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Supplementary Information for

Micro-Estimates of Wealth for all Low- and Middle-Income Countries

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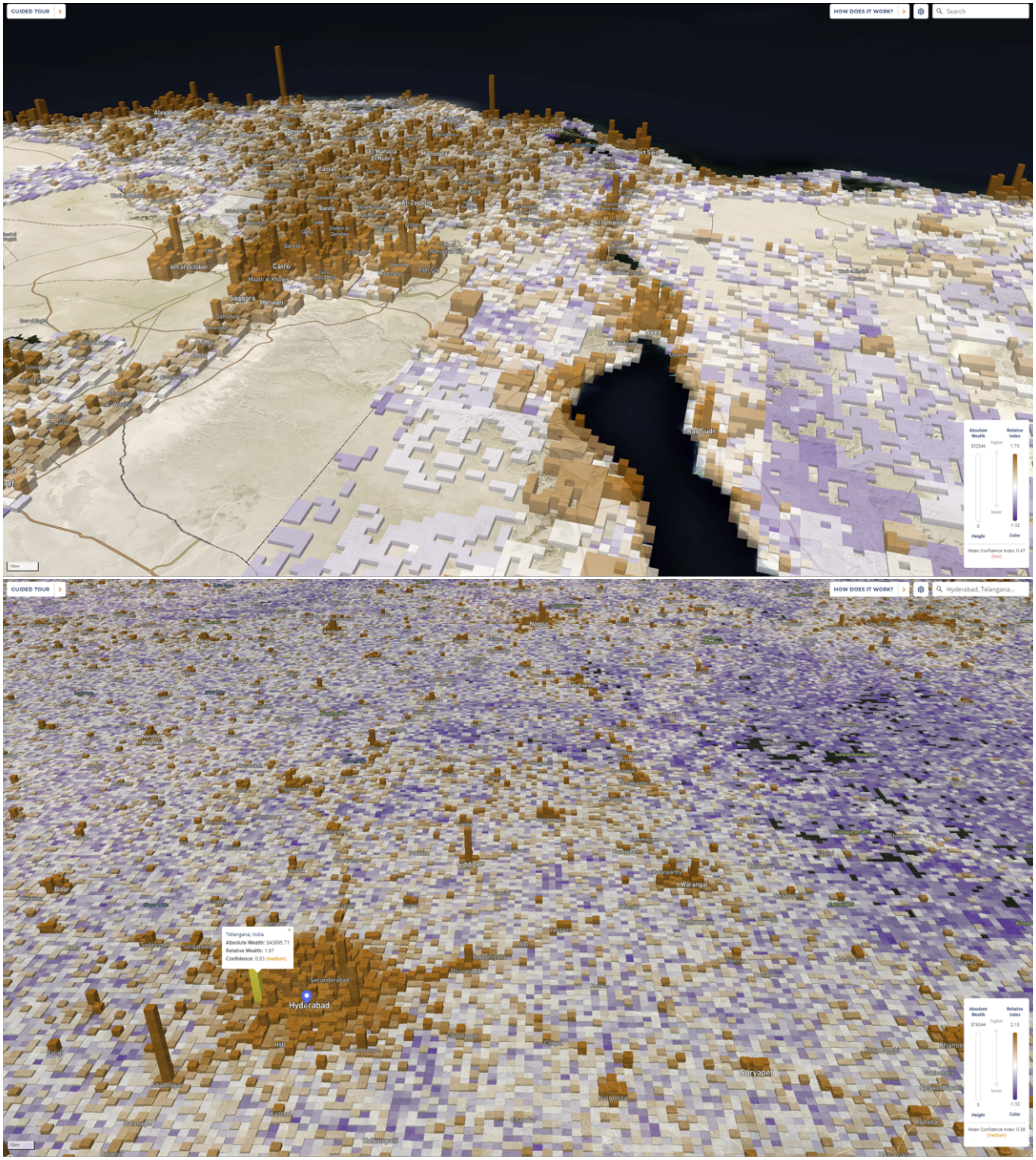


Fig. S1. Screenshots of the interactive data visualization. Each grid cell corresponds to a 2.4km grid cell. Absolute wealth (in dollars) indicated by the height of the grid cell. Relative wealth (relative to other cells in that country) indicated by colors ranging from blue (poorest) to red (wealthiest). a) Region around the Suez canal. b) Region around Hyderabad, India.

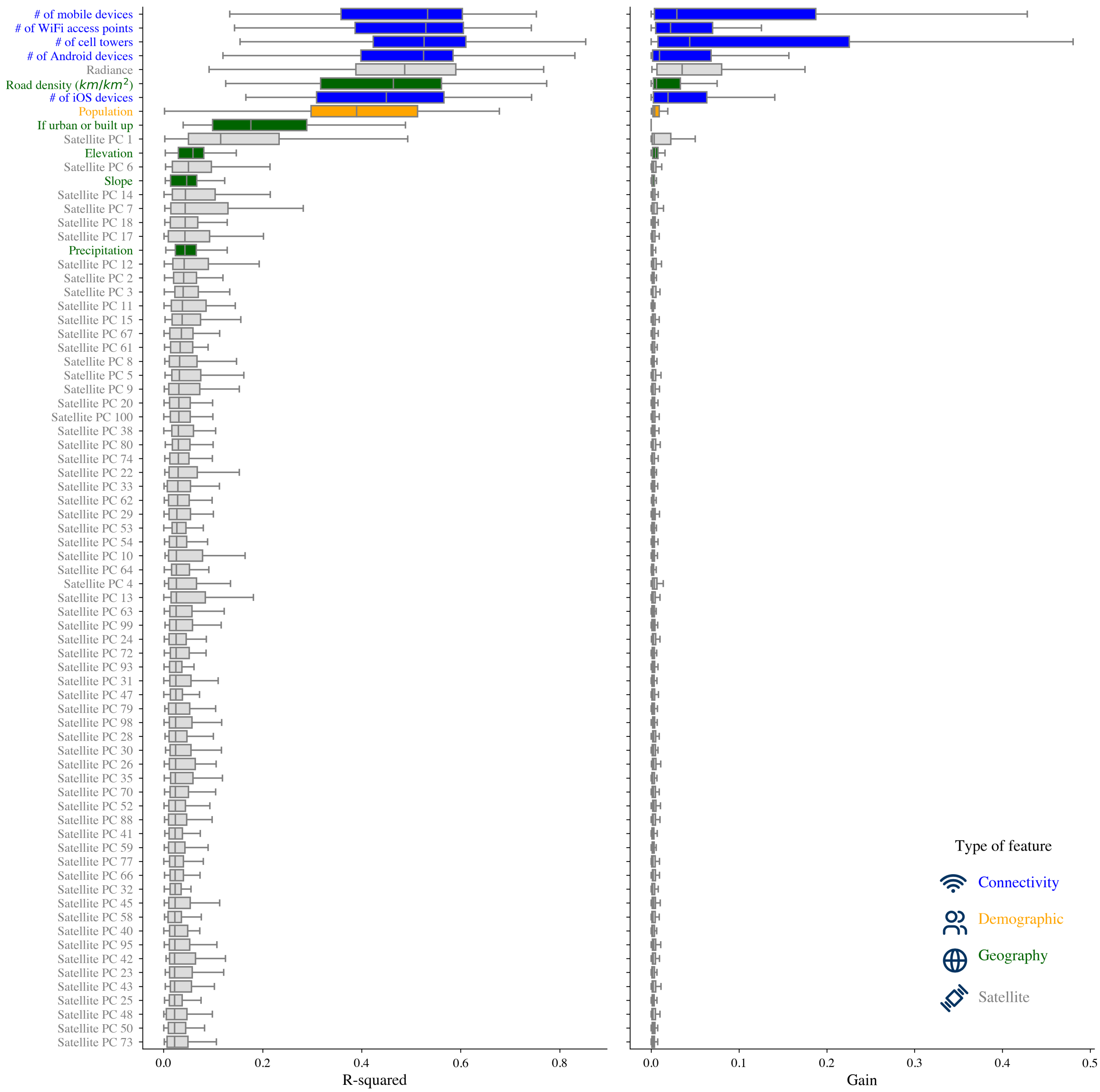


Fig. S2. Which input data are most useful? Two different measures of the importance of each input variable in predicting sub-regional wealth. We show the distribution of feature importances for each feature as a boxplot, where the distribution is obtained from training 56 country-specific models with 5-fold cross-validation. a) The R^2 value from a univariate regression of wealth on each feature. b) Gain measures the total contribution of each feature to the final fitted model. Details on each variable are provided in Table S2. Box plots indicate median (center line), interquartile range (shaded box), and 1.5x interquartile range (whiskers).

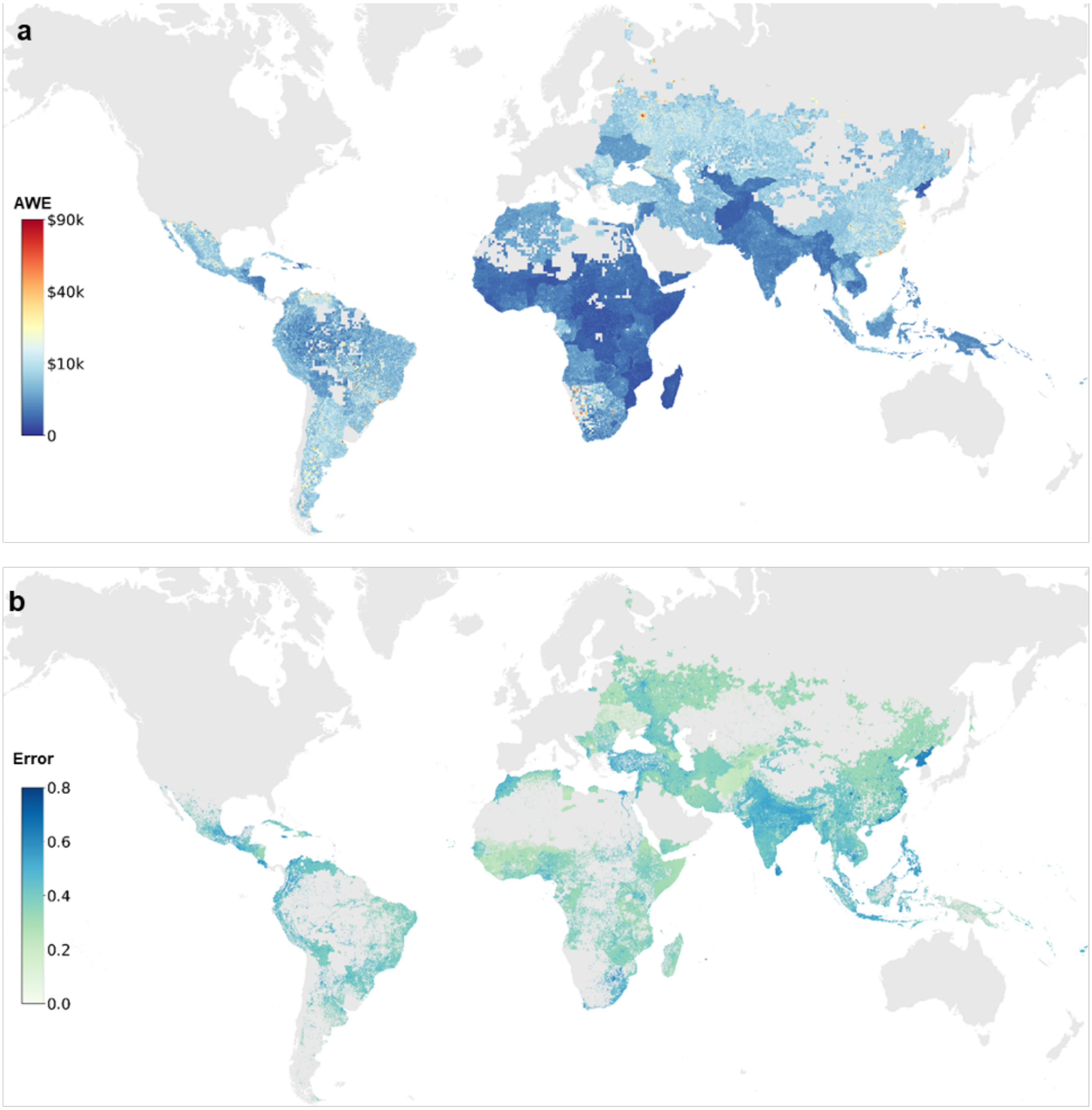


Fig. S3. Estimates of absolute wealth and of model error. a) Absolute wealth estimates (AWE), which indicate the estimate of the average GDP per capita of households in each grid cell. RWI estimates are converted to AWE estimates using information about the income distribution of each country. b) Predicted absolute error of each grid cell, obtained by regressing the absolute residual of the wealth prediction model (i.e., the model that generates the estimates in Fig. 1) on a vector of observable characteristics of each grid cell.

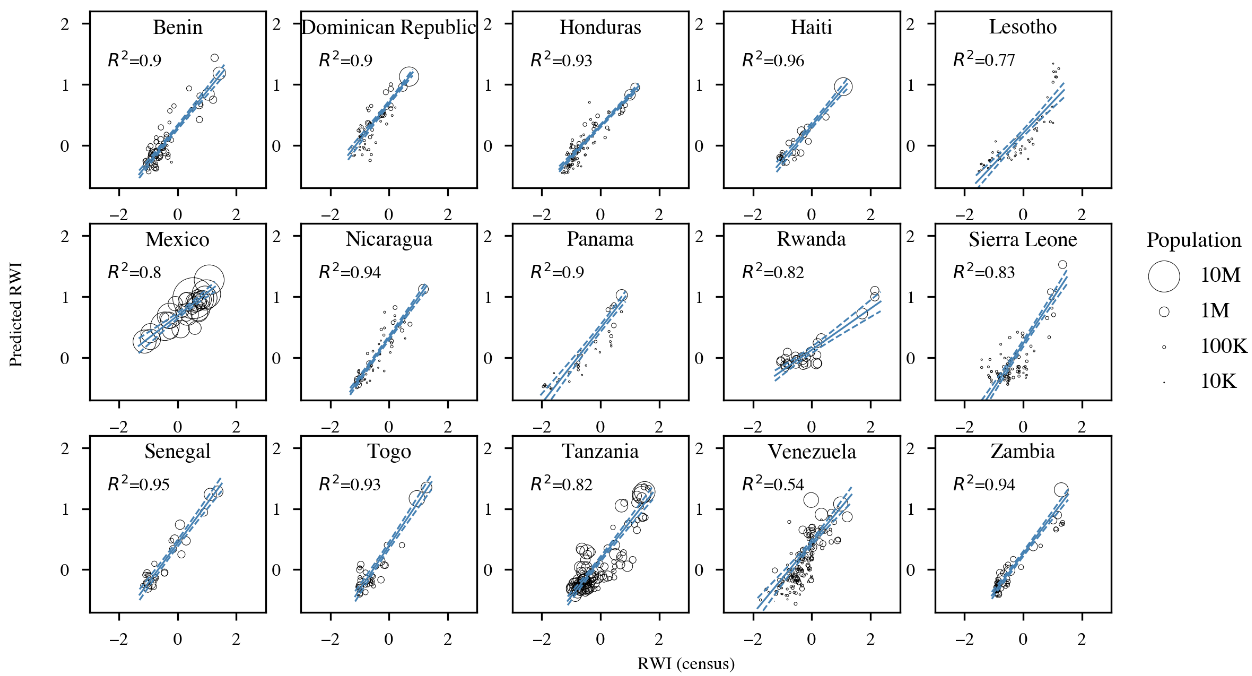
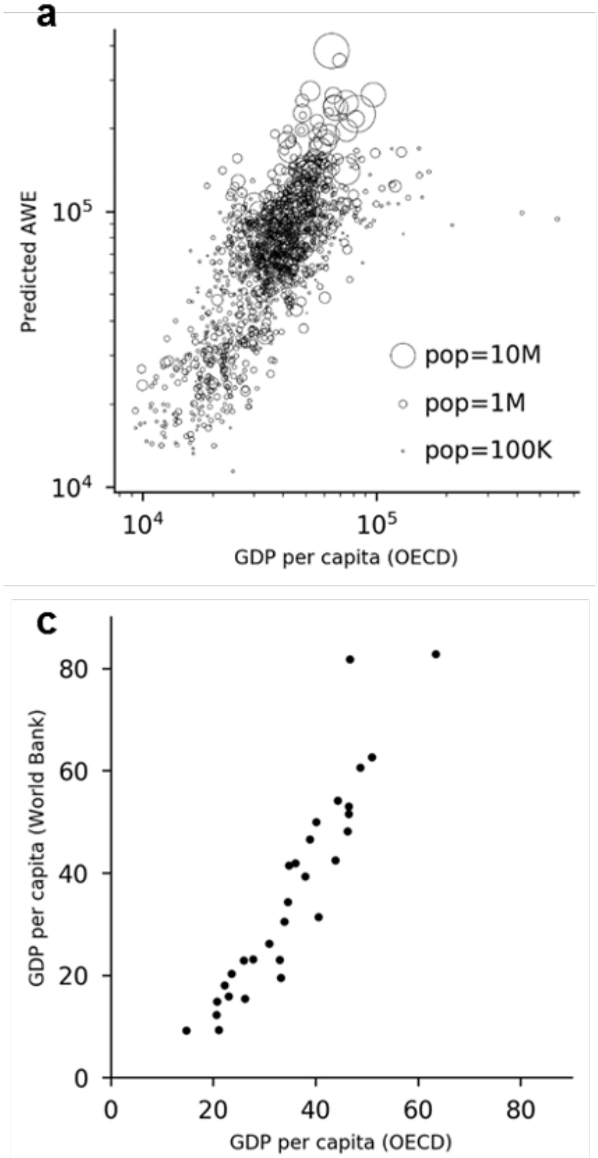


Fig. S4. Model validation using census data in low- and middle-income countries. For each of 15 countries with publicly available census data, we compare the average RWI of each second-level administrative region, as predicted by the ML model, to the average wealth captured in the census (see Methods). Each dot represents an administrative region, sized by population. Blue line indicates population-weighted regression line, with 95% confidence intervals as dashes. Average R^2 across all models is 0.86.



b

	Country	*Year*	*# Units*	*R^2 (AWE)*	*R^2 (RWI)*
1	Austria	2017	35	0.488	0.536
2	Belgium	2018	44	0.621	0.735
3	Bulgaria	2017	28	0.779	0.648
4	Croatia	2017	21	0.502	0.663
5	Czechia	2017	14	0.914	0.818
6	Denmark	2018	11	0.528	0.652
7	Estonia	2018	5	0.996	0.977
8	Finland	2017	19	0.896	0.887
9	France	2016	101	0.070	0.402
10	Germany	2017	401	0.297	0.308
11	Greece	2017	52	0.046	0.305
12	Hungary	2018	19	0.201	0.296
13	Italy	2017	110	0.000	0.022
14	Japan	2016	47	0.259	0.282
15	Rep. of Korea	2018	17	0.021	0.032
16	Latvia	2017	6	0.951	0.981
17	Netherlands	2018	40	0.107	0.248
18	New Zealand	2017	12	0.495	0.570
19	Norway	2018	18	0.456	0.424
20	Poland	2017	73	0.609	0.634
21	Portugal	2017	25	0.787	0.709
22	Romania	2017	42	0.899	0.820
23	Slovakia	2018	8	0.881	0.904
24	Slovenia	2018	12	0.744	0.629
25	Spain	2017	59	0.441	0.457
26	Sweden	2017	21	0.702	0.607
27	Switzerland	2017	26	0.289	0.358
28	Turkey	2018	81	0.744	0.773
29	United Kingdom	2018	179	0.034	0.064
30	USA	2018	179	0.259	0.298
	Mean (30 OECD countries)			***0.500***	***0.535***

Fig. S5. Model validation in high-income nations. Figures compare the model's estimates of wealth to data provided by the OECD for 30 member countries. a) The 30 nations contain 1540 unique second-level administrative regions, each of which is represented by a dot that is sized proportional to the population of the region. Figure shows the OECD's estimate of per capita GDP for the region (x-axis) vs. the Absolute Wealth Estimates (AWE) of the region generated by the ML model. Population-weighted regression line R^2 = 0.59. b) We separately calculate, for each of the 30 OECD countries with available GDP data, the R^2 that results from regressing predicted AWE on GDPpc, across all admin-2 regions within each country. c) The estimate of a country's GDPpc from the World Bank, which forms the basis for the AWE estimates, is generally larger than the average regional GDPpc as reported in the OECD data. Values on axes represent thousands of US Dollars.

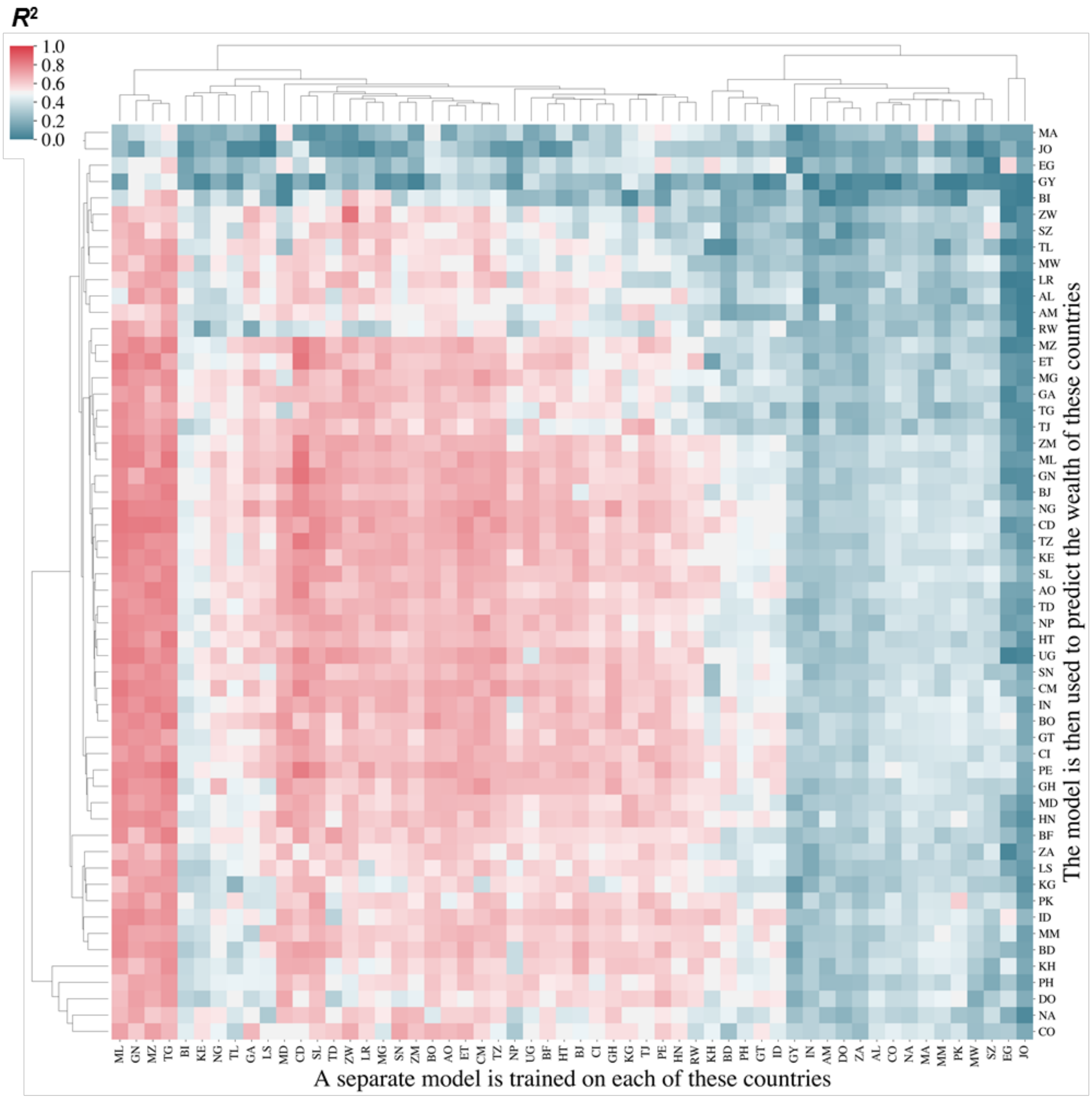


Fig. S6. Geographic generalizability of wealth predictions. For each of the 56 countries with ground truth wealth data, a separate model is trained using data from just that country (the columns in the above matrix). Those models are then tested on previously unseen data from each of the countries (the rows in the matrix). Colors indicate the R^2 between the model's predictions and ground truth. Models generally perform better on nearby and similar countries. Rows and columns are ordered using a hierarchical clustering algorithm (UPGMA).

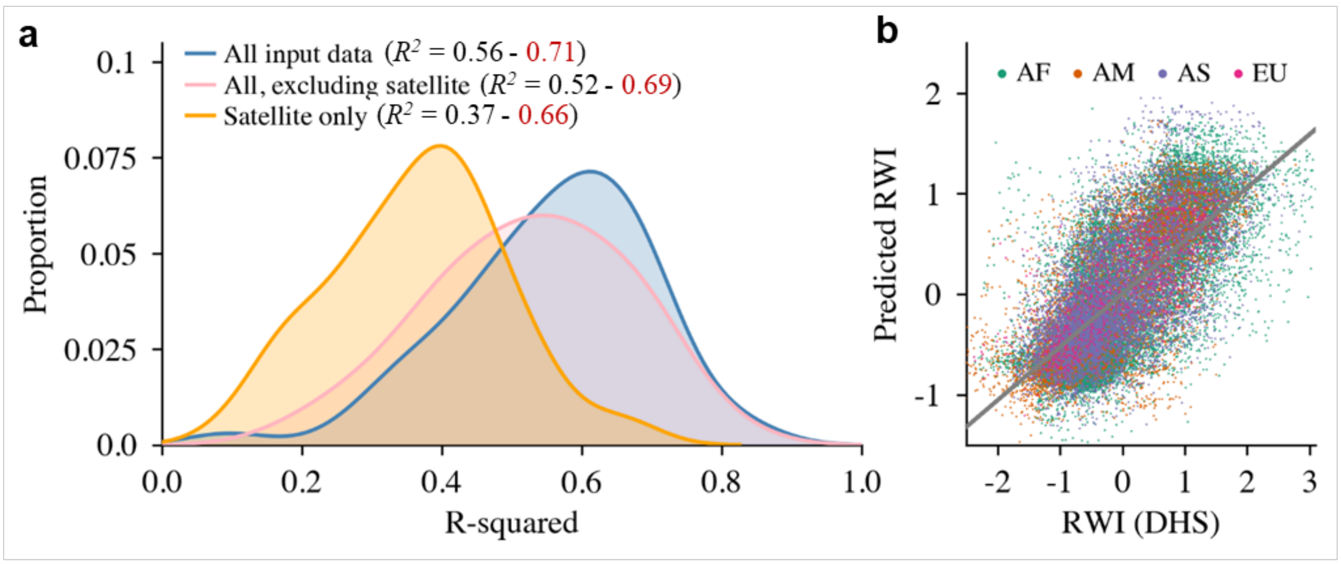


Fig. S7. Models trained only on satellite data do not perform as well as models that include other input data. a) The distribution of performance across the 56 LMIC's, measured using spatially-stratified cross-validation, is shown as three kernel density plots, one for each subset of input data. The legend reports the average performance (R^2) in black, and the average performance using standard cross-validation in red (to facilitate comparison to prior work). b) Scatter-plot shows relationship between the actual wealth index (from survey data) and the predicted wealth index (output by the model), using all 66,819 labeled survey locations on four continents (AF=Africa, AM=Americas, AS=Asia, EU=Europe).

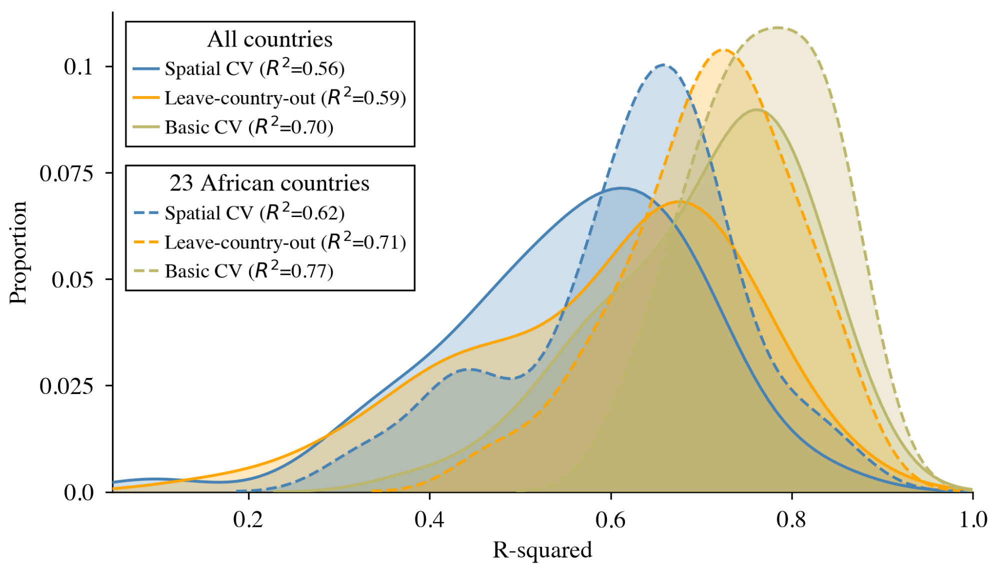


Fig. S8. Predictive performance is higher when evaluated on a more homogeneous set of African nations. Solid lines show the distribution of model performance, across 56 countries with ground truth data, using 3 different approaches to cross-validation – these results are identical to Fig. 3a. Dashed lines show the distribution of model performance, evaluated across the 23 African countries studied by Yeh et al (2020).

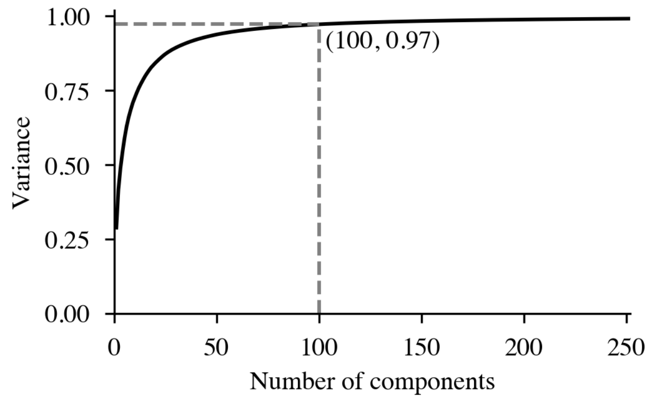


Fig. S9. Feature engineering from satellite imagery. To reduce the dimensionality of the raw satellite imagery, we first use a neural network to extract 2048 features from the data (see Methods), and then apply principal component analysis (PCA) to the set of 2048 features. Figure shows the cumulative proportion of variance explained by the first k principal components. Our final model uses 100 components, which cumulatively explain 97% of the total variance of the 2048-dimensional image features.

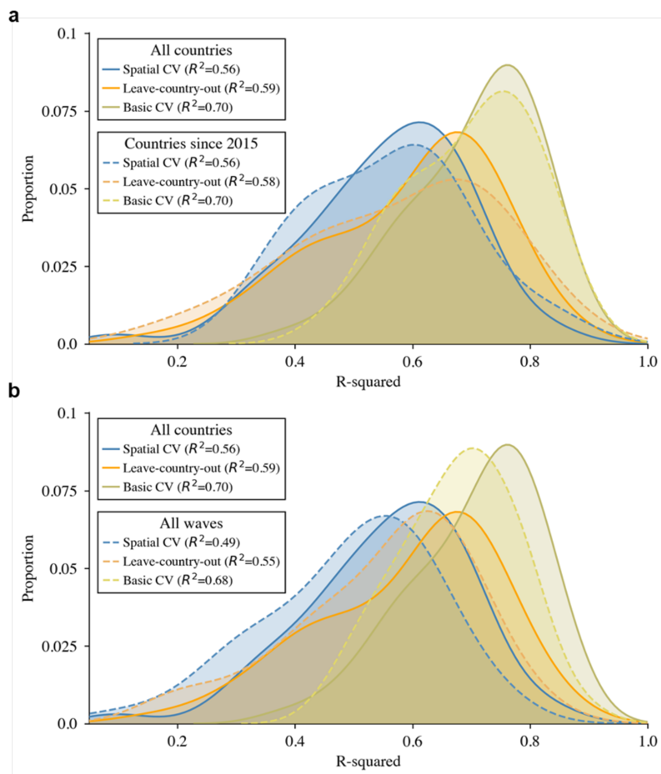


Fig. S10. Model performance when trained using surveys from different periods in time. a) Performance using recent data only. The solid lines (labeled "All countries") reproduce the analysis of Fig. 3a, and show the distribution of model performance for a model trained on 56 countries with DHS data, using 3 different approaches to model cross-validation. The dashed lines indicate the performance for a model that is trained on the subset of 24 countries where DHS data was collected in 2015 or later. b) Performance using all available survey waves. Several countries have conducted multiple DHS surveys since 2000. The figure compares the main model's performance (using 56 survey-waves from 56 countries) to the performance of a model trained and evaluated on all available DHS data (117 survey-waves from 56 countries).

a

Country	Code	DHS Year	Census	R^2
Benin	BJ	2017-18	2013	0.90
Dom. Rep.	DO	2013	2010	0.90
Haiti	HT	2016-17	2003	0.96
Honduras	HN	2011-12	2001	0.93
Lesotho	LS	2014	2006	0.77
Rwanda	RW	2014-15	2012	0.82
Senegal	SN	2016	2002	0.95
Sierra Leone	SL	2013	2004	0.83
Tanzania	TZ	2015-16	2012	0.82
Togo	TG	2013-14	2010	0.93
Zambia	ZM	2018	2010	0.94

b

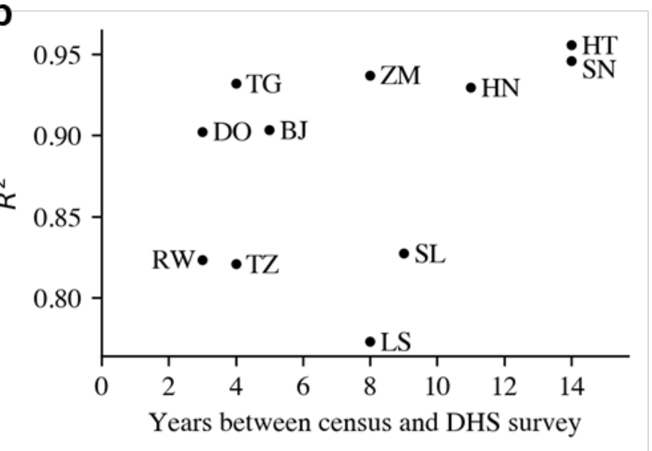


Fig. S11. Validation accuracy for 11 countries with DHS and census data. a) Of the 56 countries used to train the model, 11 have publicly available census data with asset information. The table indicates the dates of the most recent DHS survey and census in each country, as well as the correspondence (R^2) between the model predictions and the census data (see also Fig. S4). b) Figure illustrates that there is no clear relationship between the gap in years between the most recent DHS survey and census (x-axis) against the validation accuracy of the model, for each of these 11 countries.

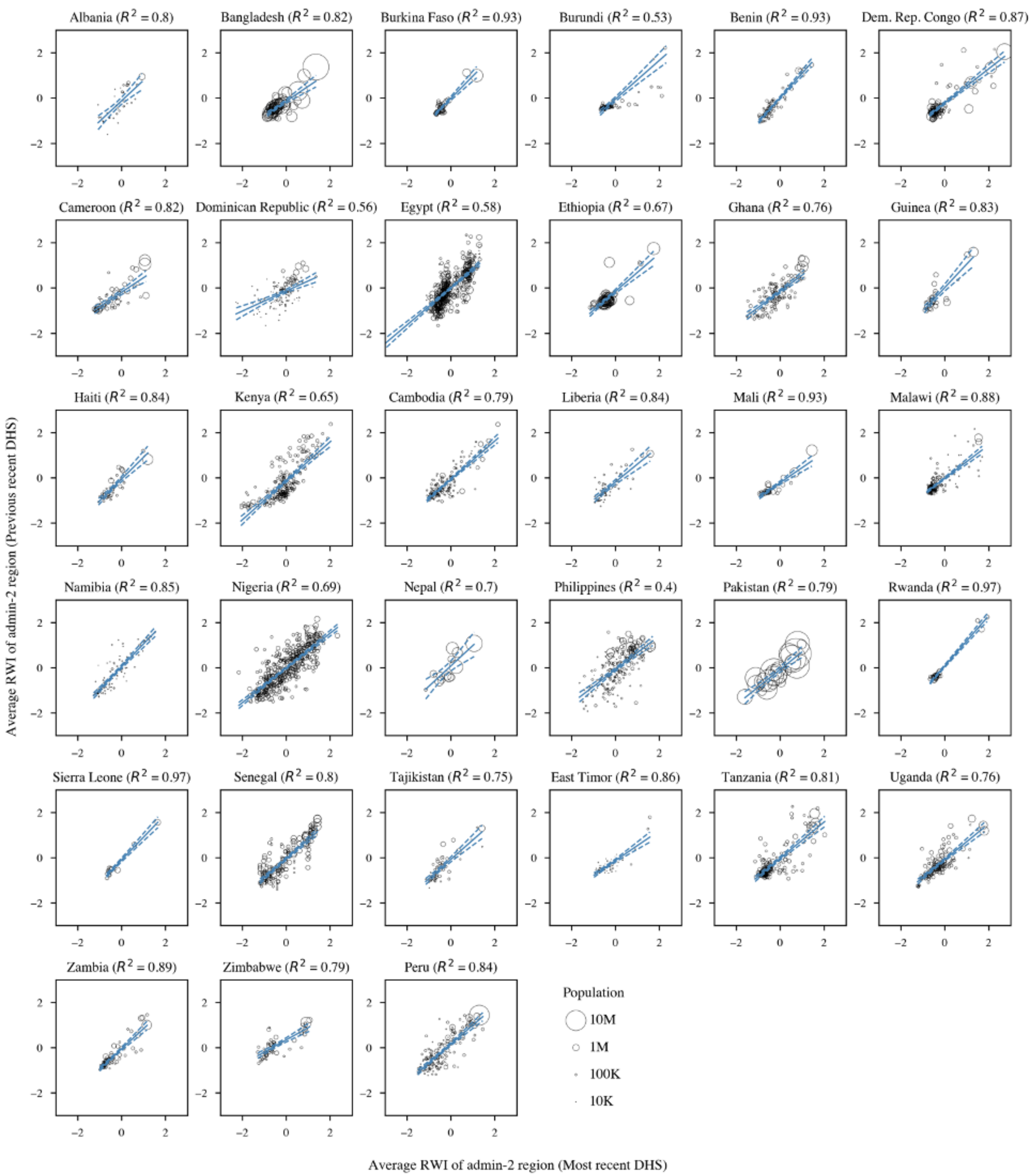
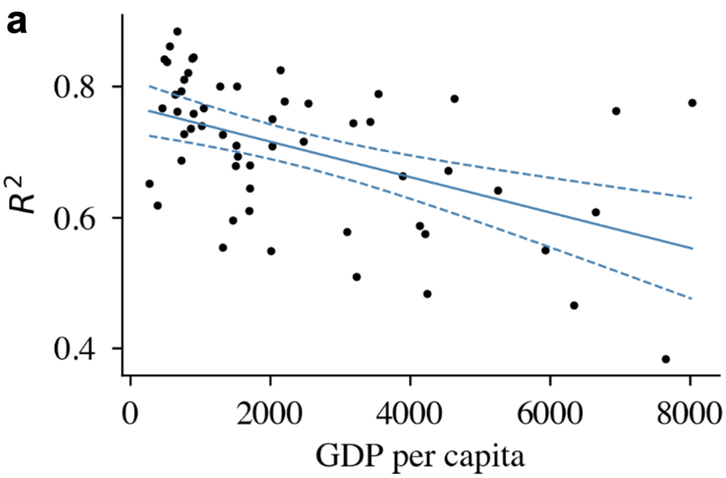


Fig. S12. Temporal stability of within-country wealth over time. For each country with two or more DHS since 2000, each subfigure plots the relationship between the average RWI of each 2nd-level administrative unit as computed from the most recent DHS (x-axis) against the average RWI of the same unit as computed from the previous DHS. Each circle represents an administrative region. Blue line indicates population-weighted regression line, with 95% confidence intervals as dashes. Median (mean) R^2 across all countries is 0.81 (0.78).

a



b

	β	SE
Low income	-0.0228	0.041
Upper middle income	-0.2084***	0.052
Gini	-0.3560	0.283
ln(Country population)	-0.0021	0.013
Is island	-0.0336	0.057
Is landlocked	0.0083	0.040
Is Africa	0.0490	0.106
Is Asia	-0.0633	0.097
Is America	0.1085	0.109
Constant	0.7570***	0.230
Observations	56	
R^2	0.404	

Note: Lower-middle income is omitted country category.
*significant at 10 percent; ** 5 percent; *** 1 percent.

Fig. S13. Model performance and country characteristics. a) For each of the 56 countries with ground truth data from the DHS, the figure plots the country-level R^2 (measured using basic 5-fold cross-validation) against that country's GDP per capita, as measured in Table S6. b) Coefficients and standard errors from a regression of the country-level R^2 on country-level characteristics, for the 56 countries with ground truth data, indicates that model performance is slightly worse in upper middle-income countries (relative to the omitted category of lower-middle income countries, but is not significantly different in low-income countries or specific continents.

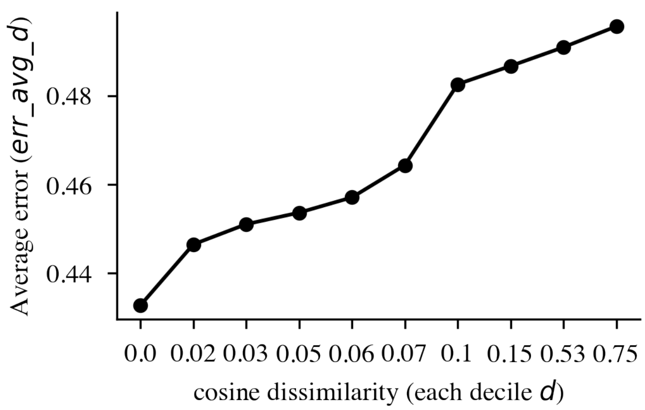


Fig. S14. Models perform better on countries with similar characteristics. X-axis shows the 10 deciles of the cosine dissimilarity distribution (i.e., one minus cosine similarity). Y-axis indicates the average prediction error across test countries, where a separate model for each test country is trained using data from countries at least d dissimilar to the test country.

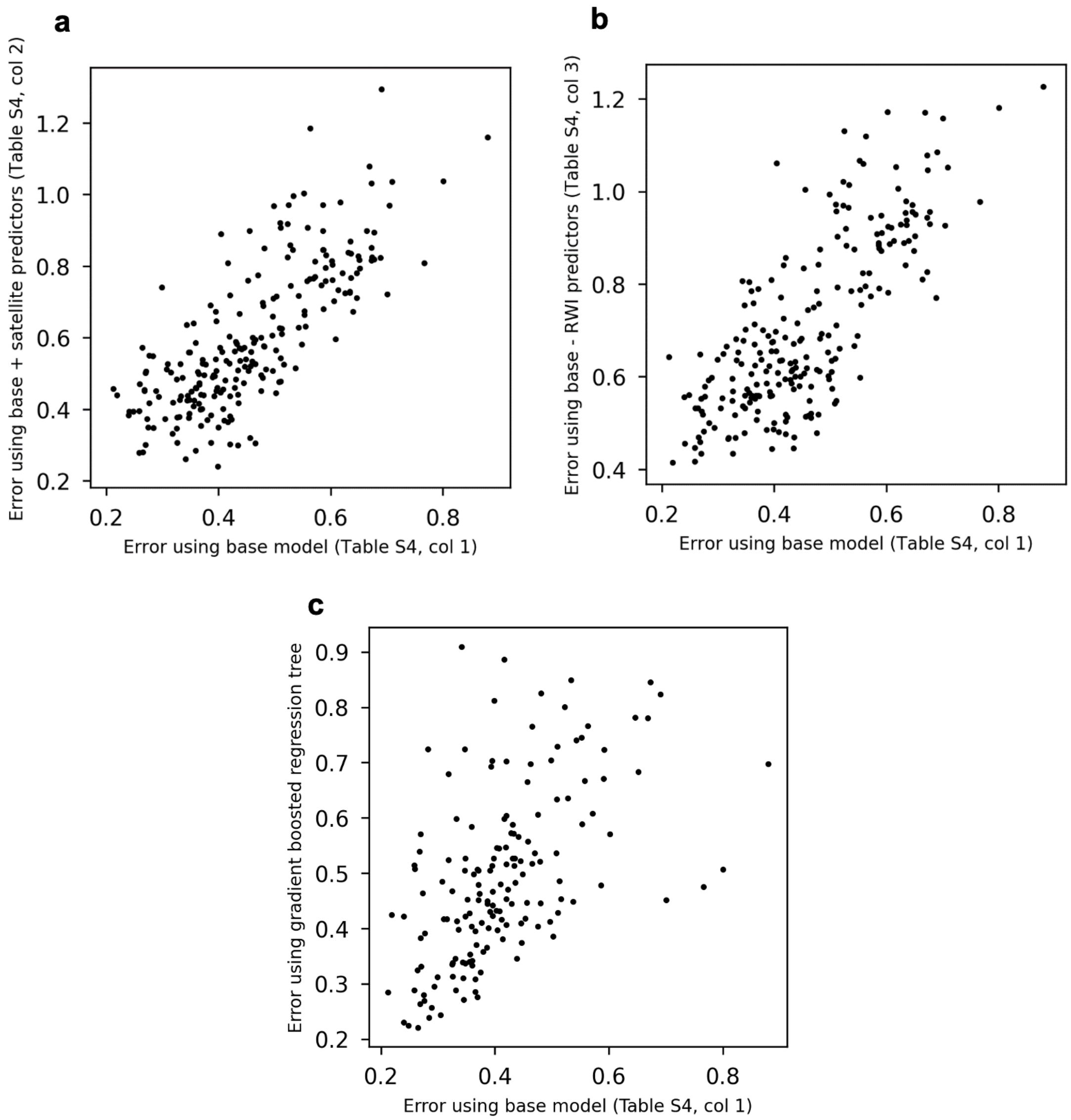


Fig. S15. Stability of error estimation to different model specifications. Figure compares the median error of all grid cells in a country from the base model (defined by column 1 of Table S4, and plotted on the x-axis of both figures) to three alternative model specifications (plotted on the y-axis). Each dot represents a country. a) Alternate model includes 100 satellite-based features (defined by column 2 of Table S4). b) Alternate model limited to only features not used to predict RWI (defined by column 3 of Table S4). c) Alternate model uses a gradient boosting algorithm to predict model error, using the same predictors as the base model.

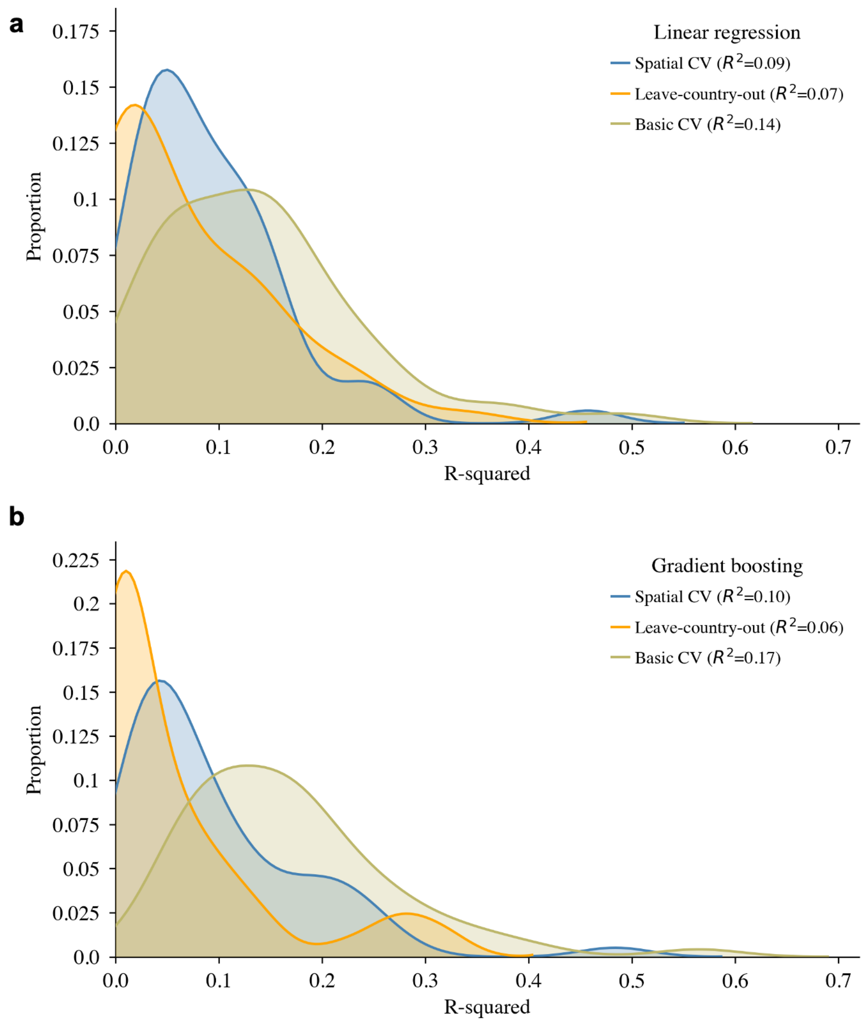


Fig. S16. Distribution of R-squared values from cross-validated predictions of absolute model error. Both figures present the distribution of model performance, across 56 countries with ground truth data, using 3 different approaches to cross-validation, where the target variables is the absolute value of the residual from the wealth prediction model, and the predictor variables are listed in Table S4. a) R^2 values obtained from a linear regression model (as in Table S4). b) R^2 values obtained from a gradient boosted regression tree (as in Fig S17).

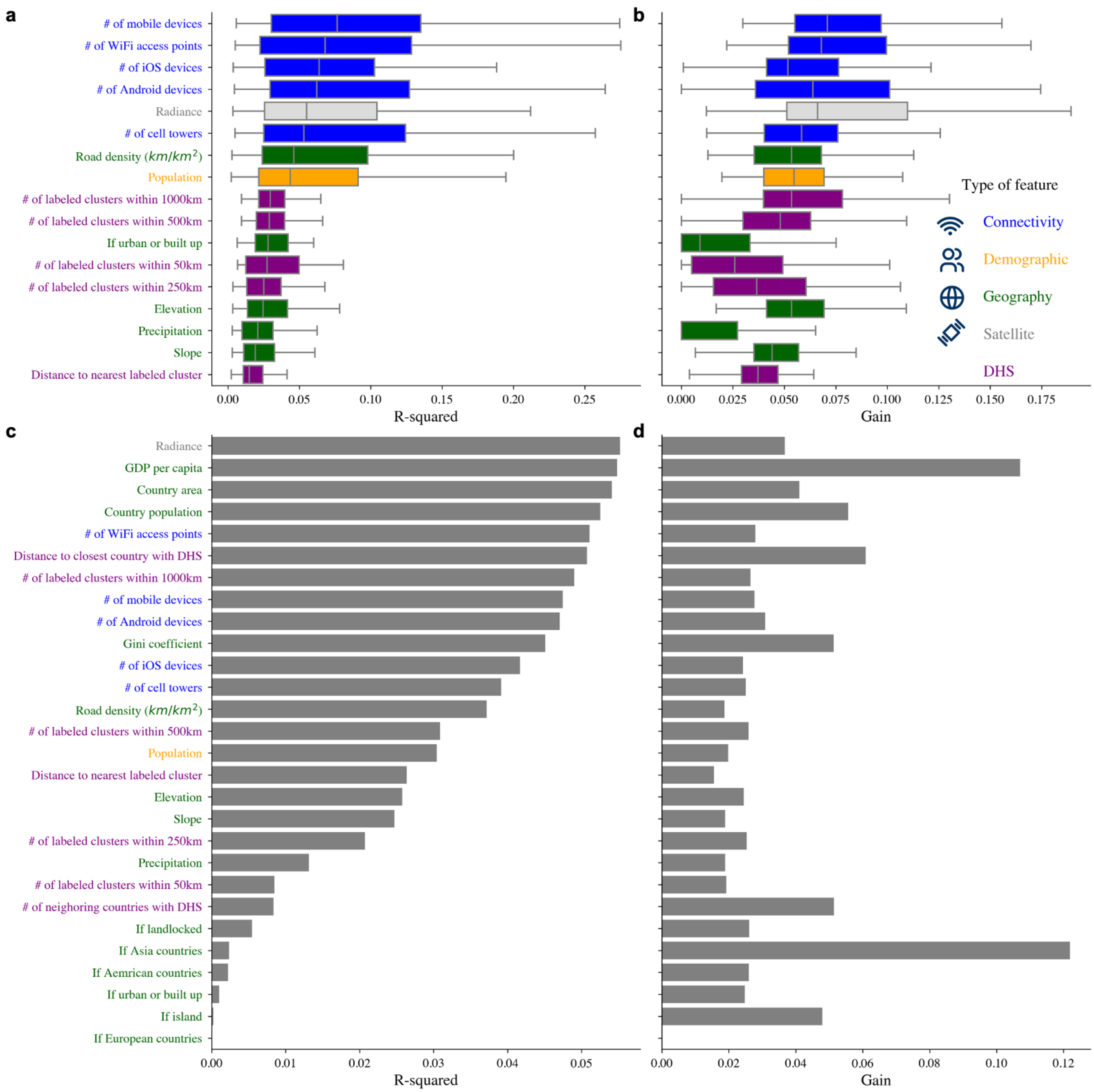


Fig. S17. Feature importances of gradient boosting algorithm used to predict model error. Top panels indicate the distribution of feature importances in predicting model error, where the distribution is obtained from training 56 country-specific models with 5-fold cross-validation. Bottom panels indicate the value of feature importance when a single model is trained on all of the labeled data from all countries. (i.e., all of the absolute residuals of the wealth prediction model from all locations with DHS data). a) and c) indicate the R^2 value from a univariate regression of wealth on each feature. b) and d) indicate Gain, the total contribution of each feature to the final fitted model. Details on each variable are provided in Table S2. Box plots indicate median (center line), interquartile range (shaded box), and 1.5x interquartile range (whiskers).

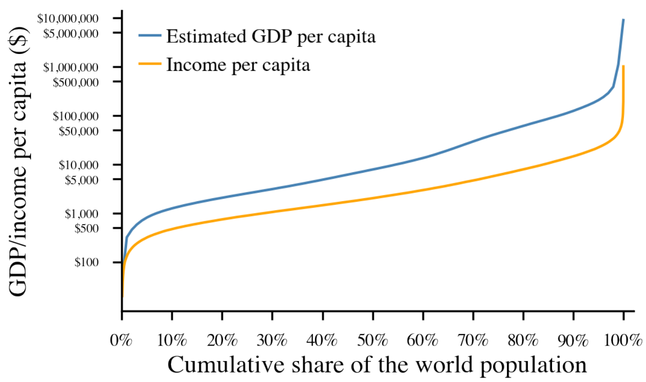


Fig. S18. The global income and estimated wealth distribution. Orange line shows the global income distribution in 2013, based on household income surveys for more than a hundred countries. Blue line shows the distribution of predicted "absolute wealth", a measure of per capita GDP, which is derived from the Relative Wealth Index that is the focus of this paper.

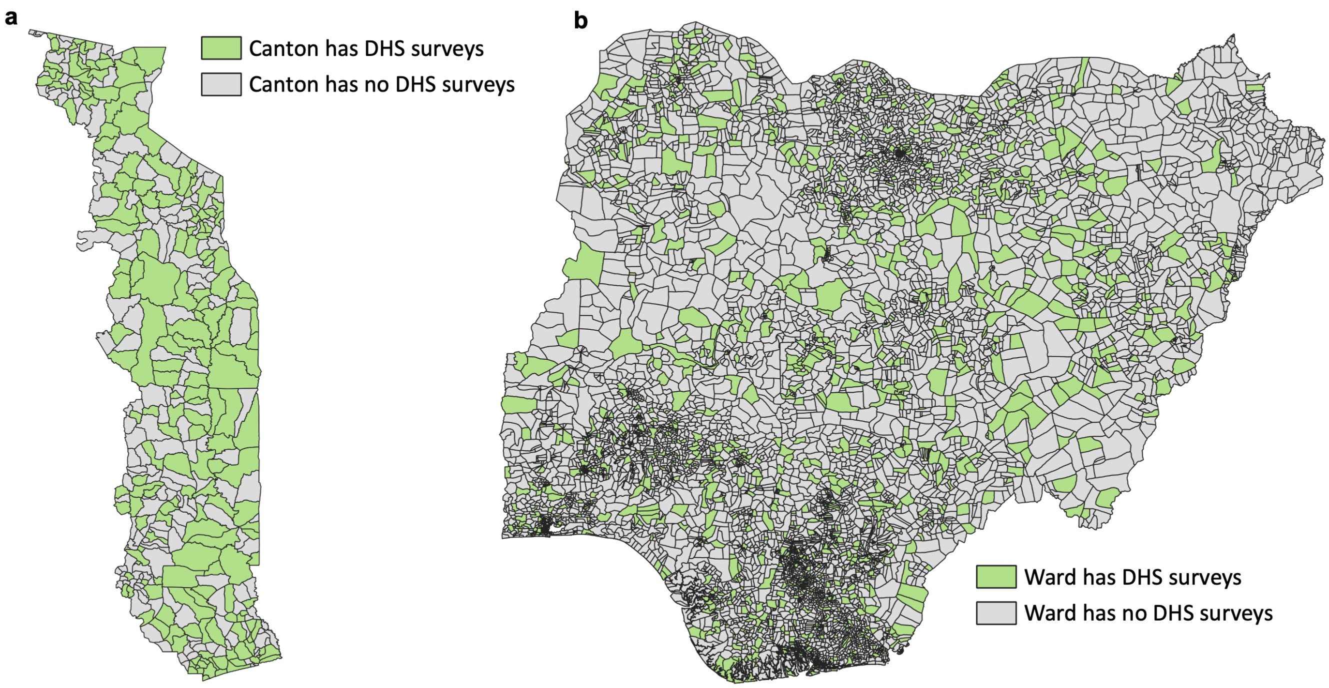


Fig. S19. Maps of Demographic and Health Survey coverage in Togo and Nigeria. a) Map of Togo highlights, in green, the 47.8% of cantons in Togo in which at least one household was surveyed in the 2013-14 DHS survey; unsurveyed cantons shown in grey. b) Map of Nigeria shows, in green, wards with at least one surveyed household in the 2018 DHS survey (13.83% of wards); unsurveyed wards are shown in grey (86.17%).

Table S1. Ground truth data.

	Country	Code	Survey Year	# households	# villages
1	Albania	AL	2017-18	15,823	715
2	Angola	AO	2015-16	16,109	625
3	Armenia	AM	2015-16	7,893	313
4	Bangladesh	BD	2014	17,270	599
5	Benin	BJ	2017-18	13,776	540
6	Bolivia	BO	2008	19,526	998
7	Burkina Faso	BF	2010	13,617	541
8	Burundi	BI	2016-17	15,921	552
9	Cambodia	KH	2014	15,825	611
10	Cameroon	CM	2011	14,189	577
11	Chad	TD	2014-15	17,233	624
12	Colombia	CO	2010	50,218	4,868
13	Congo (DRC)	CD	2013-14	16,680	492
14	Cote d'Ivoire	CI	2011-12	9,394	341
15	Dominican Republic	DO	2013	11,464	524
16	Egypt	EG	2014	27,904	1,817
17	eSwatini / Swaziland	SZ	2006-07	4,756	270
18	Ethiopia	ET	2016	16,157	622
19	Gabon	GA	2012	9,638	332
20	Ghana	GH	2014	11,716	423
21	Guatemala	GT	2014-15	21,263	853
22	Guinea	GN	2018	7,912	401
23	Guyana	GY	2009	5,418	312
24	Haiti	HT	2016-17	13,405	450
25	Honduras	HN	2011-12	20,985	1,128
26	India	IN	2015-16	598,733	28,393
27	Indonesia	ID	2002-03	31,393	1,319
28	Jordan	JO	2012	15,190	806
29	Kenya	KE	2014	36,224	1,585
30	Kyrgyz Republic	KG	2012	7,989	314
31	Lesotho	LS	2014	9,402	399
32	Liberia	LR	2013	9,333	322
33	Madagascar	MG	2008-09	17,578	585
34	Malawi	MW	2015-16	26,361	850
35	Mali	ML	2018	8,918	328
36	Moldova	MD	2005	11,066	399
37	Morocco	MA	2003-04	11,513	480
38	Mozambique	MZ	2011	13,899	609
39	Myanmar	MM	2015-16	12,500	441
40	Namibia	NA	2013	9,849	550
41	Nepal	NP	2016	11,040	383
42	Nigeria	NG	2018	39,540	1,359
43	Pakistan	PK	2017-18	14,517	560
44	Peru	PE	2009	26,809	1,131
45	Philippines	PH	2017	26,673	1,213
46	Rwanda	RW	2014-15	12,699	492
47	Senegal	SN	2016	4,437	214
48	Sierra Leone	SL	2013	12,629	435
49	South Africa	ZA	2016	11,083	746
50	Tajikistan	TJ	2017	7,821	365
51	Tanzania	TZ	2015-16	12,563	608
52	Timor-Leste	TL	2016	11,502	455
53	Togo	TG	2013-14	9,549	330
54	Uganda	UG	2016	19,284	685
55	Zambia	ZM	2018	12,595	535
56	Zimbabwe	ZW	2015	10,534	400
	Total			***1,457,315***	***66,819***

Notes: The relative wealth prediction model is trained on nationally representative Demographic and Health Surveys from 56 countries. See www.dhsprogram.com.

Table S2. Data Sources.

	Resolution	Source	Min	Mean	Median	Max
INPUT DATA						
Road density*	lat/lon	Open Street Map[1]	0	0.0007	0	0.08
Urban or built up*	15 arc-seconds	NASA (MODIS)[2]				
Elevation*	3 arc-seconds (∼ 90 meters)	USGS[3]	-24	612	294	7643
Slope*	3 arc-seconds (∼90 meters)	USGS[3]	0.0	0.024	0.008	2.108
Precipitation*	0.25-degree	NASA/Japan Aerospace Exploration Agency[4]	-48.7	1.7	0.0	2233.6
Population*	1 arc-second (∼30m)	Humanitarian Data Exchange[5]	10	608	73	516163
# Cell towers+	2.4km tiles	Facebook[6]	0	13	0	71004
# WiFi access points+	2.4km tiles	Facebook[6]	0	369	1	1949963
# Mobile devices+	2.4km tiles	Facebook[6]	0	217	0	454962
# Android devices+	2.4km tiles	Facebook[6]	0	168	0	291831
# iOS devices+	2.4km tiles	Facebook[6]	0	49	0	204058
Nightlights / Radiance (VIIRS)*	15 arc-seconds	National Centers for Environmental Information Earth Observation Group[7]	0.0	1.9	0.3	58843.3
Satellite Imagery+	0.58 m/pixel	Digital Globe[8] (Bing tile 15)				
GROUND TRUTH DATA						
Household survey*	cluster	Demographic and Health Surveys[9]				
Census data*	level-2 admin	IPUMS[10]				
Regional GDPpc	TL3 regions	OECD[11]				
Togo	GPS coordinates	Government of Togo				
PPI data+	GPS coordinates	GiveDirectly[12]				
GDP and Gini*	country	Multiple - see Table S6				

Notes: Summary statistics for the different datasets that are used as input to the machine learning algorithms. We use the most recently available data layer from each source. Publicly available data denoted by *; Data requiring license or other restrictions denoted by $^+$.

Sources:
1 http://www.openstreetmap.org
2 http://www.landcover.org/data/lc/
3 https://lta.cr.usgs.gov/SRTM1Arc
4 https://disc.gsfc.nasa.gov/
5 https://data.humdata.org/dataset/highresolutionpopulationdensitymaps
6 https://research.fb.com/category/connectivity/
7 https://www.ngdc.noaa.gov/eog
8 http://www.digitalglobe.com/
9 http://www.dhsprogram.com/
10 https://international.ipums.org/international/
11 https://stats.oecd.org/Index.aspx?DataSetCode=PDB_LV
12 http://www.givedirectly.org/

Table S3. Census validation data.

	Country	Survey Year	# Households	# Individuals	# Admin units	$\mathbf{R^2}$
1	Benin	2013	180,621	1,009,693	77	0.90
2	Dominican Republic	2010	268,637	943,784	67	0.90
3	Haiti	2003	179,190	838,045	28	0.96
4	Honduras	2001	123,584	608,620	99	0.93
5	Lesotho	2006	41,726	180,208	64	0.77
6	Mexico	2015	2,927,196	11,344,365	32	0.80
7	Nicaragua	2005	105,629	515,485	70	0.94
8	Panama	2010	95,579	341,118	36	0.90
9	Rwanda	2012	242,461	1,038,369	30	0.82
10	Senegal	2002	107,999	994,562	28	0.95
11	Sierra Leone	2004	82,518	494,298	108	0.83
12	Tanzania	2012	950,776	4,498,022	114	0.82
13	Togo	2010	121,237	584,859	37	0.93
14	Venezuela	2001	543,475	2,306,489	158	0.54
15	Zambia	2010	250,805	1,321,973	55	0.94
	Total		***6,221,433***	***27,019,890***	***1,003***	***Avg: 0.86***

Notes: Census data from 27 million individuals in 15 countries were used to provide independent validation of the wealth estimates. Data obtained from IPUMS (1). The final column indicates the proportion of variance in wealth (as measured in the census) explained by the model's wealth estimates (RWI) – see Fig. S4.

Table S4. Predictors of model error

	(1) Base specification		(2) Incl. imagery features		(3) Excluding all RWI features	
	β	SE	β	SE	β	SE
Characteristics defined at the level of the grid cell						
ln(Dist. to closest DHS cluster)	0.0217**	0.01	0.0153	0.01	0.0206**	0.01
ln(# DHS clusters w/in 50 km)	-0.0115***	0.003	-0.0084***	0.003	-0.0158***	0.003
ln(# DHS clusters w/in 250 km)	-0.0131***	0.002	-0.0144***	0.002	-0.0106***	0.002
ln(# DHS clusters w/in 500 km)	-0.0004	0.001	0.0025	0.002	-0.0013	0.001
ln(# DHS clusters w/in 1000 km)	0.0225***	0.002	0.0231***	0.002	0.023***	0.002
ln(Slope)	-0.1535**	0.07	-0.2316***	0.082		
ln(Elevation)	0.0144***	0.001	0.0087***	0.002		
ln(Precipitation)	0.0166***	0.004	0.0147***	0.004		
Is urban or built up	-0.0751***	0.006	-0.0685***	0.007		
Road density	-0.7382*	0.382	0.8917*	0.497		
ln(Radiance)	-0.0033	0.004	-0.0195***	0.004		
ln(Tile population)	0.012***	0.002	0.0112***	0.002		
ln(# cell towers)	0.0022	0.004	-0.0015	0.004		
ln(# Wifi access points)	0.0227***	0.003	0.0208***	0.003		
ln(# mobile devices)	0.1581***	0.02	0.1696***	0.021		
ln(# Android devices)	-0.1423***	0.02	-0.1493***	0.02		
ln(# iOS devices)	-0.0304***	0.003	-0.0308***	0.003		
Characteristics defined at the level of the country						
ln(# neighbor countries w/ DHS data)	0.0124**	0.005	0.0236***	0.006	0	0.005
ln(Dist. to next-closest DHS country)	0.0846***	0.007	0.0922***	0.008	0.0761***	0.007
Is country an island	0.0209**	0.01	0.0449***	0.011	-0.0038	0.01
Is country landlocked	-0.0153**	0.006	-0.0638***	0.007	-0.0155***	0.006
Is America	-0.1066***	0.01	-0.1101***	0.012	-0.0934***	0.009
Is Asia	0.071***	0.007	-0.0025	0.009	0.0825***	0.007
Is Europe	-0.041***	0.015	-0.129***	0.018	-0.0664***	0.014
ln(Country Area)	-0.0349***	0.004	-0.0407***	0.004	-0.034***	0.003
ln(Country population)	0.0044*	0.003	0.0187***	0.003	0.011***	0.003
ln(Country GDP per capita)	-0.0151***	0.004	-0.0313***	0.005	0.0039	0.004
Gini	0.5347***	0.04	0.1347***	0.047	0.578***	0.039
Satellite image features?	No		Yes		No	
Constant	-0.225***	0.059	-0.0905	0.069	-0.1614***	0.058
R^2	0.061		0.117		0.029	

Notes: Table shows coefficients and standard errors from a linear regression of absolute model error (defined as the absolute value of the residual from the wealth prediction model, estimated on DHS clusters with ground truth labels) on observable characteristics of the DHS centroid's location. Each column corresponds to a different set of regressors. Data sources for country-level characteristics are provided in Table S6. Distance to next closest DHS country measures the distance between the centroids of countries (as defined by https://developers.google.com/public-data/docs/canonical/countries_csv); # DHS Neighbor Countries counts the number of DHS countries that share a border with the country in which the cluster is located. We add one to values before taking the natural log to avoid undefined values. *significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Table S5. Estimates of model error in all low and middle-income countries.

			Estimated error			Mean squared error		
	Country	Code	Mean	Median	S.D.	Mean	Median	S.D.
1	Afghanistan	AF	0.217	0.213	0.024			
2	Albania	AL	0.440	0.435	0.061	0.551	0.203	1.257
3	Algeria	DZ	0.325	0.308	0.060			
4	American Samoa	AS	0.647	0.673	0.057			
5	Angola	AO	0.373	0.368	0.029	0.390	0.227	0.524
6	Argentina	AR	0.400	0.394	0.052			
7	Armenia	AM	0.427	0.408	0.049	0.467	0.242	0.634
8	Azerbaijan	AZ	0.260	0.240	0.053			
9	Bangladesh	BD	0.494	0.503	0.051	0.414	0.264	0.467
10	Belarus	BY	0.288	0.273	0.039			
11	Belize	BZ	0.378	0.359	0.049			
12	Benin	BJ	0.316	0.305	0.032	0.282	0.113	0.444
13	Bhutan	BT	0.378	0.365	0.040			
14	Bolivia	BO	0.396	0.387	0.035	0.472	0.256	0.610
15	Bosnia & Herzegovina	BA	0.360	0.351	0.046			
16	Botswana	BW	0.393	0.377	0.036			
17	Brazil	BR	0.395	0.392	0.047			
18	Bulgaria	BG	0.409	0.407	0.046			
19	Burkina Faso	BF	0.301	0.294	0.026	0.258	0.062	0.718
20	Burundi	BI	0.269	0.259	0.030	0.429	0.169	0.805
21	Cabo Verde	CV	0.532	0.528	0.062			
22	Cambodia	KH	0.503	0.497	0.061	0.387	0.191	0.559
23	Cameroon	CM	0.364	0.355	0.033	0.372	0.202	0.445
24	Central African Republic	CF	0.382	0.380	0.013			
25	Chad	TD	0.346	0.348	0.023	0.335	0.067	0.797
26	China	CN	0.372	0.349	0.064			
27	Colombia	CO	0.476	0.465	0.054	0.659	0.209	1.152
28	Comoros	KM	0.537	0.510	0.055			
29	Congo	CG	0.335	0.333	0.013			
30	Congo, Dem. Rep.	CD	0.378	0.375	0.019	0.307	0.082	0.612
31	Costa Rica	CR	0.530	0.537	0.055			
32	Cote d'Ivoire	CI	0.361	0.348	0.040	0.404	0.210	0.593
33	Cuba	CU	0.412	0.398	0.045			
34	Djibouti	DJ	0.341	0.336	0.024			
35	Dominica	DM	0.573	0.592	0.057			
36	Dominican Republic	DO	0.430	0.434	0.049	0.709	0.378	0.890
37	Ecuador	EC	0.443	0.429	0.051			
38	Egypt	EG	0.455	0.476	0.077	0.466	0.252	0.585
39	El Salvador	SV	0.417	0.420	0.038			
40	Equatorial Guinea	GQ	0.335	0.325	0.031			
41	Eritrea	ER	0.279	0.276	0.012			
42	Eswatini	SZ	0.469	0.454	0.044	0.466	0.309	0.521
43	Ethiopia	ET	0.359	0.360	0.029	0.236	0.075	0.427
44	Fiji	FJ	0.502	0.481	0.050			
45	Gabon	GA	0.390	0.387	0.021	0.347	0.182	0.418
46	Gambia	GM	0.291	0.271	0.045			
47	Georgia	GE	0.334	0.315	0.048			
48	Ghana	GH	0.348	0.330	0.047	0.363	0.180	0.567
49	Grenada	GD	0.583	0.591	0.046			
50	Guatemala	GT	0.460	0.456	0.054	0.553	0.311	0.704
51	Guinea	GN	0.250	0.241	0.029	0.258	0.117	0.459
52	Guinea-Bissau	GW	0.352	0.346	0.020			
53	Guyana	GY	0.412	0.399	0.039	0.388	0.192	0.548
54	Haiti	HT	0.338	0.326	0.043	0.318	0.127	0.492
55	Honduras	HN	0.437	0.420	0.049	0.401	0.226	0.529
56	India	IN	0.465	0.466	0.053	0.506	0.264	0.651
57	Indonesia	ID	0.438	0.431	0.068	0.580	0.300	0.767
58	Iran, Islamic Rep.	IR	0.368	0.363	0.042			

59	Iraq	IQ	0.374	0.347	0.064			
60	Jamaica	JM	0.543	0.553	0.044			
61	Jordan	JO	0.459	0.449	0.060	0.801	0.530	0.864
62	Kazakhstan	KZ	0.288	0.277	0.061			
63	Kenya	KE	0.391	0.371	0.047	0.363	0.139	0.602
64	Kiribati	KI	0.523	0.499	0.049			
65	Korea, Dem. People's Republic	KP	0.607	0.602	0.012			
66	Kyrgyzstan	KG	0.255	0.248	0.029	0.364	0.161	0.519
67	Lao People's Dem. Republic	LA	0.376	0.359	0.048			
68	Lebanon	LB	0.470	0.480	0.042			
69	Lesotho	LS	0.448	0.439	0.035	0.300	0.171	0.414
70	Liberia	LR	0.284	0.275	0.030	0.239	0.097	0.402
71	Libya	LY	0.281	0.259	0.050			
72	Madagascar	MG	0.359	0.360	0.026	0.288	0.100	0.593
73	Malawi	MW	0.378	0.366	0.034	0.401	0.132	0.756
74	Malaysia	MY	0.505	0.513	0.047			
75	Maldives	MV	0.671	0.669	0.059			
76	Mali	ML	0.274	0.269	0.025	0.206	0.065	0.387
77	Marshall Islands	MH	0.566	0.552	0.040			
78	Mauritania	MR	0.270	0.264	0.025			
79	Mauritius	MU	0.582	0.586	0.037			
80	Mexico	MX	0.447	0.445	0.065			
81	Micronesia, Fed. Sts.	FM	0.537	0.510	0.047			
82	Moldova	MD	0.403	0.396	0.049	0.565	0.268	0.735
83	Mongolia	MN	0.290	0.268	0.049			
84	Montenegro	ME	0.288	0.270	0.049			
85	Morocco	MA	0.437	0.420	0.050	0.640	0.298	0.792
86	Mozambique	MZ	0.372	0.366	0.027	0.300	0.138	0.510
87	Myanmar	MM	0.405	0.389	0.058	0.374	0.180	0.532
88	Namibia	NA	0.466	0.452	0.038	0.526	0.267	0.699
89	Nauru	NR	0.686	0.690	0.045			
90	Nepal	NP	0.425	0.414	0.052	0.378	0.217	0.473
91	Nicaragua	NI	0.342	0.326	0.044			
92	Niger	NE	0.275	0.270	0.020			
93	Nigeria	NG	0.385	0.373	0.044	0.406	0.189	0.597
94	North Macedonia	MK	0.273	0.259	0.047			
95	Pakistan	PK	0.430	0.420	0.052	0.550	0.270	0.753
96	Papua New Guinea	PG	0.339	0.333	0.024			
97	Paraguay	PY	0.416	0.403	0.044			
98	Peru	PE	0.438	0.423	0.047	0.430	0.212	0.573
99	Philippines	PH	0.514	0.516	0.057	0.487	0.232	0.645
100	Romania	RO	0.364	0.369	0.043			
101	Russian Federation	RU	0.346	0.318	0.050			
102	Rwanda	RW	0.343	0.331	0.044	0.395	0.159	0.622
103	Saint Lucia	LC	0.644	0.652	0.057			
104	Samoa	WS	0.547	0.523	0.056			
105	Sao Tome & Principe	ST	0.445	0.417	0.060			
106	Senegal	SN	0.401	0.386	0.039	0.279	0.133	0.410
107	Serbia	RS	0.321	0.319	0.046			
108	Sierra Leone	SL	0.274	0.265	0.029	0.211	0.078	0.626
109	Solomon Islands	SB	0.399	0.395	0.020			
110	Somalia	SO	0.301	0.299	0.018			
111	South Africa	ZA	0.514	0.509	0.055	0.834	0.292	1.402
112	Sri Lanka	LK	0.567	0.572	0.039			
113	St. Vincent and the Grenadines	VC	0.629	0.646	0.059			
114	Sudan	SD	0.413	0.405	0.028			
115	Suriname	SR	0.359	0.341	0.040			
116	Syrian Arab Republic	SY	0.375	0.355	0.052			
117	Tajikistan	TJ	0.296	0.289	0.029	0.509	0.266	0.596
118	Tanzania	TZ	0.331	0.325	0.032	0.315	0.162	0.442
119	Thailand	TH	0.441	0.442	0.031			

120	Timor-Leste	TL	0.416	0.395	0.046	0.308	0.132	0.455
121	Togo	TG	0.295	0.284	0.031	0.196	0.093	0.267
122	Tonga	TO	0.571	0.533	0.061			
123	Tunisia	TN	0.404	0.396	0.056			
124	Turkey	TR	0.480	0.479	0.054			
125	Turkmenistan	TM	0.375	0.371	0.017			
126	Tuvalu	TV	0.595	0.563	0.052			
127	Uganda	UG	0.356	0.345	0.034	0.285	0.132	0.413
128	Ukraine	UA	0.223	0.219	0.047			
129	Uzbekistan	UZ	0.322	0.310	0.039			
130	Vanuatu	VU	0.433	0.420	0.032			
131	Venezuela, RB	VE	0.421	0.410	0.037			
132	Viet Nam	VN	0.399	0.402	0.038			
133	West Bank and Gaza	PS	0.468	0.470	0.042			
134	Yemen	YE	0.351	0.343	0.041			
135	Zambia	ZM	0.374	0.369	0.025	0.318	0.138	0.602
136	Zimbabwe	ZW	0.365	0.357	0.031	0.304	0.109	0.496

Notes: Table indicates mean, median, and standard deviation of predicted model error in all LMICs (columns 3-5). In countries where ground truth DHS data exist, table reports mean, median, and standard deviation of mean squared prediction error (columns 6-8).

Table S6. Sources of country-level data.

Country	Code	GDP per capita	Year (GDP)	Source (GDP per capita)	Gini	Year (Gini)	Source (Gini)	
1	Afghanistan	AF	520.90	2018	World Bank[1]	0.278	-	[6]
2	Albania	AL	5253.63	2018	World Bank[1]	0.29	2012	World Bank[2]
3	Algeria	DZ	4278.85	2018	World Bank[1]	0.276	2011	World Bank[2]
4	American Samoa	AS	11398.78	2017	World Bank[1]	0.387	-	WS[4]
5	Angola	AO	3432.39	2018	World Bank[1]	0.427	2008	World Bank[2]
6	Argentina	AR	11652.57	2018	World Bank[1]	0.406	2017	World Bank[2]
7	Armenia	AM	4212.07	2018	World Bank[1]	0.336	2017	World Bank[2]
8	Azerbaijan	AZ	4721.18	2018	World Bank[1]	0.266	2005	World Bank[2]
9	Bangladesh	BD	1698.26	2018	World Bank[1]	0.324	2016	World Bank[2]
10	Belarus	BY	6289.94	2018	World Bank[1]	0.254	2017	World Bank[2]
11	Belize	BZ	5025.18	2018	World Bank[1]	0.533	1999	World Bank[2]
12	Benin	BJ	901.95	2018	World Bank[1]	0.478	2015	World Bank[2]
13	Bhutan	BT	3360.27	2018	World Bank[1]	0.374	2017	World Bank[2]
14	Bolivia	BO	3548.59	2018	World Bank[1]	0.44	2017	World Bank[2]
15	Bosnia & Herzegovina	BA	5951.32	2018	World Bank[1]	0.33	2011	World Bank[2]
16	Botswana	BW	8258.64	2018	World Bank[1]	0.533	2015	World Bank[2]
17	Brazil	BR	8920.76	2018	World Bank[1]	0.533	2017	World Bank[2]
18	Bulgaria	BG	9272.63	2018	World Bank[1]	0.374	2014	World Bank[2]
19	Burkina Faso	BF	731.17	2018	World Bank[1]	0.353	2014	World Bank[2]
20	Burundi	BI	275.43	2018	World Bank[1]	0.386	2013	World Bank[2]
21	Cabo Verde	CV	3654.01	2018	World Bank[1]	0.472	2007	World Bank[2]
22	Cambodia	KH	1512.13	2018	World Bank[1]	0.379	-	[5]
23	Cameroon	CM	1526.88	2018	World Bank[1]	0.466	2014	World Bank[2]
24	Central African Republic	CF	509.97	2018	World Bank[1]	0.562	2008	World Bank[2]
25	Chad	TD	730.24	2018	World Bank[1]	0.433	2011	World Bank[2]
26	China	CN	9770.85	2018	World Bank[1]	0.386	2015	World Bank[2]
27	Colombia	CO	6651.29	2018	World Bank[1]	0.497	2017	World Bank[2]
28	Comoros	KM	1445.45	2018	World Bank[1]	0.453	2013	World Bank[2]
29	Congo, Dem. Rep.	CD	561.78	2018	World Bank[1]	0.421	2012	World Bank[2]
30	Congo, Rep.	CG	2147.77	2018	World Bank[1]	0.489	2011	World Bank[2]
31	Costa Rica	CR	12026.55	2018	World Bank[1]	0.483	2017	World Bank[2]
32	Cote d'Ivoire	CI	1715.53	2018	World Bank[1]	0.415	2015	World Bank[2]
33	Cuba	CU	8541.21	2017	World Bank[1]	0.38	2003	[7]
34	Djibouti	DJ	2050.20	2018	World Bank[1]	0.416	2017	World Bank[2]
35	Dominica	DM	7031.71	2018	World Bank[1]	0.47	2013	[8]
36	Dominican Republic	DO	7650.07	2018	World Bank[1]	0.457	2016	World Bank[2]
37	Ecuador	EC	6344.87	2018	World Bank[1]	0.447	2017	World Bank[2]
38	Egypt, Arab Rep.	EG	2549.14	2018	World Bank[1]	0.318	2015	World Bank[2]
39	El Salvador	SV	4058.24	2018	World Bank[1]	0.38	2017	World Bank[2]
40	Equatorial Guinea	GQ	10173.96	2018	World Bank[1]	0.38	-	GA[4]
41	Eritrea	ER	811.38	2011	World Bank[1]	0.292	2016	[9]
42	Eswatini	SZ	4139.96	2018	World Bank[1]	0.515	2009	World Bank[2]
43	Ethiopia	ET	772.31	2018	World Bank[1]	0.391	2015	World Bank[2]
44	Fiji	FJ	6202.16	2018	World Bank[1]	0.367	2013	World Bank[2]
45	Gabon	GA	8029.82	2018	World Bank[1]	0.38	2017	World Bank[2]
46	Gambia, The	GM	712.45	2018	World Bank[1]	0.359	2015	World Bank[2]
47	Georgia	GE	4344.63	2018	World Bank[1]	0.379	2017	World Bank[2]
48	Ghana	GH	2202.31	2018	World Bank[1]	0.435	2016	World Bank[2]
49	Grenada	GD	10833.66	2018	World Bank[1]	0.512	-	LC[4]
50	Guatemala	GT	4549.01	2018	World Bank[1]	0.483	2014	World Bank[2]
51	Guinea	GN	885.25	2018	World Bank[1]	0.337	2012	World Bank[2]
52	Guinea-Bissau	GW	777.97	2018	World Bank[1]	0.507	2010	World Bank[2]
53	Guyana	GY	4634.68	2018	World Bank[1]	0.446	1998	World Bank[2]
54	Haiti	HT	868.28	2018	World Bank[1]	0.411	2012	World Bank[2]
55	Honduras	HN	2482.73	2018	World Bank[1]	0.505	2017	World Bank[2]
56	India	IN	2015.59	2018	World Bank[1]	0.357	2011	World Bank[2]
57	Indonesia	ID	3893.60	2018	World Bank[1]	0.381	2017	World Bank[2]
58	Iran, Islamic Rep.	IR	5627.75	2017	World Bank[1]	0.4	2016	World Bank[2]

59	Iraq	IQ	5878.04	2018	World Bank[1]	0.295	2012	World Bank[2]
60	Jamaica	JM	5355.58	2018	World Bank[1]	0.455	2004	World Bank[2]
61	Jordan	JO	4247.77	2018	World Bank[1]	0.337	2010	World Bank[2]
62	Kazakhstan	KZ	9331.05	2018	World Bank[1]	0.275	2017	World Bank[2]
63	Kenya	KE	1710.51	2018	World Bank[1]	0.408	2015	World Bank[2]
64	Kiribati	KI	1625.29	2018	World Bank[1]	0.37	2006	World Bank[2]
65	Korea, D.P.R.	KP	1700.00	2015	CIA[3]	0.85	2004	[12]
66	Kosovo	XK	4281.29	2018	World Bank[1]	0.29	2017	World Bank[2]
67	Kyrgyz Republic	KG	1281.36	2018	World Bank[1]	0.273	2017	World Bank[2]
68	Lao PDR	LA	2567.54	2018	World Bank[1]	0.364	2012	World Bank[2]
69	Lebanon	LB	8269.79	2018	World Bank[1]	0.318	2011	World Bank[2]
70	Lesotho	LS	1324.28	2018	World Bank[1]	0.542	2010	World Bank[2]
71	Liberia	LR	674.21	2018	World Bank[1]	0.353	2016	World Bank[2]
72	Libya	LY	7235.03	2018	World Bank[1]	0.307	-	[10]
73	Madagascar	MG	460.75	2018	World Bank[1]	0.426	2012	World Bank[2]
74	Malawi	MW	389.40	2018	World Bank[1]	0.447	2016	World Bank[2]
75	Malaysia	MY	11238.96	2018	World Bank[1]	0.41	2015	World Bank[2]
76	Maldives	MV	10223.64	2018	World Bank[1]	0.384	2009	World Bank[2]
77	Mali	ML	901.40	2018	World Bank[1]	0.33	2009	World Bank[2]
78	Marshall Islands	MH	3621.17	2018	World Bank[1]	0.391	-	TV[4]
79	Mauritania	MR	1218.60	2018	World Bank[1]	0.326	2014	World Bank[2]
80	Mauritius	MU	11238.69	2018	World Bank[1]	0.358	2012	World Bank[2]
81	Mexico	MX	9698.08	2018	World Bank[1]	0.434	2016	World Bank[2]
82	Micronesia, Fed. Sts.	FM	3058.43	2018	World Bank[1]	0.401	2013	World Bank[2]
83	Moldova	MD	3189.36	2018	World Bank[1]	0.259	2017	World Bank[2]
84	Mongolia	MN	4103.70	2018	World Bank[1]	0.323	2016	World Bank[2]
85	Montenegro	ME	8760.69	2018	World Bank[1]	0.319	2014	World Bank[2]
86	Morocco	MA	3237.88	2018	World Bank[1]	0.395	2013	World Bank[2]
87	Mozambique	MZ	490.17	2018	World Bank[1]	0.54	2014	World Bank[2]
88	Myanmar	MM	1325.95	2018	World Bank[1]	0.381	2015	World Bank[2]
89	Namibia	NA	5931.45	2018	World Bank[1]	0.591	2015	World Bank[2]
90	Nauru	NR	9030.07	2018	World Bank[1]	0.371	-	SB[4]
91	Nepal	NP	1025.80	2018	World Bank[1]	0.328	2010	World Bank[2]
92	Nicaragua	NI	2028.90	2018	World Bank[1]	0.462	2014	World Bank[2]
93	Niger	NE	411.69	2018	World Bank[1]	0.343	2014	World Bank[2]
94	Nigeria	NG	2028.18	2018	World Bank[1]	0.43	2009	World Bank[2]
95	North Macedonia	MK	6083.72	2018	World Bank[1]	0.356	2015	World Bank[2]
96	Pakistan	PK	1472.89	2018	World Bank[1]	0.335	2015	World Bank[2]
97	Papua New Guinea	PG	2722.60	2018	World Bank[1]	0.419	2009	World Bank[2]
98	Paraguay	PY	5871.47	2018	World Bank[1]	0.488	2017	World Bank[2]
99	Peru	PE	6947.26	2018	World Bank[1]	0.433	2017	World Bank[2]
100	Philippines	PH	3102.71	2018	World Bank[1]	0.401	2015	World Bank[2]
101	Romania	RO	12301.19	2018	World Bank[1]	0.359	2015	World Bank[2]
102	Russian Federation	RU	11288.87	2018	World Bank[1]	0.377	2015	World Bank[2]
103	Rwanda	RW	772.97	2018	World Bank[1]	0.437	2016	World Bank[2]
104	Samoa	WS	4392.47	2018	World Bank[1]	0.387	2013	World Bank[2]
105	Sao Tome & Principe	ST	2001.14	2018	World Bank[1]	0.308	2010	World Bank[2]
106	Senegal	SN	1521.95	2018	World Bank[1]	0.403	2011	World Bank[2]
107	Serbia	RS	7234.00	2018	World Bank[1]	0.285	2015	World Bank[2]
108	Sierra Leone	SL	522.86	2018	World Bank[1]	0.34	2011	World Bank[2]
109	Solomon Islands	SB	2162.65	2018	World Bank[1]	0.371	2013	World Bank[2]
110	Somalia	SO	498.66	2018	World Bank[1]	0.397	2012	[11]
111	South Africa	ZA	6339.57	2018	World Bank[1]	0.63	2014	World Bank[2]
112	South Sudan	SS	283.49	2016	World Bank[1]	0.463	2009	World Bank[2]
113	Sri Lanka	LK	4102.48	2018	World Bank[1]	0.398	2016	World Bank[2]
114	St. Lucia	LC	10315.03	2018	World Bank[1]	0.512	2016	World Bank[2]
115	St. Vincent & Grenadines	VC	7377.68	2018	World Bank[1]	0.512	-	LC[4]
116	Sudan	SD	977.27	2018	World Bank[1]	0.354	2009	World Bank[2]
117	Suriname	SR	5950.21	2018	World Bank[1]	0.576	1999	World Bank[2]
118	Syrian Arab Republic	SY	2032.62	2007	World Bank[1]	0.358	2004	World Bank[2]
119	Tajikistan	TJ	826.62	2018	World Bank[1]	0.34	2015	World Bank[2]

120	Tanzania	TZ	1050.68	2018	World Bank[1]	0.378	2011	World Bank[2]
121	Thailand	TH	7273.56	2018	World Bank[1]	0.365	2017	World Bank[2]
122	Timor-Leste	TL	2035.53	2018	World Bank[1]	0.287	2014	World Bank[2]
123	Togo	TG	671.84	2018	World Bank[1]	0.431	2015	World Bank[2]
124	Tonga	TO	4364.02	2018	World Bank[1]	0.376	2015	World Bank[2]
125	Tunisia	TN	3446.61	2018	World Bank[1]	0.328	2015	World Bank[2]
126	Turkey	TR	9311.37	2018	World Bank[1]	0.419	2016	World Bank[2]
127	Turkmenistan	TM	6966.64	2018	World Bank[1]	0.408	1998	World Bank[2]
128	Tuvalu	TV	3700.71	2018	World Bank[1]	0.391	2010	World Bank[2]
129	Uganda	UG	643.14	2018	World Bank[1]	0.428	2016	World Bank[2]
130	Ukraine	UA	3095.17	2018	World Bank[1]	0.25	2016	World Bank[2]
131	Uzbekistan	UZ	1532.37	2018	World Bank[1]	0.353	2003	World Bank[2]
132	Vanuatu	VU	3033.41	2018	World Bank[1]	0.376	2010	World Bank[2]
133	Venezuela, RB	VE	16054.49	2014	World Bank[1]	0.469	2006	World Bank[2]
134	Vietnam	VN	2563.82	2018	World Bank[1]	0.353	2016	World Bank[2]
135	West Bank and Gaza	PS	3198.87	2018	World Bank[1]	0.337	2016	World Bank[2]
136	Yemen, Rep.	YE	944.41	2018	World Bank[1]	0.367	2014	World Bank[2]
137	Zambia	ZM	1539.90	2018	World Bank[1]	0.571	2015	World Bank[2]
138	Zimbabwe	ZW	2147.00	2018	World Bank[1]	0.432	2011	World Bank[2]

Notes: While most of the country-level statistics come from the World Bank's Open Data portal, when the required indicators are missing we use data from the alternative data sources listed above. Sources below.
[1] https://data.worldbank.org/indicator/ny.gdp.pcap.cd
[2] https://data.worldbank.org/indicator/SI.POV.GINI?locations=US-AF
[3] https://www.cia.gov/library/publications/the-world-factbook/rankorder/2004rank.html
[4] No Gini available. Gini from closest neighbor, based on orthodromic distance, is used instead (and country code is indicated in the table when applicable).
[5] https://www.cia.gov/library/publications/the-world-factbook/rankorder/2172rank.html
[6] http://hdr.undp.org/en/content/income-gini-coefficient
[7] https://watermark.silverchair.com/bey026.pdf
[8] https://www.indexmundi.com/dominica/distribution_of_family_income_gini_index.html
[9] https://pdfs.semanticscholar.org/1f1d/6a9df57105dba86090b5904422af6f087b9a.pdf
[10] http://www.ecineq.org/ecineq_nyc17/FILESx2017/CR2/p426.pdf
[11] https://canada-vs-somalia.weebly.com/somalia.html
[12] https://www.piie.com/blogs/north-korea-witness-transformation/distribution-income-north-korea

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1. Center, Minnesota Population, *Integrated Public Use Microdata Series, International: Version 7.2 [dataset.* (IPUMS, Minneapolis, MN), (2019).