Supplementary

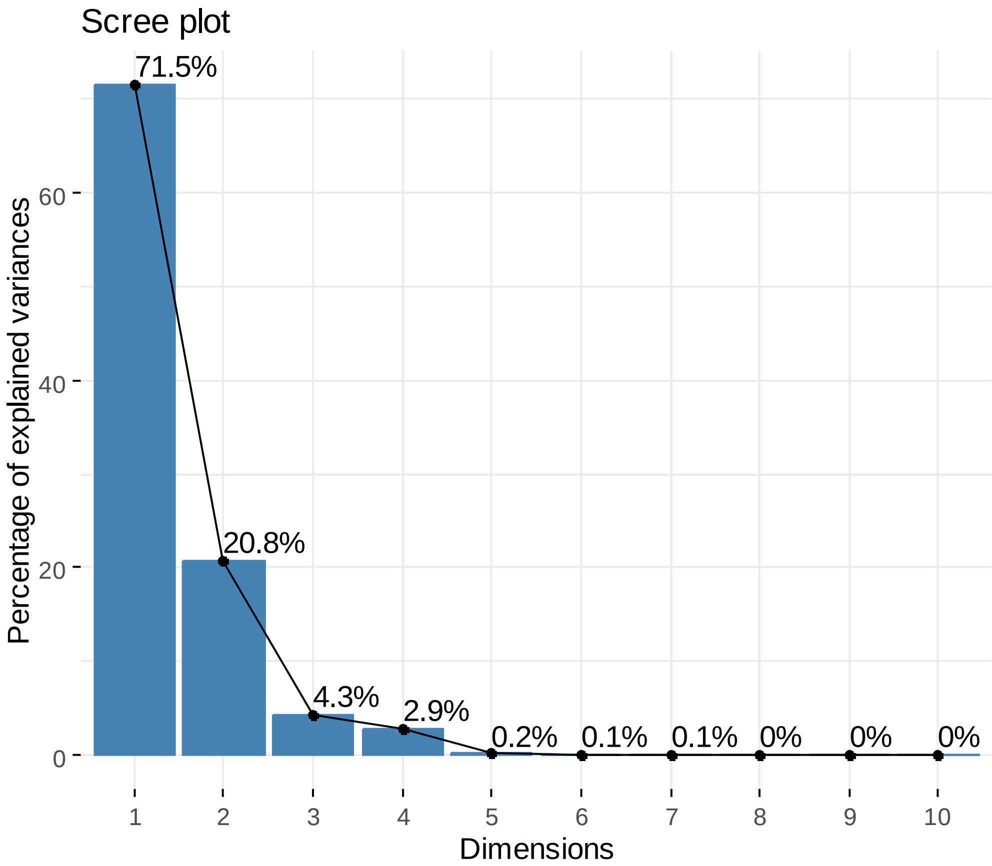
Supplementary Table 1 Principal component analysis of 19 bioclimatic variables

Variables	Describe	Principal Component		
		PC1	**PC2**	**PC3**
BIO1	Annual Mean Temperature	**0.272**	0.112	0.224
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))	**-0.205**	0.177	-0.145
BIO3	Isothermality (BIO2/BIO7) (×100)	-0.129	**0.403**	-0.123
BIO4	Temperature Seasonality (standard deviation ×100)	0.039	**-0.476**	0.128
BIO5	Max Temperature of Warmest Month	**0.266**	-0.093	0.261
BIO6	Min Temperature of Coldest Month	**0.262**	0.181	0.200
BIO7	Temperature Annual Range (BIO5-BIO6)	-0.059	**-0.447**	0.041
BIO8	Mean Temperature of Wettest Quarter	0.221	0.029	**0.447**
BIO9	Mean Temperature of Driest Quarter	**0.253**	0.220	0.097
BIO10	Mean Temperature of Warmest Quarter	**0.272**	-0.069	0.264
BIO11	Mean Temperature of Coldest Quarter	0.243	**0.253**	0.168
BIO12	Annual Precipitation	**0.272**	-0.013	-0.271
BIO13	Precipitation of Wettest Month	0.256	0.077	**-0.266**
BIO14	Precipitation of Driest Month	0.255	-0.147	**-0.257**
BIO15	Precipitation Seasonality (Coefficient of Variation)	-0.198	**0.286**	0.066
BIO16	Precipitation of Wettest Quarter	0.255	0.110	**-0.269**
BIO17	Precipitation of Driest Quarter	0.248	-0.165	**-0.275**
BIO18	Precipitation of Warmest Quarter	**0.211**	0.210	-0.162
BIO19	Precipitation of Coldest Quarter	0.250	-0.124	**-0.303**

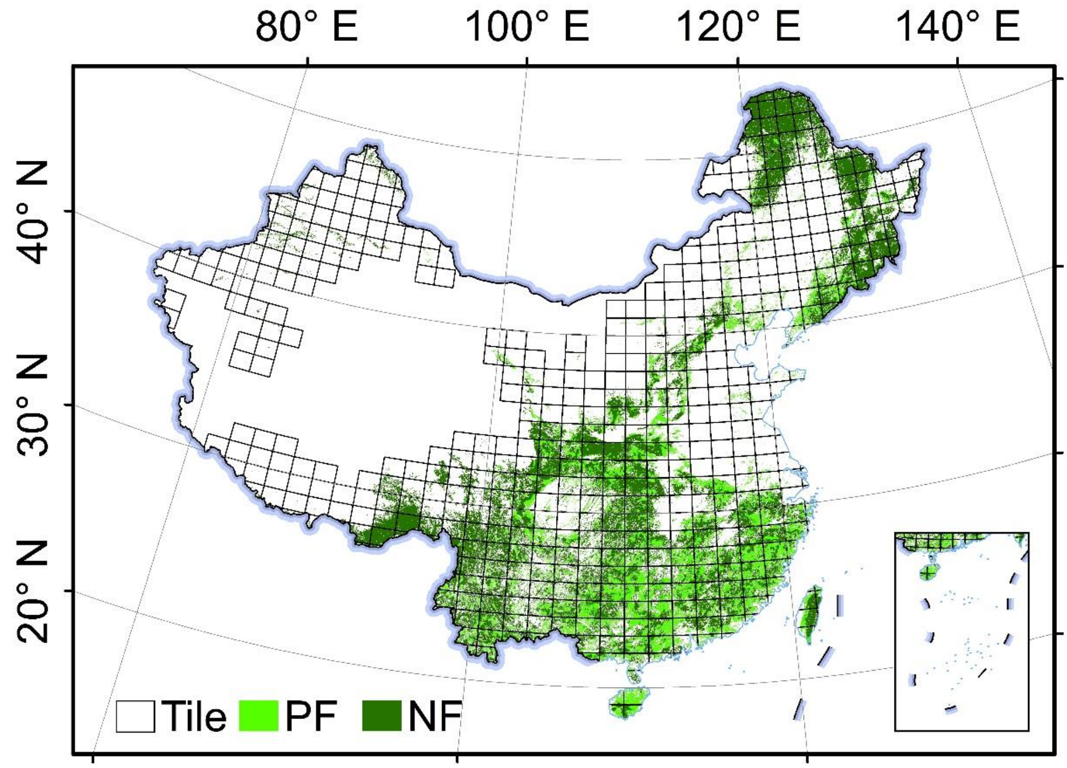
PC1 is related to BIO1, BIO2, BIO5, BIO6, BIO9, BIO10, BIO12 and BIO18

PC2 is related to BIO3, BIO4, BIO7, BIO11 and BIO15

PC3 is related to BIO8, BIO13, BIO14, BIO16, BIO17 and BIO19.



Supplementary Figure1. Scree plot of 19 bioclimatic variables



Supplementary Figure 2. 1°×1° grids for China's forest region. PF: planted forest, NF: Natural forest.

Supplementary Table 2. The thirteen alternative machine learning algorithms and their accuracies(R^2)

Model	Validation								Test							
	CT	WT	QT	TM	TS	TD	TN	SE	CT	WT	QT	TM	TS	TD	TN	SE
DecisionTree	-0.1443	0.2008	0.2540	0.6540	0.5230	0.4843	0.2743	0.3521	-0.0116	0.2232	0.0815	0.7207	0.5480	0.5409	0.2882	0.3586
ExtraTree	-0.1450	0.1879	0.1295	0.6354	0.4200	0.4582	0.2306	0.3115	-0.2244	0.2527	0.1297	0.6657	0.4828	0.5660	0.2398	0.3526
GaussianProcess	-2.9984	-1.5756	-2.2477	-13.0362	-1.2202	-2.3692	-2.7937	-1.2905	-2.8423	-1.5995	-2.5428	-11.2968	-1.1853	-2.1186	-2.8901	-1.2705
XGB	0.3311	0.5718	0.5109	0.7942	0.7106	0.7077	0.5845	0.6573	0.3402	0.5857	0.3609	0.8241	0.7272	0.7586	0.6031	0.6690
RandomForest	0.4124	0.6017	0.5546	0.8113	0.7343	0.7067	0.6236	0.6609	0.4262	0.6121	0.5363	0.8414	0.7641	0.7724	0.6272	0.6749
Bagging	0.3646	0.5661	0.5268	0.7961	0.7043	0.6699	0.5859	0.6309	0.3674	0.5791	0.4387	0.8287	0.7315	0.7487	0.6055	0.6457
HistGradientBoost	0.3935	0.6039	0.5093	0.8051	0.7325	0.6931	0.6234	0.6685	0.4092	0.6113	0.4526	0.8341	0.7572	0.7825	0.6303	0.6885
LGBM	0.3986	0.6052	0.5202	0.8083	0.7234	0.6962	0.6262	0.6726	0.4203	0.6112	0.4552	0.8362	0.7513	0.7845	0.6341	0.6891
GradientBoosting	0.4208	0.5950	0.5484	0.8095	0.7260	0.7007	0.6223	0.6605	0.4543	0.5923	0.4930	0.8433	0.7435	0.7705	0.6228	0.6796
MLP	0.3990	0.5198	0.1415	0.5954	0.7076	0.6016	0.5953	0.6659	0.4311	0.5120	0.2354	0.7695	0.7170	0.6685	0.5900	0.6685
AdaBoost	0.1650	0.4622	0.4775	0.6436	0.5348	0.5867	0.5443	0.3152	0.1700	0.4808	0.4589	0.7705	0.6095	0.5980	0.5434	0.3559
KNeighbors	-0.0304	0.3386	0.3247	0.5851	0.4612	0.5574	0.0958	0.3883	0.0013	0.3779	0.1892	0.6067	0.5253	0.6302	0.1312	0.4284
CatBoost	0.4263	0.6109	0.5814	0.8162	0.7409	0.7322	0.6271	0.6749	0.4501	0.6203	0.5022	0.8444	0.7602	0.7922	0.6275	0.6924

Supplementary Table 3. The hyperparameters and their range for different models.

Algorithm	Python Package	Hyperparameter Range
RF	sklearn.ensemble.RandomForestRegressor	max_depth:[3,18] n_estimators:[5000, 8000] max_features:['auto', 'sqrt', 'log2'] min_samples_split:[2, 10] min_samples_leaf:[2, 10] random_state: 2023
GBDT	sklearn.ensemble.GradientBoostingRegressor	max_depth:[2, 10] learning_rate: [0.001,0.005,0.01,0.05,0.1] n_estimators:[4000, 5000] subsample:[0.7, 0.9] max_features: ['auto', 'sqrt', 'log2'] min_samples_split:[2, 10] random_state:2023
HistGradientBoost	sklearn.ensemble.HistGradientBoostingRegressor	max_depth:[2, 10] learning_rate: [0.001,0.02,0.03,0.005,0.01,0.05,0.1] max_leaf_nodes:[30, 40] min_samples_leaf:[15, 25] random_state:2023
LightGBM	lightgbm	reg_alpha: [0.001, 10.0] reg_lambda: [0.001, 10.0] num_leaves: [11, 333] min_child_samples: [5, 100] max_depth: [3, 20] learning_rate: [0.001,0.005,0.01,0.05,0.1] colsample_bytree: [0.1, 0.5] n_estimators: [7000, 8000] cat_smooth: [10, 100] cat_l2: [1, 20] min_data_per_group: [50, 200] cat_feature: [10, 60] n_jobs: -1 random_state: 2023
CatBoost	catboost	depth: [3, 10] learning_rate: [0.001,0.005,0.01,0.05,0.1] iterations: [5000, 9000] max_bin: [200, 400] min_data_in_leaf: [1, 30] l2_leaf_reg: [0.0001, 1.0, log=True] subsample: [0.6, 0.9] random_state: 2023

Supplementary Table 4. The optimal hyperparameter parameter values for different MLAs.

Vegetation division	Algorithm	Hyperparameter values
CT	RF	(max_depth =8,n_estimators=6589,max_features= 'auto',min_samples_leaf=9,min_samples_split =8,random_state=2023)
	GBDT	{'max_depth': 4, 'learning_rate': 0.001, 'n_estimators': 4909, 'subsample': 0.7234085712326702, 'max_features': 'auto', 'min_samples_split':10 ,'random_state': 2023}
	CatBoost	(depth=10,learning_rate=0.1,iterations=86,max_bin=320,min_data_in_leaf=27,l2_leaf_reg=0.17934206956587195,subsample=0.6773452775007673,random_seed=2023)
WT	RF	(max_depth =19,n_estimators=348,max_features= 'sqrt',min_samples_leaf=1,min_samples_split =3,random_state=2023)
	LGBM	{'reg_alpha': 4.188760632650688, 'reg_lambda': 4.255499587500175, 'num_leaves': 75, 'min_child_samples': 7, 'max_depth': 19, 'learning_rate': 0.001, 'colsample_bytree': 0.4928730464443524, 'n_estimators': 7117, 'cat_smooth': 84, 'cat_l2': 15, 'min_data_per_group': 193, 'cat_feature': 28, 'random_state': 2023}
	CatBoost	(depth=12,learning_rate=0.05,iterations=133,max_bin=314,min_data_in_leaf=8,l2_leaf_reg=0.0021616691540516635,subsample= 0.827218563526197,random_seed=2023)
QT	RF	(max_depth =9,n_estimators=100,max_features= 'auto',min_samples_leaf=1,min_samples_split =2,random_state=2023)
	GBDT	{'max_depth': 5, 'learning_rate': 0.001, 'n_estimators': 4873, 'subsample': 0.6338013854778914, 'max_features': 'sqrt', 'min_samples_split':8 ,'random_state': 2023}
	CatBoost	(depth=7,learning_rate=0.1,iterations=90,max_bin=337,min_data_in_leaf=4,l2_leaf_reg=0.0008155227484111563,subsample=0.7808941610379249,random_seed=2023)
TM	HistGradientBoost	(learning_rate=0.05, max_leaf_nodes=33, max_depth=5, min_samples_leaf=21, l2_regularization=0.0001, max_bins=200, early_stopping='auto', random_state=2023)
	GBDT	{'max_depth': 5, 'learning_rate': 0.001, 'n_estimators': 4970, 'subsample': 0.7323582473497865, 'max_features': 'auto', 'min_samples_split':9 ,'random_state': 2023}
	CatBoost	(depth=5,learning_rate=0.1,iterations=228,max_bin=298,min_data_in_leaf=14,l2_leaf_reg=0.912715671115768,subsample=0.7691332886798857,random_seed=2023)
TS	RF	(max_depth =12,n_estimators=105,max_features= 'auto',min_samples_leaf=2,min_samples_split =8,random_state=2023)
	LightGBM	{'reg_alpha': 3.0022329902119083, 'reg_lambda': 6.129604703602383, 'num_leaves': 69, 'min_child_samples': 38, 'max_depth': 15, 'learning_rate': 0.001, 'colsample_bytree': 0.48372749547013316, 'n_estimators': 7571, 'cat_smooth': 82, 'cat_l2': 5, 'min_data_per_group': 128, 'cat_feature': 41, 'random_state': 2023}
	CatBoost	(depth=7,learning_rate=0.005,iterations=4164,max_bin=215,min_data_in_leaf=24,l2_leaf_reg=0.00017571003237103587,subsample=0.8817081947911567,random_seed=2023)
TD	HistGradientBoost	(learning_rate=0.1, max_leaf_nodes=39, max_depth=4, min_samples_leaf=22, l2_regularization=0.0001, max_bins=200,

		early_stopping='auto', random_state=2023)
	LightGBM	{'reg_alpha': 2.1333544399270994, 'reg_lambda': 7.980678166407649, 'num_leaves': 217, 'min_child_samples': 5, 'max_depth': 5, 'learning_rate': 0.003, 'colsample_bytree': 0.43984300935044063, 'n_estimators': 7992, 'cat_smooth': 76, 'cat_l2': 7, 'min_data_per_group': 187, 'cat_feature': 47, 'random_state': 2023}
	CatBoostRegressor	(depth=5,learning_rate=0.01,iterations=5203,max_bin=246,min_data_in_leaf=6,l2_leaf_reg=0.00045191356462636874,subsample=0.6391293474573634,random_seed=2023)
TN	HistGradientBoost	(learning_rate=0.05, max_leaf_nodes=38, max_depth=6, min_samples_leaf=20, l2_regularization=0.0001, max_bins=200, early_stopping='auto', random_state=2023)
	LightGBM	{'reg_alpha': 3.0022329902119083, 'reg_lambda': 6.129604703602383, 'num_leaves': 69, 'min_child_samples': 38, 'max_depth': 15, 'learning_rate': 0.001, 'colsample_bytree': 0.48372749547013316, 'n_estimators': 7571, 'cat_smooth': 82, 'cat_l2': 5, 'min_data_per_group': 128, 'cat_feature': 41, 'random_state': 2023}
	CatBoost	(depth=10,learning_rate=0.1,iterations=155,max_bin=319,min_data_in_leaf=1,l2_leaf_reg=0.33907394509650335,subsample=0.7682844712570389,random_seed=2023)
SE	LightGBM	{'reg_alpha': 6.116715128459515, 'reg_lambda': 5.231647634428009, 'num_leaves': 18, 'min_child_samples': 73, 'max_depth': 8, 'learning_rate': 0.002, 'colsample_bytree': 0.4726653436124117, 'n_estimators': 7288, 'cat_smooth': 67, 'cat_l2': 6, 'min_data_per_group': 79, 'cat_feature': 36, 'random_state': 2023}
	MLP	{'hidden_layer_sizes': (200, 200, 200), 'activation': 'relu', 'solver': 'adam', 'alpha': 0.0001, 'batch_size': 'auto', 'learning_rate': 'constant', 'learning_rate_init': 0.001, 'max_iter': 155, 'random_state': 2023}
	CatBoost	(depth=7,learning_rate=0.005,iterations=6248,max_bin=383,min_data_in_leaf=20,l2_leaf_reg=0.6887500276693759,subsample=0.7127716543175433,random_seed=2023)

Supplementary Table 5. The training results of different MLAs

Vegetation division	Algorithm	Train		Validation	
		R2	RMSE	R2	RMSE
CT	RF	0.6102	4.6402	0.4394	25.6178
	GBDT	0.6463	4.5287	0.4398	25.6177
	CatBoost	0.7573	4.1219	0.4307	25.8266
WT	RF	0.9286	2.2631	0.6108	11.9231
	LGBM	0.8303	2.8096	0.6112	11.9211
	CatBoost	0.8309	2.8073	0.6085	11.9593
QT	RF	0.9326	4.7895	0.5135	56.7438
	GBDT	0.8846	5.4791	0.5430	55.6378
	CatBoost	0.9637	4.1029	0.5648	54.1309
TM	HistGradientBoost	0.8729	1.9054	0.8129	4.3884
	GBDT	0.9059	1.7673	0.8139	4.3779
	CatBoost	0.8969	1.8083	0.8202	4.3006
TS	RF	0.9068	3.2872	0.7365	18.0381
	LightGBM	0.8685	3.5823	0.7456	17.7228
	CatBoost	0.9375	2.9747	0.7493	17.5945
TD	HistGradientBoost	0.8555	4.8085	0.7125	32.2791
	LightGBM	0.9485	3.7154	0.7065	32.6168
	CatBoostRegressor	0.9834	2.8009	0.7235	31.5870
TN	HistGradientBoost	0.6581	4.0517	0.6246	17.1609
	LightGBM	0.8080	3.5072	0.6292	17.0570
	CatBoost	0.7633	3.6956	0.6198	17.2713
SE	LightGBM	0.7273	3.3467	0.6722	12.2440
	MLP	0.7013	3.4237	0.6571	12.5179
	CatBoost	0.7899	3.1354	0.6774	12.1481

Supplementary Table 6. Mean and standard deviation of forest age in provinces

Province	Mean	S.D.
Anhui	30.0438	13.18046
Beijing	23.72932	6.941676
Chongqing	44.21707	14.81873
Fujian	34.71088	14.08378
Gansu	62.91986	28.90555
Guangdong	32.2954	14.03617
Guangxi	35.98391	14.40237
Guizhou	38.97128	14.09774
Hainan	31.67802	14.70032
Hebei	20.04016	9.452565
Heilongjiang	76.63183	26.88827
Henan	26.42557	13.65384
Hong Kong	2.905065	3.205983
Hubei	44.2699	17.3144
Hunan	30.98115	11.84794
Inner Mongolia	95.71522	35.21181

Jiangsu	22.35844	11.39468
Jiangxi	34.05567	13.07562
Jilin	75.20958	26.22582
Liaoning	29.84999	21.79875
Macao	3.805029	2.552609
Ningxia	44.01774	22.64126
Qinghai	115.7855	47.51708
Shaanxi	52.42966	20.90854
Shandong	15.81338	6.811547
Shanghai	5.695209	3.581797
Shanxi	30.59349	11.17819
Sichuan	75.09604	32.48283
Taiwan	53.18191	20.35996
Tianjin	15.6741	6.724648
Tibet	83.86414	30.52417
Xinjiang	103.28	50.83277
Yunnan	54.69701	21.25958
Zhejiang	35.3726	13.07106

Supplementary Table 7. Mean and standard deviation of forest age in eight vegetation zones

Vegetation zone	Mean	S.D.
CT	106.6109	24.25592
WT	27.47919	13.87375
QT	136.9514	36.23872
TM	52.04598	26.27037
TS	106.0278	56.54841
TD	59.32036	33.32852
TN	67.25398	22.54142
SE	48.23603	26.65255

Supplementary Table 8. Field measurements of forest age collected from published papers

ID	Longitude	Latitude	Year	Mean age (2020)	Reference
1	23.2450	113.4210	2020	6	Chen et al., (2022)
2	23.2260	113.3930	2020	10	Chen et al., (2022)
3	23.2560	113.4190	2020	15	Chen et al., (2022)
4	23.2120	113.3940	2020	20	Chen et al., (2022)
5	23.2550	113.3810	2020	30	Chen et al., (2022)
6	24.5200	114.4300	2010-2011	40	Di Y et al. (2012)
7	26.8814	117.9353	2017	10	Feng et al., (2021)
8	30.0800	110.5600	2010	40	Hu et al., (2012)
9	31.4300	110.3500	2010	45	Hu et al., (2012)
10	23.4800	100.5300	2013	67	Li et al. (2015)
11	23.0502	109.3289	2021	3	Li et al., (2021)
12	23.0535	109.3329	2021	8	Li et al., (2021)
13	23.1118	109.2420	2021	18	Li et al., (2021)

14	23.0533	109.1602	2021	21	Li et al., (2021)
15	25.3300	114.5700	2012	53	Qiu et al., (2020)
16	25.3300	114.5700	2012	53	Qiu et al., (2020)
17	25.3300	114.5700	2012	36	Qiu et al., (2020)
18	22.0483	110.4658	2020	5	Song et al., (2021)
19	21.9192	110.5008	2020	15	Song et al., (2021)
20	22.0222	110.5003	2020	5	Song et al., (2021)
21	36.4200	109.5300	2013	79	Sun et al., (2020)
22	23.7700	101.2700	2013	22	Tong et al. (2013)
23	23.7700	101.2700	2013	37	Tong et al. (2013)
24	23.9000	101.2700	2013	52	Tong et al. (2013)
25	28.6017	104.5672	2011	26	Wu et al. (2023)
26	28.6093	104.5769	2015	13	Wu et al. (2023)
27	22.0263	106.9073	2013	30	Wu et al. (2023)
28	22.0243	106.9102	2013	30	Wu et al. (2023)
29	22.0264	106.9132	2013	30	Wu et al. (2023)
30	22.8667	108.1667	2012	25	Wu et al. (2023)
31	21.9667	109.2833	2012	30	Wu et al. (2023)
32	26.6993	109.6076	2010	23	Wu et al. (2023)
33	26.7003	109.6077	2010	23	Wu et al. (2023)
34	24.7633	109.8933	2012	21	Wu et al. (2023)
35	34.0909	110.4029	2012	25	Wu et al. (2023)
36	30.9189	110.6969	2015	30	Wu et al. (2023)
37	27.2938	112.8481	2013	18	Wu et al. (2023)
38	27.2943	112.8486	2013	17	Wu et al. (2023)
39	27.3545	113.3865	2013	21	Wu et al. (2023)
40	26.8139	117.5247	2014	27	Wu et al. (2023)
41	26.8072	117.5408	2014	20	Wu et al. (2023)
42	52.9783	122.5456	2010	36	Wu et al. (2023)
43	25.9500	108.3700	2017	36	Zhou et al., 2018
44	18.7400	108.8500	2011-2016	59	Zhu et al. (2017)
45	24.4500	113.6800	2011-2016	52	Zhu et al. (2017)
46	24.8900	113.0300	2011-2016	49	Zhu et al. (2017)
47	24.9600	112.9600	2011-2016	98	Zhu et al. (2017)
48	25.3200	114.1500	2011-2016	71	Zhu et al. (2017)
49	25.7100	100.0400	2011-2016	56	Zhu et al. (2017)
50	25.7200	100.0500	2011-2016	85	Zhu et al. (2017)
51	25.7200	100.0500	2011-2016	108	Zhu et al. (2017)
52	25.8300	111.6500	2011-2016	31	Zhu et al. (2017)
53	25.8000	112.8700	2011-2016	26	Zhu et al. (2017)
54	25.6800	118.1900	2011-2016	40	Zhu et al. (2017)
55	26.1700	106.6500	2011-2016	45	Zhu et al. (2017)
56	26.5800	116.3400	2011-2016	61	Zhu et al. (2017)
57	27.0200	111.3400	2011-2016	40	Zhu et al. (2017)
58	27.0100	117.0700	2011-2016	64	Zhu et al. (2017)
59	27.8400	98.6800	2011-2016	41	Zhu et al. (2017)
60	27.9000	117.3600	2011-2016	84	Zhu et al. (2017)
61	27.9200	117.3500	2011-2016	93	Zhu et al. (2017)
62	27.7300	117.6300	2011-2016	74	Zhu et al. (2017)

63	27.6000	117.4600	2011-2016	54	Zhu et al. (2017)
64	28.2900	99.1600	2011-2016	114	Zhu et al. (2017)
65	28.1100	117.0000	2011-2016	63	Zhu et al. (2017)
66	29.1000	115.5700	2011-2016	56	Zhu et al. (2017)
67	28.9300	118.0600	2011-2016	88	Zhu et al. (2017)
68	29.2400	118.1000	2011-2016	78	Zhu et al. (2017)
69	29.2200	119.5200	2011-2016	60	Zhu et al. (2017)
70	30.0300	102.8300	2011-2016	54	Zhu et al. (2017)
71	29.7700	110.0900	2011-2016	94	Zhu et al. (2017)
72	31.1700	102.9900	2011-2016	69	Zhu et al. (2017)
73	31.3500	102.8300	2011-2016	69	Zhu et al. (2017)
74	31.5100	110.4300	2011-2016	94	Zhu et al. (2017)
75	32.2200	102.6100	2011-2016	78	Zhu et al. (2017)
76	34.0500	107.7000	2011-2016	84	Zhu et al. (2017)
77	34.0700	107.6900	2011-2016	64	Zhu et al. (2017)
78	33.9300	112.1600	2011-2016	38	Zhu et al. (2017)
79	34.4800	110.5700	2011-2016	32	Zhu et al. (2017)
80	36.3100	118.0500	2011-2016	47	Zhu et al. (2017)
81	37.2600	122.4600	2011-2016	48	Zhu et al. (2017)
82	37.8600	111.4600	2011-2016	52	Zhu et al. (2017)
83	39.9900	115.0200	2011-2016	72	Zhu et al. (2017)
84	39.9500	115.4300	2011-2016	79	Zhu et al. (2017)
85	39.9600	115.4300	2011-2016	79	Zhu et al. (2017)
86	40.5700	115.7700	2011-2016	41	Zhu et al. (2017)
87	40.3900	117.4600	2011-2016	30	Zhu et al. (2017)
88	40.3100	117.5700	2011-2016	45	Zhu et al. (2017)
89	41.2700	125.4100	2011-2016	52	Zhu et al. (2017)
90	42.2000	127.5100	2011-2016	67	Zhu et al. (2017)
91	42.8100	127.9100	2011-2016	99	Zhu et al. (2017)
92	44.4900	81.2600	2011-2016	153	Zhu et al. (2017)
93	44.7800	129.2400	2011-2016	72	Zhu et al. (2017)
94	45.3800	127.6000	2011-2016	63	Zhu et al. (2017)
95	46.4700	131.1100	2011-2016	89	Zhu et al. (2017)
96	47.6700	128.0700	2011-2016	57	Zhu et al. (2017)
97	47.9900	88.2600	2011-2016	46	Zhu et al. (2017)
98	51.7800	123.0200	2011-2016	109	Zhu et al. (2017)
99	52.8200	123.2400	2011-2016	100	Zhu et al. (2017)