρ			0.69	17.63	0.74	18.94
Adj. R^2						
Log-likelihood						
N	519		519		519	

Notes: Numbers in parentheses are t-stat values. To find standard errors divide the coefficient estimate by its t-stat value. ρ is a model's the spatial effect estimate. See Elhorst (2014) for the details on ρ is SAR and SEM models. '***' indicates statistical significance at the 99% confidence level; '**' indicates statistical significance at the 95% confidence level; and '*' indicates statistical significance at the 90% confidence level.

The expected marginal effects of land use type on GCP in 2000 in the basin using the estimates from Table C.7 are given in Table C.8.

Table C.8. Expected impact of an additional square kilometer of cropland, pasture, or urban land use in lieu of a forest square kilometer on GCP from model (C.6)[9]

Variable	OLS	SAR	SEM
Cropland	0.209***	0.149***	0.153***
Pasture	0.007*	0.002	0.005
Urban	0.252***	0.169**	0.093

Notes: For OLS and SEM, $\%\Delta Y = 100\left(e^{\beta_i} - 1\right)$. For SAR, $\%\Delta Y = 100\left(e^{\delta\beta_i} - 1\right)$ where the coefficient δ is equal to the mean of the diagonal elements of $(\mathbf{I} - \rho\mathbf{W})^{-1}$. This indicates the direct effect of a change in land use in *j* on Y_j only and does not include the impact of a change in land use in *j* on Y_{-j}. Mean values used to calculate the marginal effects of land use type on GCP given the interactive variables are *Distance to Major River*: 537.02; *Distance to Coast*: 735.32; and *Soil category*: 2.60.

Table C.9 contains each model's basin 2000 GDP prediction and 95th prediction interval estimates from estimates of model (C.6). Table C.6 also indicates the percentile of the Student's t-distribution under each estimation technique that sets the sum of $\widehat{Y}_j$ across all *j* equal to observed basin 2000 GDP.

Table C.9: Predicted and observed basin 2000 GDP (billions of 2005 US$) using estimated model (C.6)

	Predicted			Observed
	OLS	**SAR**	**SEM**	
Expected basin GDP	52.73	49.24	32.40	98.95

[9] If all partial cells were dropped from the analysis the marginal impacts are,

Variable	OLS	SAR	SEM
Cropland	0.226***	0.169***	0.177***
Pasture	0.007*	-0.002	-0.004
Urban	0.268***	0.197***	0.126*

95th prediction interval lower bound	3.35	5.66	3.67	
95th prediction interval upper bound	852.53	430.52	288.10	
Percentile of t-distribution that matches predicted to observed	0.445	0.631	1.003	

C.IV.b. The effects of landscape variables using alternative landscape land use categories

The model that explains marginal differences in land use type's contribution to 2000 GCP using the *CTL* map is given by,

$$Y_j = f(O_j, O_j \times River_j, O_j \times Coast_j, O_j \times Soil_j, D_j, \\ D_j \times River_j, D_j \times Coast_j, D_j \times Soil_j, River_j, Coast_j, Soil_j) \quad \text{(C.7)}$$

In model (C.7) the impact of deforest on GCP is not mediated by soil type. Deforest is not typically associated with cropland.

C.IV.c. Model (C.7) estimate

We include *Partial$_j$* in model (C.7) to reduce the bias forest cover would have on GCP in partial cells and mitigate the downward bias on urban, cropland, and pasture cover's impact on GCP. OLS, SAR and SEM estimates of a linear version of model (C.7) are given in Table C.10.

Table C.10. Estimates of model (C.7) where Y_j is logged

Variable	OLS		SAR		SEM	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	17.98	48.29	4.98	6.91	17.15	29.68
Other	-3.17E-06	-0.03	5.32E-05	0.72	2.47E-04	2.83
Other x River	9.02E-08	1.13	6.44E-08	1.02	-9.29E-08	-1.21
Other x Coast	-1.90E-09	-0.03	-7.15E-08	-1.48	-5.25E-08	-0.81
Other x Soil	1.74E-05	0.71	9.18E-06	0.47	-4.61E-06	-0.22
Deforest	3.20E-04	4.46	1.46E-04	2.53	1.79E-04	2.23
Deforest x River	1.55E-07	1.18	2.14E-07	2.05	1.86E-07	1.36
Deforest x Coast	-1.36E-07	-1.11	-1.38E-07	-1.41	-1.29E-07	-1.02
River	1.24E-04	0.38	-3.79E-04	-1.46	5.85E-05	0.10
Coast	-6.77E-04	-2.72	3.43E-05	0.17	2.29E-05	0.04
Soil	-0.16	-1.60	-0.06	-0.72	-0.03	-0.36
Partial	-0.09	-0.51	-0.15	-1.09	-0.04	-0.19
ρ			0.72	18.74	0.78	21.93
Adj. R^2						
Log-likelihood						
N	519		519		519	

Notes: Numbers in parentheses are t-stat values. To find standard errors divide the coefficient estimate by its t-stat value. ρ is a model's the spatial effect estimate. See Elhorst (2014) for the details on ρ is SAR and SEM models. '***' indicates statistical significance at the 99% confidence level; '**' indicates statistical significance at the 95% confidence level; and '*' indicates statistical significance at the 90% confidence level.

The expected marginal effects of land use type on GCP in 2000 in the basin using the estimates from Table C.10 are given in Table C.11.

Table C.11. Expected impact of an additional square kilometer of other or deforest use in lieu of a forest square kilometer on GCP from model (C.7)[10]

Variable	OLS	SAR	SEM
Other	0.009***	0.007***	0.015***
Deforest	0.030***	0.018***	0.018***

Notes: For OLS and SEM, $\%\Delta Y = 100\left(e^{\beta_i} - 1\right)$. For SAR, $\%\Delta Y = 100\left(e^{\delta\beta_i} - 1\right)$ where the coefficient δ is equal to the mean of the diagonal elements of $(\mathbf{I} - \rho\mathbf{W})^{-1}$. This indicates the direct effect of a change in land use in *j* on Y_j only and does not include the impact of a change in land use in *j* on Y_{-j}. Mean values used to calculate the marginal effects of land use type on GCP given the interactive variables are *Distance to Major River*: 537.02; *Distance to Coast*: 735.32; and *Soil category*: 2.60.

Table C.12 contains each model's basin 2000 GDP prediction and 95th prediction interval estimates from estimates of model (C.7). Table C.12 also indicates the percentile of the Student's t-distribution under each estimation technique that sets the sum of $\widehat{Y}_j$ across all *j* equal to observed basin 2000 GDP.

Table C.12. Predicted and observed basin 2000 GDP (billions of 2005 US$) using estimated model (C.7)

	Predicted			**Observed**
	OLS	**SAR**	**SEM**	
Expected basin GDP	40.56	41.97	31.92	98.95
95th prediction interval lower bound	2.62	4.84	3.84	
95th prediction interval upper bound	630.20	364.16	266.06	
Percentile of t-distribution that matches predicted to observed	0.644	0.778	1.045	

C.VI. Expected gains in economic productivity to each land use type from 2000 to 2050

Eventually we use the estimated relationships between GCP and grid cell land-use mix in 2000 to estimate the expected economic ramifications of land-use change predicted by the two 2050 Amazon basin scenarios, GOV and BAU. However, to translate year 2000 relationships between GCP and land use pattern to such relationships in 2050 we first have to estimate expected gains in land use productivity from 2000 to 2050.

Urban land is primarily used to create manufactured products and generate services (although there are some agricultural production processing jobs in urban areas as well).

[10] If all partial cells were dropped from the analysis the marginal impacts are,

Variable	OLS	SAR	SEM
Other	0.008***	0.004*	0.009***
Deforest	0.027***	0.014***	0.014***

Estimates of the proportion of urban workforce in each industrial sector observed in Brazil (our proxy for the entire basin) from 1990 to 2007 and a linear extrapolation to 2050 are given in Table C.13.

Table C.13: Proportion of Brazilian urban workforce in each industrial sector

	1990	1995	2001	2005	2006	2007	2050 Est.
Manufacturing	0.253	0.221	0.216	0.234	0.231	0.237	0.204
Services	0.681	0.683	0.707	0.689	0.694	0.705	0.739
Agriculture	0.065	0.096	0.077	0.079	0.075	0.068	0.057

We also estimated the average per annum gains in productivity in each industrial sector in Brazil (Table C.14).

Table C.14. Average per annum gains in productivity in each industrial sector in Brazil

Manufacturing	2.90% per annum
Services	2.55% per annum
Agriculture	20.20% every 10 years

Therefore, urban land's productivity is expected to increase by a factor of 3.6 by 2050:

$$(0.204 \times 1.029^{50}) + (0.739 \times 1.0255^{50}) + (0.057 \times 1.202^{5}) = 3.60. \qquad \text{(C.8)}$$

To measure the expected productivity gains in cropland in the Amazon we estimate average per annum increases in maize, soybean, and sugarcane yield in Brazil from 1980 to 2010 (FAOSTAT 2012) and then extrapolate the linear trend to 2050. Table C.15 gives expected yield in Brazil for each crop as of 2050 and predicted percentage gain between 2000 and 2050.

Table C.15. Expected Brazilian yields as of 2050 (Hg ha^{-1})

	Yield	Relative gain from 2000
Sugarcane	1,059,577	57%
Maize	71,861	162%
Soybean	45,088	88%

Next we project the expected mix of cropland in Brazil in maize, soybean, and sugarcane production as of 2050 (Table C.16).

Table C.16. Expected Brazilian harvest area as of 2050 (Ha)

	Harvest area	Relative gain from 2000
Sugarcane	13,338,480	175%
Maize	14,300,356	23%
Soybean	41,651,642	205%
Total	69,290,478	130%

Therefore, the productivity of a representative hectare of cropland in Brazil is expected to increase by a factor of 1.97 by 2050:

$$\left(\frac{13{,}338{,}480}{69{,}290{,}478}\right) \times 1.57 + \left(\frac{14{,}300{,}356}{69{,}290{,}478}\right) \times 2.62 + \left(\frac{41{,}651{,}642}{69{,}290{,}478}\right) \times 1.88 = 1.97. \qquad \text{(C.9)}$$

Finally, we assume that the productivity of forest and pasture land will not change from 2000 to 2050.

We want these estimated productivity gains to be compatible with the CTL land use classes of other, deforest, and forest (Soares-Filho et al. 2006). We assumed that the productivity of the other land use would increase by,

$$(1.97 \times 0.8422) + \big(3.60 \times (1 - 0.8422)\big) = 2.23 \qquad \text{(C.10)}$$

where 0.8422 is other's ratio of cropland in 2000 to cropland plus urban land in 2000. Further we assumed that forest and deforest (assumed to mostly be pasture) would not experience productivity gains between 2000 and 2050.

C.VII. Opportunity cost of conservation

The two 2050 Amazon basin scenarios, GOV and BAU, are given by grid cell maps with the same land use categories at the CTL map: other (*O*), deforest (*D*), and forest (*R*). Therefore, we predict 2050 GCP in each grid cell *j* using estimated model (C.7), expected productivity gains by land use type, and land use distribution as given by a 2050 scenario map,

$$\log(\hat{Y}_j) = \hat{\beta}_0 + \hat{\beta}_1\theta O_j + \hat{\beta}_2(\theta O_j River_j) + \hat{\beta}_3(\theta O_j Coast_j) + \hat{\beta}_4(\theta O_j Soil_j) + $$
$$+\hat{\beta}_5\gamma D_j + \hat{\beta}_6(\gamma D_j River_j) + \hat{\beta}_7(\gamma D_j Coast_j) + $$
$$\hat{\beta}_8 River_j + \hat{\beta}_9 Coast_j + \hat{\beta}_{10} Soil_j \qquad \text{(C.11)}$$

where θ is the productivity multiplier for the other land use, γ is the productivity multiplier for the deforest land use, $\hat{\beta}_k$ are the estimated coefficients listed in Table C.10, O_j and D_j come from the scenario maps GOV or BAU, and $River_j$, $Coast_j$, and $Soil_j$ are as before. Notice that the productivity multipliers effectively mean that there is more land in the basin in 2050 than in 2000. In other words, every square kilometer of other and deforest land use in 2050 is equivalent to θ and γ square kilometers of other and deforest land from 2000 in a productivity sense (we always assume that forest productivity will not increase between 2000 and 2050). Also note that we assume real prices for all products made in Brazil do not change from 2000 to 2050.

After transforming $\log(\hat{Y}_j)$ to $\hat{Y}_j$ we multiply it by 63/100 to convert the \$2005 US values to \$2000 US values.[11] In Table C.17 we give 2050 basin GDP prediction and 95th prediction

[1111] According to the IMF the Purchasing Power Parity GDP deflator in Brazil where 2005 equals 100 is, interval estimates using both the BAU and GOV maps and assuming $\theta = 2.23$ and $\gamma = 1$. Table C.17 also indicates the predicted 2050 basin GDP using the percentile of the t-distribution under each estimation technique that sets the sum of predicted 2000 $\hat{Y}_j$ across all *j* equal to observed basin 2000 GDP. We call this the calibrated expectation.

Table C.17. Predicted 2050 GDP (2000 US$) using model (C.7) assuming $\boldsymbol{\theta = 2.23}$ and $\boldsymbol{\gamma = 1}$.

	OLS	SAR	SEM
	BAU		
Expected basin GDP	176.59	1294.46	106.85
5th prediction interval lower bound	11.61	150.42	12.81
95th prediction interval upper bound	2687.31	11141.97	892.00
Calibrated expectation	431.93	3042.04	331.20
	GOV		
Expected basin GDP	103.56	512.34	86.77
5th prediction interval lower bound	6.73	59.01	10.35
95th prediction interval upper bound	1596.15	4449.97	728.29
Calibrated expectation	254.37	1208.34	269.74

In Table C.18 we give the same basin GDP predictions assuming $\theta = 1.5$ and $\gamma = 1$.

Table C.18. Predicted 2050 GDP (2000 US$) using model (C.7) assuming $\boldsymbol{\theta = 1.5}$ and $\boldsymbol{\gamma = 1}$.

	OLS	SAR	SEM
	BAU		
Expected basin GDP	128.47	537.45	55.53
5th prediction interval lower bound	8.48	62.73	6.71
95th prediction interval upper bound	1946.40	4605.71	459.72
Calibrated expectation	313.78	1260.83	171.36
	GOV		
Expected basin GDP	65.70	158.68	40.64
5th prediction interval lower bound	4.28	18.34	4.88
95th prediction interval upper bound	1009.61	1373.46	338.57
Calibrated expectation	161.22	373.73	125.84

The various predicted economic opportunity costs of GOV2050 in lieu of BAU2050 (GOV2050 – BAU2050 from Tables C.17 and C.18) is given in Table C.19

Table C.19.

	OLS	SAR	SEM
	Assuming $\boldsymbol{\theta = 2.23}$ and $\boldsymbol{\gamma = 1}$		

2000	2001	2002	2003	2004	2005
63.0	68.7	75.9	86.3	93.3	100

Expected basin GOV GDP less BAU GDP	-73.02	-782.12	-20.08
5th prediction interval lower bound	-4.89	-91.42	-2.46
95th prediction interval upper bound	-1091.16	-6692.00	-163.71
Calibrated expectation	-177.57	-1833.70	-61.47
	Assuming $\theta = 1.5$ and $\gamma = 1$		
Expected basin GOV GDP less BAU GDP	-62.77	-378.77	-14.88
5th prediction interval lower bound	-4.20	-44.39	-1.83
95th prediction interval upper bound	-936.79	-3232.25	-121.15
Calibrated expectation	-152.57	-887.10	-45.52

Finally to turn the 2050 opportunity cost values into present values as of 2000 we multiply each value by 1 / $(1.05)^{49}$ (we assume a 5% discount rate in this analysis). See Table C.20.

Table C.20

	OLS	**SAR**	**SEM**
	Assuming $\theta = 2.23$ and $\gamma = 1$		
Expected basin GOV GDP less BAU GDP	-6.69	-71.61	-1.84
5th prediction interval lower bound	-0.45	-8.37	-0.23
95th prediction interval upper bound	-99.91	-612.75	-14.99
Calibrated expectation	-16.26	-167.9	-5.63
	Assuming $\theta = 1.5$ and $\gamma = 1$		
Expected basin GOV GDP less BAU GDP	-5.75	-34.68	-1.36
5th prediction interval lower bound	-0.38	-4.06	-0.17
95th prediction interval upper bound	-85.78	-295.96	-11.09
Calibrated expectation	-13.97	-81.23	-4.17

C.IX. Analysis caveats

We make several large assumptions in this analysis:

- We assume real prices of goods produced in the Basin do not change over time. Of course if they all changed at the same rate over time then the opportunity costs estimated in Table 24 would all inflate or deflate at the same rate. However, if prices change at different rates from 2000 to 2050 then the estimates in Tables 23 and 24 will be off.
- Our assumption that forest and pasture will not experience productivity gains from 2000 to 2050 could be erroneous.
- Of course there are concerns about the accuracy of the G-Econ database and maps.
- On a related note, do G-Econ's maps of GCP accurately capture the value added at each stage of the production process? For example, pasture land is used to "create" cattle. Eventually the cattle is sold and butchered as well for meat. Let us say that the pasture land used to raise the cattle is in grid cell *j* and the butcher that prepares the meat and sells it to wholesalers and retail outlets is in grid cell *k*. Is all value from the meat ascribed to grid cell k or does j gets its fair share for its raw meat input?

- As we saw above, climate and some landscape features seem to have affected GCP. However, a lack of downscaled predictions on future climate in the Basin makes the inclusion of any climate variables in future GCP predictions impossible.
- As we noted above, landscapes produce many valuable goods and services that are not captured by GDP and GCP measures. Presumably the aggregate value of these goods and services will be larger on the GOV2050 landscape than they are on the BAU2050 landscape. Will the gap be large enough to overcome the conventional wealth gap between the BAU2050 and GOV2050 landscapes?

D. Population Maps and Estimates

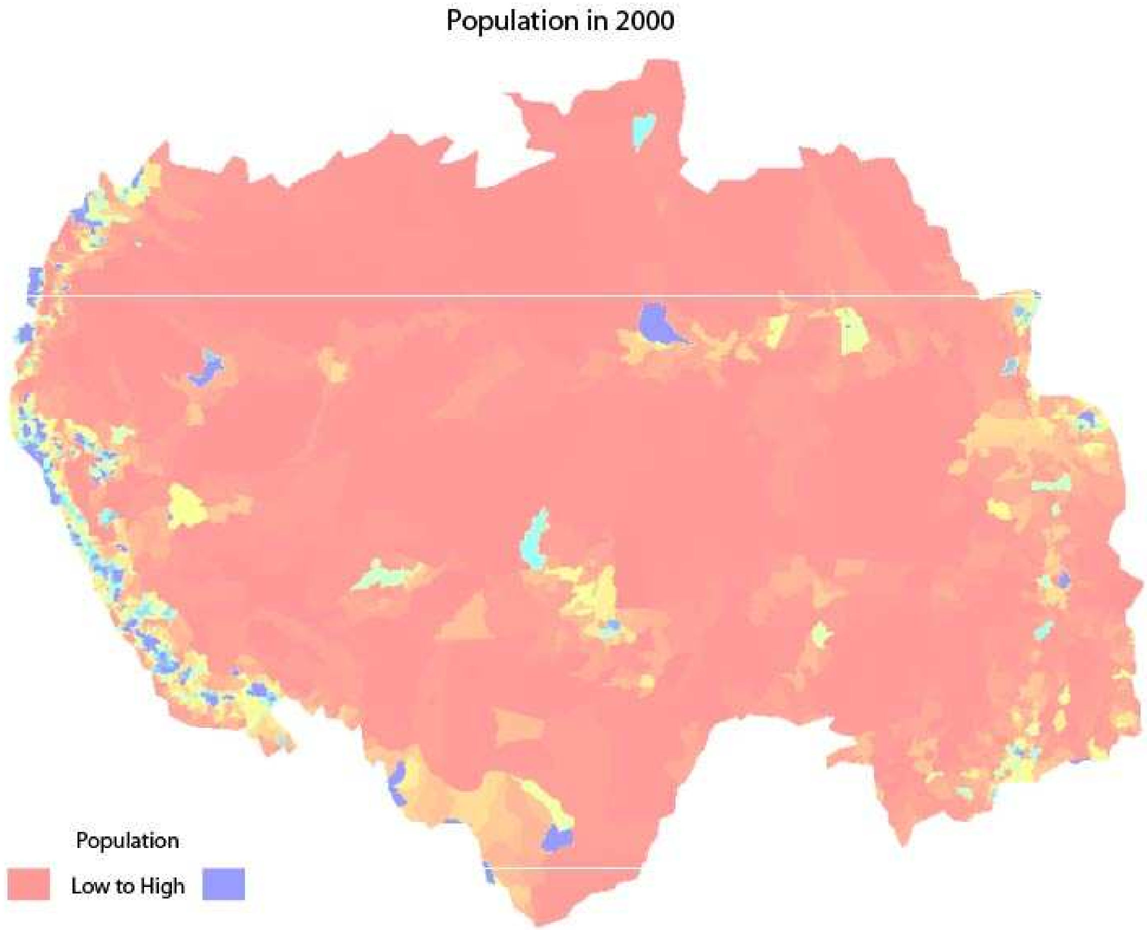
1. We downloaded gridded population data for South America from the Socioeconomic Data and Applications Center (SEDAC) found on the CEISIN Columbia website:

    -http://sedac.ciesin.columbia.edu/gpw/global.jsp

Specifically we obtained population data for the years 1990, 1995, 2000, 2005, 2010, and 2015

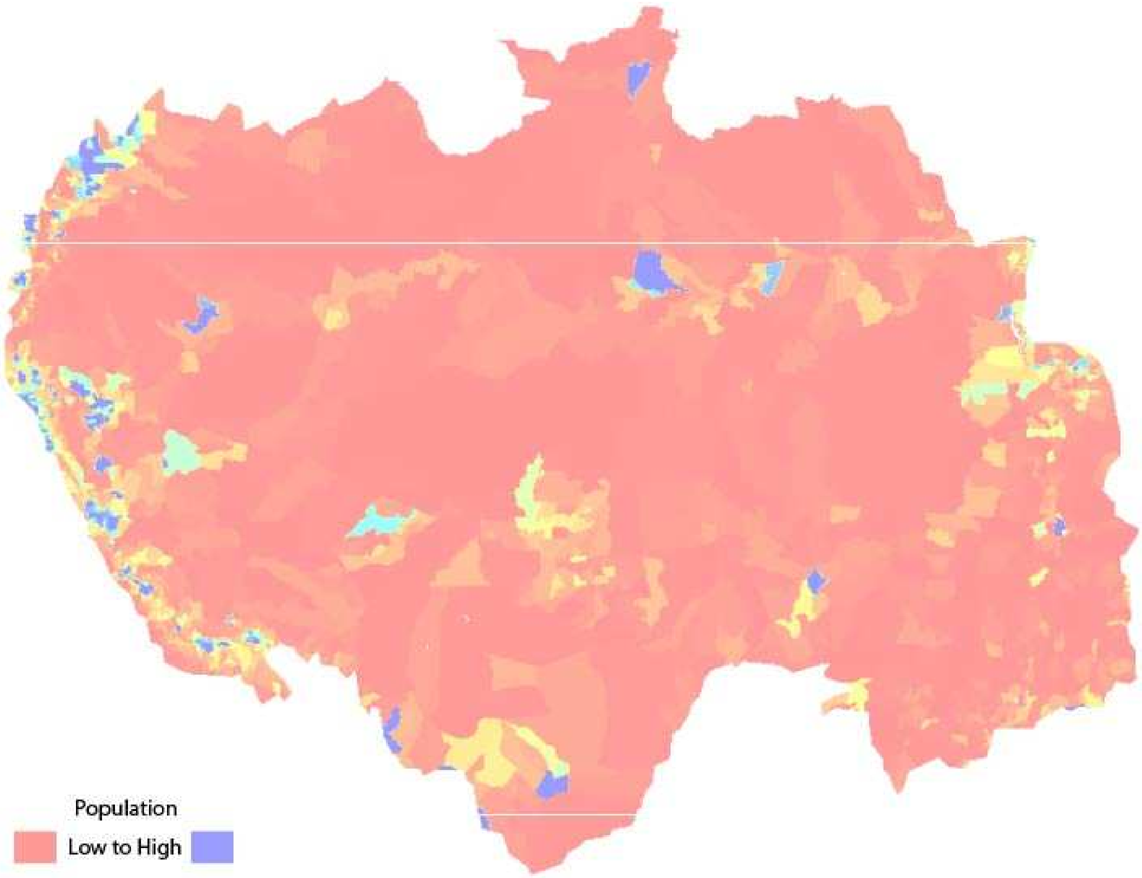
2. This information came in the form of raster datasets with a 2.5' resolution (.04166 decimal degrees, or 5 kilometers squared); after extracting these datasets with the mask of our study area, we called them "popin90" for 1990, "popin00" for 2000, etc.

Example map:



3. The maps give people per grid cell.
4. In order to determine population growth rates, we undertook a series of raster calculations, which included dividing the population data for a specific year by that of 5 years before:
For example: “popin05” / “popin00”
This yields the average growth rate over 5 years during that specific period; we called those maps “popdiv05_00” etc.
5. Having obtained these intermediate growth rates, we averaged the 5 rates together to obtain an average 5 year growth rate over time. We called this the “popchangeave”.
6. We then performed another calculation, raising that raster dataset to the 10^{th} power such that we could have a 50 year growth rate raster, called “poprate50”. Lastly we multiplied that raster by the “popin00” map, obtaining an estimate raster for the population of Brazil in 2050. This map is shown below and entitled “popin2050”:

Population in 2050 Estimate



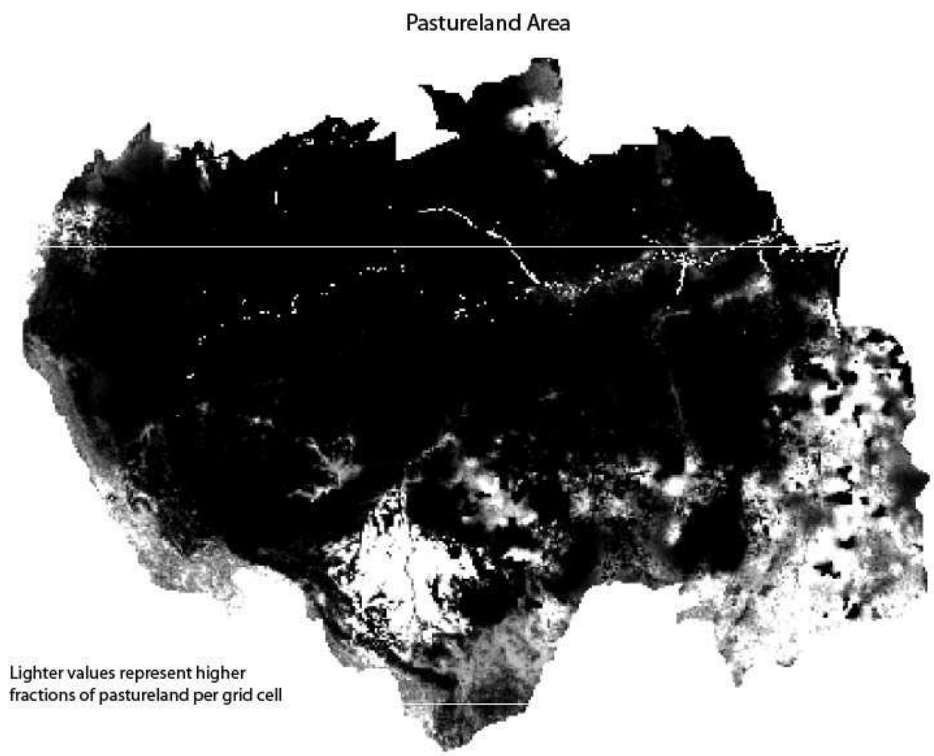
E. Cropland and Urban Maps and Estimates

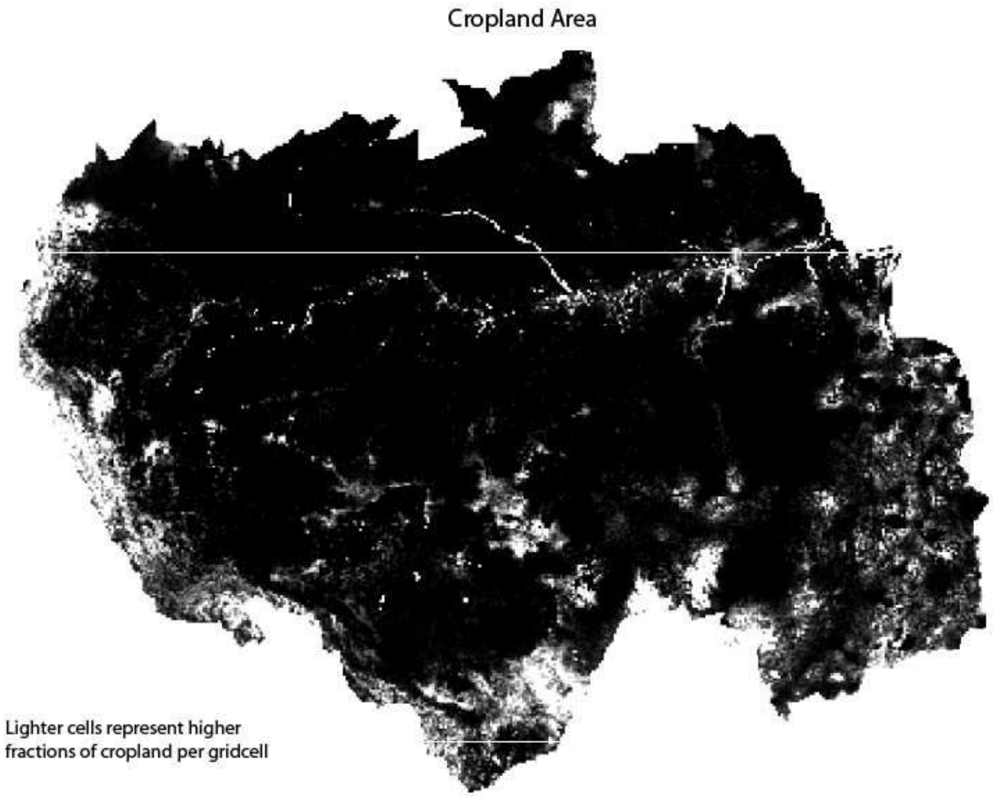
Process Information for Crop and Pasture Land Data

1. We obtained world crop and pasture data from the “Navin RamanKutty” site, the information posted was sourced to: Ramankutty et al. (2008), "Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000", Global Biogeochemical Cycles, Vol. 22, GB1003, doi:10.1029/2007GB002952

2. The information came in ASCII format at 5 minute resolution in latitude by longitude. Each grid cell contained a number from 0 to 1, representing the fraction of the grid cell which was occupied by either cropland or pastureland (1 being all, 0 being none).

3. Having obtained this information, we converted the ASCII files to raster datasets, and then extracted them with the mask of our study area. These maps we called “pasturearea” and “croplandarea”.

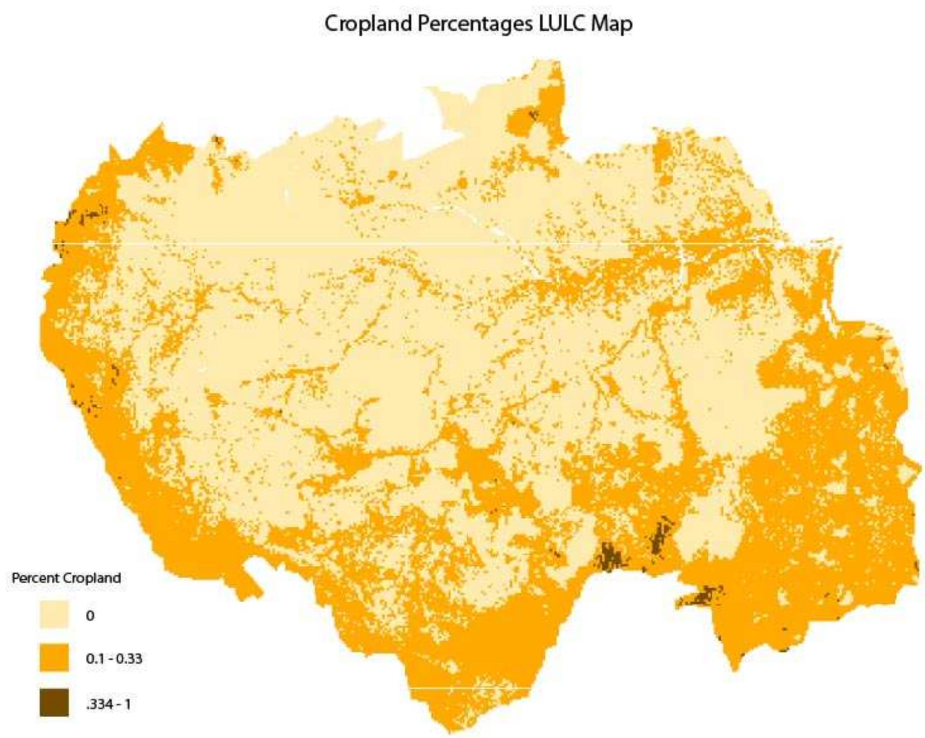


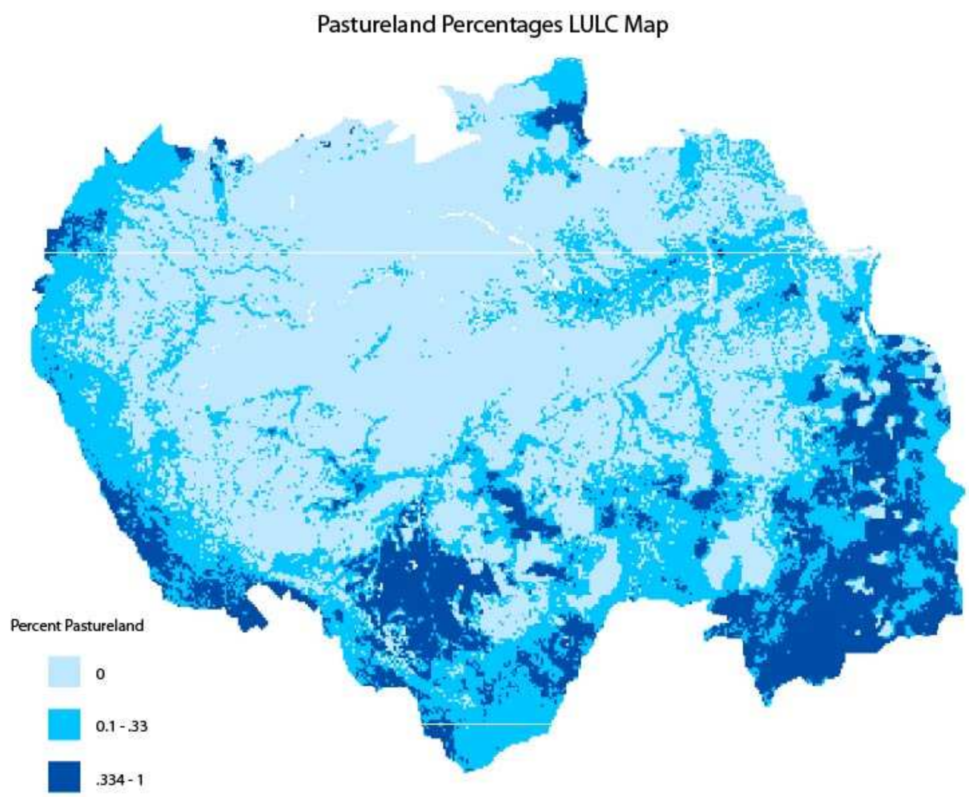


4. In order to inform our other LULC raster datasets, we then reclassified the previous two maps such that there would be three LULC classes for each

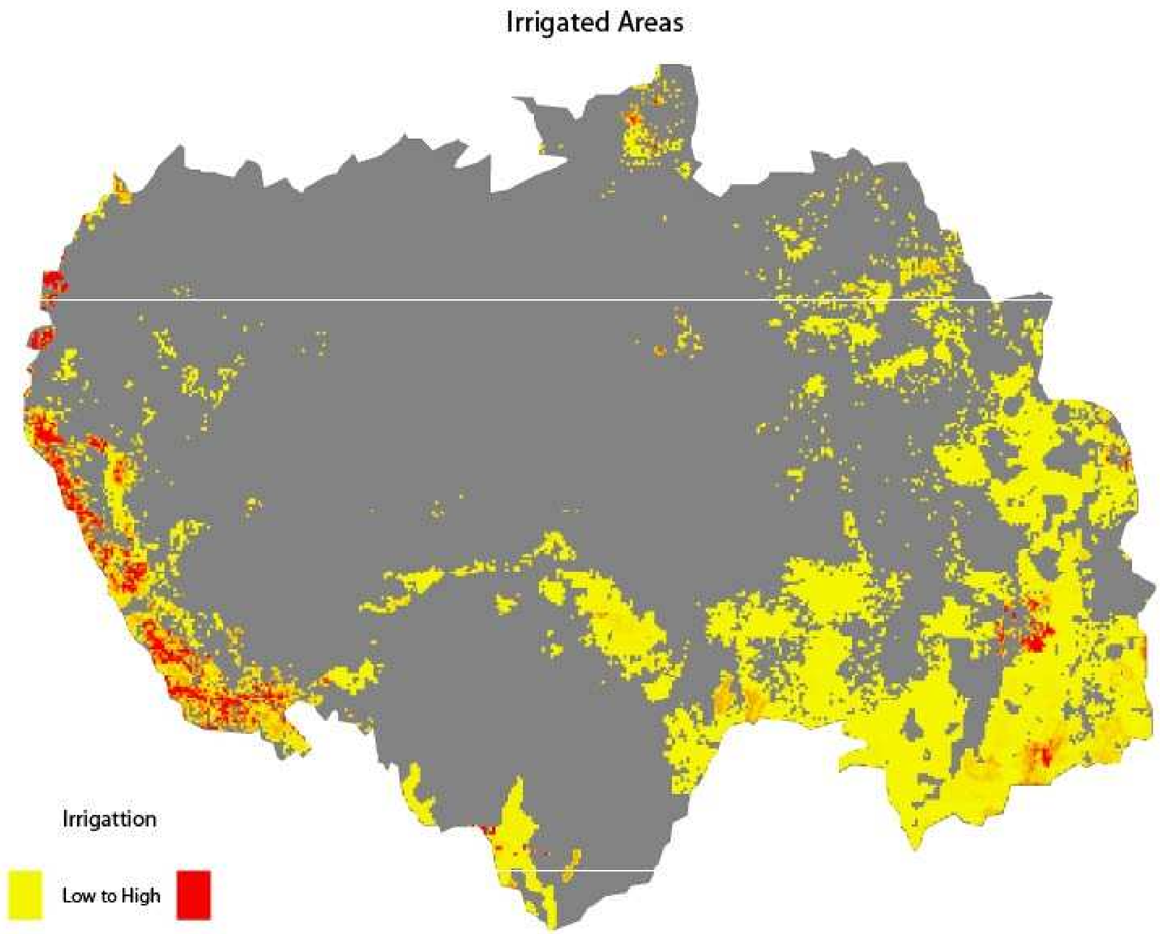
- 1 → grid cell with no cropland or pasture land
- 2 → grid cell with cropland or pasture land fraction greater than 0 and less than 1/3
- 3 → grid cell with cropland or pasture land fraction greater than 1/3

5. These maps we called “crop_a_r” and “pasture_a_r”, and were then used to inform another LULC raster dataset for use on our model





6. Lastly we created an Irrigated Areas map, entitled “irramazon”, not yet used but pictured below


Irrigated Areas
Irrigattion
Low to High

F. Annual Water Yield Model Comparison: InVEST vs IBIS-THMB

For this analysis we compared of InVEST and IBIS-THMB annual water yield estimates for current dam watersheds in the Basin.

We used the InVEST Water Yield model that estimates annual water yield (Tallis et al. 2011; see sub-appendix A for details on model parameters). The water yield model is based on the Budyko curve and annual average precipitation. The model has a number of limitations. First, it is based on annual averages and neglects extreme events and the temporal dimensions of water supply. Second, the model assumes that all water produced in a watershed in excess of evapotranspiration arrives at the watershed outlet. It only considers surface water. Third, the model does not consider sub-annual patterns of water delivery timing. Water yield is a provisioning function, but hydropower benefits are also affected by flow regulation. The timing of peak flows and delivery of minimum operational flows throughout the year. Still, this model provides a useful initial assessment of how landscape scenarios may affect the annual delivery of water.

In contrast to the relatively simple InVEST model, IBIS is a biophysically-based model that integrates a variety of terrestrial ecosystem processes within a single, mechanistic model to simultaneously calculate a wide range of processes, including the land surface water and energy balances (Kucharik et al. 2000). IBIS is integrated with THMB, the terrestrial hydrological model with biogeochemistry. This latter model is driven by climate data and surface runoff and sub-surface drainage provided by IBIS to simulate the water balance of the Basin. The equations are solved with a 1-h time step. See Coe et al (2009) for additional details.

Table 1. Comparison of InVEST and IBIS-THMB annual water yield estimates for current dam watersheds in the Basin.

		InVEST		IBIS-THMB		
ws_id	Watershed Area	WY Volume (cu. m)	Rank	WY Volume (cu. m)	Rank	% Difference (IBIS-InVEST)
1	18,900,000,000	30,040,793,262	3	10,823,300,000	6	-178%
2	8,100,000,000	12,700,071,277	9	3,904,780,000	12	-225%
3	16,200,000,000	21,070,368,237	5	10,001,800,000	7	-111%
4	473,700,000,000	272,976,737,439	1	205,873,000,000	1	-33%
5	90,200,000,000	46,852,497,253	2	22,732,500,000	4	-106%
6	57,000,000,000	22,498,241,638	4	27,836,800,000	2	19%
7	7,900,000,000	3,924,522,452	12	3,212,130,000	13	-22%
8	62,500,000,000	17,523,124,695	7	16,672,900,000	5	-5%
9	60,800,000,000	20,866,742,578	6	24,136,700,000	3	14%
10	14,000,000,000	14,641,619,385	8	9,419,770,000	8	-55%
11	5,500,000,000	5,246,406,158	11	5,372,260,000	10	2%
12	8,000,000,000	7,797,104,004	10	5,535,090,000	9	-41%
13	4,800,000,000	2,767,814,355	13	3,988,920,000	11	31%

Results
InVEST overestimated annual water yield compared to IBIS-THMB for 11 of the 13 watersheds. Specifically InVEST overestimated the highs and underestimated the lows per pixel annual yield values compared to IBIS-THMB for the Basin. This latter result is likely due to InVEST not capturing the inter-annual dimensions of water supply that are captured IBIS. In the Amazon Basin seasonality, the wet and dry seasons, can be dramatic and the magnitude of this effect varies spatially across the basin. Interestingly the relative ranking of the watersheds by the two models are similar.

Sub-appendix A. InVEST Water Yield

Water yield map circa 2000:

7. We combined the current watersheds and enhanced 2000 LULC map. The resulting map is known as “amazon2000_p” and is found in the “HydropowerInputs” folder. For each grid cell the enhanced LULC map indicates:
    a. The current watershed ID
    b. forest (= 2), deforest (= 1), or other (= 3) according to the raster “LULC2000” (this raster is based on the raster “amazonscen” from Coe’s group);
    c. whether or not the cell is in a current ARPA (= 1 in the “in_ARPA” field in map “ARPA_1_2.shp”);
    d. whether or not the cell is an urban cell according to the urban extent grid map (= 2 in value field from raster “urbextent” from Columbia University - CIESIN);
    e. proportion of grid cell in cropland in 2000 (= 1 if 0.00; = 2 if 0.01-0.30; or =3 if 0.31 – 1.00); and
        i. “Agricultural Lands in the Year 2000 (M3-Cropland and M3-Pasture Data)” from http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html).
    f. proportion of grid cell in pasture in 2000 (0.00; 0.01-0.30; or 0.31 – 1.00)
        i. “Agricultural Lands in the Year 2000 (M3-Cropland and M3-Pasture Data)” from http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html).
8. For each LULC type Alex assigned an ETK and Root Depth according to data used by Heather Tallis in a Cauca, Colombia analysis. This Access geodatabase is called “biophysicaltable_wy_cur”
    g. Cauca is a Department of Colombia. Located in the south-western part of the country, facing the Pacific Ocean to the west, the Valle del Cauca Department to the north, Tolima Department to the northeast, Huila Department to the east and the Nariño Department to the south, Putumayo and Caqueta Departments are located and bordering the southeast portion of Cauca Department as well.

Root_depth Rules		root depth Value	etk
If Urban LULC	pasture and cropland at 1	500	350
Urban LULC	pasture and cropland at 2, or other at 1	2000	500
Urban LULC	pasture or cropland at 3, other at 1	2667	750
Urban LULC	pasture or cropland at 3, other at 2 or 3	2667	700
Not Urban	Pasture and cropland at 1	4000	650
Not Urban	Pasture and cropland at 1 and 2, or 2 and 2	3000	700

Not Urban	Pasture and cropland at 1 and 3	2667	750
Not Urban	Pasture and cropland at 2 and 3	2667	1000

9. We obtained soil depth and plant available water content maps for the Amazon from the Harmonized World Soil Database v 1.2 (HWSD). These projected maps are called depths_p and pawc_p, respectively, and are found in the "FinalHydropowerModelInputs" folder.
    h. http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/
    i. Here is some detailed information on how we calculated the depths_p and pawc_p maps.
        i. HWSD is a gridded map of the world.
        ii. We exported the Access data to MS Excel. The Excel file is called soil_data.xlsx. Table D_AWC.xlsx was a lookup table for this part of the analysis.
        iii. The formula for DEPTHS is (REF_DEPTH x 10) / (SHARE /100) where SHARE is the portion of the row in the grid cell, REF_DEPTH is in cm, and the 10 converts cm to mm. We add across rows in the same grid cell to get the weighted average of reference depth in mm in each grid cell.
        iv. The formula for PAWC is (AWC) / (SHARE /100) where AWC is available water content in mm / m and SHARE is the portion of the row in the grid cell. We add across rows in the same grid cell to get the weighted average of PAWC in each grid cell.
10. We used circa 2000 precipitation and evapotranspiration maps from Michael Coe. The projected maps, ppt_p and pet_p, are found in the "FinalHydropowerModelInputs" folder.
11. We used the "watersheds_current_dams" shapefile watersheds and the "subwatersheds_current_dams" shapefile and are found in the "FinalHydropowerModelInputs" folder.
12. The 2000 water yield map is given by "wyield_cur" and is found in the "WaterYield" folder.
13. The Coe water yield map for the same area is given by "wy_cur_coe"

Water yield map 2050 – business as usual:

14. We combined the "all" watersheds and enhanced business as usual 2050 LULC map. This map is named "amznbau2050_p" and is found in the "FinalHydropowerModelInputs" folder. For each grid cell the enhanced business as usual 2050 LULC map indicates,
    d. watershed ID
    e. forest (= 2), deforest (= 1), or other (= 3) according to the raster "bau2050lulc" (this raster is based on the raster "BAU_2050" from Coe's group); and
    f. whether or not the cell is in a current or future ARPA (= 1 or = 2 in the "in_ARPA" field in map "ARPA_1_2.shp").

15. For each LULC type Alex assigned an ETK and Root Depth according to data used by Heather Tallis in a Cauca, Colombia analysis. This Access geodatabase is called "biophysicaltable_wy_bau".

	Root depth value	etk
If deforest (= 1)	2667	900
If forest (=2)	4000	650
If other (=3)	2000	750

16. We obtained soil depth and plant available water content maps for the Amazon from the Harmonized World Soil Database v 1.2. These projected maps are called depths_p and pawc_p, respectively, and are found in the "FinalHydropowerModelInputs" folder.
    g. http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/
17. We used circa 2000 precipitation and evapotranspiration maps from Michael Coe. The projected maps, ppt_p and pet_p, are found in the "HydropowerInputs" folder.
18. We used the "watersheds_all_dams" shapefile watersheds and the "subwatersheds_all_dams" shapefile and are found in the "FinalHydropowerModelInputs" folder.
19. The 2050 – business as usual water yield map is given by "wyield_bau" and is found in the "WaterYield" folder.
20. The Coe water yield map for the same area is given by "wy_bau_coe"

Water yield map 2050 – government:

1. We combined the "all" watersheds and enhanced government 2050 LULC map. This map is named "amzngov2050_p" and is found in the "FinalHydropowerModelInputs" folder. For each grid cell the enhanced government 2050 LULC map indicates,
    a. watershed ID
    b. forest (= 2), deforest (= 1), or other (= 3) according to the raster "gov2050lulc" (this raster is based on the raster "GOV_2050" from Coe's group); and
    c. whether or not the cell is in a current or future ARPA (= 1 or = 2 in the "in_ARPA" field in map "ARPA_1_2.shp").
2. For each LULC type Alex assigned an ETK and Root Depth according to data used by Heather Tallis in a Cauca, Colombia analysis. This Access geodatabase is called "biophysicaltable_wy_gov".

	Root depth value	etk
If deforest (= 1)	2667	900
If forest (=2)	4000	650
If other (=3)	2000	750

3. We obtained soil depth and plant available water content maps for the Amazon from the Harmonized World Soil Database v 1.2.
    a. http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/
4. We used circa 2000 precipitation and evapotranspiration maps from Michael Coe.
5. We used the “all” watersheds and subwatersheds map and is found in the “WaterYield” folder.
6. The 2050 - government water yield map is given by “wyield_gov”.
7. The Coe water yield map for the same area is given by “wy_gov_coe”

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