



Supplement of

Predicting global terrestrial biomes with the LeNet convolutional neural network

Hisashi Sato and Takeshi Ise

Correspondence to: Hisashi Sato (hsatoscb@gmail.com)

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Supplementary Information

Supplementary Information 1

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Descriptions of the CNN model, employed computer, and parameter settings

A CNN consists of multiple layers: an input layer, multiple hidden layers, and a single output layer. Information (data map)

- 5 flows forward from the input layer, through the hidden layers and toward the output layer, which shows classification of the information. The building block of CNN is the artificial neuron. Each neuron receives one or more input signals, and calculates a weighted sum of input signals, and the resultant signal is transmitted to neurons in the next layer and so forth. Hidden layers of the CNN contain convolution layer(s), which is a learnable filter that activates when it detects some specific type of feature at some spatial position in the data map. Another important component of a CNN is the pooling layer(s),
- 10 which reduces the data map through down-sampling.

We employed the LeNet CNN for this study. This CNN is composed of eight layers, one input, two sets of convolution and pooling layers, two fully connected layers, and one output layer. Intuitively, the convolution and pooling layers function as a feature extraction block, while fully connected layers function as a classification block. LeNet was originally developed for classifying handwritten digits (10 categories). Recent CNNs such as AlexNet and GoogLeNet contain a larger number of hidden layers and were designed for classifying data maps into tens of thousands of categories. Here, as we categorize VCEs

into only 15 categories, LeNet provides be a reasonable option for balancing capability and computational load.

Besides the number of hidden layers, LeNet has some differences compared to other modern CNNs. In fully connected CNN layers, information is converted by an activating function before transmitting to the next layer. LeNet uses Sigmoid as an activation function, while other CNNs typically use the rectified linear unit (ReLU), which only transforms negative input

20 values into zero. For reducing the size of data map in the pooling layers, LeNet uses the subsampling approach, while other modern CNNs use the max pooling approach, which selects the maximum values in the assigned local data-map. Therefore, other CNNs should be explored for increasing accuracy for training, although this will increase the computational load.

Parameter settings remained set to the default values, except for the "% for validation" parameter, which determines the fraction of training data to be allocated for validation of the trained model. Since different climatic datasets are used for validation purposes as described in the main text, the default value of 25% for the parameter was changed to 0%, thereby allocating the entirety of the data to training.

Unchanged parameters include the training epochs, which determine how many passes through the training data are performed, and the base learning rate, which determines how quickly the CNN learns. In the training of a CNN, neuron weights and biases were updated and adjusted repeatedly by using the supervised learning back-propagation algorithm along

- 30 with the Stochastic-Gradient-Descent solver, which is the optimization function for adjusting weights according to the error they caused. The amount that the weights are updated during training is referred to as the learning rate. Learning rates that are too small result in lower training efficiency and may get stuck on a local-optimal solution. By contrast, learning rates that are too large result in a less optimal solution, may cause oscillation of model performance over training epochs, and may result in a numerical overflow in the worst case. Here, we employed the step down procedure for the learning rate: it starts
- 35 from 0.01, and when 33% of training epochs pass, the learning rate is multiplied by 0.1 (in the DIGITs implementations, policy is "Step Down", base learning rate is 0.01, step size is 33%, and gamma is 0.1). As we conducted 30 training epochs, the learning rate was 0.01 during the 1st to 10th epochs, 0.001 during 11th to 20th epochs, and 0.0001 for 21th to 30th epochs. For all training in this study, we visually confirmed that the model performance gradually increases through training epochs, and no oscillation pattern was observed.

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Global climate datasets used in this study.

Data ID	Description	Citation	URL
CRU TS v. 4.00	Observation-based climate dataset. Monthly, 0.5° grid. Period available: 1901–2015.	Harris et al. (2020)	http://www.cru.uea.a c.uk/cru/data/hrg/
NCEP/NCAR reanalysis	Climate dataset incorporating observations and numerical weather prediction model output. Daily, T62 (latitude 94 × longitude 192). Period available: 1948–present.	Kalnay et al. (1996)	https://rda.ucar.edu/d atasets/ds090.0/
HadGEM2-ES	Output of the Hadley Centre Global Environment Model version 2. Monthly, latitude 1.25 degree \times longitude 1.875 degree. Period available: 1861–2005 (historical) and 2006–2100 (future scenarios).	Collins et al. (2011)	https://esgf- node.llnl.gov/project s/cmip5/
MIROC-ESM	Output of the MIROC Earth System Model version 2010. Monthly, T42 (latitude 64 × longitude 128). Period available: 1861–2005 (historical) and 2006–2100 (future scenarios).	Watanabe et al. (2011)	https://esgf- node.llnl.gov/project s/cmip5/

Reference

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- Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K. C., Ropelewski, C., Wang, J., Leetmaa, A., Reynolds, R., Jenne, R., and Joseph, D.: The NCEP/NCAR 40-year reanalysis project, B. Am. Meteorol. Soc., 77, 437-471, 1996.
- 55 Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H., Nozawa, T., Kawase, H., Abe, M., Yokohata, T., Ise, T., Sato, H., Kato, E., Takata, K., Emori, S., and Kawamiya, M.: MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments, Geoscientific Model Development, 4, 845-872, 10.5194/gmd-4-845-2011, 2011.

Influence of VCEs on training and test accuracies for simulation of the geographical distribution of terrestrial biomes using a selection of different climate datasets. The values in brackets indicate the computational time for training. For each climate dataset, the annual mean bio-temperature and the annual precipitation from 1971 to 1980 were standardized and log transformed, then employed for drawing VCEs.

Examples of VCE, representing	Training	Test accuracy for each climatic data set					
mean annual bio- temperature and	framing	NCEP/	HadGEM2	MIROC	Augrago		
precipitation.	accuracy	NCAR	-ES	-ESM	Average		
A RGB colour tile. Red and green ranges were used to represent temperature and precipitation, respectively [15 minutes]	58.3%	45.6%	48.6%	41.3%	48.5%		
Two tiles using the "Topo.colour" colour scheme of R [34 minutes]	59.1%	45.2%	48.5%	41.6%	48.6%		
Two tiles using the "Gray.scale" colour scheme of R [23 minutes]	58.5%	45.4%	48.6%	41.8%	48.6%		
Two pie charts [22 minutes]	59.7%	45.2%	47.9%	41.4%	50.9%		

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Design of combination experiment of annual means of climatic variables and its resulting accuracies. "Air Temp" is the annual average of bio-temperature. "Prec." is the annual precipitation. "Rad Short" is the annual average of downward shortwave radiation (whole day mean). "Humid" is the annual average of the volumetric humidity of air. For models with one climate variable, the selected climatic variable was allocated to the R channel. For models with two climate variables, the R and G channels were used. For models with three climate variables, all RGB channels were used.

Model	Comb	oinations o (annua	f climate v al means)	ariables	Training	Test accuracy for each climatic data set				
no.	Air Temp	Prec	Rad Short	Humid	accuracy	NCEP/ NCAR	HadGEM2 -ES	MIROC -ESM	Average	
1	0				38.1%	34.3%	34.7%	31.5%	33.5%	
2		0			35.2%	29.5%	31.8%	28.9%	30.1%	
3			0		35.8%	30.9%	23.5%	21.0%	25.1%	
4				0	36.3%	29,4%	33.2%	25.7%	29.5%	
5	0	0			57.3%	45.6%	48.8%	41.4%	45.3%	
6	0		0		48.7%	39.9%	33.3%	30.8%	34.7%	
7	0			0	54.3%	41.4%	45.6%	40.7%	42.6%	
8		0	0		52.1%	39.8%	40.5%	36.5%	38.9%	
9		0		0	52.3%	42.2%	46.5%	35.4%	41.4%	
10			0	0	50.9%	38.4%	31.4%	27.6%	32.5%	
11	0	0	0		63.0%	46.4%	48.2%	44.6%	46.4%	
12	0	0		0	62.5%	45.1%	49.6%	42.2%	45.6%	
13	0		0	0	58.5%	41.5%	38.9%	35.3%	38.6%	
14		0	0	0	61.3%	42.0%	41.9%	36.6%	40.2%	

75	Design of combination	experiment of	f monthly means o	f climatic	variables and it	s resulting accuracies.	"Air Temp" is the
10	Debign of Comomation				witholes with it		in ionip io mo

Model	Comb	inations of (month	f climatic v ly means)	ariables	Training	Test accuracy for each climate data set				
no.	Air Temp	Prec	Rad Short	Humid	accuracy	NCEP/ NCAR	HadGEM2 -ES	MIROC -ESM	Average	
1	0				61.8%	51.3%	51.3%	39.2%	47.3%	
2		0			79.4%	41.7%	36.8%	33.9%	37.5%	
3			0		61.2%	39.5%	29.7%	31.3%	33.5%	
4				0	68.3%	39.7%	40.7%	34.8%	38.4%	
5	0	0			83.2%	52.7%	51.5%	43.5%	49.2%	
6	0		0		72.2%	51.8%	39.8%	36.9%	42.8%	
7	0			0	73.7%	52.4%	49.4%	41.8%	47.9%	
8		0	0		80.5%	48.3%	43.4%	36.3%	42.7%	
9		0		0	81.5%	47.4%	48.7%	40.1%	45.4%	
10			0	0	75.0%	48.4%	43.0%	38.6%	43.3%	
11	0	0	0		82.4%	52.1%	51.5%	42.6%	48.7%	
12	0	0		0	81.8%	51.8%	51.3%	41.2%	48.1%	
13	0		0	0	77.9%	54.9%	44.4%	42.9%	47.4%	
14		0	0	0	82.6%	49.7%	51.0%	41.8%	47.5%	

monthly average of the air temperature. Other climatic items are as described in the caption in table S3.

- Influence of transformation of climatic variables for drawing VCE on training and test accuracies of the biome mapping 80 simulations. Before drawing the VCE, each climatic item was standardized to between 0.0 and 1.0. These standardized climatic variables were then transformed by one of the four transformation schemes for each experiment. Graphs on the leftmost column show how the original variables (horizontal axis) were transformed. This experiment employs VCE with a RGB colour tile, in which the red and green ranges represent the annual mean bio-temperature and annual precipitation, 85 respectively.

Scheme to transform	Training	Test accuracy for each climatic data set						
climatic variables for drawing	accuracy	NCEP/	HadGEM2	MIROC	Average			
VCE	accuracy	NCAR	-ES	-ESM	Average			
Linear								
	57.8%	45.5%	41.3%	48.6%	45.1%			
	56.9%	45.9%	41.6%	48.2%	45.2%			
Sigmoid (gain=5)								
	56.9%	45.3%	40.9%	48.5%	44.9%			
Sigmoid (gain=10)								
	56.2%	44.5%	41.0%	48.3%	44.6%			

Design of how the monthly mean air temperature and monthly precipitation were superimposed to colour channels for 90 drawing VCE, and its resulting accuracies. "R", "G", and "B", respectively, represent the red, green, and blue channels, of 91 the RGB colour representation. Although there are no major differences in the models of either the training or test accuracies, 92 we selected model no. 4, which has the highest average test accuracy.

Madal	Colour	channel	Training	Test accuracy for each data set					
no. Air temp Prec		Drees	Training	NCEP/	HadGEM2	MIROC	Avenage		
		Prec	accuracy	NCAR	-ES	-ESM	Average		
1	R	G	81.2%	53.2%	52.2%	42.7%	49.4%		
2	R	В	81.8%	52.4%	52.3%	42.8%	49.2%		
3	G	R	81.3%	53.2%	50.5%	43.2%	49.0%		
4	В	R	81.4%	52.9%	52.4%	43.6%	49.6%		
5	G	В	82.7%	53.6%	52.3%	42.3%	49.4%		
6	В	G	81.4%	52.7%	51.0%	44.0%	49.3%		

100

Confusion matrix for biome classification for training accuracy with annual mean bio-temperature and annual precipitation. Columns represent the true classes, while rows represent the CNN model prediction. The shaded cells along the upper-left to lower-right diagonal represent correct classifications. For each cell, the upper line indicates the number of simulation grids, while the lower line indicates its percentage within the column, which in turn indicates the fraction of correct classifications of the corresponding biome class.

Predicted class 10 12 13 14 15 2 3 4 5 6 9 11 1 324 0 463 0 0 0 0 88 29 0 0 0 0 0 1 1. Polar Desert/Rock/Ice 35.8% 0.0% 51.2% 0.0% 0.0% 0.0% 0.0% 9.7% 0.1% 3.2% 0.0% 0.0% 0.0% 0.0% 0.0% 4689 650 23 145 20 12 0 4 4 0 0 0 0 2. Desert 0.0% 0.0% 0.4% 2.6% 0.1% 0.4% 0.1% 0.2% 0.1% 0.0% 0.0% 0.0% 0.0% 84.4% 11.7% 3192 48 0 50 1386 8 157 8 8 0 0 0 3. Tundra 1.0% 0.1% 65.5% 0.2% 0.0% 1.0% 0.0% 28.4% 0.2% 3.2% 0.2% 0.2% 0.0% 0.0% 0.0% 0 637 2383 119 901 391 69 28 27 13 0 0 3 0 4 4. Open Shrubland 0.0% 13.9% 8.5% 0.6% 0.3% 0.0% 0.0% 0.1% 0.0% 52.1% 2.6% 19.7% 1.5% 0.1% 0.6% 325 719 46 205 27 0 123 58 0 0 640 1 4 0 2 5. Dense Shrubland 0.0% 9.5% 0.0% 0.0% 0.2% 0.0% 2.7% 2.1% 0.0% 29.8% 33.4% 1.3% 5.7% 0.1% 15.1% 127 3190 446 0 60 8 518 213 561 520 99 140 128 0 12 6. Grassland/Steppe 0.0% 1.0% 0.1% 8.6% 3.5% 9.3% 8.6% 1.6% 7.4% 0.0% 0.2% 2.1% 53.0% 2.3% 2.1% 0 8 8 380 145 487 3680 426 18 59 542 162 0 47 932 Actual class 7. Savanna 0.1% 0.1% 0.9% 0.0% 0.7% 0.0% 5.5% 2.1% 7.1% 53.4% 6.2% 0.3% 7.9% 2.3% 13.5% 2 1 935 16 34 127 124 5750 77 940 724 317 0 11 116 8. Eg/Dc Mixed Forest 0.0% 0.0% 10.2% 0.2% 0.4% 1.4% 1.4% 62.7% 0.8% 10.2% 7.9% 3.5% 0.0% 0.1% 1.3% 0 0 0 0 0 803 334 219 2 0 0 5 0 2 0 9. Bor Dc Forest 0.0% 0.0% 0.4% 0.0% 0.0% 0.0% 0.0% 58.8% 24.5% 16.0% 0.1% 0.1% 0.0% 0.0% 0.0% 0 28 0 0 18 0 1406 163 2160 23 0 0 0 10. Bor Eg Forest 0.1% 0.0% 0.7% 0.0% 0.0% 0.5% 0.0% 0.1% 0.6% 0.0% 0.0% 0.0% 37.0% 4.3% 56.8% 0 0 6 182 17 203 0 1698 132 0 0 11. Tmp Dc Forest 0.0% 0.0% 0.0% 0.3% 0.3% 8.1% 0.8% 0.0% 0.2% 5.9% 0.0% 0.0% 0.1% 9.0% 75.4% 335 372 652 111 90 61 0 29 12 0 0 0 0 8 1 12. Tmp NI Eg-Forest 0.0% 0.0% 0.0% 0.0% 0.5% 5.4% 3.7% 20.0% 0.0% 22.3% 39.0% 0.1% 0.7% 6.6% 1.7% 0 0 20 22 53 0 208 35 0 1 38 1 67 2 2 13. Tmp BI-Eg Forest 0.0% 0.0% 0.0% 0.2% 4.5% 4.9% 11.8% 8.5% 0.0% 0.2% 46.3% 14.9% 0.4% 0.4% 7.8% 0 0 0 25 8 1397 17 1 41 16 0 71 424 2 3 14. Tro Dc Forest 0.0% 0.0% 0.0% 0.0% 1.2% 0.1% 0.4% 69.7% 0.8% 0.0% 0.1% 2.0% 0.8% 21.1% 3.5% 0 5 0.1% 4 800 17 0 0 60 61 0 32 4588 0 0 15. Tro Eg Forest 0.0% 0.0% 0.0% 0.0% 14.4% 0.3% 0.0% 0.0% 1.1% 0.0% 0.6% 82.4% 1.1%

Percentage of correct classification for all grids: 57.7%.

Abbreviations: Bor, boreal; Tmp, temperate; Tro, tropical; Eg, evergreen; Dc, deciduous; Nl, needleleaf; Bl, broadleaf.

Same as table S7, but confusion matrix for biome classification for training accuracy with monthly mean air temperature and monthly precipitation.

		Predicted class														
1		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	1. Polar Desert/Rock/Ice	574 63.4%	7 0.8%	298 32.9%	3 0.3%	0 0.0%	1 0.1%	0 0.0%	19 2.1%	0 0.0%	3 0.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
	2. Desert	5 0.1%	5048 90.9%	10 0.2%	367 6.6%	46 0.8%	65 1.2%	8 0.1%	2 0.0%	0 0.0%	0	0 0.0%	0 0.0%	1 0.0%	3 0.1%	0 0.0%
	3. Tundra	104 2.1%	2 0.0%	4059 83.3%	1 0.0%	0 0.0%	77 1.6%	10 0.2%	533 10.9%	0 0.0%	71 1.5%	8 0.2%	2 0.0%	0 0.0%	4 0.1%	2 0.0%
	4. Open Shrubland	3 0.1%	626 13.7%	11 0.2%	2778 60.7%	226 4.9%	486 10.6%	333 7.3%	1 0.0%	0 0.0%	13 0.3%	10 0.2%	31 0.7%	0 0.0%	36 0.8%	21 0.5%
	5. Dense Shrubland	0 0.0%	24 1.1%	1 0.0%	415 19.3%	955 44.4%	201 9.3%	296 13.8%	34 1.6%	0 0.0%	1 0.0%	60 2.8%	7 0.3%	8 0.4%	77 3.6%	71 3.3%
	6. Grassland/Steppe	1 0.0%	22 0.4%	45 0.7%	315 5.2%	99 1.6%	4426 73.5%	521 8.7%	211 3.5%	11 0.2%	33 0.5%	96 1.6%	69 1.1%	16 0.3%	35 0.6%	122 2.0%
Idss	7. Savanna	0 0.0%	11 0.2%	4 0.1%	241 3.5%	174 2.5%	485 7.0%	4314 62.6%	305 4.4%	62 0.9%	13 0.2%	184 2.7%	63 0.9%	61 0.9%	323 4.7%	654 9.5%
inal d	8. Eg/Dc Mixed Forest	0 0.0%	1 0.0%	660 7.2%	10 0.1%	29 0.3%	76 0.8%	175 1.9%	6700 73.0%	255 2.8%	611 6.7%	428 4.7%	96 1.0%	20 0.2%	17 0.2%	96 1.0%
ACI	9. Bor Dc Forest	0 0.0%	0 0.0%	2 0.1%	0 0.0%	0	9 0.7%	25 1.8%	208 15.2%	1079 79.0%	36 2.6%	6 0.4%	0	0 0.0%	0	0 0.0%
	10. Bor Eg Forest	0 0.0%	0 0.0%	35 0.9%	0 0.0%	0	8 0.2%	18 0.5%	758 19.9%	18 0.5%	2935 77.1%	2 0.1%	31 0.8%	0 0.0%	0	0 0.0%
	11. Tmp Dc Forest	0 0.0%	2 0.1%	1 0.0%	4 0.2%	5 0.2%	48 2.1%	33 1.5%	137 6.1%	1 0.0%	8 0.4%	1828 81.2%	127 5.6%	58 2.6%	0	0 0.0%
	12. Tmp NI Eg-Forest	0 0.0%	0 0.0%	0 0.0%	21 1.3%	21 1.3%	26 1.6%	49 2.9%	179 10.7%	0 0.0%	165 9.9%	229 13.7%	909 54.4%	53 3.2%	3 0.2%	16 1.0%
	13. Tmp Bl-Eg Forest	0 0.0%	0 0.0%	0 0.0%	4 0.9%	28 6.2%	54 12.0%	31 6.9%	19 4.2%	0 0.0%	0	44 9.8%	1 0.2%	246 54.8%	3 0.7%	19 4.2%
	14. Tro Dc Forest	0 0.0%	0 0.0%	1 0.0%	5 0.2%	20 1.0%	18 0.9%	344 17.2%	18 0.9%	0 0.0%	0	2 0.1%	0 0.0%	1 0.0%	1241 61.9%	355 17.7%
	15. Tro Eg Forest	0 0.0%	0 0.0%	0 0.0%	0	10 0.2%	47 0.8%	262 4.7%	32 0.6%	0 0.0%	0	0 0.0%	1 0.0%	2 0.0%	151 2.7%	5064 90.9%

Percentage of correct classification for all grids: 73.6%.

110 Abbreviations: Bor, boreal; Tmp, temperate; Tro, tropical; Eg, evergreen; Dc, deciduous; Nl, needleleaf; Bl, broadleaf.

Results of the sensitivity test in which training and test accuracy were compared among models trained and validated using monthly climate averaged over one of three time periods.

	Training	Test accuracy					
Time period	accuracy	NCEP/ NCAR	HadGEM2 -ES	MIROC -ESM	Average		
10 years (1971-1980; Control)	81.4%	52.9%	52.4%	43.6%	49.6%		
20 years (1961-1980)	77.5%	52.2%	52.4%	44.8%	49.8%		
30 years (1951-1980)	76.0%	52.4%	52.7%	43.7%	49.6%		

115 Table S10

Results of the sensitivity test in which training and test accuracy were compared among models trained using one of four aggregation grains of training data grids. Test accuracy for the CRU dataset in this analysis was obtained by model evaluation for grains not used in training.

Aggregation grain	Training	Test accuracy							
of CRU data grids	accuracy	CPU	NCEP/	HadGEM2	MIROC				
-		CKU	NCAR	-ES	-ESM				
1×1 (0.5°)	80.2%	80.4%	53.1%	50.5%	43.5%				
2×2 (1.0°)	80.6%	78.2%	53.3%	51.4%	42.9%				
4×4 (2.0°)	81.2%	76.1%	52.8%	51.7%	43.9%				
8×8 (4.0°)	81.0%	72.2%	52.7%	51.2%	42.6%				

Examples of training images representing annual mean bio-temperature and annual precipitation of the CRU dataset. Climatic conditions averaged over 1971 to 1980 for each biome type were employed. The bottom-right image shows how the panel colour was determined by standardized climatic variables.



Annual Precipitation

125

Examples of training images representing monthly mean air temperature and monthly precipitation from the CRU dataset. Climatic conditions, averaged from 1971 to 1980, for each biome type were employed. For the Northern hemisphere, the leftmost pillar represents the January climate, while rightmost pillar represents the December climate for each image. For the

130 Southern hemisphere, the leftmost pillar represents the July climate, while the rightmost pillar represents the June climate for each image. The image at the bottom-right corner shows how the pillar colour was determined from the standardized climatic variables.



Geographical distribution of certainty of the most plausible biome from the CNN model that was trained with either annual (a, c, e, g) or monthly (b, d, f, h) mean climate images from the CRU dataset. Four climatic datasets were employed to generate these maps. (a, b) CRU dataset; (c, d) NCEP/NCAR dataset; (e, f) output of the Had2GEM-ES dataset; (g, h) output of the MIROC-ESM dataset.



(a) Annual mean air temperature and (b) annual precipitation averaged from the 1971-1980 period of the CRU dataset. (c)

145

Differences in annual mean air temperature (1971-1980 average) and (d) annual precipitation (1971-1980 average) between the CRU dataset and the NCEP/NCAR reanalysis data. The CRU and HadGEM2-ES dataset outputs for mean air temperature and annual precipitation are presented in (e) and (f), respectively. Similarly, the CRU and MIROC-ESM dataset outputs for mean air temperature and annual precipitation are presented in (g) and (h), respectively.



150 Global biome compositions computed by the CNN model using monthly means of two climate models (Had2GEM-ES and MIROC-ESM) under historical (1971–1980) and future (2091–2100) climatic conditions. Future climatic conditions were further divided into two scenarios (RCP2.6 and RCP8.5). Differences in grid areas along the latitude were taken into consideration. Colour definitions are available in figure 1.



155

(a) Mean annual air temperature and (b) annual precipitation averaged from the 1971–1980 period of the HadGEM2-EM dataset. Changes in (c) mean annual air temperature and (d) precipitation from 1971–1980 to 2091–2100 under the RCP2.6 scenario. Changes in (e) mean annual air temperature and (f) precipitation from 1971–1980 to 2091–2100 under the RCP8.5 scenario.

160 sce



Same as figure S6, but with the MIROC-ESM dataset.



Same as figure 5, but certainty map of the predicted biome.

