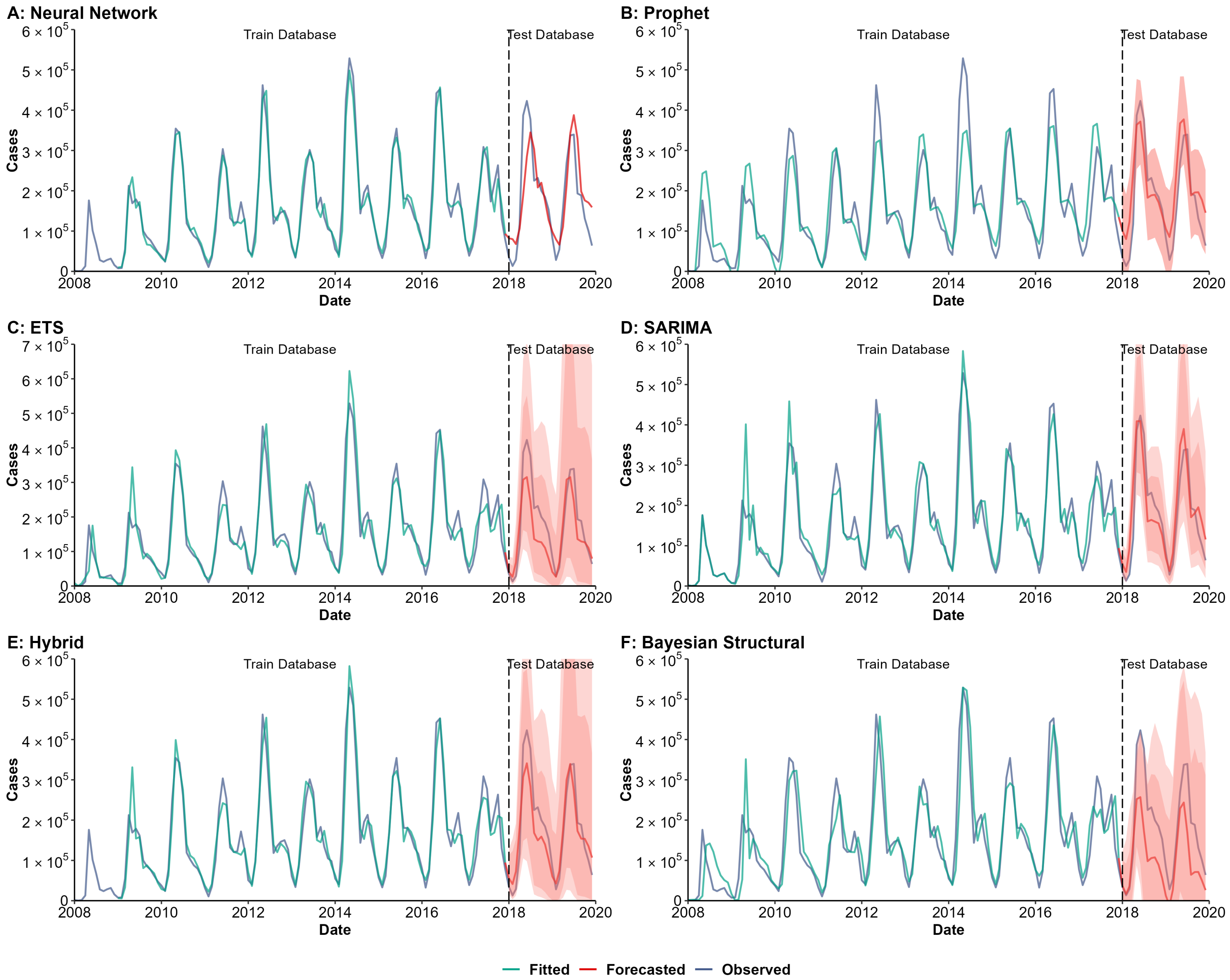
Supplementary Appendix 1:

Temporal trends and shifts of 24 notifiable infectious diseases in China before and after the COVID-19 epidemic



G : RMSE of Models

Method	Train	Test	All
Neural Network	23166.29	70971.66	36809.15
Prophet	54896.06	63577.44	56435.77
ETS	40789.02	63654.84	45406.79
SARIMA	41585.50	53910.64	43880.76
Hybrid*	33623.95	48913.70	36878.46
Bayesian Structural	55537.49	98552.75	64723.40

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	13.13	38.83	17.80
Prophet	37.35	42.87	38.27
ETS	22.63	35.12	24.71
SARIMA	18.83	33.32	21.24
Hybrid*	16.08	32.86	19.13
Bayesian Structural	34.59	64.98	39.65

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.29	1.07	0.42
Prophet	0.65	1.08	0.83
ETS	0.47	1.07	0.56
SARIMA	0.44	0.71	0.49
Hybrid*	0.38	0.84	0.47
Bayesian Structural	0.67	1.80	0.85

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

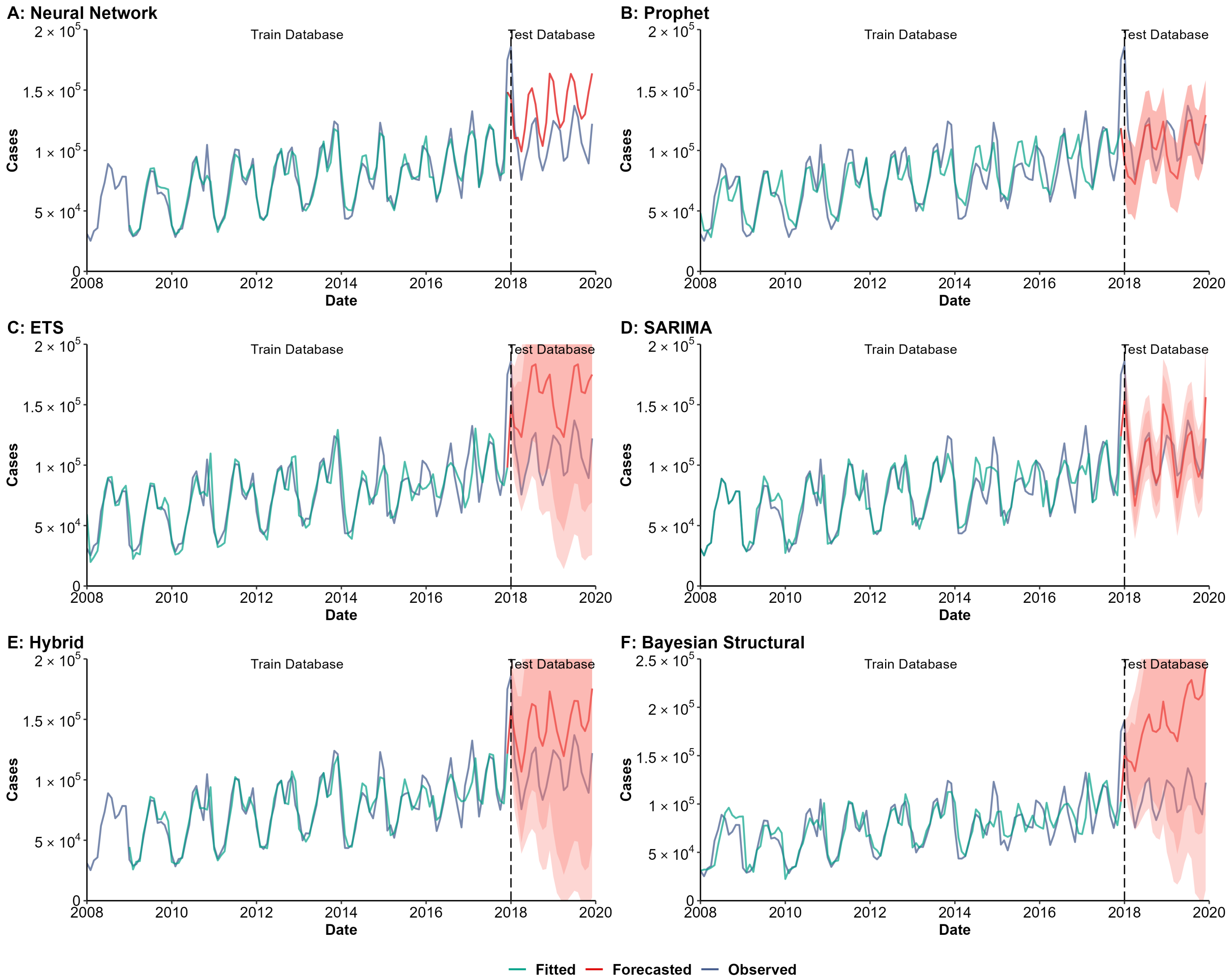
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.96	0.66	0.90
Prophet	0.78	0.79	0.77
ETS	0.88	0.81	0.86
SARIMA	0.88	0.81	0.87
Hybrid*	0.92	0.88	0.90
Bayesian Structural	0.78	0.81	0.71

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 1. Training and comparing variant time series models for hand, foot, and mouth disease (HFMD).

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	6985.44	32542.37	15247.00
Prophet	15061.22	26530.72	17502.77
ETS	14680.65	52087.52	25135.36
SARIMA	12083.49	15076.35	12631.64
Hybrid*	10831.05	38817.79	19234.08
Bayesian Structural	16986.54	80925.42	36495.74

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	6.55	23.09	9.56
Prophet	15.13	16.02	15.28
ETS	13.26	36.59	17.15
SARIMA	10.37	9.05	10.15
Hybrid*	9.38	29.40	13.02
Bayesian Structural	15.32	52.15	21.46

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.39	1.76	0.69
Prophet	0.76	1.56	1.05
ETS	0.66	4.02	1.17
SARIMA	0.59	0.50	0.56
Hybrid*	0.49	2.45	0.96
Bayesian Structural	0.80	6.24	1.79

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

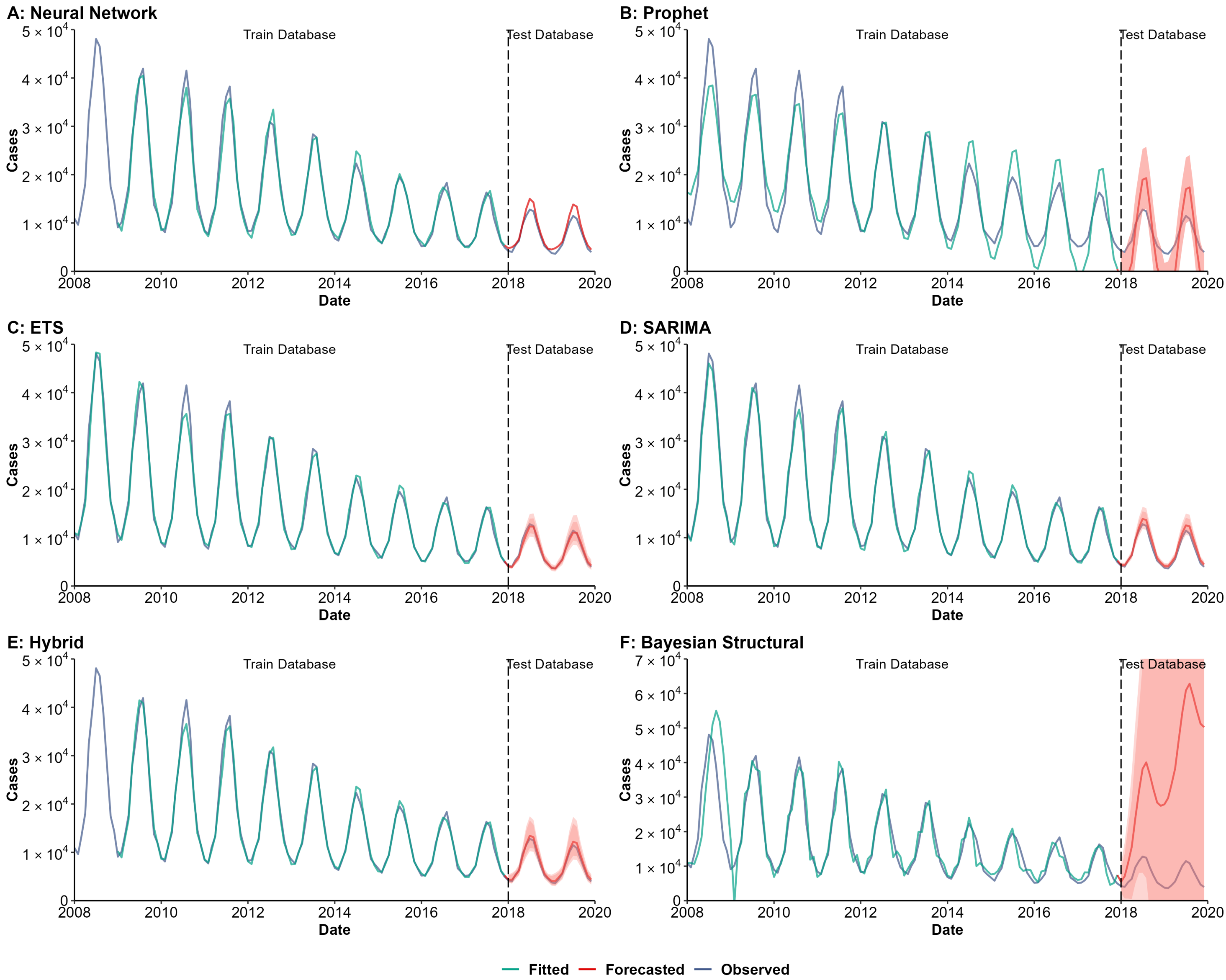
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.93	0.21	0.79
Prophet	0.67	0.05	0.63
ETS	0.69	0.06	0.61
SARIMA	0.79	0.63	0.81
Hybrid*	0.83	0.39	0.72
Bayesian Structural	0.59	0.02	0.47

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 2. Training and comparing variant time series models for infectious diarrhea.

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	1341.81	1165.42	1311.50
Prophet	3405.67	5471.87	3828.28
ETS	1253.26	425.26	1157.16
SARIMA	1202.91	776.69	1142.96
Hybrid*	1138.60	516.65	1053.20
Bayesian Structural	4875.02	32607.31	14036.06

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	5.97	12.07	7.08
Prophet	25.90	108.66	39.69
ETS	4.50	4.48	4.50
SARIMA	4.92	8.70	5.55
Hybrid*	4.53	6.34	4.86
Bayesian Structural	17.83	123.02	35.36

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.26	0.55	0.29
Prophet	0.69	1.27	0.79
ETS	0.20	0.25	0.21
SARIMA	0.22	0.43	0.23
Hybrid*	0.20	0.30	0.22
Bayesian Structural	0.71	6.98	1.66

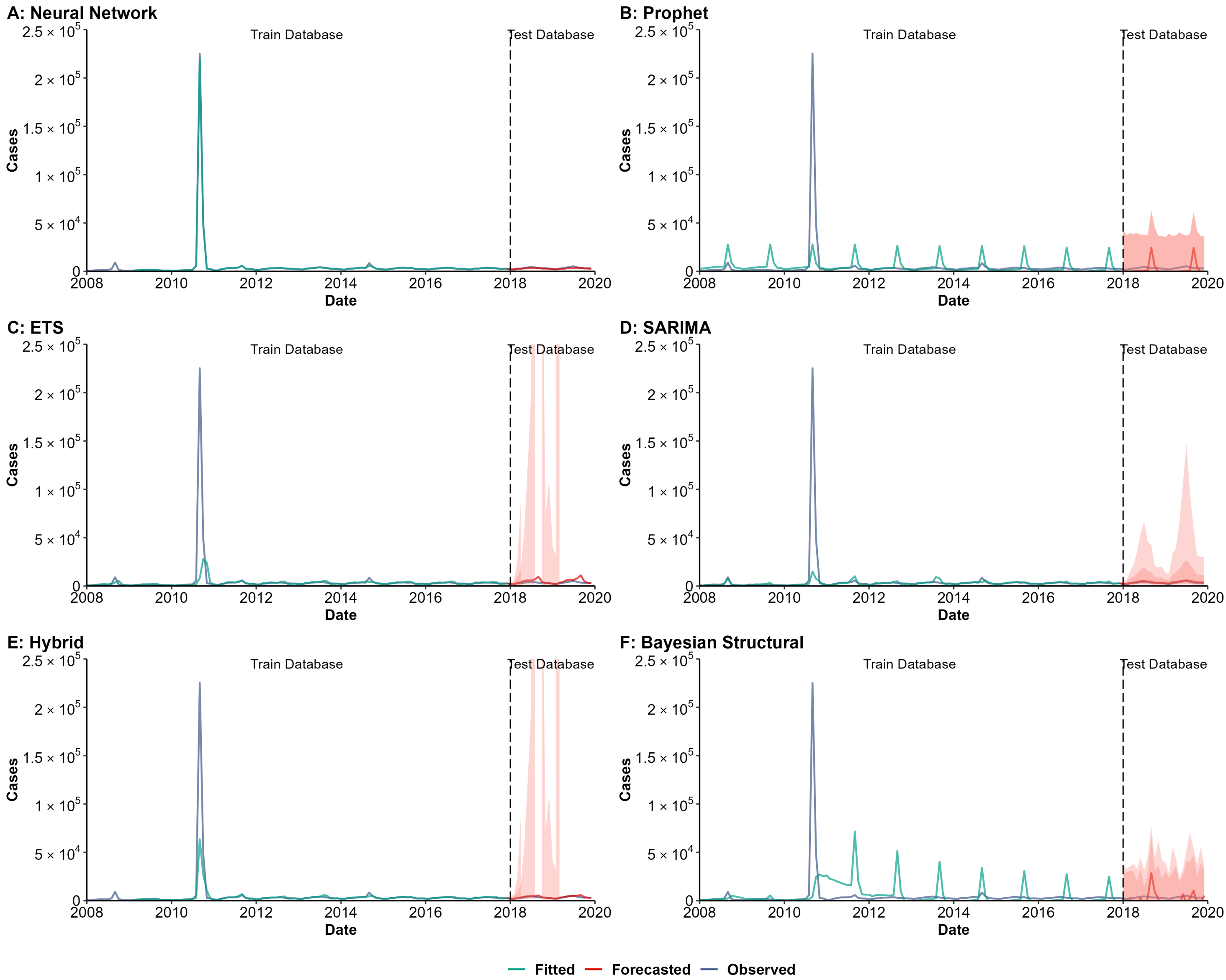
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.98	0.98	0.98
Prophet	0.89	0.97	0.87
ETS	0.99	0.98	0.99
SARIMA	0.99	0.99	0.99
Hybrid*	0.99	0.99	0.99
Bayesian Structural	0.81	0.20	0.21

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 3. Training and comparing variant time series models for dysentery. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	543.35	681.98	571.27
Prophet	19467.75	6906.05	17993.79
ETS	20016.56	2443.01	18299.74
SARIMA	19596.50	750.75	17891.70
Hybrid*	15799.07	779.98	14282.58
Bayesian Structural	23230.53	7742.52	21440.75

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	2.31	16.00	4.82
Prophet	83.04	168.50	97.29
ETS	22.76	30.15	23.99
SARIMA	20.55	18.79	20.26
Hybrid*	14.04	13.57	13.95
Bayesian Structural	119.92	145.03	124.11

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.03	2.01	0.05
Prophet	1.22	1.08	1.21
ETS	0.63	1.08	2.22
SARIMA	2.39	1.38	2.31
Hybrid*	0.46	0.88	1.24
Bayesian Structural	1.82	0.81	1.37

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

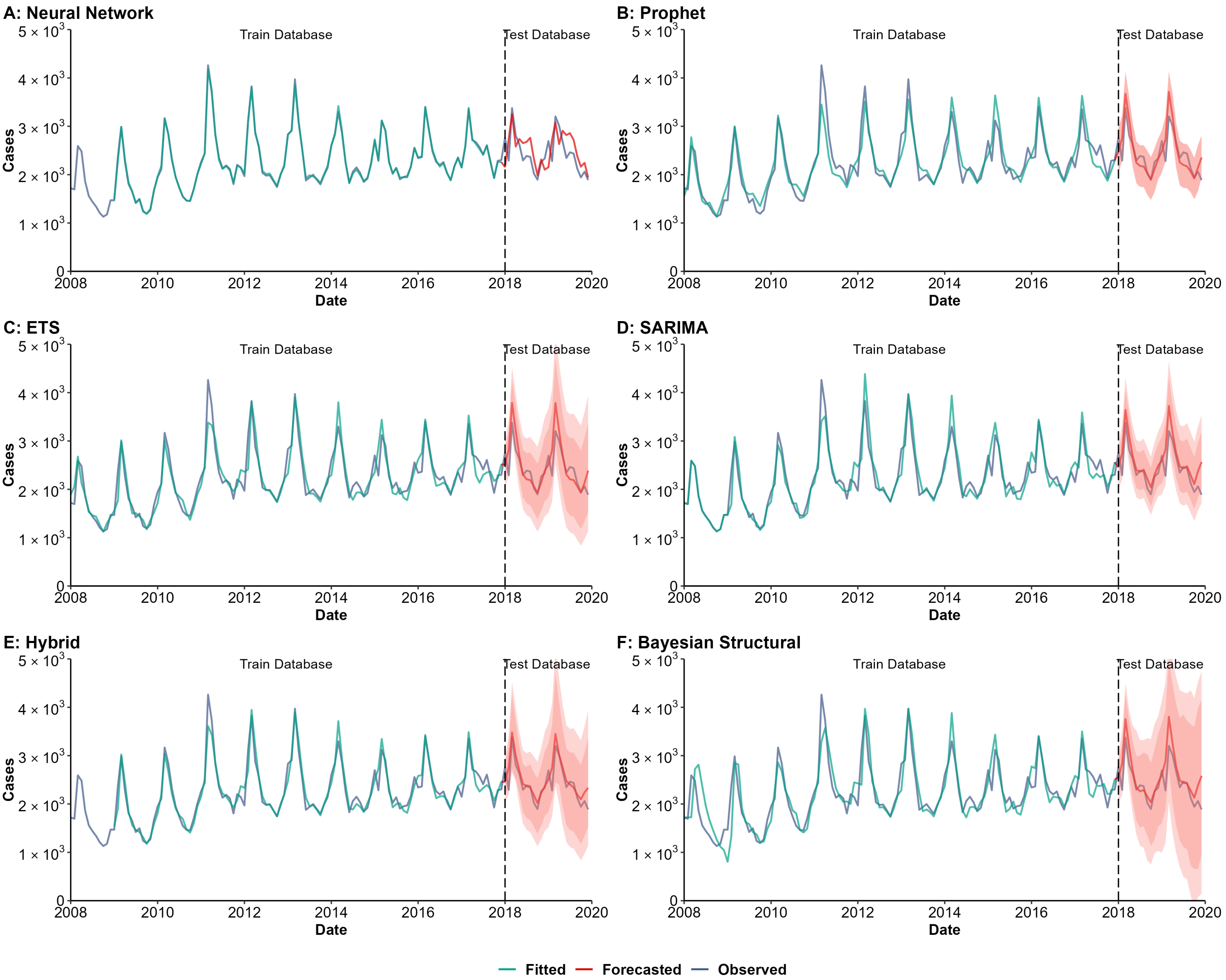
J : R-squared of Models

Method	Train	Test	All
Neural Network	1.00	0.69	1.00
Prophet	0.11	0.01	0.10
ETS	0.09	0.43	0.08
SARIMA	0.37	0.91	0.34
Hybrid*	0.94	0.66	0.93
Bayesian Structural	0.00	0.02	0.00

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 4. Training and comparing variant time series models for acute hemorrhagic conjunctivitis (AHC).

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	30.96	322.84	140.48
Prophet	223.62	254.14	228.99
ETS	222.31	277.30	232.38
SARIMA	230.76	273.79	238.47
Hybrid*	167.10	207.63	175.16
Bayesian Structural	308.89	301.30	307.64

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	0.98	11.47	2.89
Prophet	7.39	7.72	7.45
ETS	6.96	7.95	7.13
SARIMA	6.43	8.26	6.73
Hybrid*	5.07	6.45	5.32
Bayesian Structural	10.03	8.68	9.81

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.07	1.03	0.22
Prophet	0.51	0.65	0.58
ETS	0.48	0.65	0.55
SARIMA	0.47	0.71	0.51
Hybrid*	0.35	0.66	0.43
Bayesian Structural	0.66	0.75	0.70

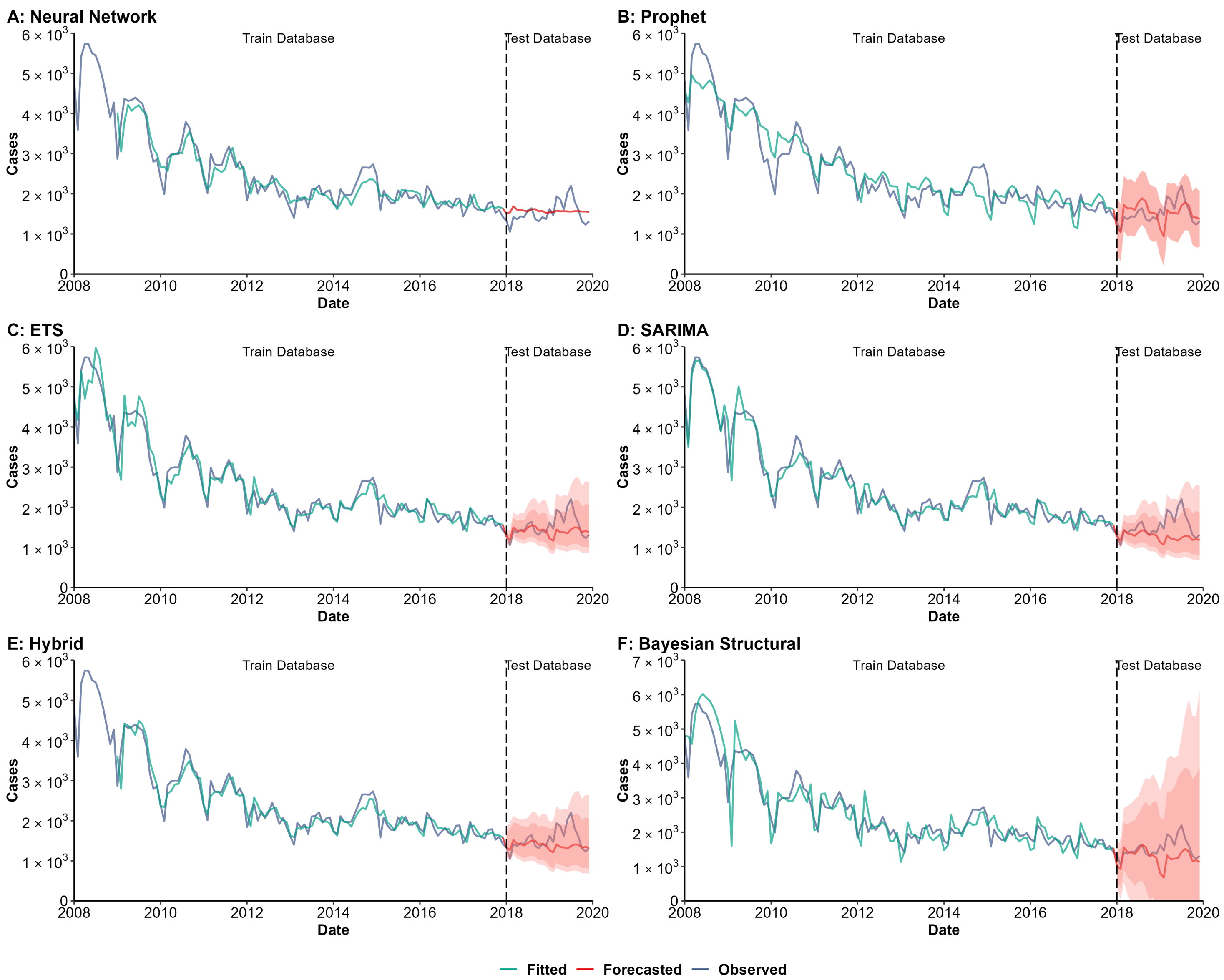
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	1.00	0.42	0.93
Prophet	0.86	0.75	0.84
ETS	0.86	0.75	0.84
SARIMA	0.86	0.74	0.85
Hybrid*	0.92	0.78	0.90
Bayesian Structural	0.76	0.72	0.75

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 5. Training and comparing variant time series models for hepatitis E. (A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	263.66	270.96	265.00
Prophet	357.82	287.41	347.08
ETS	264.30	292.03	269.12
SARIMA	252.13	388.66	279.56
Hybrid*	209.29	314.21	231.93
Bayesian Structural	408.83	398.95	407.20

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	8.39	14.44	9.49
Prophet	10.63	15.66	11.47
ETS	6.94	13.47	8.03
SARIMA	6.80	18.57	8.76
Hybrid*	6.46	13.99	7.83
Bayesian Structural	10.83	20.47	12.44

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	1.29	8.52	1.56
Prophet	1.01	1.52	1.46
ETS	0.71	2.72	0.86
SARIMA	0.73	3.81	0.91
Hybrid*	0.65	3.45	1.02
Bayesian Structural	1.05	1.78	0.88

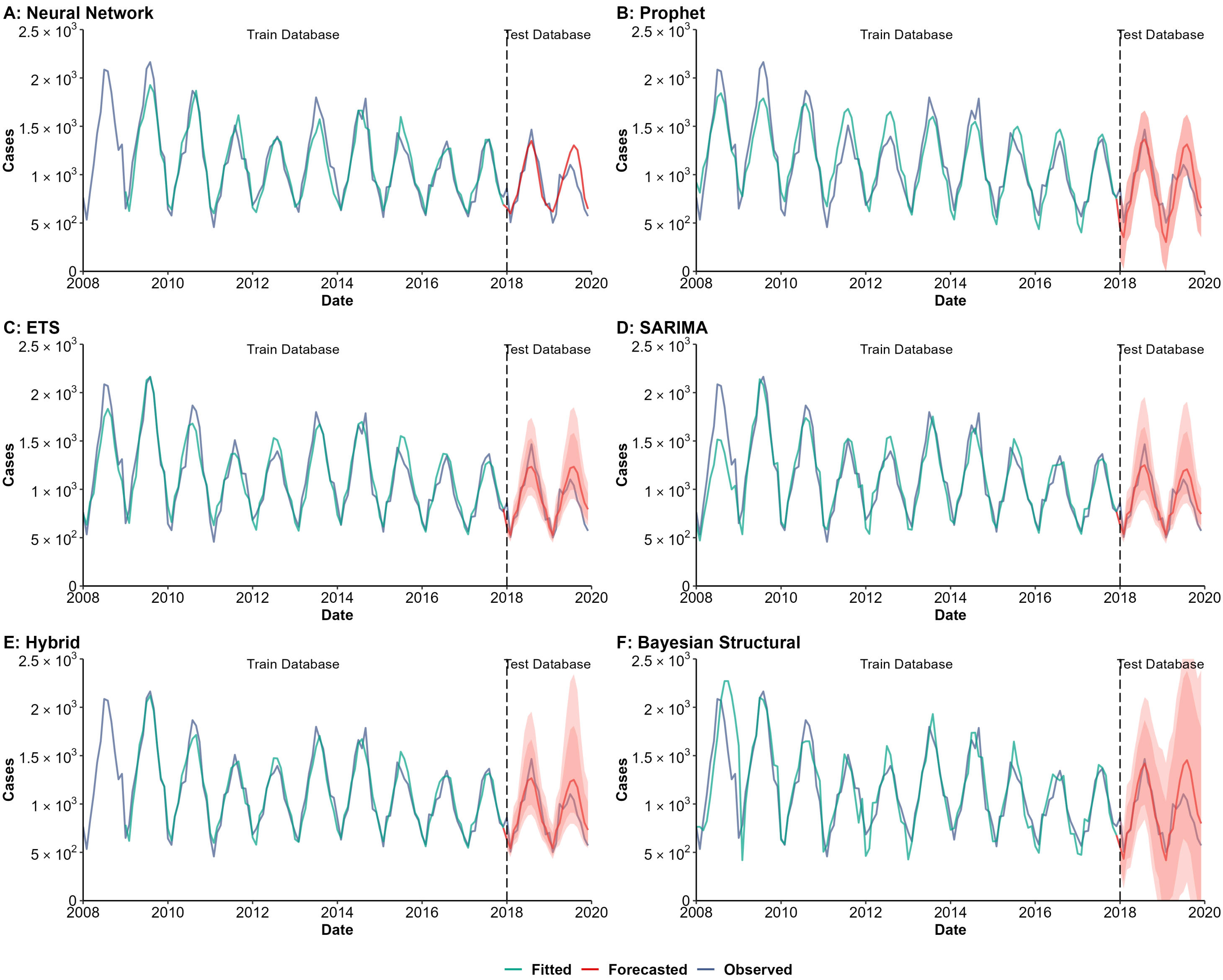
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.87	0.00	0.87
Prophet	0.89	0.14	0.89
ETS	0.94	0.06	0.94
SARIMA	0.94	0.00	0.94
Hybrid*	0.92	0.00	0.91
Bayesian Structural	0.88	0.06	0.89

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 6. Training and comparing variant time series models for hepatitis A. (A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	118.60	142.54	123.30
Prophet	157.00	180.27	161.11
ETS	114.48	146.08	120.33
SARIMA	148.40	131.32	145.69
Hybrid*	91.17	137.50	101.18
Bayesian Structural	205.33	203.74	205.07

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	8.51	12.76	9.28
Prophet	12.04	18.89	13.18
ETS	8.20	13.64	9.11
SARIMA	9.43	12.75	9.98
Hybrid*	6.83	13.25	8.00
Bayesian Structural	12.74	17.62	13.56

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.57	0.89	0.62
Prophet	0.70	0.85	0.77
ETS	0.48	1.04	0.59
SARIMA	0.61	0.96	0.65
Hybrid*	0.42	0.97	0.51
Bayesian Structural	0.74	0.96	0.72

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

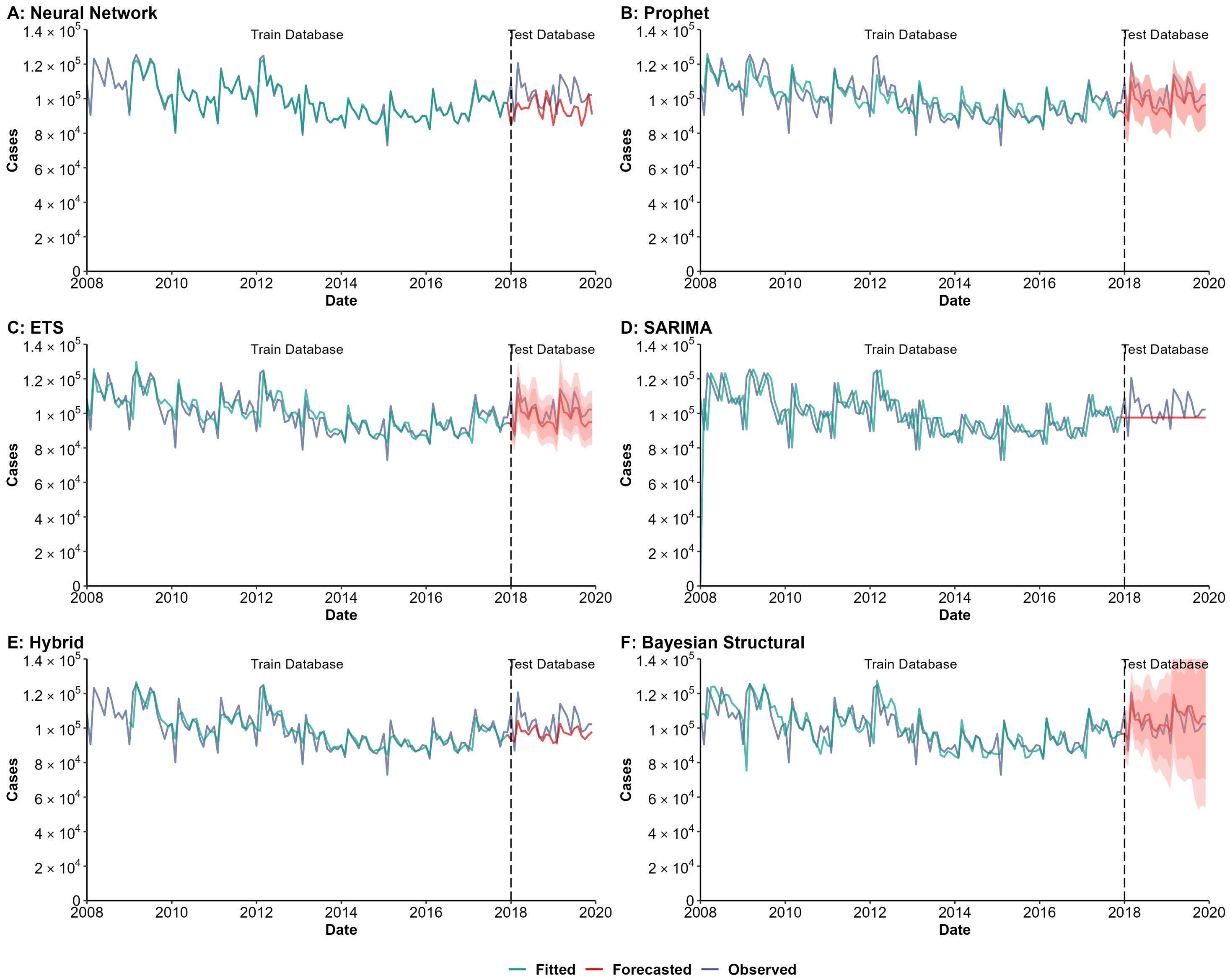
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.90	0.72	0.88
Prophet	0.84	0.71	0.82
ETS	0.91	0.67	0.90
SARIMA	0.86	0.73	0.86
Hybrid*	0.94	0.72	0.92
Bayesian Structural	0.78	0.65	0.77

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 7. Training and comparing variant time series models for enteric fever.

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	1042.85	12621.77	5463.98
Prophet	6373.59	7132.9	6506.30
ETS	6186.51	6740.76	6282.28
SARIMA	15019.02	9396.49	14236.98
Hybrid*	5483.07	8521.07	6148.12
Bayesian Structural	8381.15	5365.91	7958.34

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	0.71	10.55	2.50
Prophet	4.51	5.59	4.69
ETS	4.23	5.29	4.41
SARIMA	9.86	7.33	9.44
Hybrid*	3.73	6.67	4.26
Bayesian Structural	5.35	4.52	5.22

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.10	1.61	0.35
Prophet	0.54	1.06	0.87
ETS	0.51	0.98	0.78
SARIMA	0.99	Inf	1.16
Hybrid*	0.46	1.94	1.02
Bayesian Structural	0.65	0.91	0.83

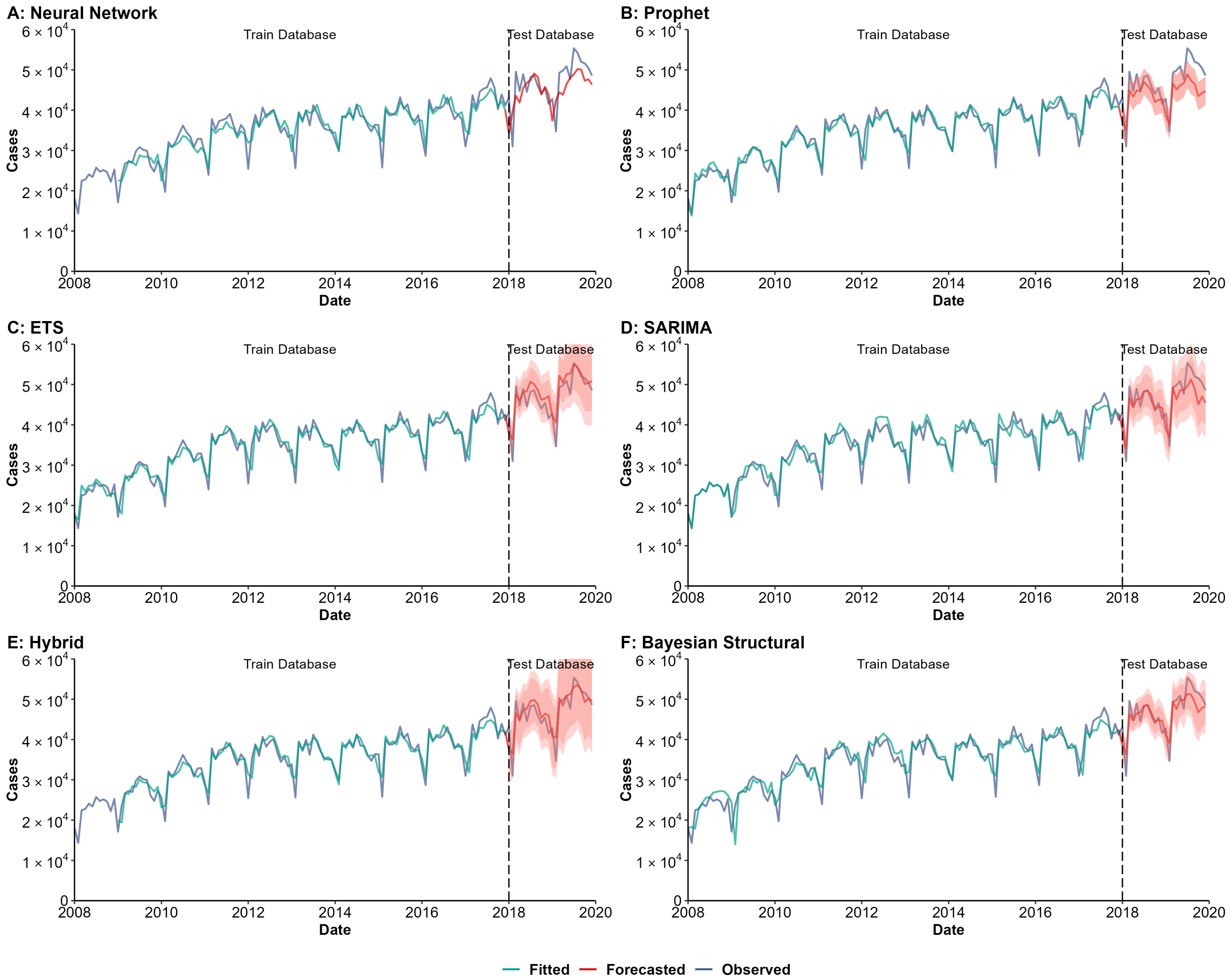
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.99	0.02	0.75
Prophet	0.67	0.67	0.64
ETS	0.70	0.71	0.67
SARIMA	0.10		0.09
Hybrid*	0.74	0.51	0.66
Bayesian Structural	0.54	0.58	0.55

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 8. Training and comparing variant time series models for hepatitis B. (A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	2281.29	4500.74	2817.99
Prophet	1746.37	4223.24	2348.22
ETS	1865.64	2945.75	2084.88
SARIMA	1943.45	2973.30	2149.63
Hybrid*	1826.06	2747.84	2025.11
Bayesian Structural	2469.89	2717.47	2512.84

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	5.13	8.43	5.73
Prophet	4.05	8.02	4.71
ETS	4.45	5.24	4.58
SARIMA	4.30	5.40	4.48
Hybrid*	4.19	4.93	4.33
Bayesian Structural	5.85	4.86	5.68

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.79	1.63	0.94
Prophet	0.41	1.65	0.74
ETS	0.45	0.97	0.70
SARIMA	0.57	0.84	0.62
Hybrid*	0.44	0.95	0.69
Bayesian Structural	0.58	0.99	0.87

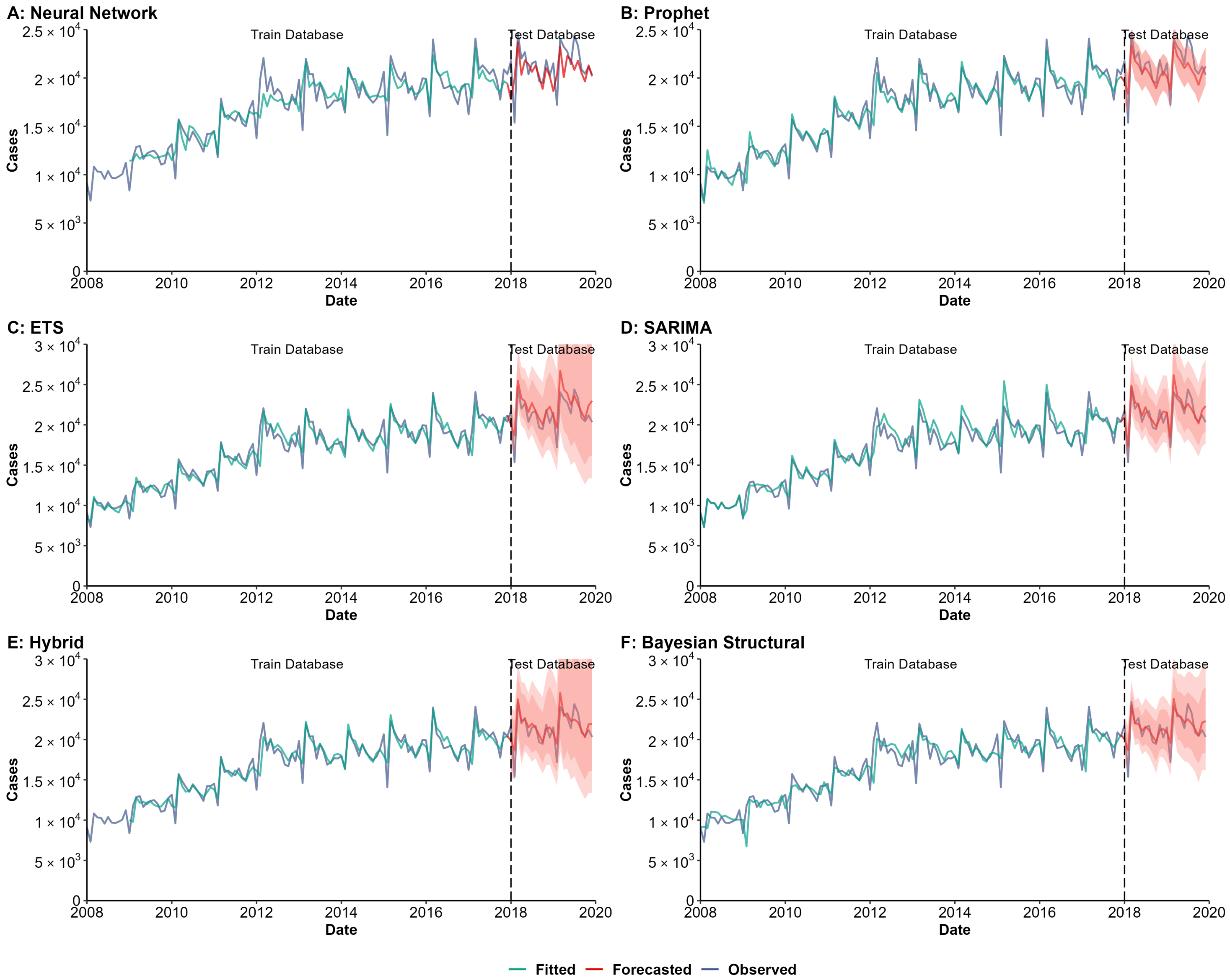
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.84	0.42	0.85
Prophet	0.93	0.76	0.93
ETS	0.93	0.78	0.94
SARIMA	0.92	0.78	0.93
Hybrid*	0.90	0.76	0.92
Bayesian Structural	0.87	0.80	0.90

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 9. Training and comparing variant time series models for syphilis. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	1312.88	1933.97	1445.79
Prophet	1006.91	1381.92	1078.50
ETS	1062.58	1478.36	1142.43
SARIMA	1076.37	1059.44	1073.56
Hybrid*	1021.07	1239.54	1064.13
Bayesian Structural	1336.63	1208.47	1316.14

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	5.75	6.89	5.96
Prophet	4.50	5.42	4.65
ETS	4.85	5.74	5.00
SARIMA	4.61	4.11	4.53
Hybrid*	4.39	4.64	4.43
Bayesian Structural	6.26	4.42	5.96

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.99	0.88	0.96
Prophet	0.44	0.94	0.66
ETS	0.48	0.73	0.65
SARIMA	0.61	0.49	0.59
Hybrid*	0.43	0.68	0.65
Bayesian Structural	0.59	0.73	0.94

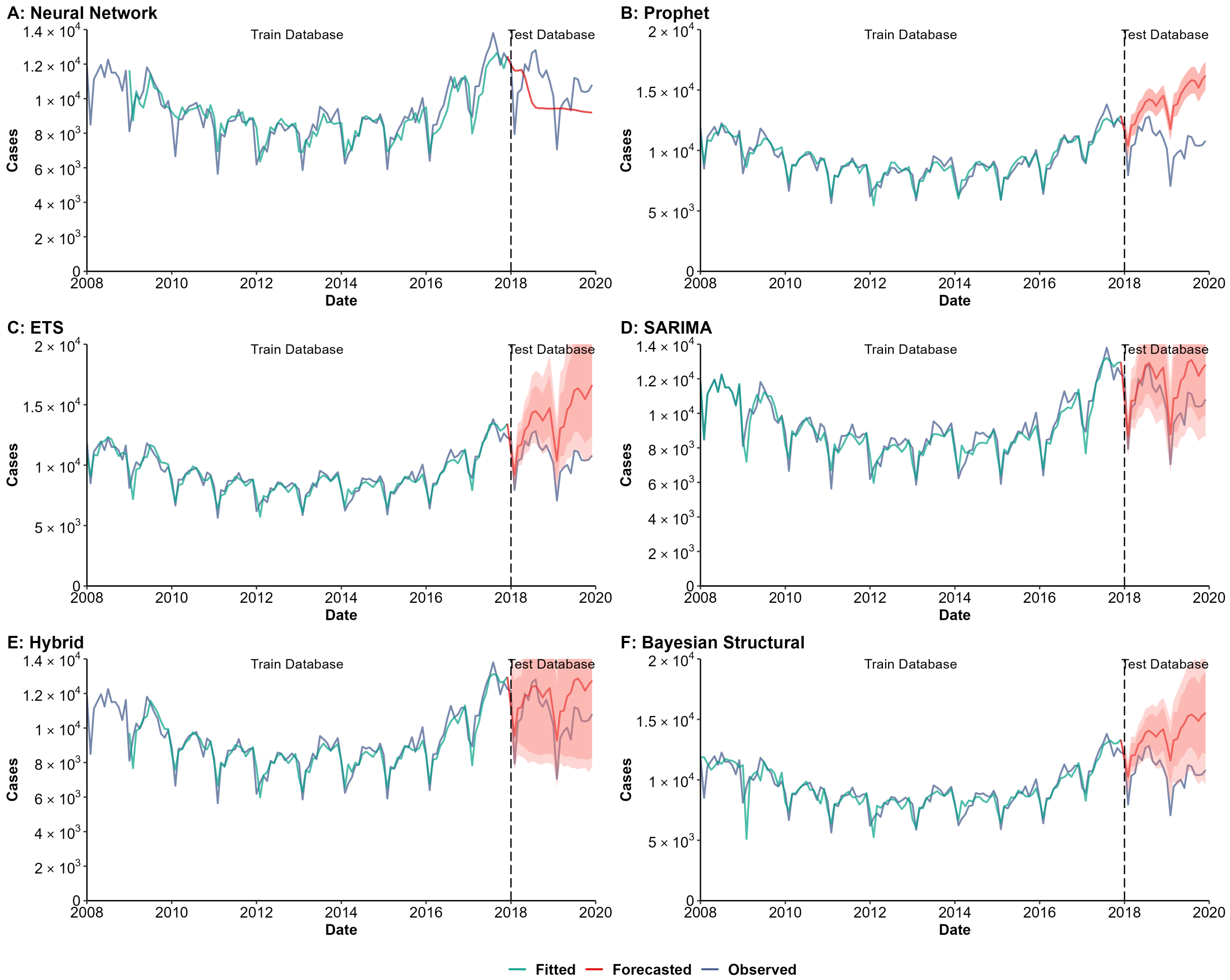
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.83	0.24	0.82
Prophet	0.93	0.69	0.93
ETS	0.92	0.68	0.92
SARIMA	0.93	0.77	0.94
Hybrid*	0.90	0.68	0.90
Bayesian Structural	0.88	0.70	0.89

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 10. Training and comparing variant time series models for hepatitis C. (A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	768.48	1740.44	1016.83
Prophet	472.50	3677.86	1562.21
ETS	528.79	3631.33	1559.10
SARIMA	531.86	1435.89	761.16
Hybrid*	512.26	1421.89	763.08
Bayesian Structural	803.90	3352.88	1553.12

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	6.21	14.24	7.67
Prophet	4.06	27.17	7.91
ETS	4.51	26.01	8.10
SARIMA	4.50	11.09	5.60
Hybrid*	4.28	11.32	5.56
Bayesian Structural	5.78	25.16	9.01

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.92	11.56	1.39
Prophet	0.47	5.15	1.37
ETS	0.52	3.45	1.26
SARIMA	0.58	1.58	0.76
Hybrid*	0.52	2.04	0.88
Bayesian Structural	0.67	4.99	1.37

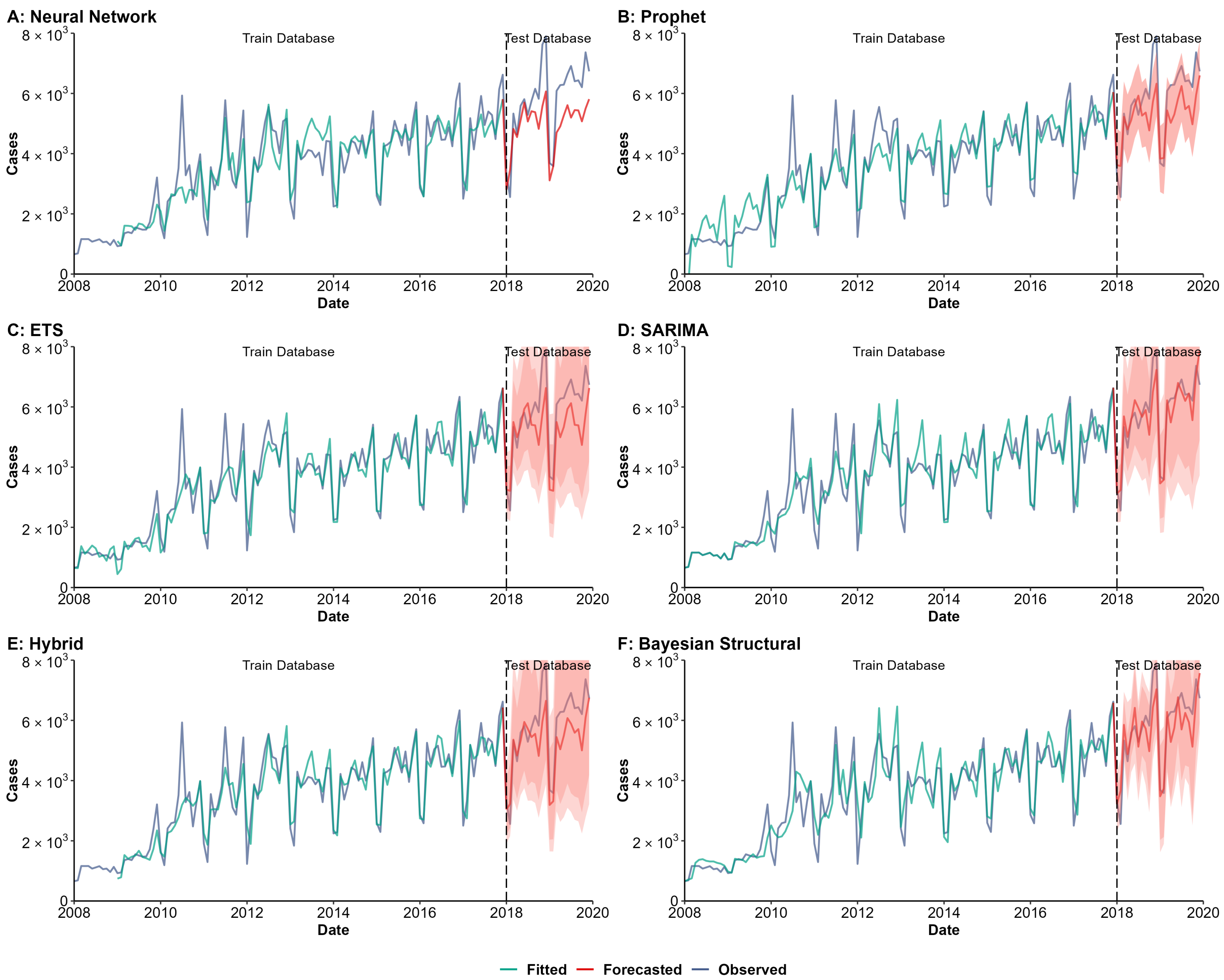
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.76	0.00	0.63
Prophet	0.92	0.09	0.60
ETS	0.90	0.17	0.63
SARIMA	0.91	0.52	0.83
Hybrid*	0.90	0.51	0.82
Bayesian Structural	0.78	0.13	0.59

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 11. Training and comparing variant time series models for gonorrhea. (A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	596.07	1073.55	707.28
Prophet	573.11	895.33	638.21
ETS	495.51	902.15	583.31
SARIMA	551.30	518.54	545.98
Hybrid*	495.41	794.69	561.81
Bayesian Structural	612.22	659.41	620.33

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	12.69	16.54	13.39
Prophet	19.42	13.55	18.44
ETS	11.50	13.56	11.84
SARIMA	10.56	7.26	10.01
Hybrid*	10.17	11.98	10.50
Bayesian Structural	13.89	9.71	13.19

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.69	1.55	0.81
Prophet	0.54	1.16	0.70
ETS	0.42	0.97	0.60
SARIMA	0.54	0.45	0.51
Hybrid*	0.39	0.88	0.57
Bayesian Structural	0.53	0.51	0.58

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

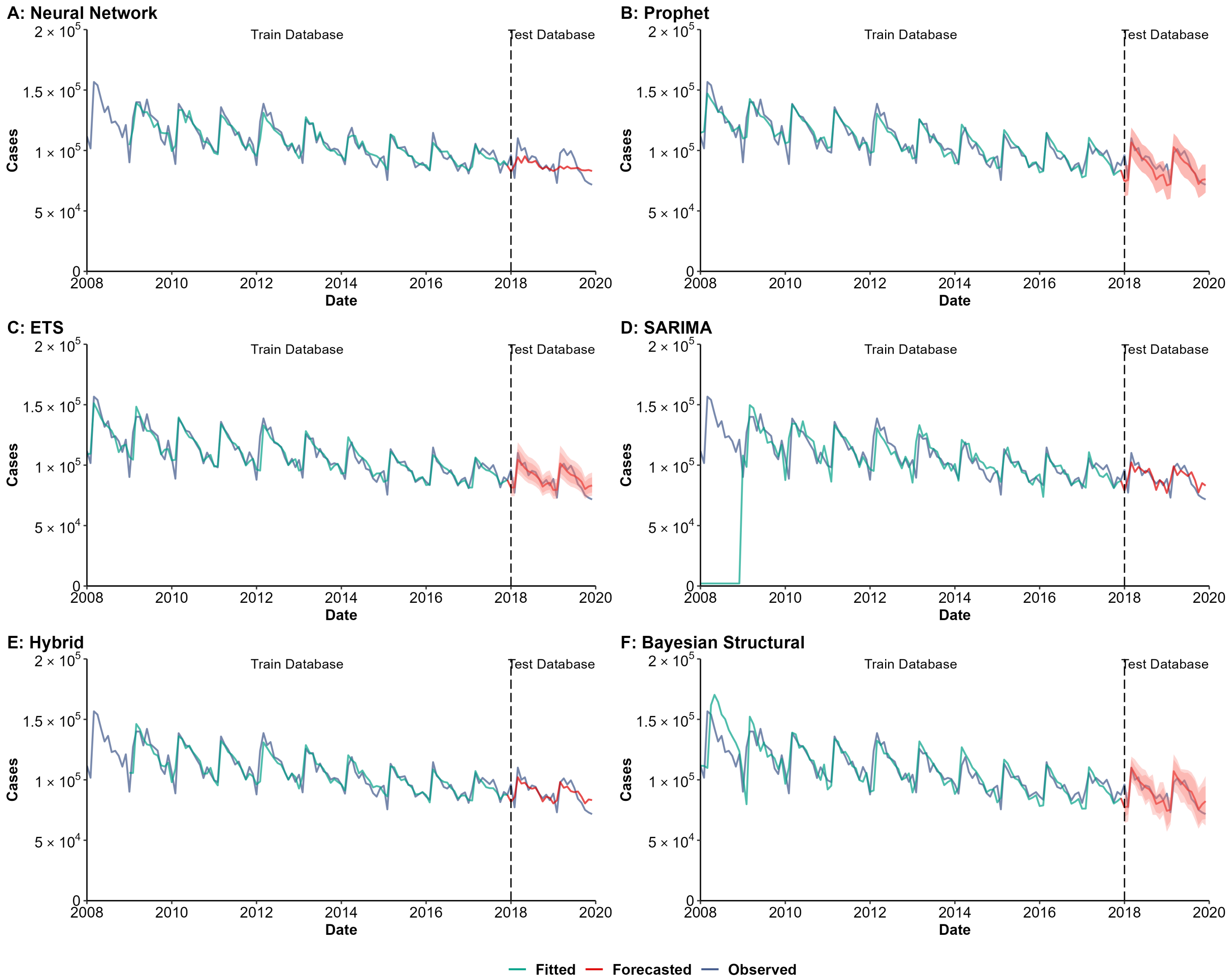
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.81	0.81	0.82
Prophet	0.86	0.79	0.87
ETS	0.90	0.74	0.90
SARIMA	0.87	0.85	0.90
Hybrid*	0.87	0.83	0.88
Bayesian Structural	0.84	0.78	0.87

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 12. Training and comparing variant time series models for acquired immunodeficiency syndrome (AIDS).

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	5030.28	9071.84	5972.14
Prophet	6212.31	7142.68	6376.80
ETS	5942.67	5897.21	5935.12
SARIMA	40903.90	7918.45	37479.66
Hybrid*	5965.29	6643.48	6094.22
Bayesian Structural	10818.75	6471.70	10223.42

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	3.60	8.56	4.50
Prophet	4.20	5.91	4.49
ETS	3.73	5.55	4.03
SARIMA	24.50	7.31	21.64
Hybrid*	3.84	6.24	4.28
Bayesian Structural	6.34	5.22	6.16

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.65	3.27	0.87
Prophet	0.48	0.82	0.72
ETS	0.43	1.10	0.67
SARIMA	2.03	0.99	1.90
Hybrid*	0.46	1.31	0.73
Bayesian Structural	0.76	0.72	0.79

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

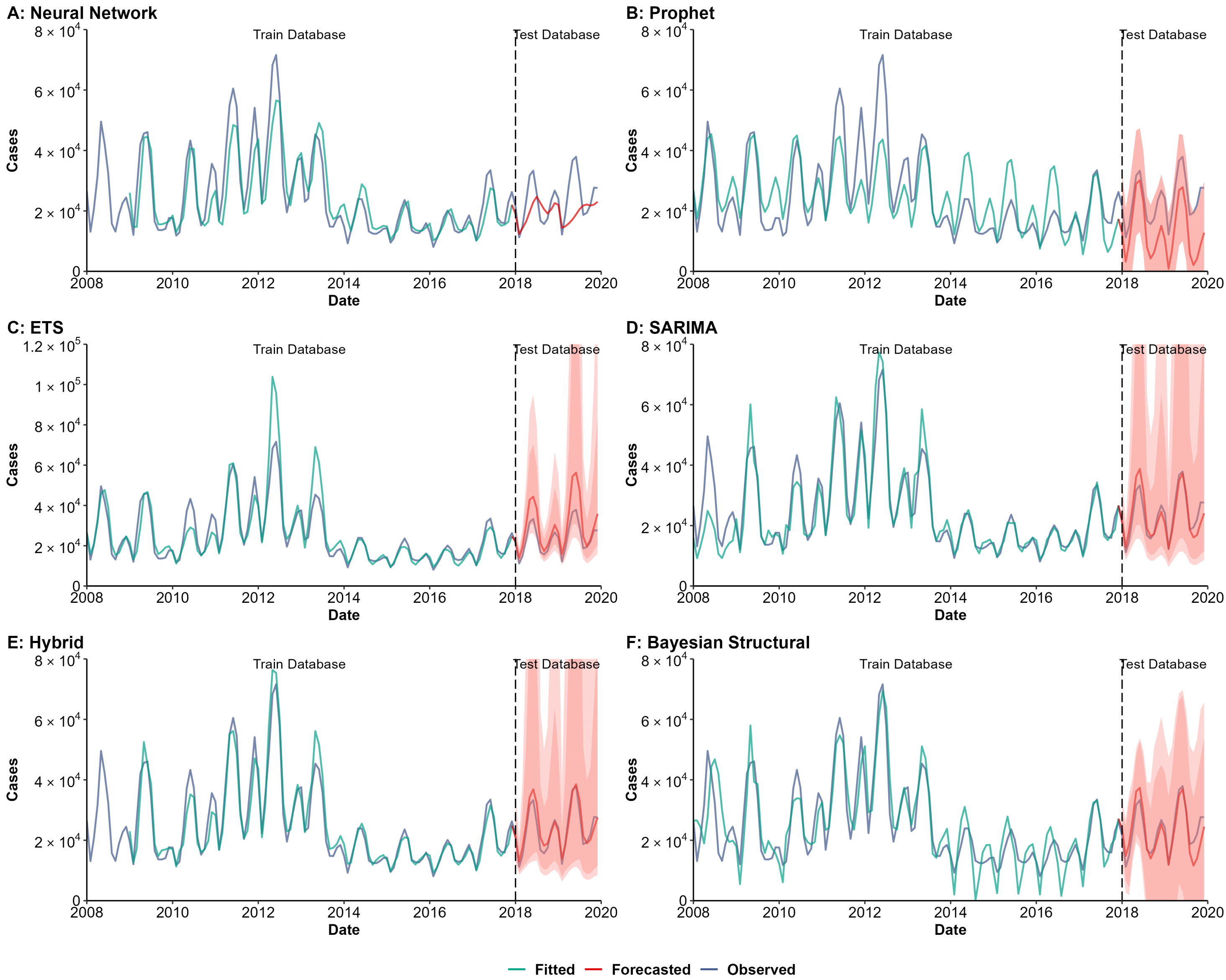
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.90	0.37	0.87
Prophet	0.86	0.69	0.87
ETS	0.88	0.68	0.89
SARIMA	0.00	0.41	0.00
Hybrid*	0.85	0.63	0.86
Bayesian Structural	0.71	0.65	0.74

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 13. Training and comparing variant time series models for tuberculosis.

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	6262.74	7847.89	6579.42
Prophet	8694.83	11301.79	9180.87
ETS	6438.00	8451.67	6815.05
SARIMA	5460.20	3226.85	5155.60
Hybrid*	3622.74	2517.62	3448.26
Bayesian Structural	6631.07	3784.71	6247.39

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	17.24	24.85	18.63
Prophet	27.51	72.56	35.01
ETS	12.86	21.30	14.27
SARIMA	14.06	11.14	13.58
Hybrid*	10.17	8.98	9.95
Bayesian Structural	27.89	14.49	25.65

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.85	2.93	1.01
Prophet	1.01	1.58	1.12
ETS	0.56	0.79	0.59
SARIMA	0.51	0.46	0.50
Hybrid*	0.41	0.37	0.42
Bayesian Structural	0.77	0.49	0.65

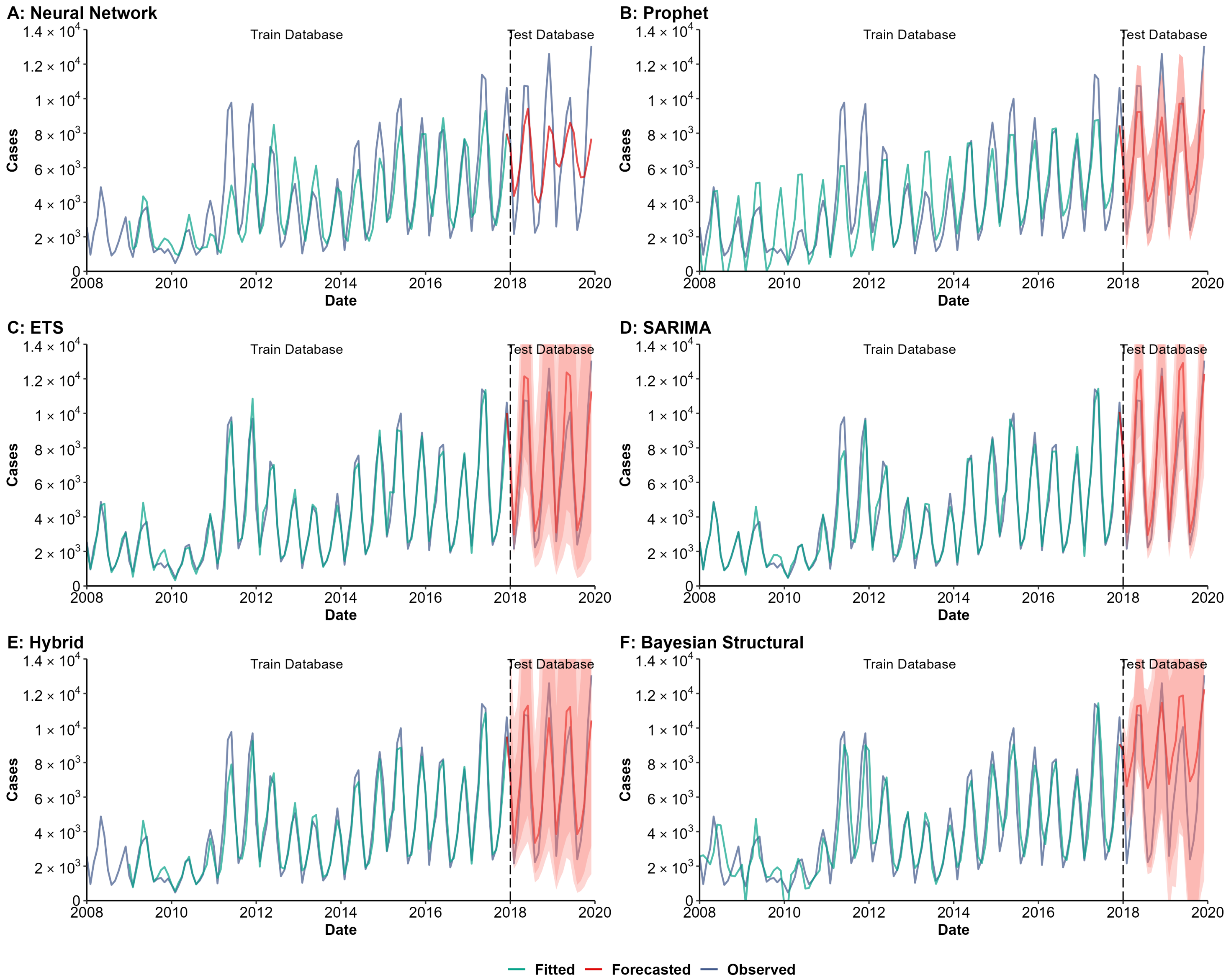
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.80	0.12	0.75
Prophet	0.58	0.76	0.51
ETS	0.86	0.90	0.84
SARIMA	0.86	0.82	0.86
Hybrid*	0.93	0.90	0.93
Bayesian Structural	0.78	0.78	0.78

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 14. Training and comparing variant time series models for mumps. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	1558.42	2408.55	1744.09
Prophet	1374.66	1735.93	1441.18
ETS	510.89	1332.81	716.64
SARIMA	572.96	1233.43	726.03
Hybrid*	680.75	1240.45	811.75
Bayesian Structural	1171.60	2831.52	1574.84

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	29.92	32.53	30.40
Prophet	37.43	25.24	35.40
ETS	11.00	18.69	12.28
SARIMA	10.42	16.31	11.40
Hybrid*	13.08	18.91	14.14
Bayesian Structural	28.96	40.55	30.89

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.84	1.61	0.97
Prophet	0.63	0.89	0.69
ETS	0.21	0.42	0.27
SARIMA	0.24	0.32	0.26
Hybrid*	0.28	0.45	0.35
Bayesian Structural	0.52	1.52	0.78

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

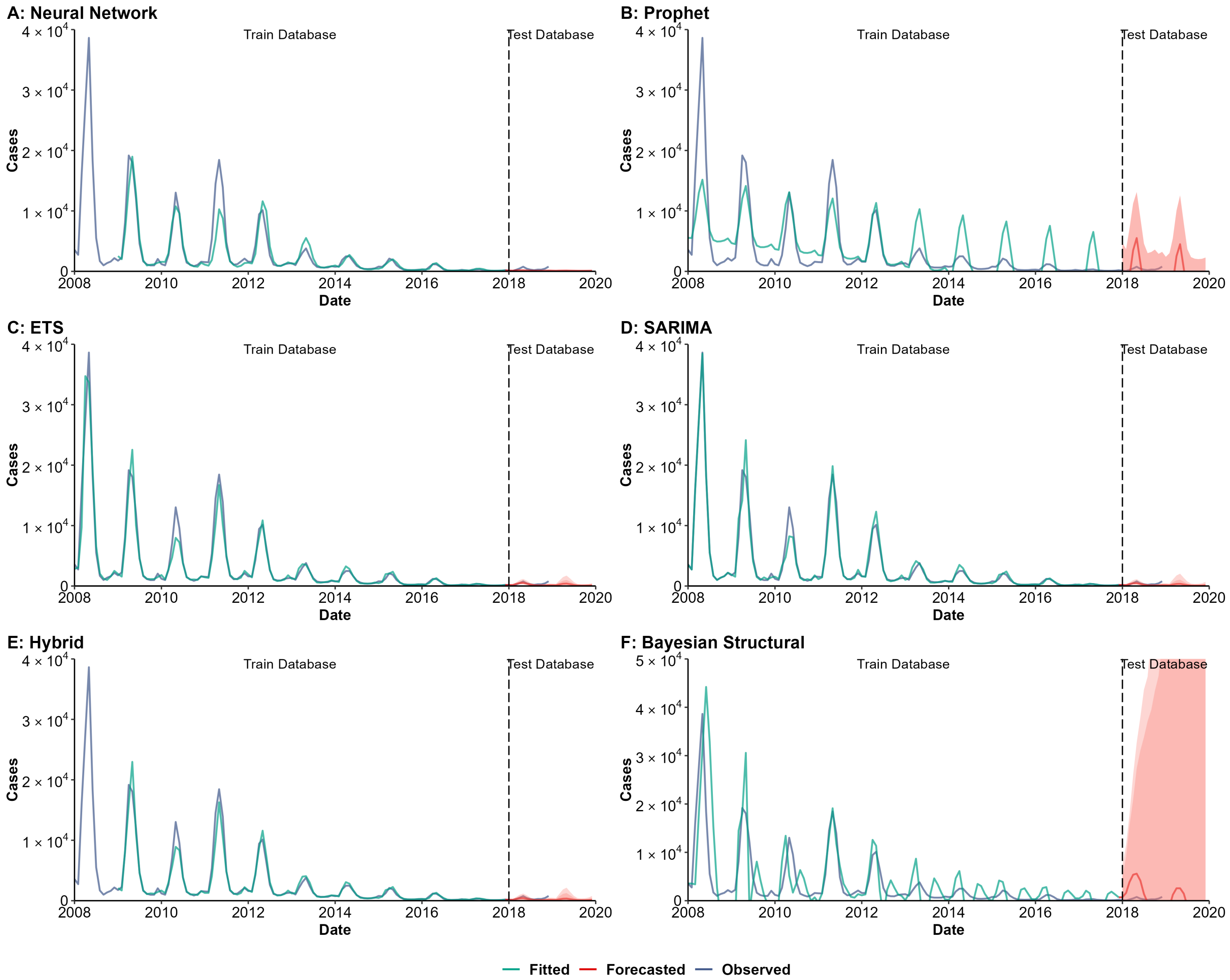
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.67	0.61	0.67
Prophet	0.73	0.88	0.77
ETS	0.96	0.87	0.94
SARIMA	0.95	0.92	0.94
Hybrid*	0.94	0.89	0.93
Bayesian Structural	0.80	0.92	0.75

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 15. Training and comparing variant time series models for scarlet fever.

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	1573.63	316.31	1496.23
Prophet	3846.07	3976.43	3858.10
ETS	1391.54	234.87	1328.67
SARIMA	1058.91	243.12	1012.29
Hybrid*	987.49	246.66	940.06
Bayesian Structural	5302.93	3056.49	5139.45

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	22.14	87.33	28.66
Prophet	100.31	184.11	107.93
ETS	15.10	58.36	19.03
SARIMA	14.79	62.87	19.16
Hybrid*	13.88	62.25	18.72
Bayesian Structural	111.03	176.40	116.97

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.59	12.61	0.61
Prophet	1.45	2.04	1.51
ETS	0.33	2.13	0.36
SARIMA	0.23	2.55	0.24
Hybrid*	0.33	3.00	0.34
Bayesian Structural	1.80	2.26	0.96

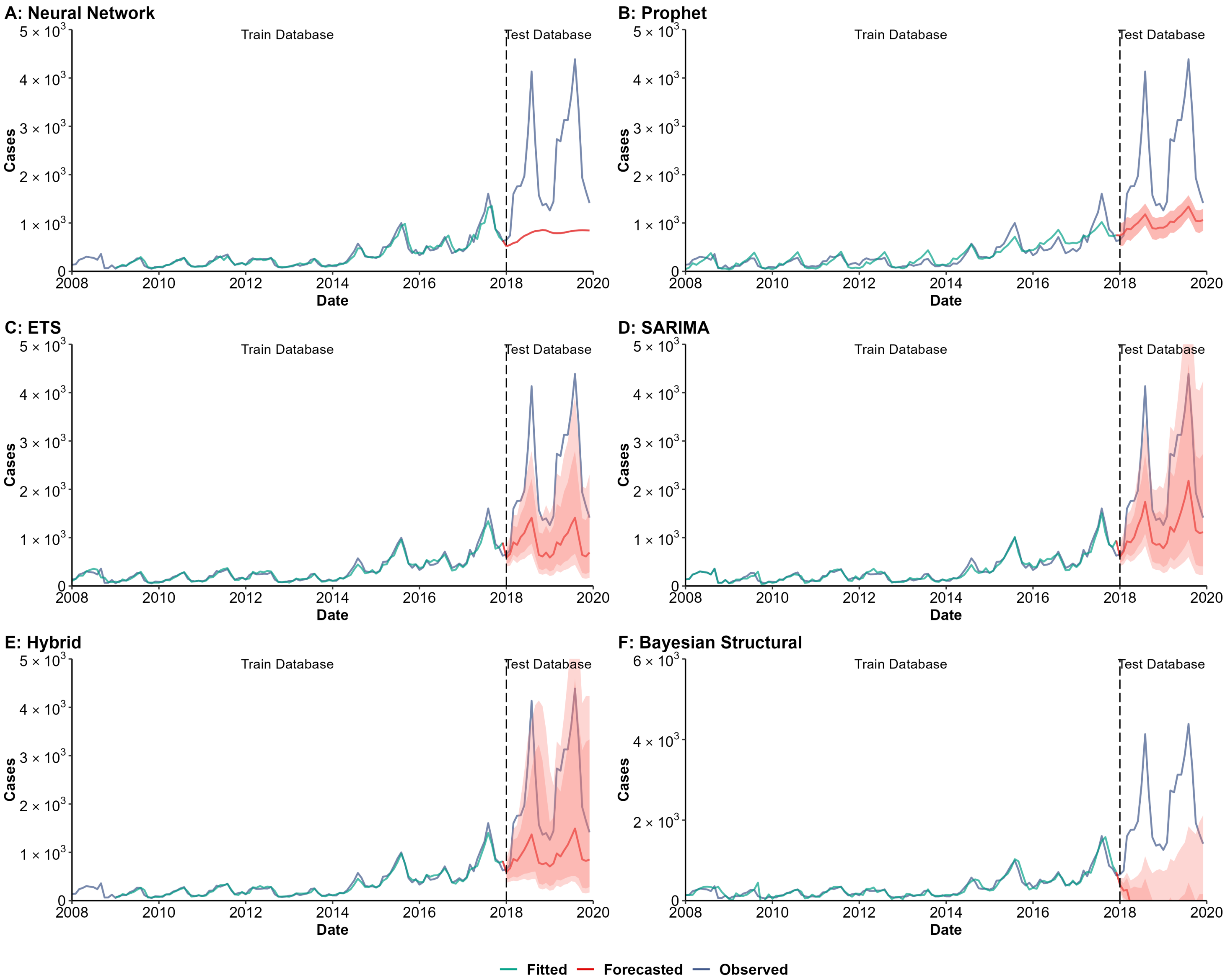
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.86	0.29	0.86
Prophet	0.56	0.26	0.53
ETS	0.94	0.20	0.94
SARIMA	0.97	0.20	0.97
Hybrid*	0.94	0.22	0.94
Bayesian Structural	0.51	0.02	0.51

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 16. Training and comparing variant time series models for rubella. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	70.71	1737.35	743.56
Prophet	118.78	1488.59	617.31
ETS	61.36	1534.59	628.99
SARIMA	59.63	1221.97	501.83
Hybrid*	51.39	1486.54	635.57
Bayesian Structural	90.84	4006.62	1637.80

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	12.81	85.94	26.11
Prophet	29.63	65.63	35.63
ETS	14.45	77.64	24.98
SARIMA	13.86	54.61	20.65
Hybrid*	11.53	71.15	22.37
Bayesian Structural	23.53	187.05	50.78

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.68	70.50	5.22
Prophet	1.14	17.72	4.23
ETS	0.54	8.12	3.10
SARIMA	0.54	4.87	2.14
Hybrid*	0.45	9.06	3.35
Bayesian Structural	0.78	19.78	6.38

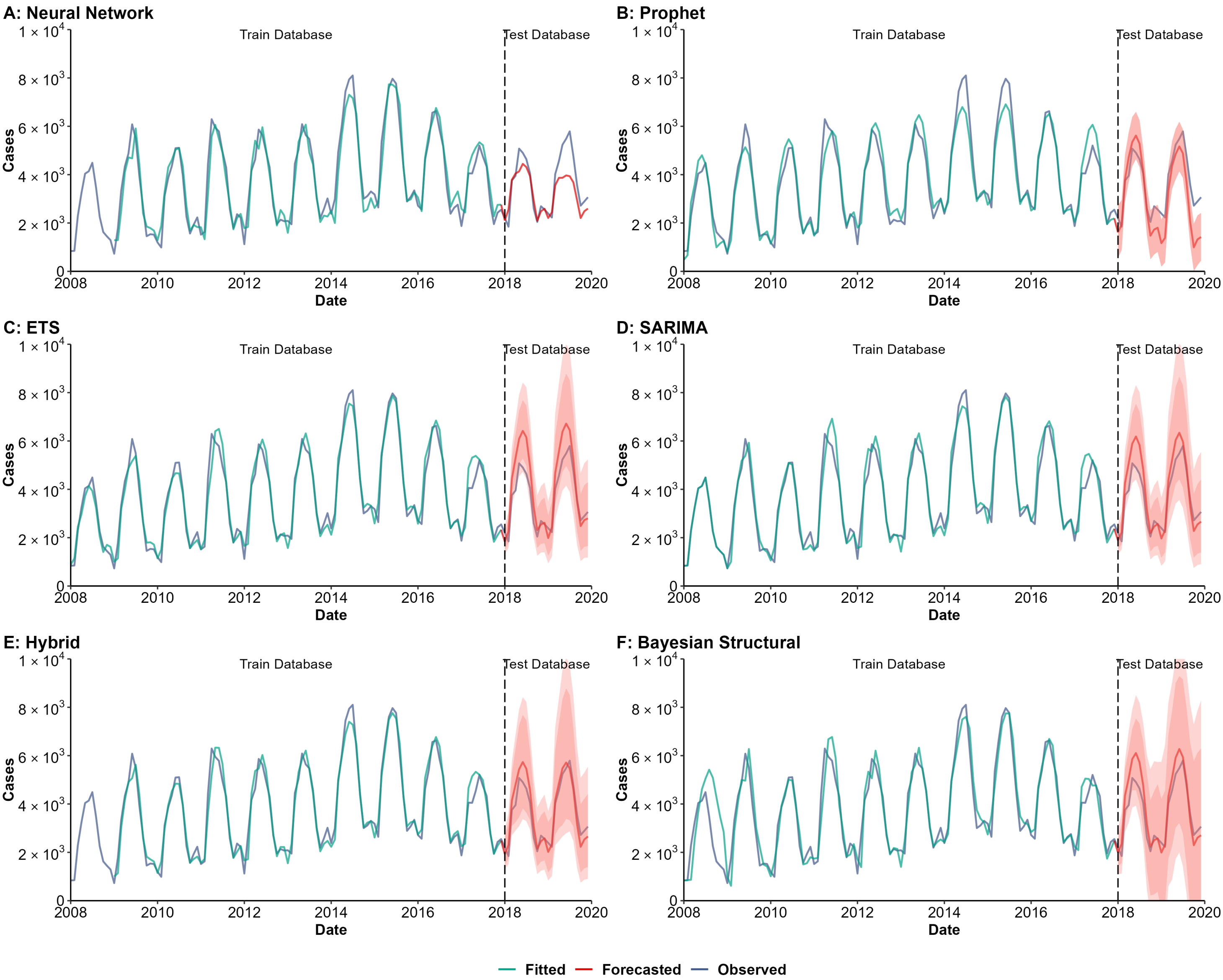
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.94	0.21	0.53
Prophet	0.81	0.84	0.75
ETS	0.95	0.77	0.76
SARIMA	0.95	0.91	0.89
Hybrid*	0.97	0.91	0.78
Bayesian Structural	0.90	0.09	0.39

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 17. Training and comparing variant time series models for pertussis. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	476.56	721.00	529.46
Prophet	502.72	896.00	586.86
ETS	402.23	784.80	487.32
SARIMA	427.34	619.29	464.87
Hybrid*	386.67	428.76	394.66
Bayesian Structural	683.38	583.40	667.76

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	12.14	14.47	12.56
Prophet	10.87	28.94	13.88
ETS	9.61	15.33	10.57
SARIMA	9.00	13.31	9.72
Hybrid*	8.91	10.65	9.23
Bayesian Structural	15.36	12.61	14.90

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.47	1.29	0.56
Prophet	0.46	0.96	0.57
ETS	0.37	0.78	0.46
SARIMA	0.37	0.66	0.42
Hybrid*	0.35	0.53	0.40
Bayesian Structural	0.58	0.63	0.60

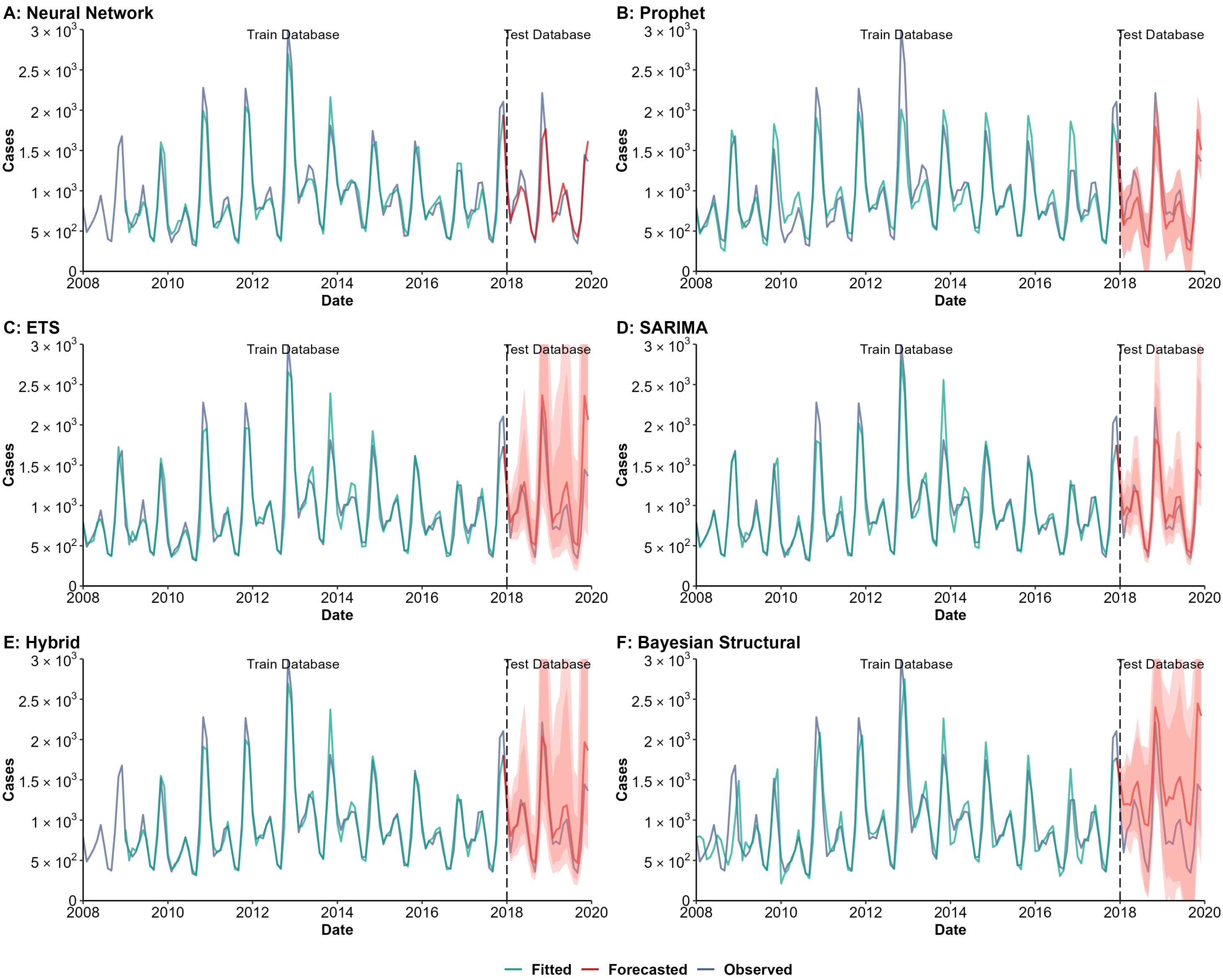
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.93	0.81	0.91
Prophet	0.92	0.82	0.89
ETS	0.95	0.94	0.93
SARIMA	0.95	0.93	0.94
Hybrid*	0.95	0.92	0.95
Bayesian Structural	0.86	0.93	0.86

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 18. Training and comparing variant time series models for brucellosis. (A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	129.41	164.96	136.56
Prophet	207.63	207.67	207.64
ETS	140.57	300.89	177.64
SARIMA	151.85	162.02	153.59
Hybrid*	129.52	198.71	144.58
Bayesian Structural	235.53	541.45	308.37

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	9.78	12.05	10.19
Prophet	14.24	21.81	15.50
ETS	9.00	20.91	10.99
SARIMA	8.90	12.89	9.57
Hybrid*	7.98	15.60	9.37
Bayesian Structural	16.77	47.16	21.84

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.32	0.42	0.33
Prophet	0.45	0.62	0.48
ETS	0.29	0.58	0.34
SARIMA	0.29	0.44	0.31
Hybrid*	0.26	0.49	0.30
Bayesian Structural	0.50	1.77	0.65

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

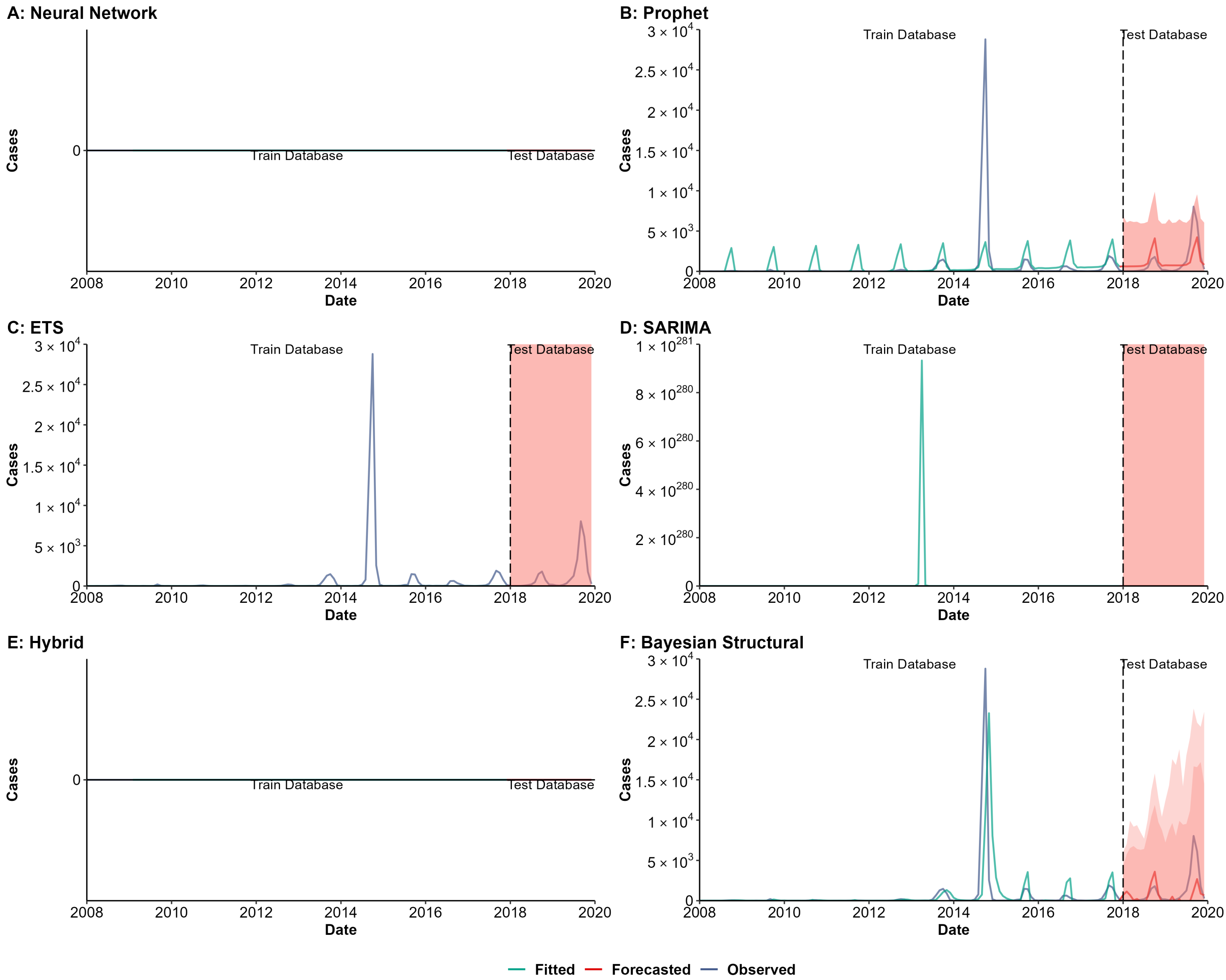
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.94	0.87	0.93
Prophet	0.82	0.87	0.82
ETS	0.92	0.84	0.87
SARIMA	0.91	0.88	0.90
Hybrid*	0.93	0.89	0.91
Bayesian Structural	0.78	0.79	0.67

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 19. Training and comparing variant time series models for hemorrhagic fever with renal syndrome (HFRS).

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



SE of Models

od	Train	Test	All
etwork	4.44779172856819e+20	Inf	Inf
het	2733.36	1408.81	2560.63
S	2990.29	2281.21	2884.24
MA	Inf	218459382244460	Inf
id*	Inf	Inf	Inf
Structural	2967.59	1848.96	2812.22

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network			
Prophet	150.38	109.44	143.56
ETS		200	
SARIMA		199.97	
Hybrid*			
Bayesian Structural	116.22	137.74	119.8

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.5		
Prophet	1.48	1.57	1.51
ETS	0.93	Inf	2.89128965216679e+47
SARIMA	0.5	0.98	0.5
Hybrid*	3.37191940041109e+275		
Bayesian Structural	1.29	1.34	1.17

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

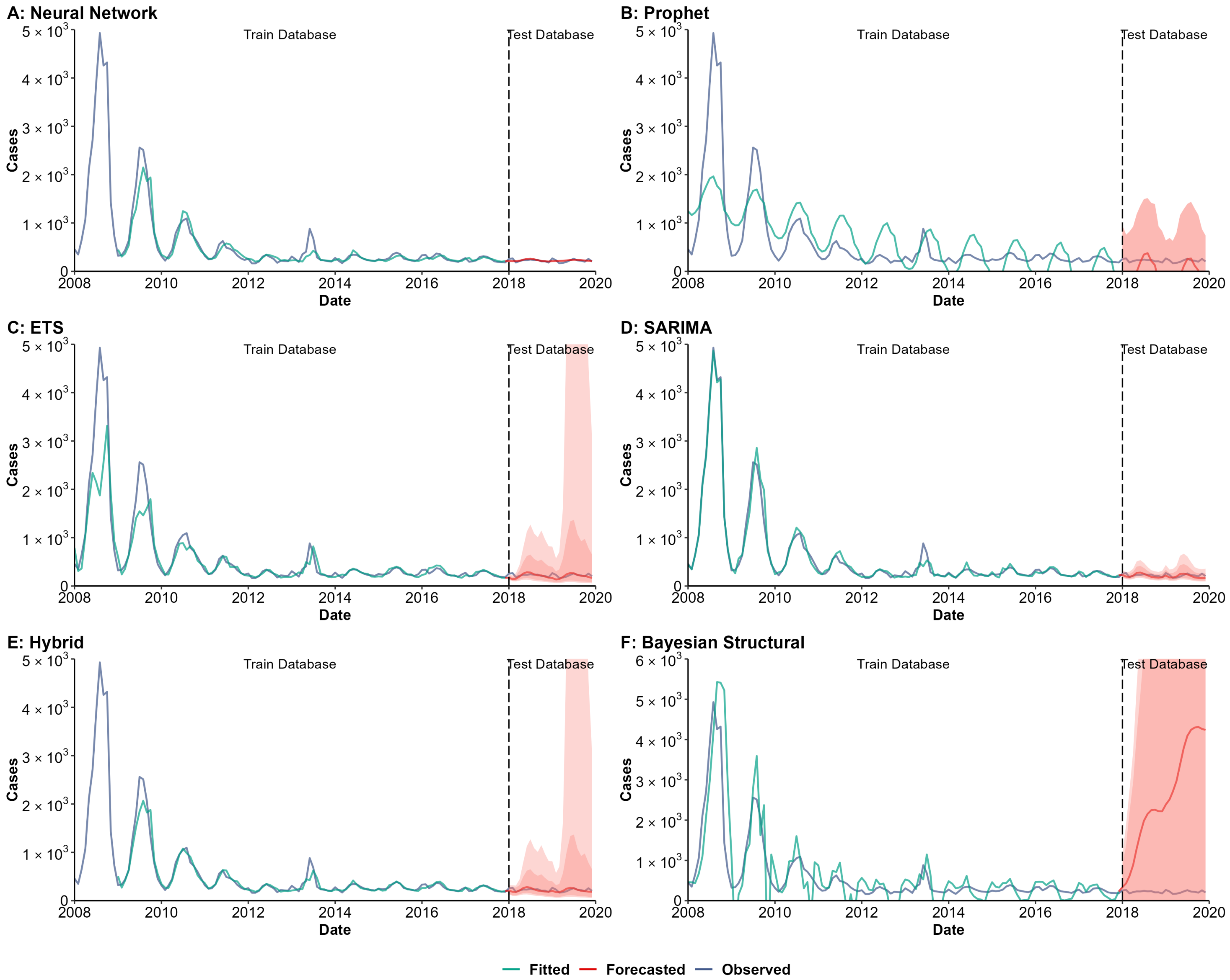
J : R-squared of Models

Method	Train	Test	All
Neural Network	0		
Prophet	0.14	0.53	0.17
ETS	0		0.01
SARIMA	0	0.01	0
Hybrid*	0		
Bayesian Structural	0.17	0.21	0.17

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 20. Training and comparing variant time series models for dengue fever.

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	143.44	28.46	130.31
Prophet	603.17	450.25	580.49
ETS	414.04	50.21	378.52
SARIMA	108.42	39.92	100.31
Hybrid*	123.31	36.83	112.63
Bayesian Structural	595.78	2665.33	1216.47

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	15.18	10.59	14.34
Prophet	81.59	136.20	90.69
ETS	18.02	17.73	17.98
SARIMA	12.43	15.32	12.91
Hybrid*	11.51	12.34	11.66
Bayesian Structural	68.73	153.70	82.89

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.92	3.20	0.96
Prophet	2.36	2.54	2.70
ETS	0.92	1.52	1.15
SARIMA	0.33	1.53	0.36
Hybrid*	0.57	1.42	0.70
Bayesian Structural	2.00	13.03	1.88

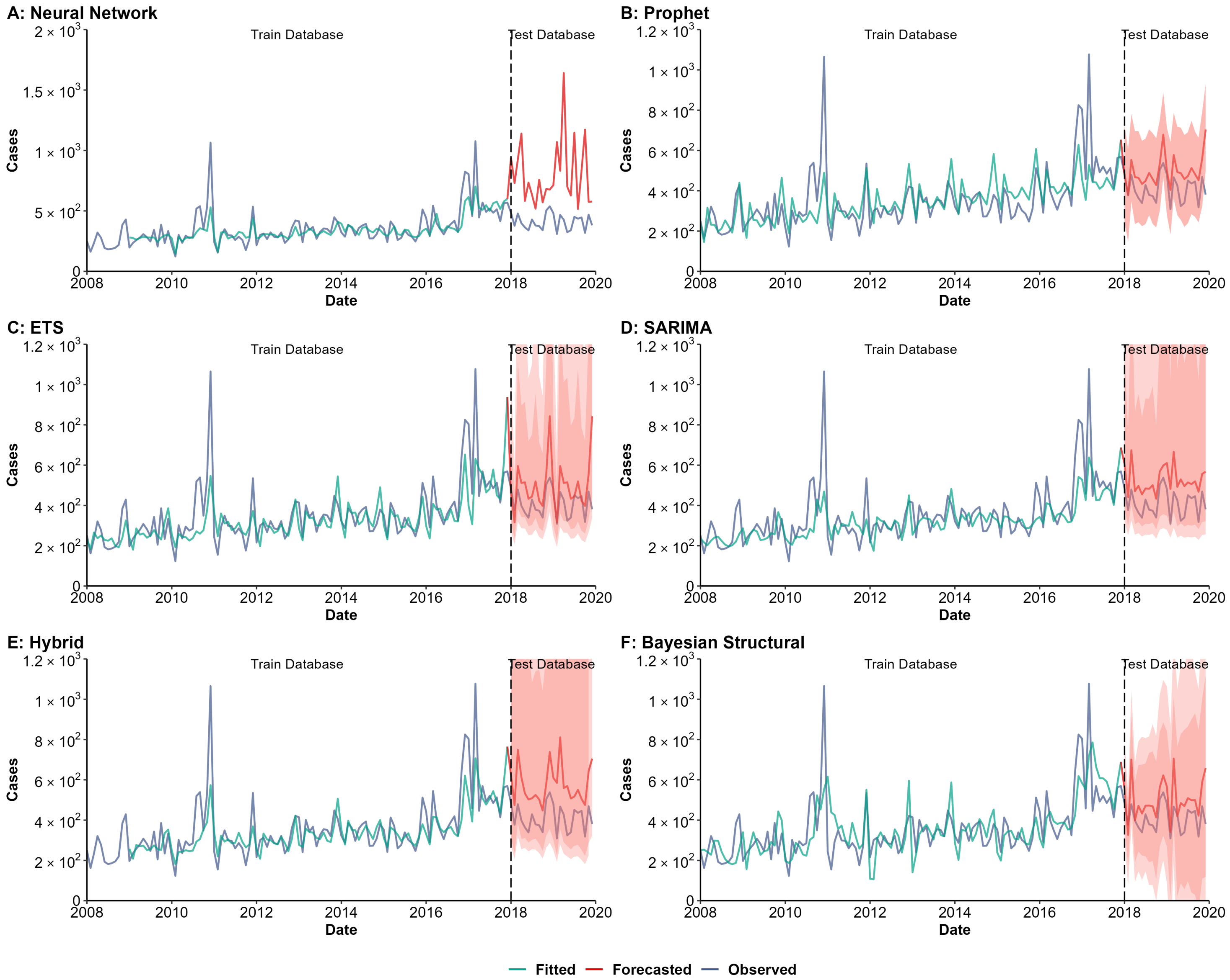
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.89	0.09	0.90
Prophet	0.50	0.05	0.47
ETS	0.85	0.04	0.86
SARIMA	0.98	0.11	0.98
Hybrid*	0.92	0.09	0.93
Bayesian Structural	0.69	0.01	0.26

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 21. Training and comparing variant time series models for malaria. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	95.45	478.23	221.44
Prophet	112.24	108.46	111.62
ETS	109.05	142.56	115.31
SARIMA	110.36	125.16	112.96
Hybrid*	97.30	182.86	117.58
Bayesian Structural	119.46	117.68	119.17

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	14.42	60.22	22.75
Prophet	19.58	19.15	19.51
ETS	18.07	20.92	18.54
SARIMA	19.26	25.01	20.22
Hybrid*	15.43	33.44	18.71
Bayesian Structural	23.15	20.69	22.74

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	1.29	1.30	1.29
Prophet	0.73	1.18	0.98
ETS	0.68	0.81	0.93
SARIMA	1.51	1.54	1.52
Hybrid*	0.58	1.80	1.26
Bayesian Structural	0.83	0.82	1.06

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

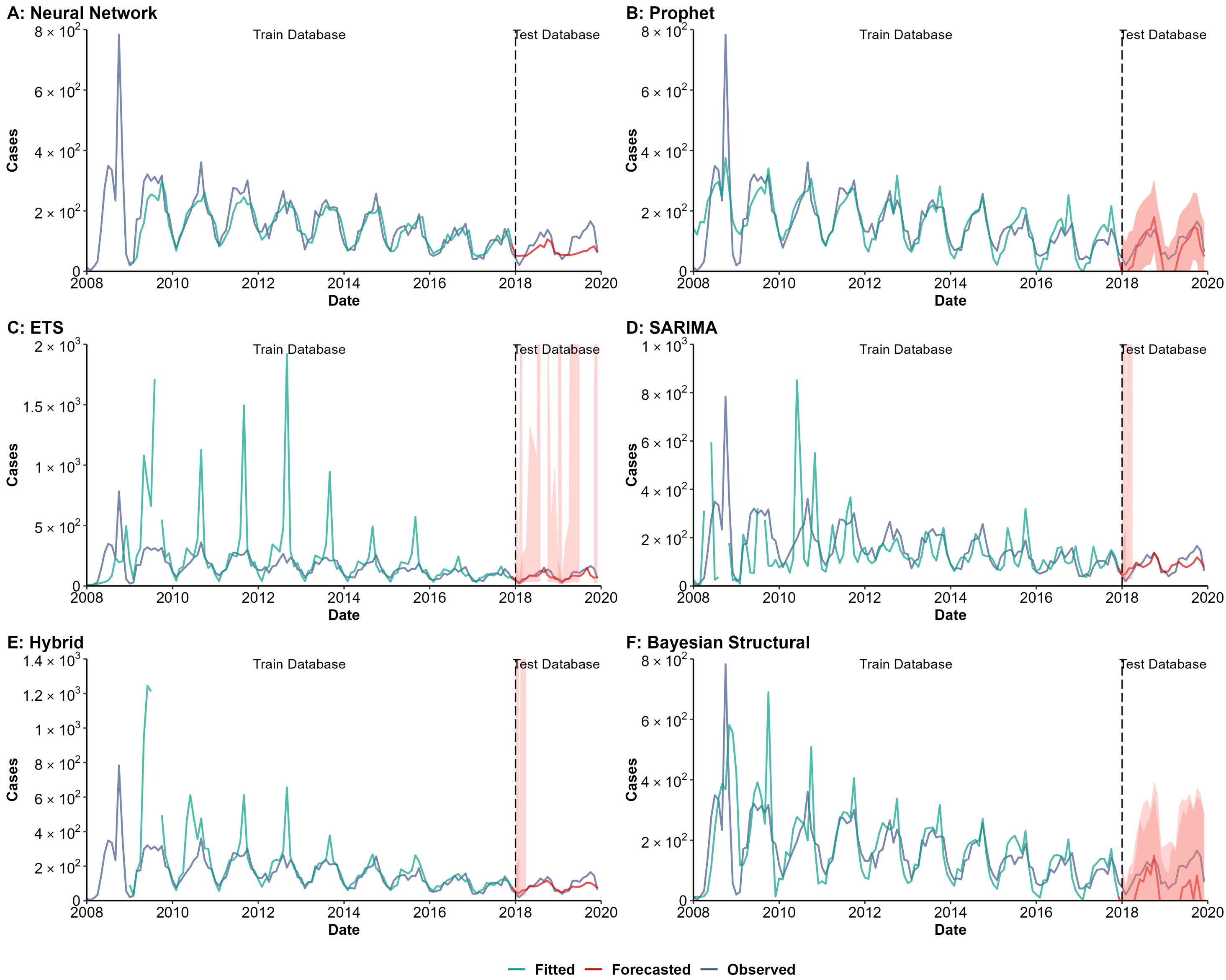
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.66	0.00	0.16
Prophet	0.44	0.30	0.41
ETS	0.50	0.24	0.41
SARIMA	0.52	0.51	0.40
Hybrid*	0.63	0.33	0.41
Bayesian Structural	0.42	0.45	0.41

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 22. Training and comparing variant time series models for echinococcosis.

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



G : RMSE of Models

Method	Train	Test	All
Neural Network	38.34	39.99	38.64
Prophet	60.30	41.46	57.59
ETS	291.56	31.64	266.29
SARIMA	119.49	28.12	109.39
Hybrid*	167.27	27.08	151.49
Bayesian Structural	99.99	85.32	97.70

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	19.05	36.51	22.23
Prophet	32.80	73.26	39.55
ETS	45.26	26.32	42.08
SARIMA	42.81	28.69	40.39
Hybrid*	26.50	25.04	26.23
Bayesian Structural	39.33	131.59	54.71

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	1.08	4.04	1.26
Prophet	0.82	1.07	0.94
ETS	2.74	1.04	0.78
SARIMA	0.90	1.49	0.93
Hybrid*	1.97	2.09	0.95
Bayesian Structural	1.26	1.83	1.03

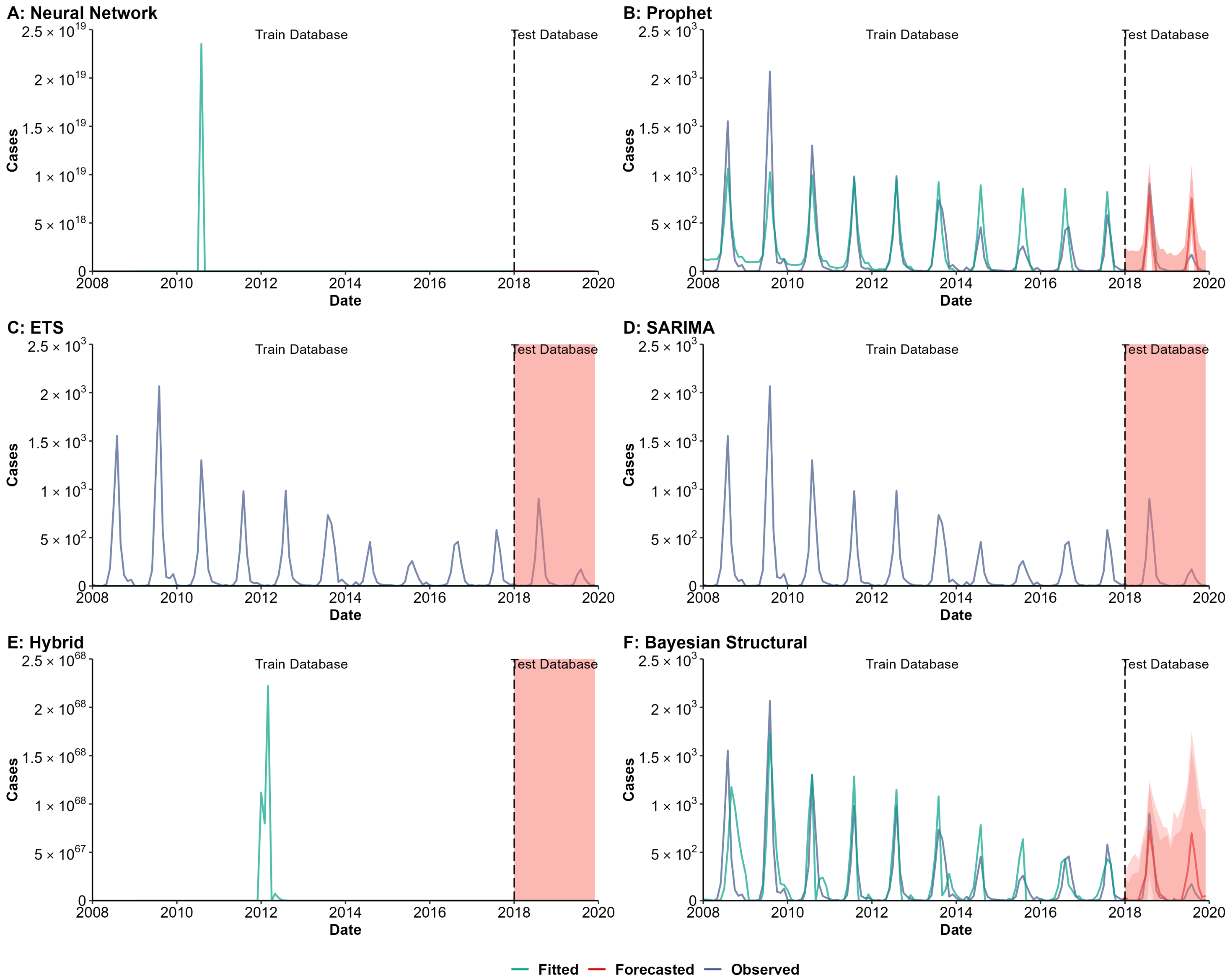
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R-squared of Models

Method	Train	Test	All
Neural Network	0.75	0.50	0.75
Prophet	0.64	0.77	0.65
ETS	0.17	0.49	0.20
SARIMA	0.11	0.60	0.14
Hybrid*	0.50	0.82	0.51
Bayesian Structural	0.40	0.54	0.44

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

Supplementary Fig. 23. Training and comparing variant time series models for typhus. **(A)** Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



of Models

Method	Train	Test	All
...rk	2263490629032368384	227.45	2047404308906152064
	173.93	182.4	175.37
	372.19	227.45	352.23
	371.73	227.02	351.77
	2.51328122802894e+67	258860.03	2.27334840709518e+67
...tural	239.91	150.99	228.51

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

H : SMAPE of Models

Method	Train	Test	All
Neural Network	199.14	200	199.29
Prophet	115.31	165.91	123.74
ETS	200	200	200
SARIMA	162.17	160.38	161.86
Hybrid*	195.83	190	194.77
Bayesian Structural	120.67	116.21	119.93

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

I : MASE of Models

Method	Train	Test	All
Neural Network	0.5	9.77215534724288e+63	0.5
Prophet	0.66	0.95	0.72
ETS	1.08	Inf	1.00657255156489e+91
SARIMA	Inf	Inf	Inf
Hybrid*	2.64628418795191e+64	0.67	0.81
Bayesian Structural	0.88	0.64	0.7

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

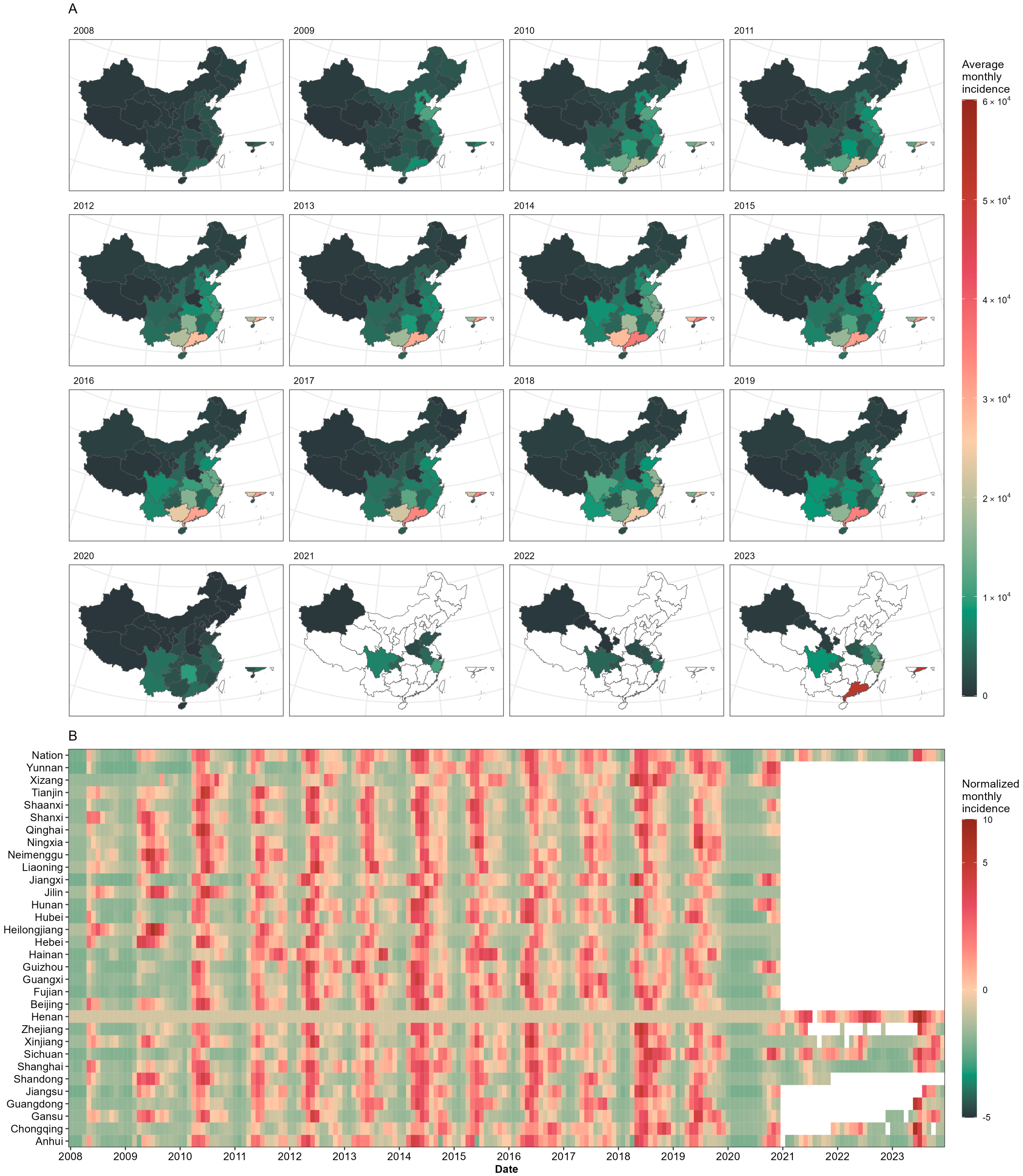
J : R-squared of Models

Method	Train	Test	All
Neural Network	0.12	0.19	0.12
Prophet	0.72	0.63	0.69
ETS	0		0
SARIMA			
Hybrid*	0.01	0.01	0
Bayesian Structural	0.56	0.61	0.57

*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

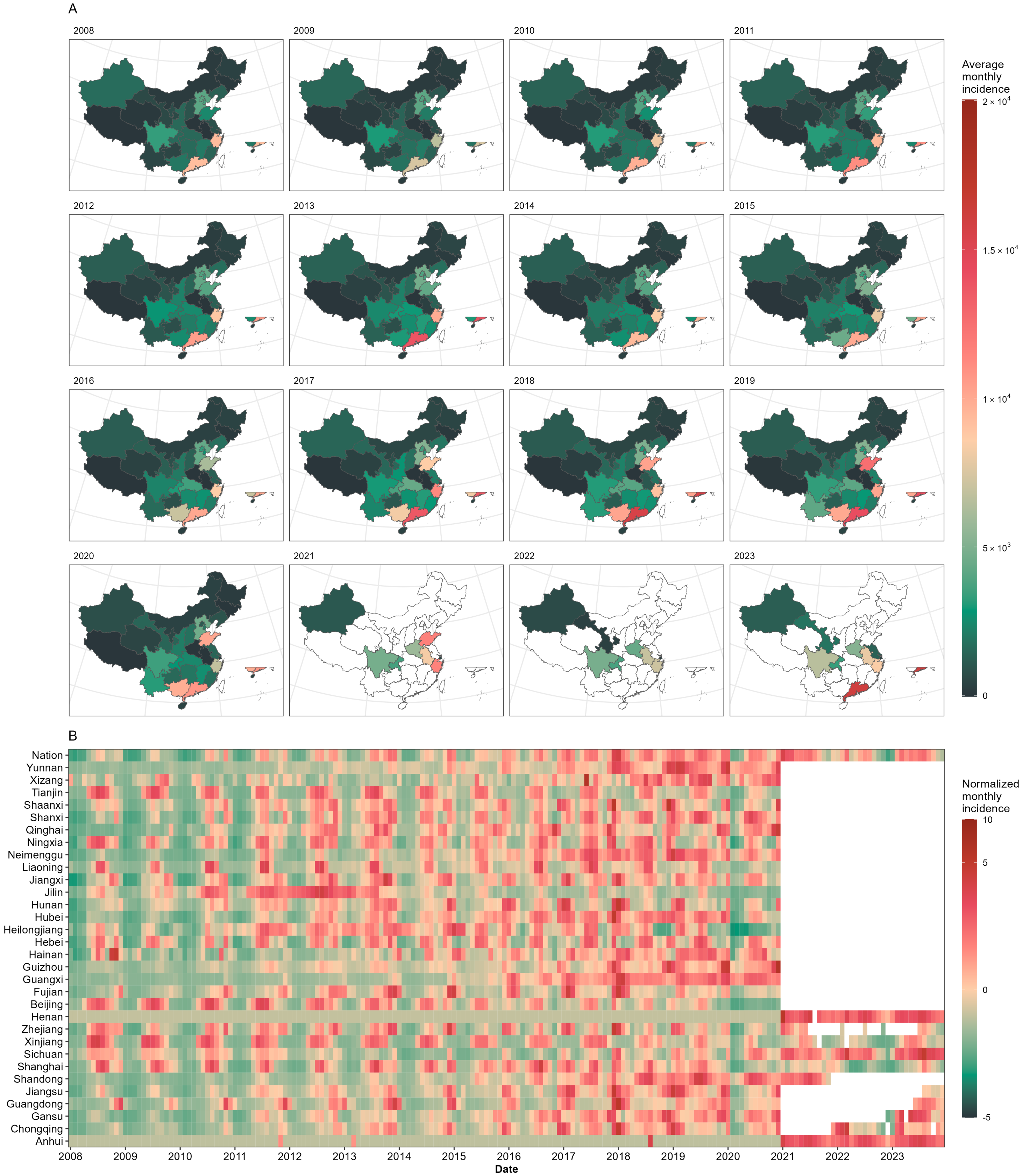
Supplementary Fig. 24. Training and comparing variant time series models for Japanese encephalitis (JE).

(A) Neural Network model; **(B)** Prophet model; **(C)** Exponential smoothing (ETS) model; **(D)** Seasonal autoregressive integrated moving average (SARIMA) model; **(E)** Hybrid models combining SARIMA, ETS, STL (seasonal and trend decomposition using loess), and neural network model; **(F)** Bayesian structural model; **(G)** Root mean square error (RMSE) of variant models; **(H)** Symmetric mean absolute percentage error (SMAPE) of variant models; **(I)** Mean absolute scaled error (MASE) of variant models; **(J)** R-squared of variant models.



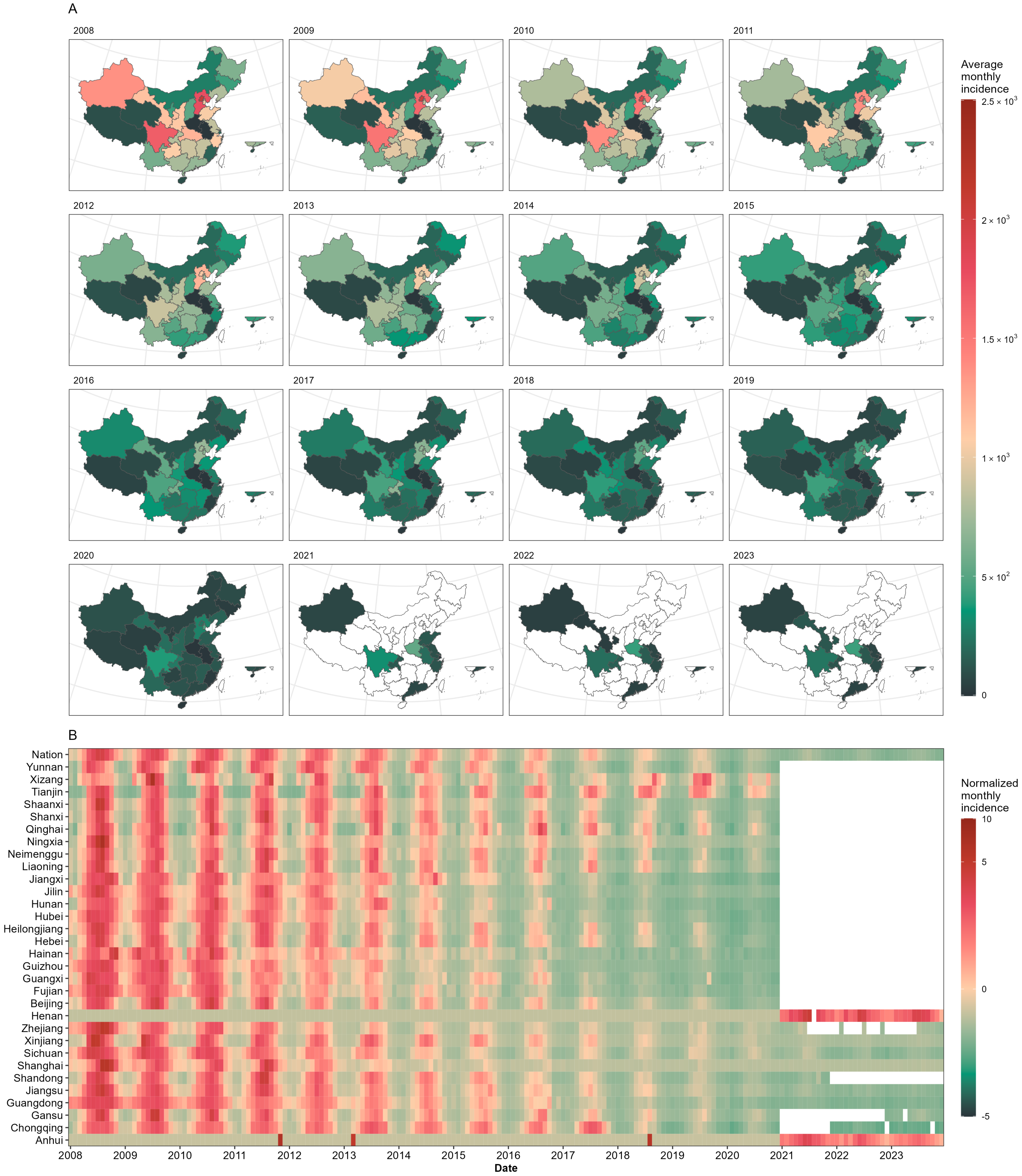
Supplementary Fig. 25. Temporal variation in the monthly incidence of hand, foot, and mouth disease (HFMD) in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



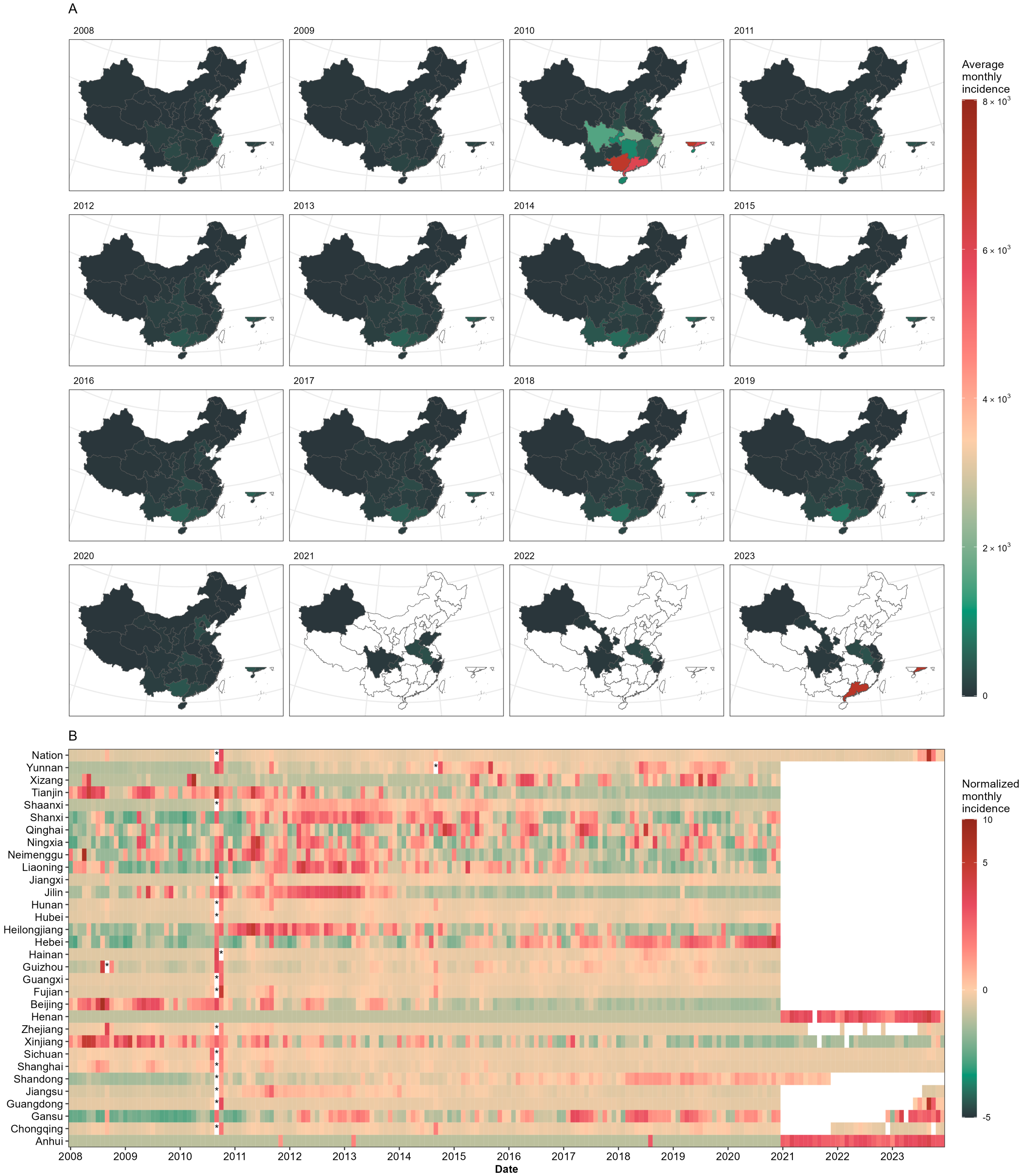
Supplementary Fig. 26. Temporal variation in the monthly incidence of infectious diarrhea in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



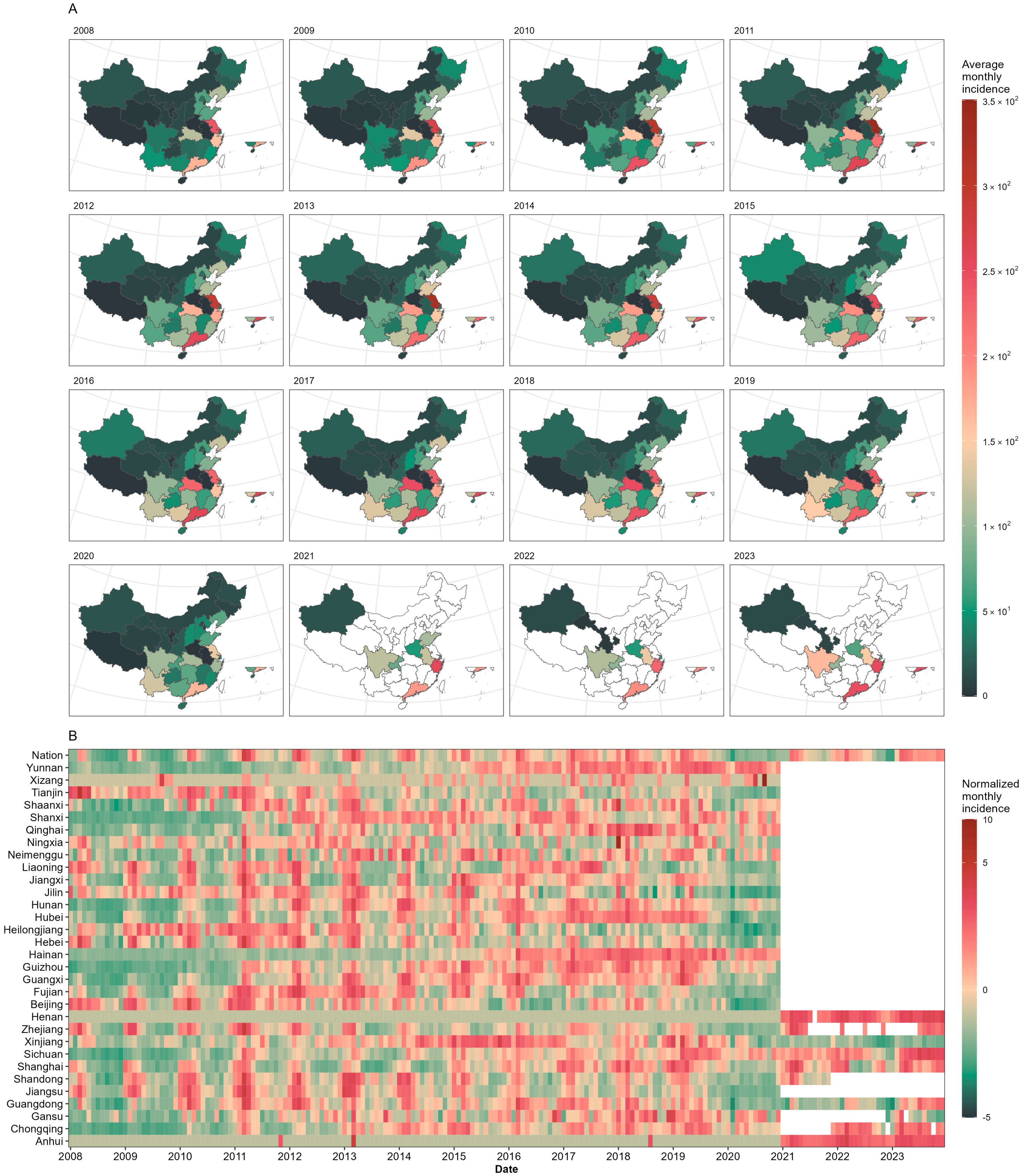
Supplementary Fig. 27. Temporal variation in the monthly incidence of dysentery in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



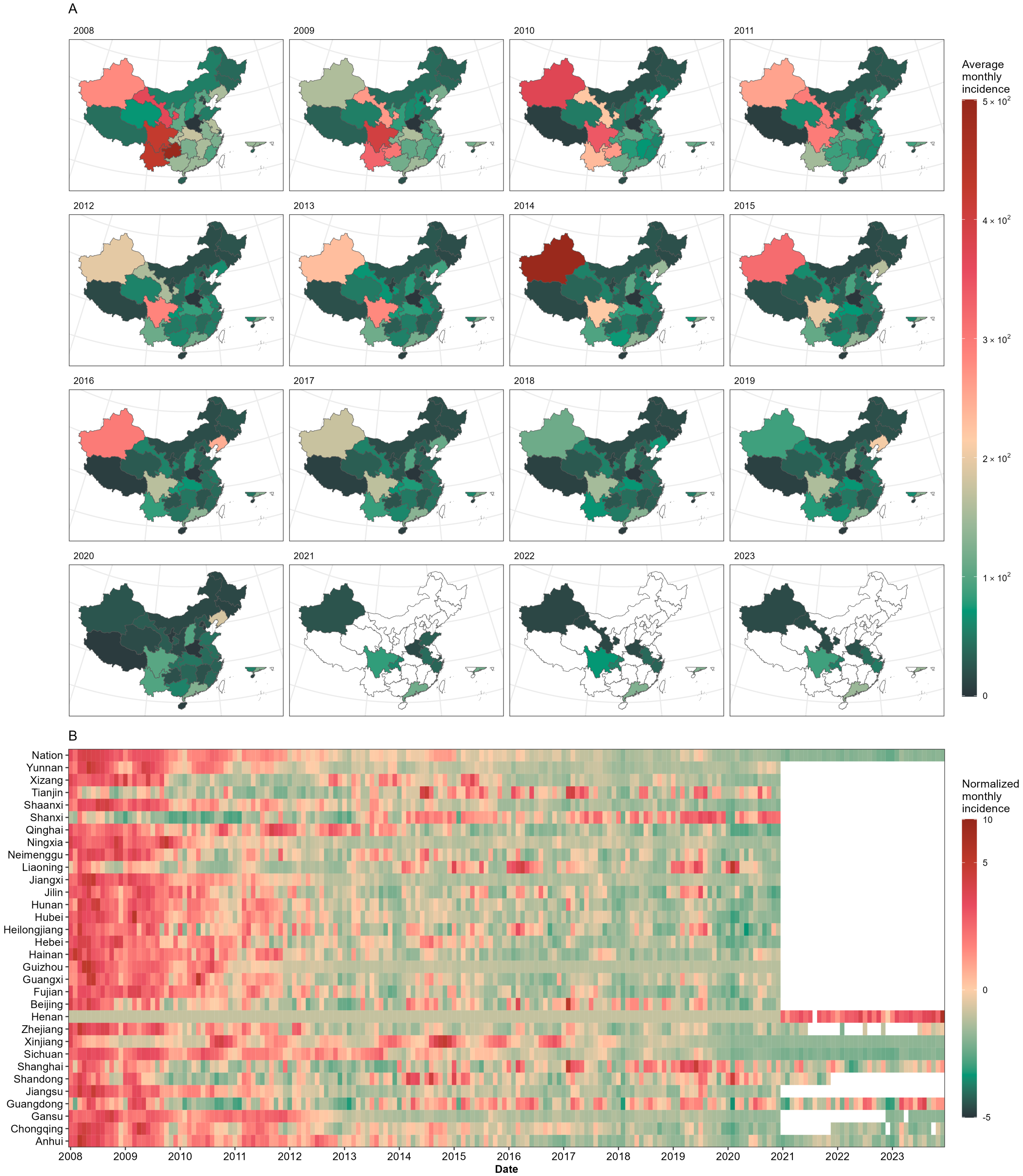
Supplementary Fig. 28. Temporal variation in the monthly incidence of acute hemorrhagic conjunctivitis (AHC) in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



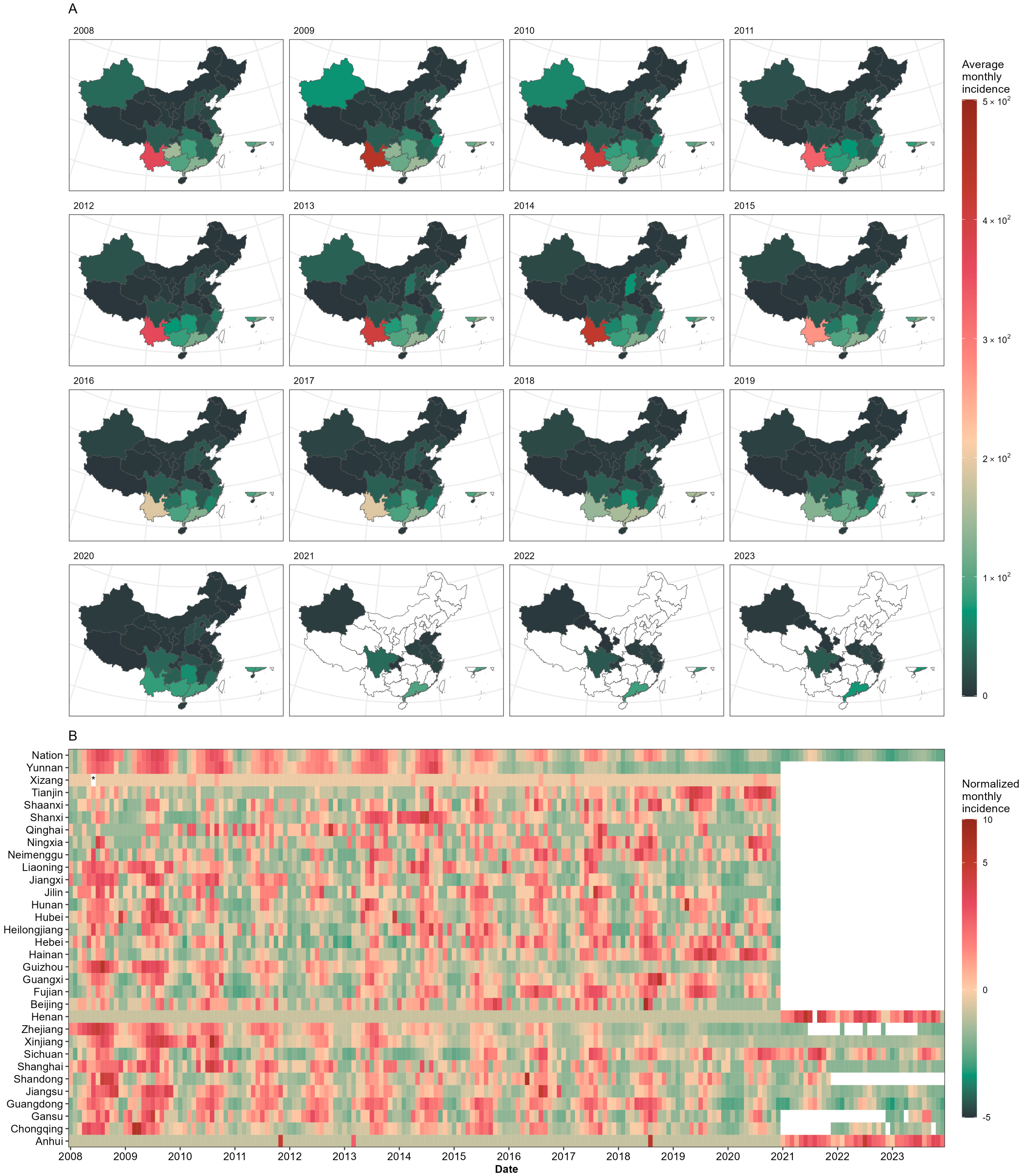
Supplementary Fig. 29. Temporal variation in the monthly incidence of hepatitis E in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



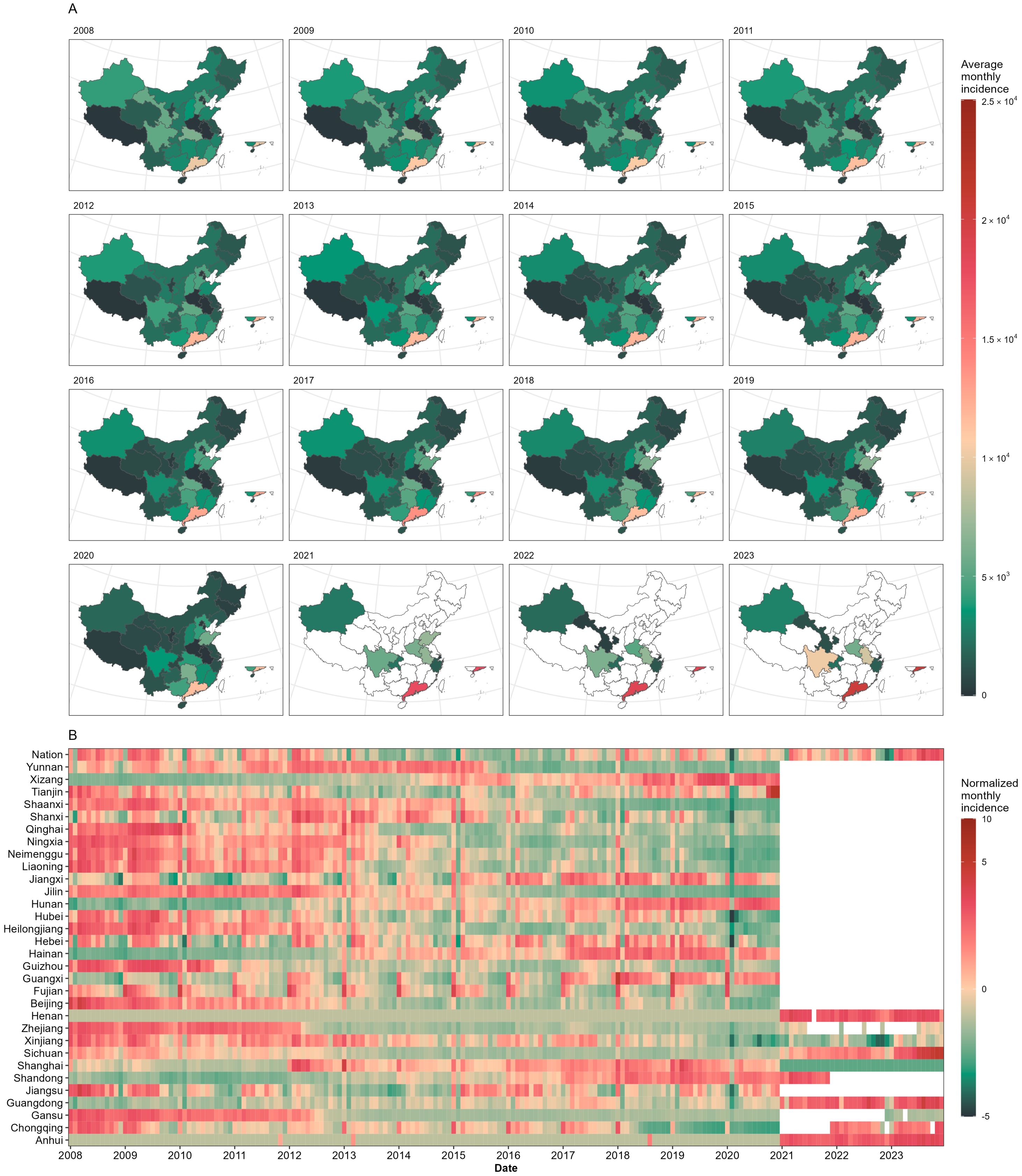
Supplementary Fig. 30. Temporal variation in the monthly incidence of hepatitis A in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



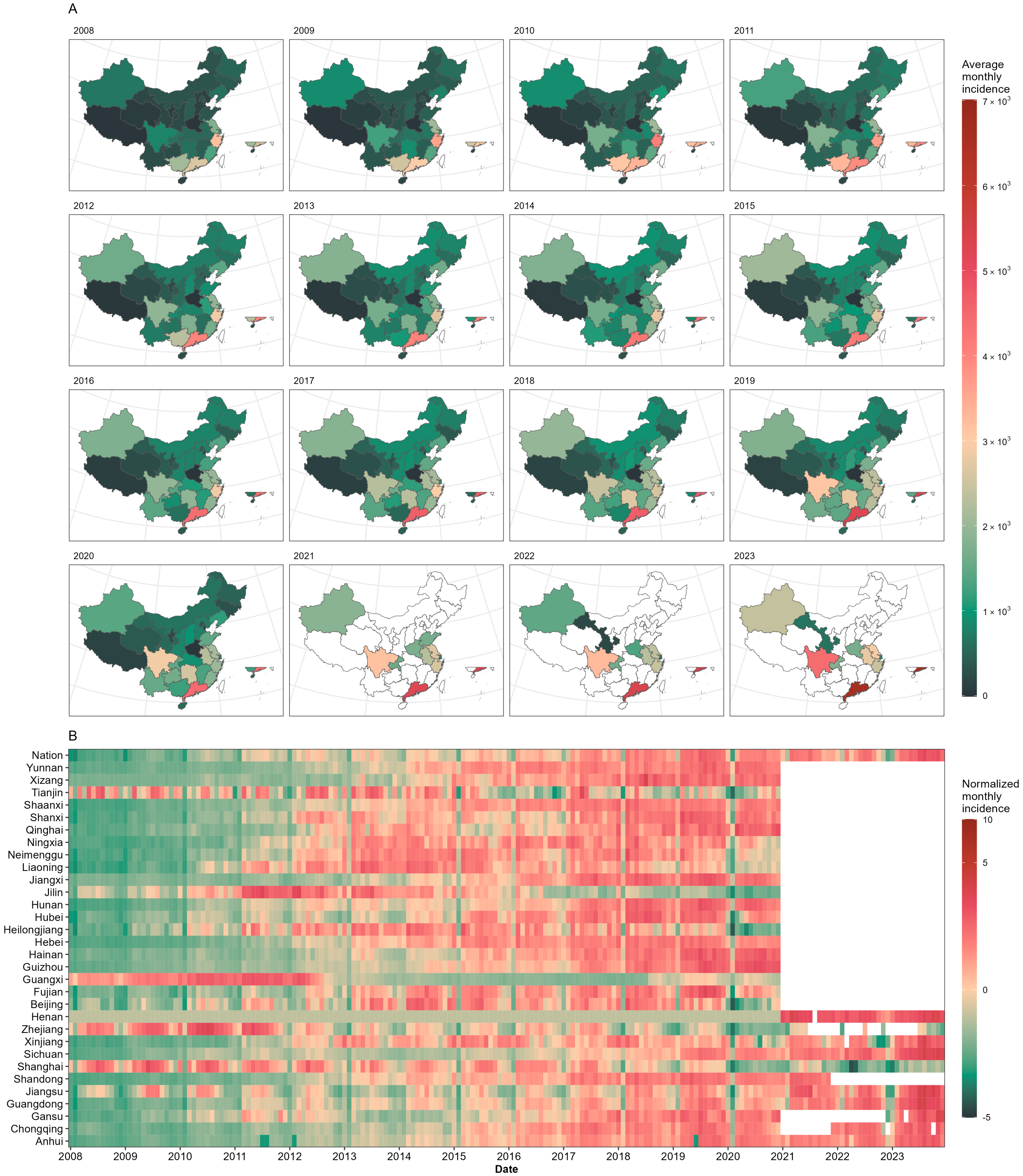
Supplementary Fig. 31. Temporal variation in the monthly incidence of enteric fever in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



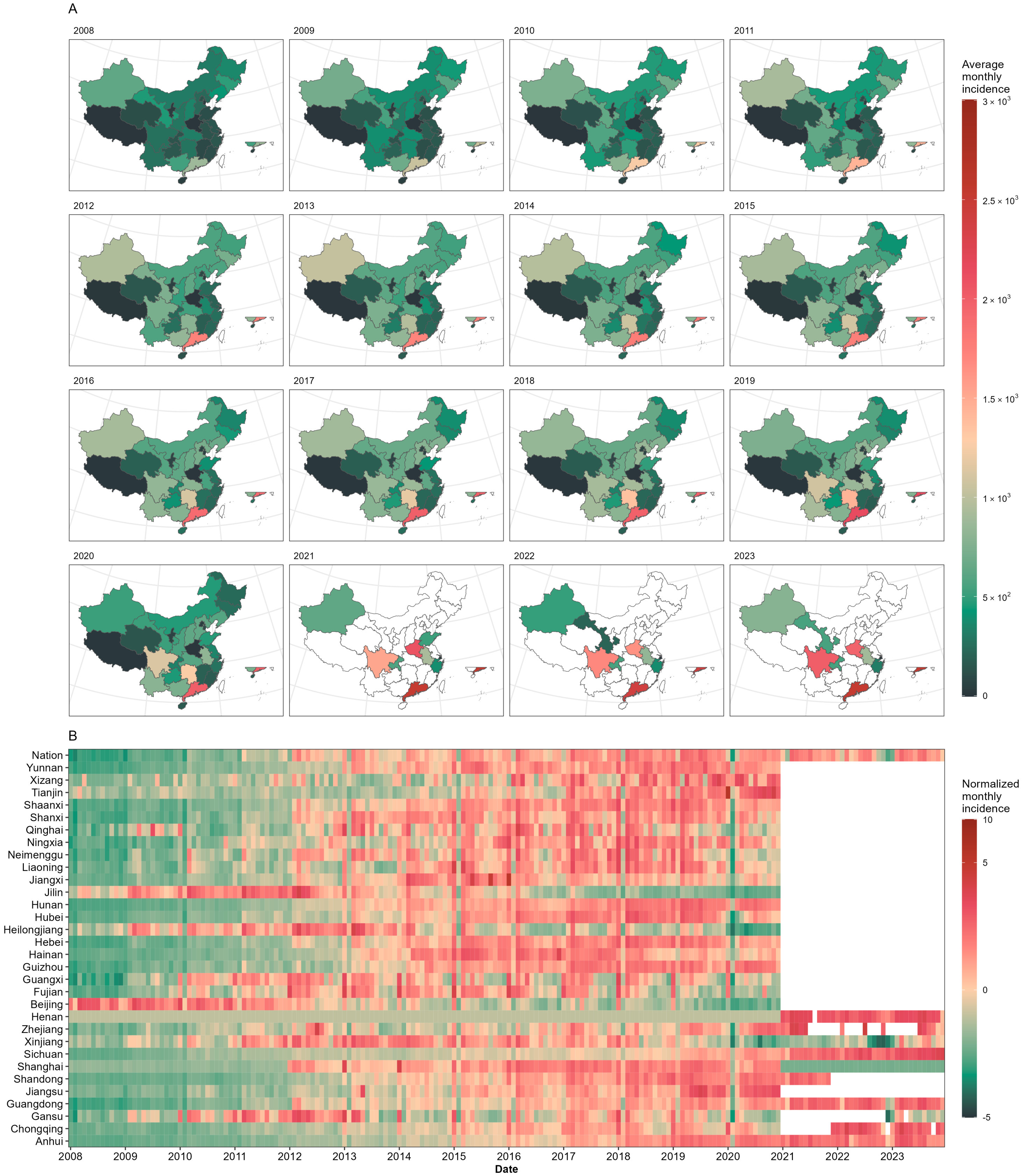
Supplementary Fig. 32. Temporal variation in the monthly incidence of hepatitis B in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



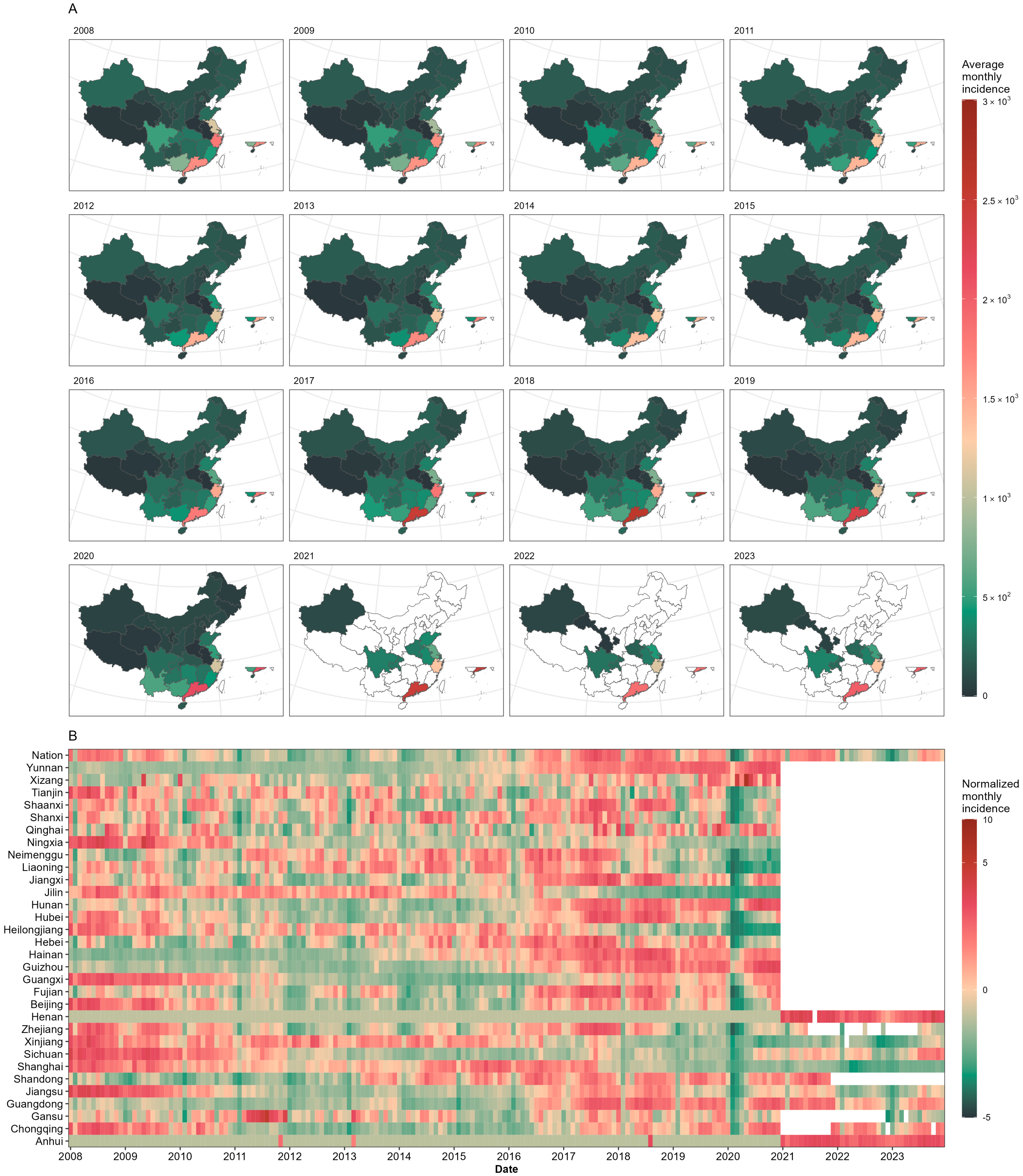
Supplementary Fig. 33. Temporal variation in the monthly incidence of syphilis in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



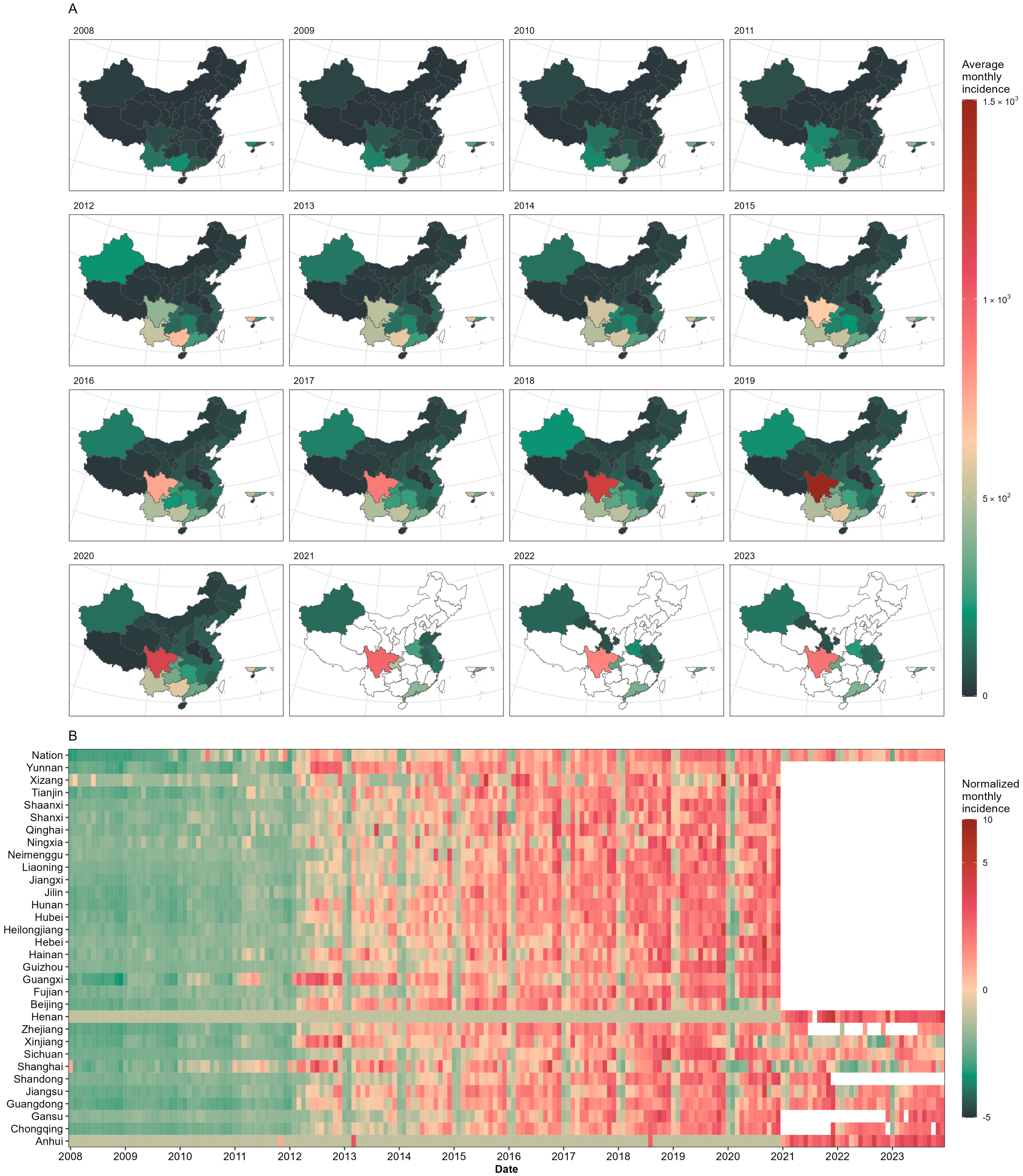
Supplementary Fig. 34. Temporal variation in the monthly incidence of hepatitis C in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



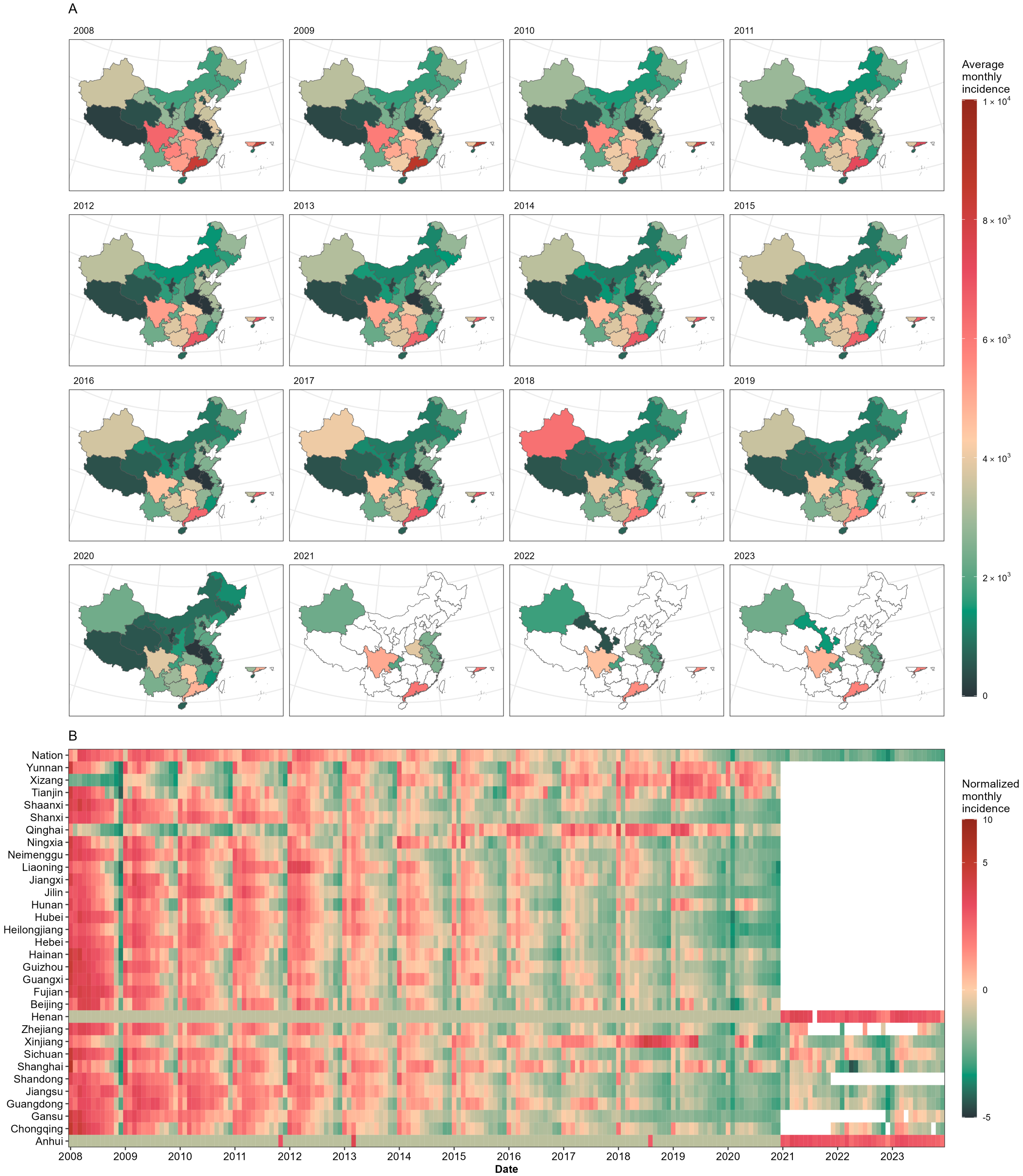
Supplementary Fig. 35. Temporal variation in the monthly incidence of gonorrhea in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



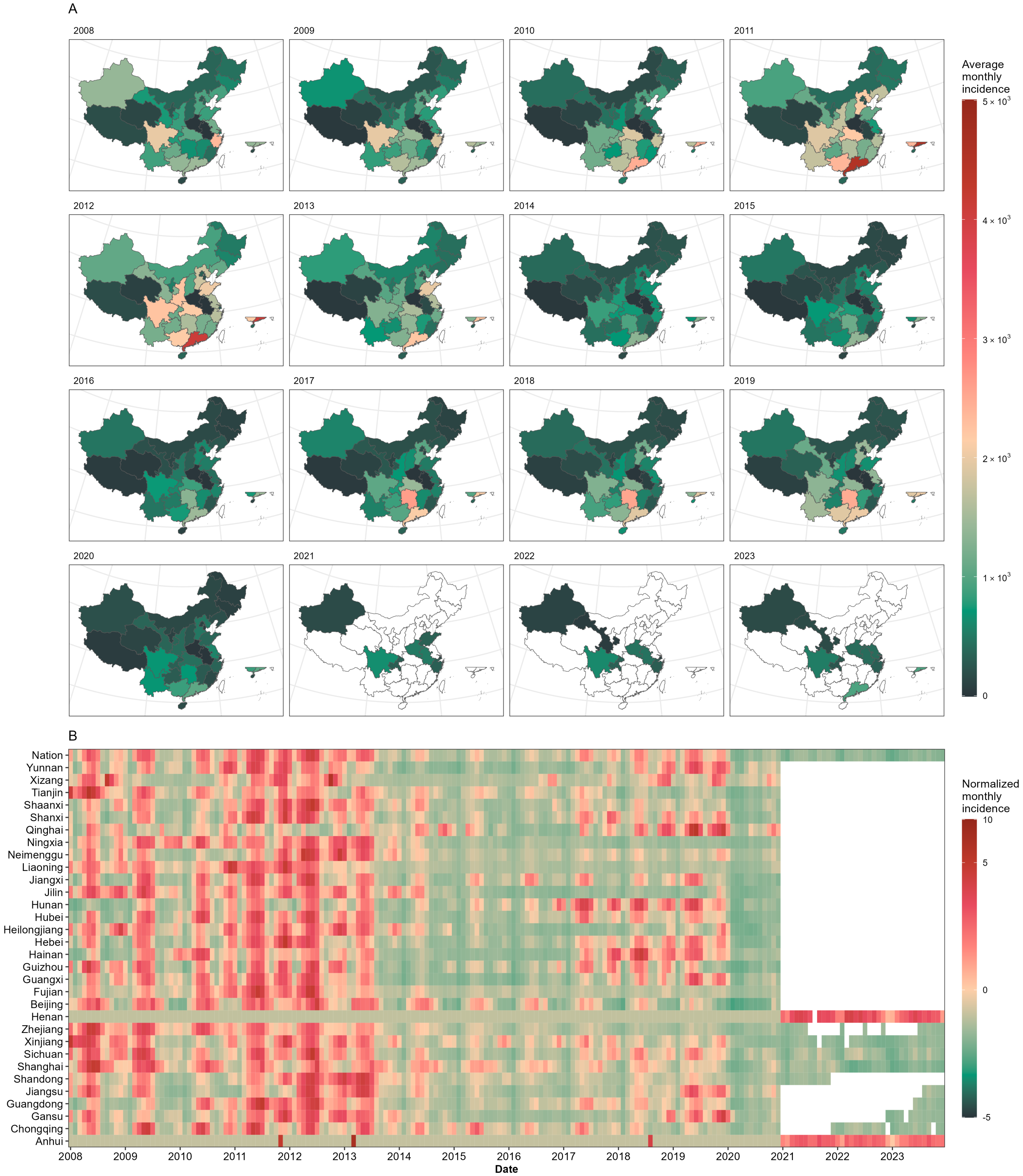
Supplementary Fig. 36. Temporal variation in the monthly incidence of acquired immunodeficiency syndrome (AIDS) in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



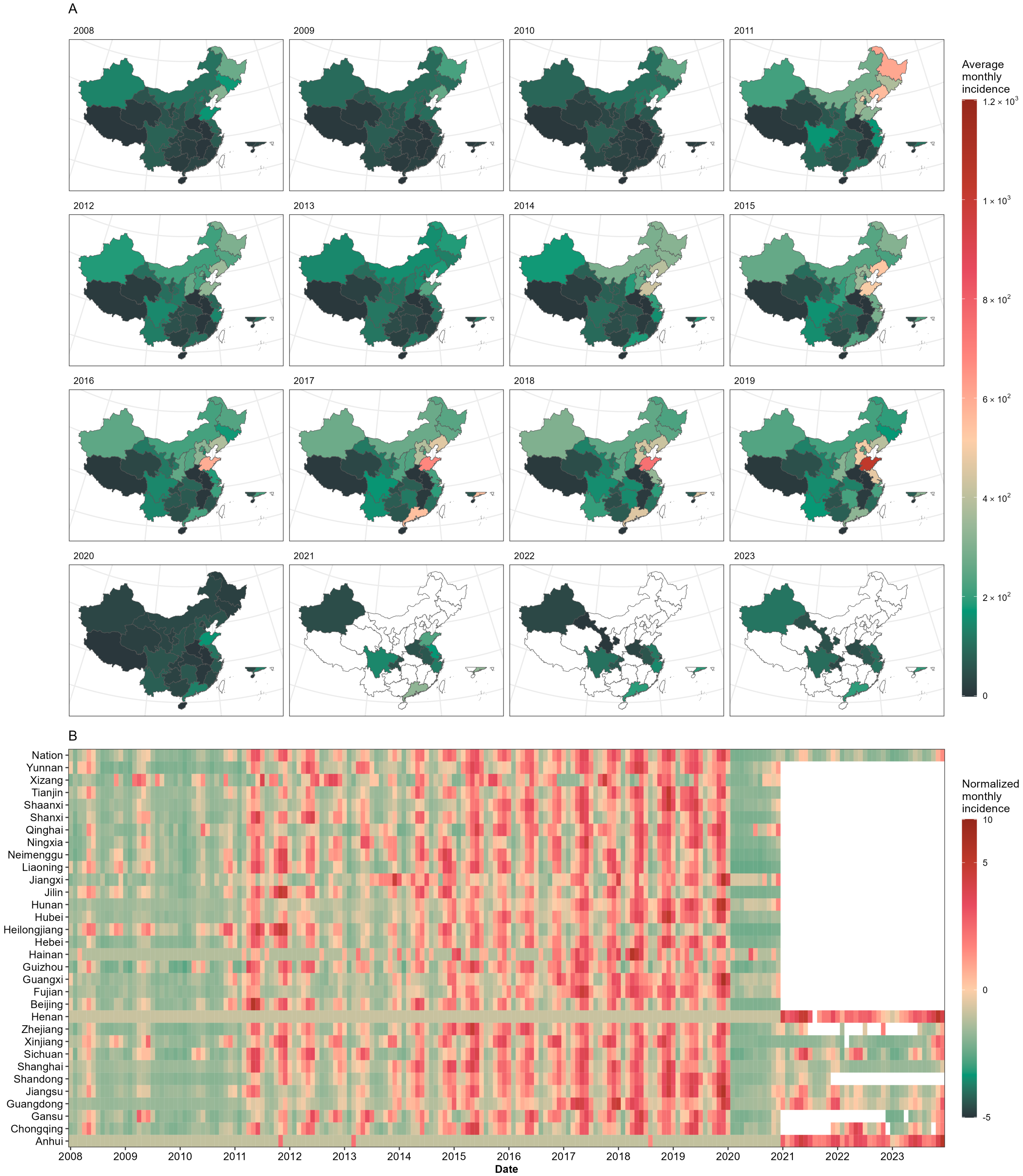
Supplementary Fig. 37. Temporal variation in the monthly incidence of tuberculosis in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



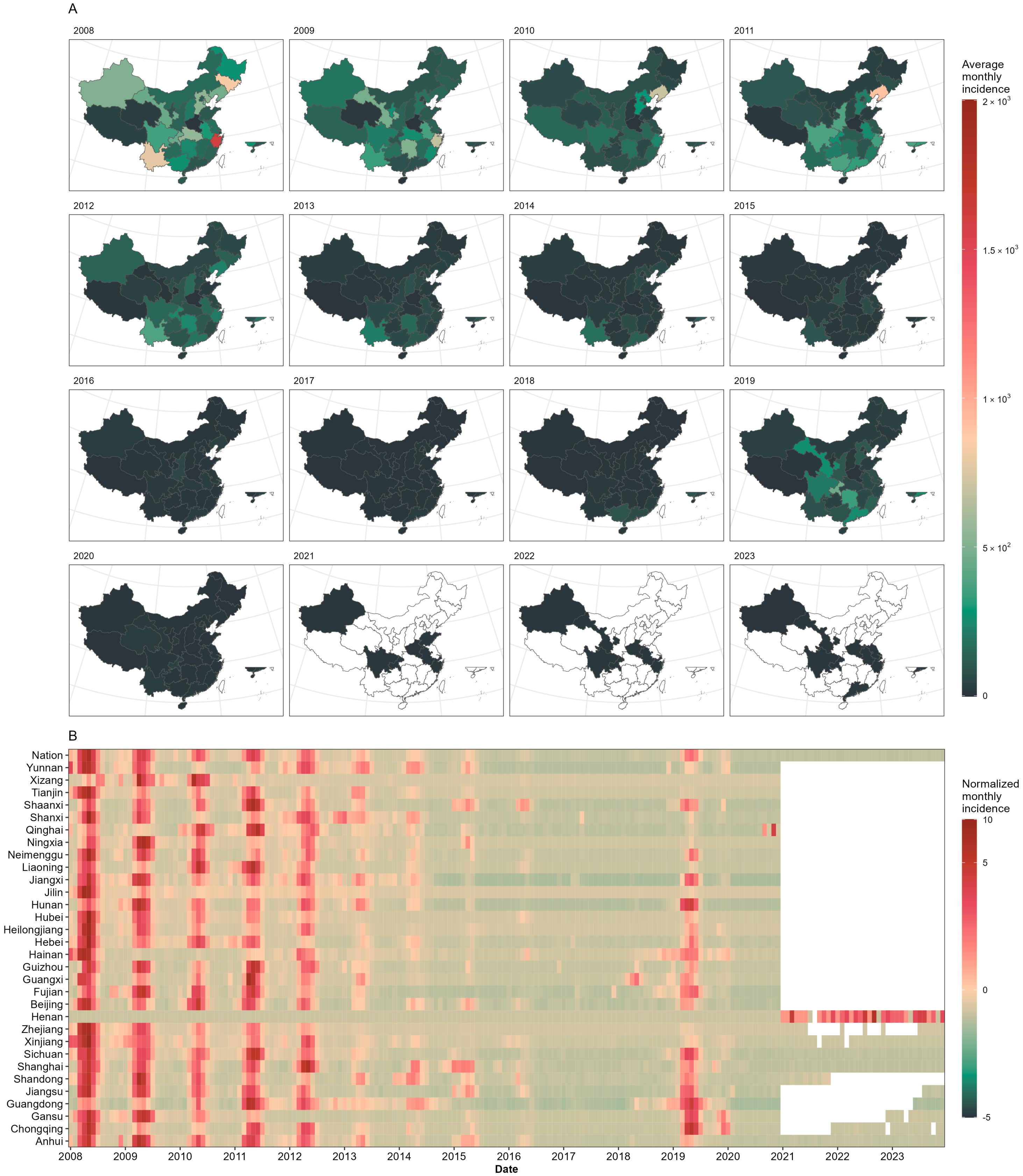
Supplementary Fig. 38. Temporal variation in the monthly incidence of mumps in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



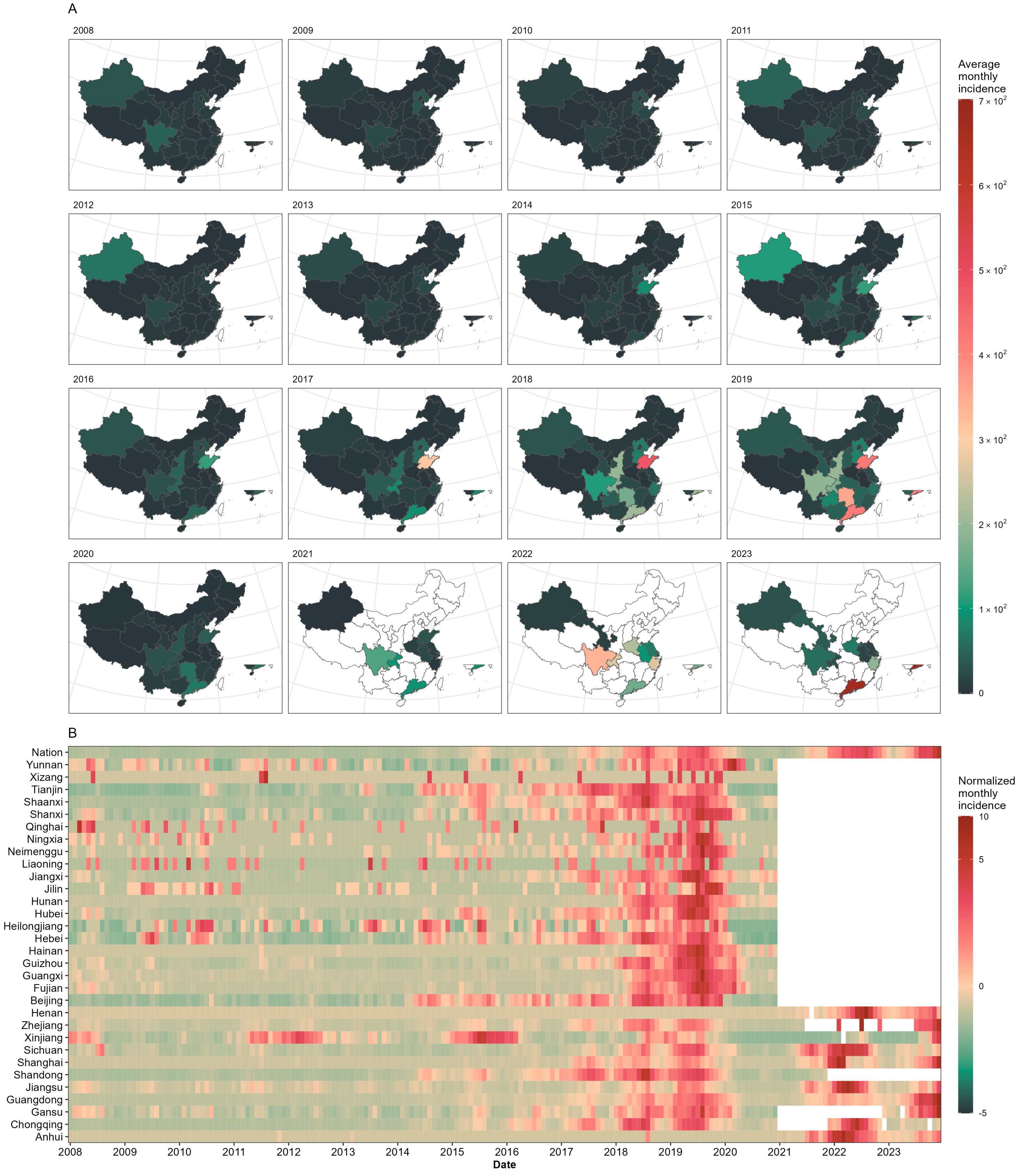
Supplementary Fig. 39. Temporal variation in the monthly incidence of scarlet fever in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



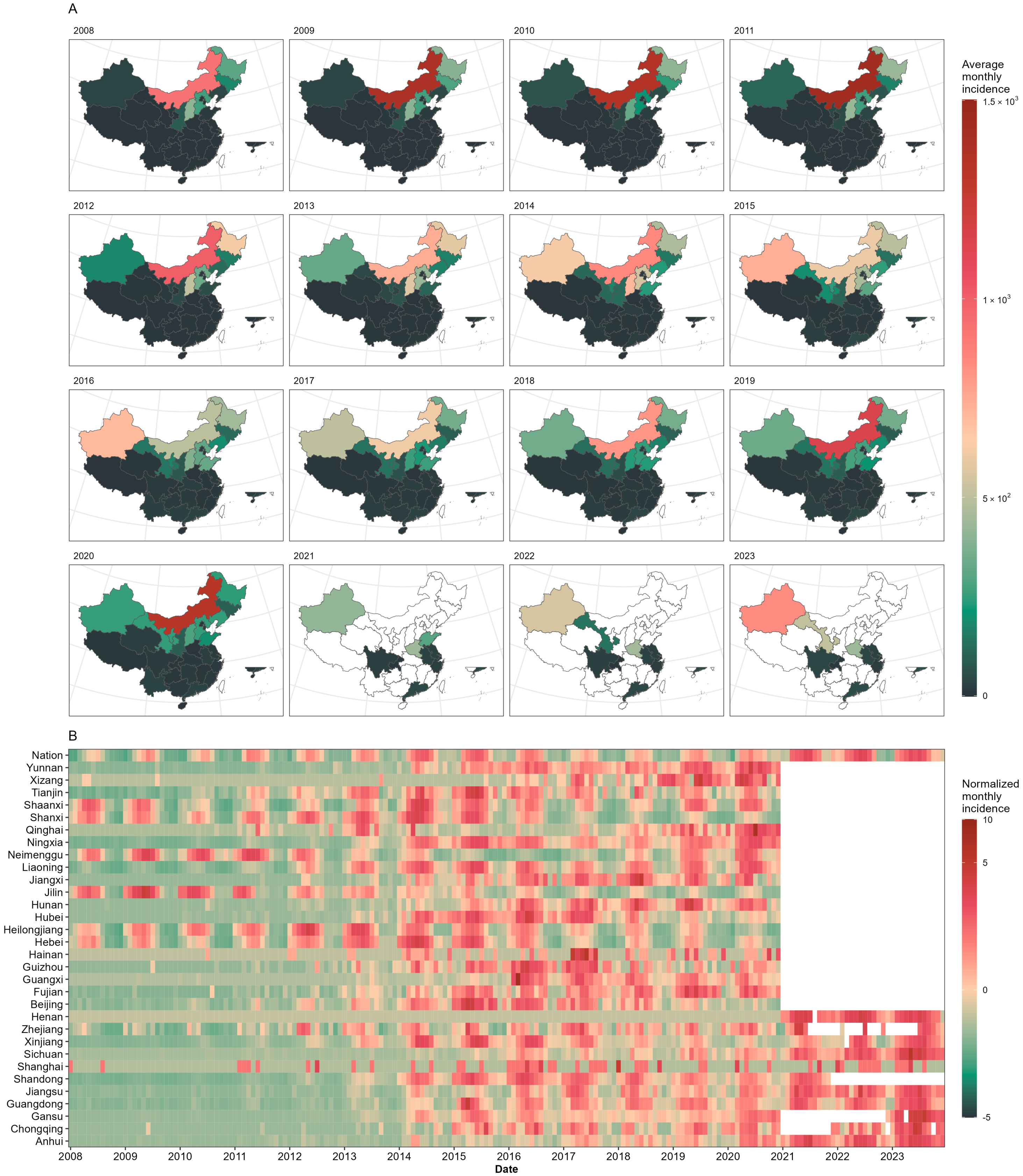
Supplementary Fig. 40. Temporal variation in the monthly incidence of rubella in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



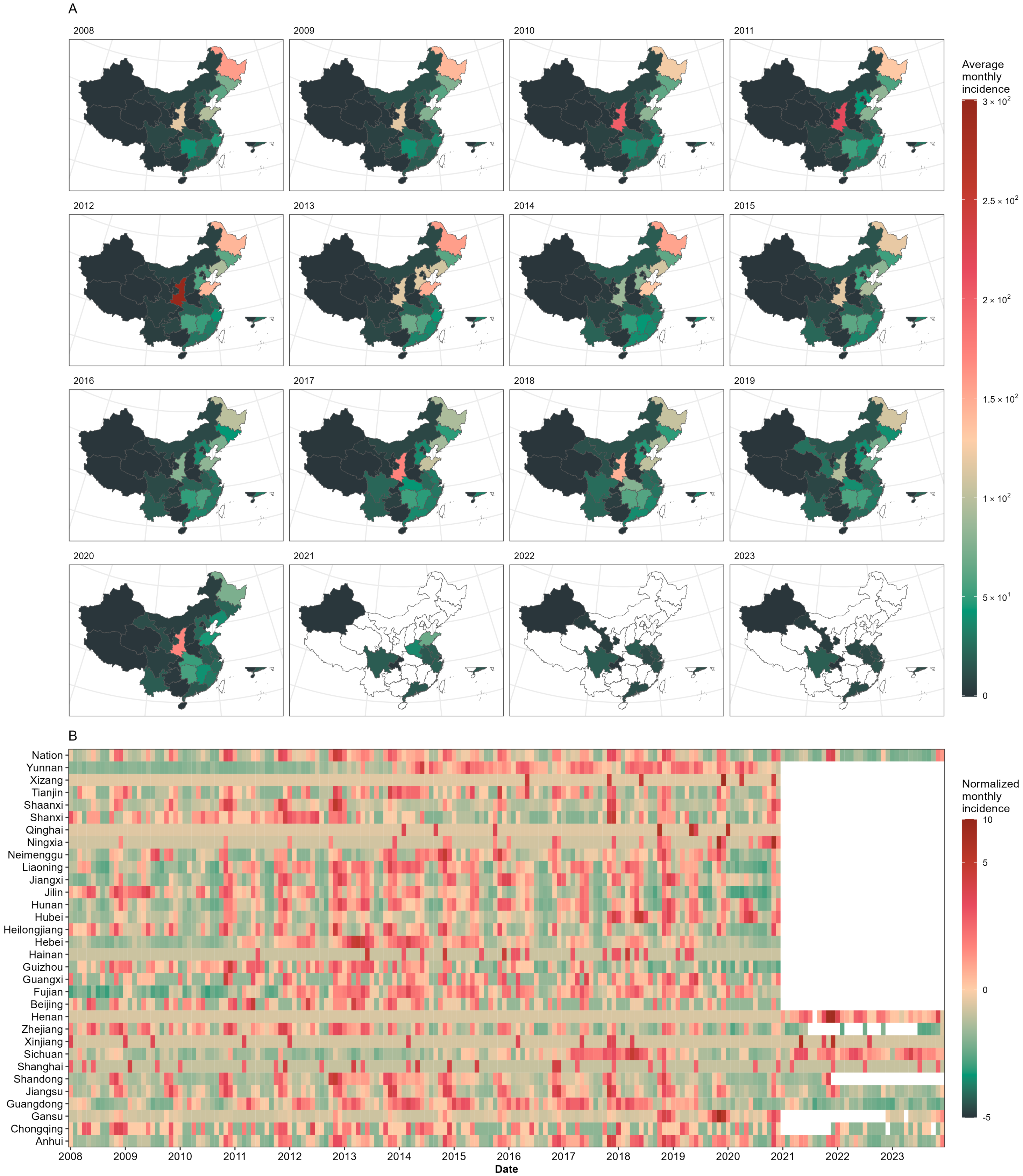
Supplementary Fig. 41. Temporal variation in the monthly incidence of pertussis in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



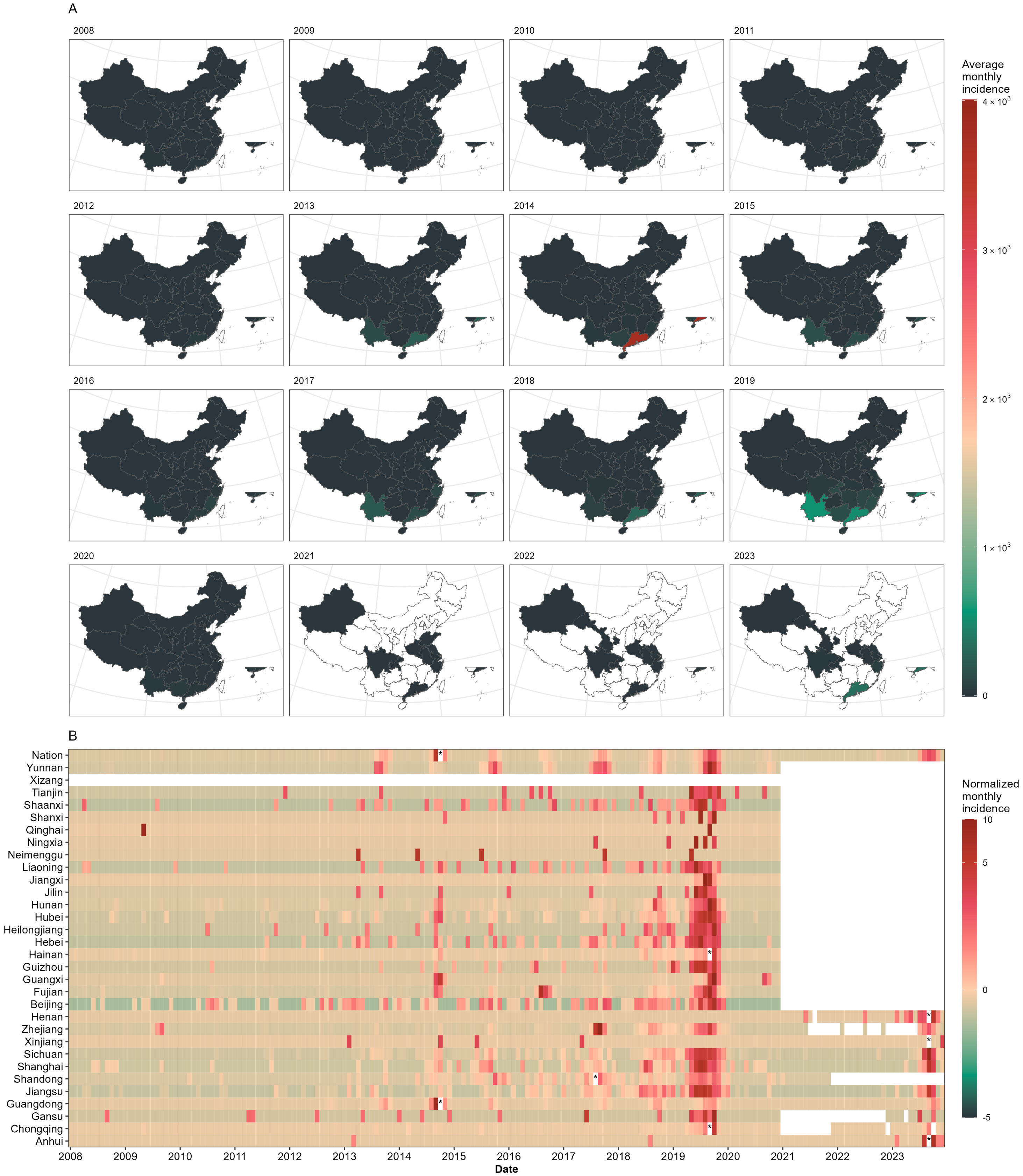
Supplementary Fig. 42. Temporal variation in the monthly incidence of brucellosis in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



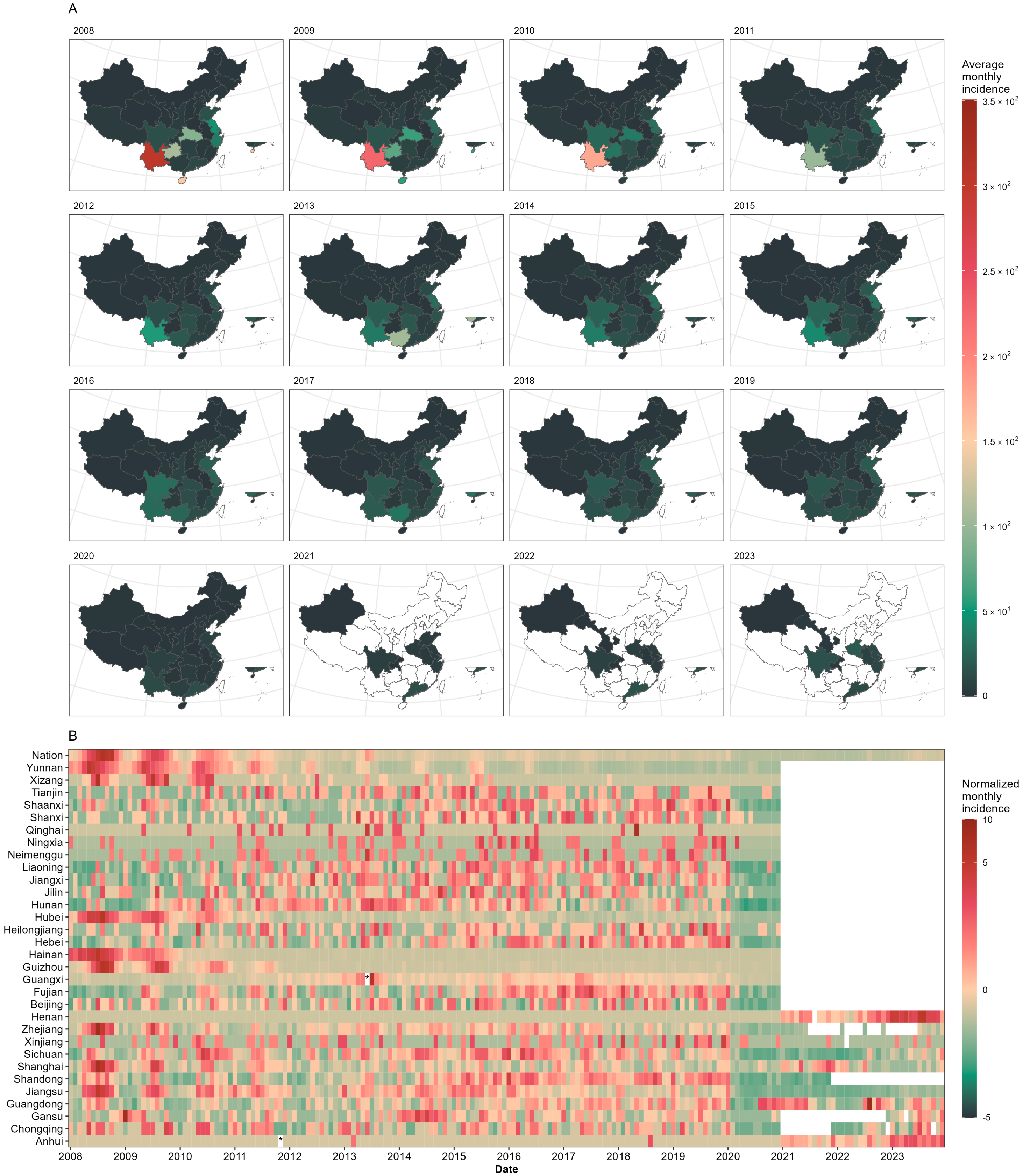
Supplementary Fig. 43. Temporal variation in the monthly incidence of hemorrhagic fever with renal syndrome (HFRS) in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



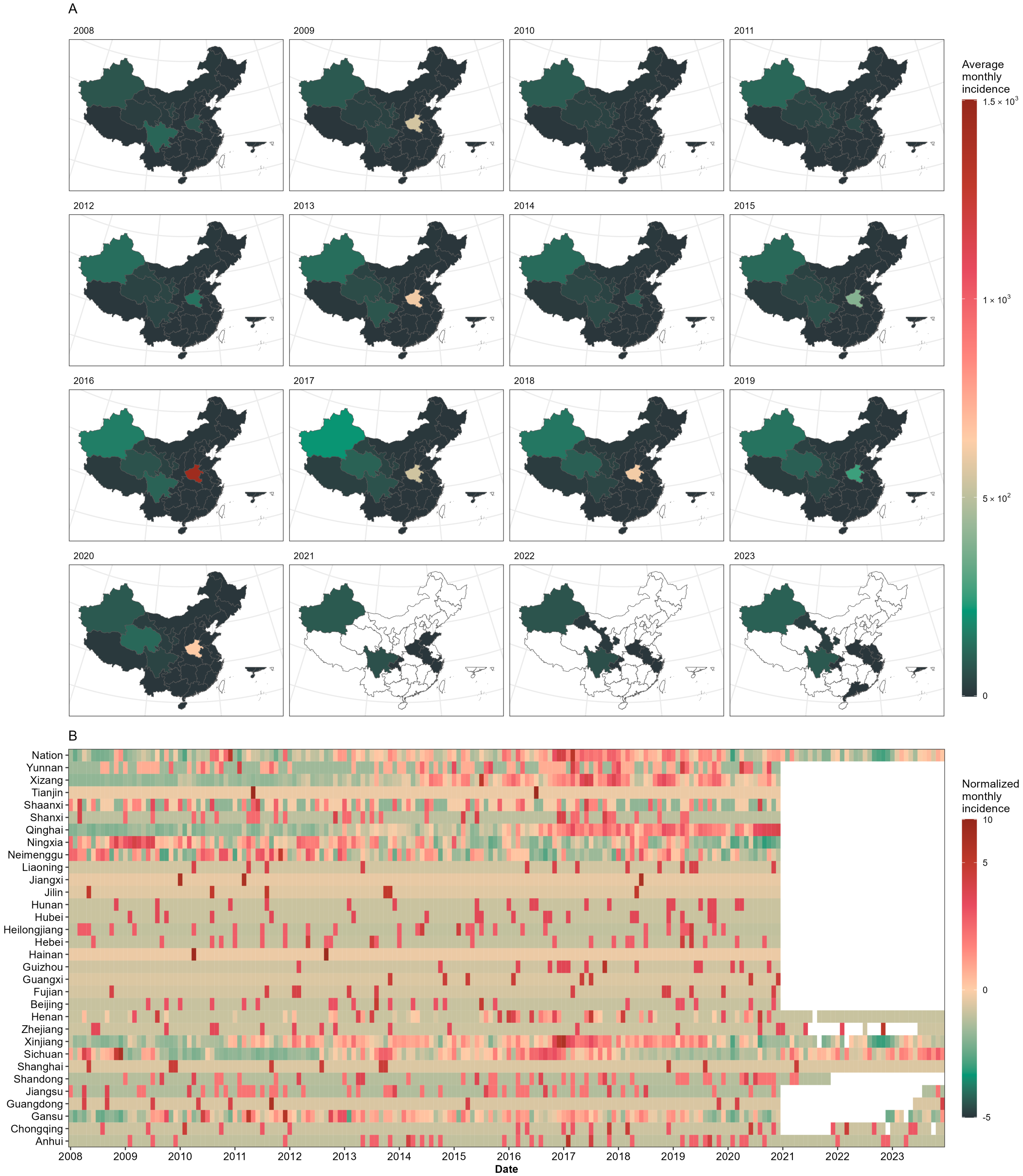
Supplementary Fig. 44. Temporal variation in the monthly incidence of dengue fever in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



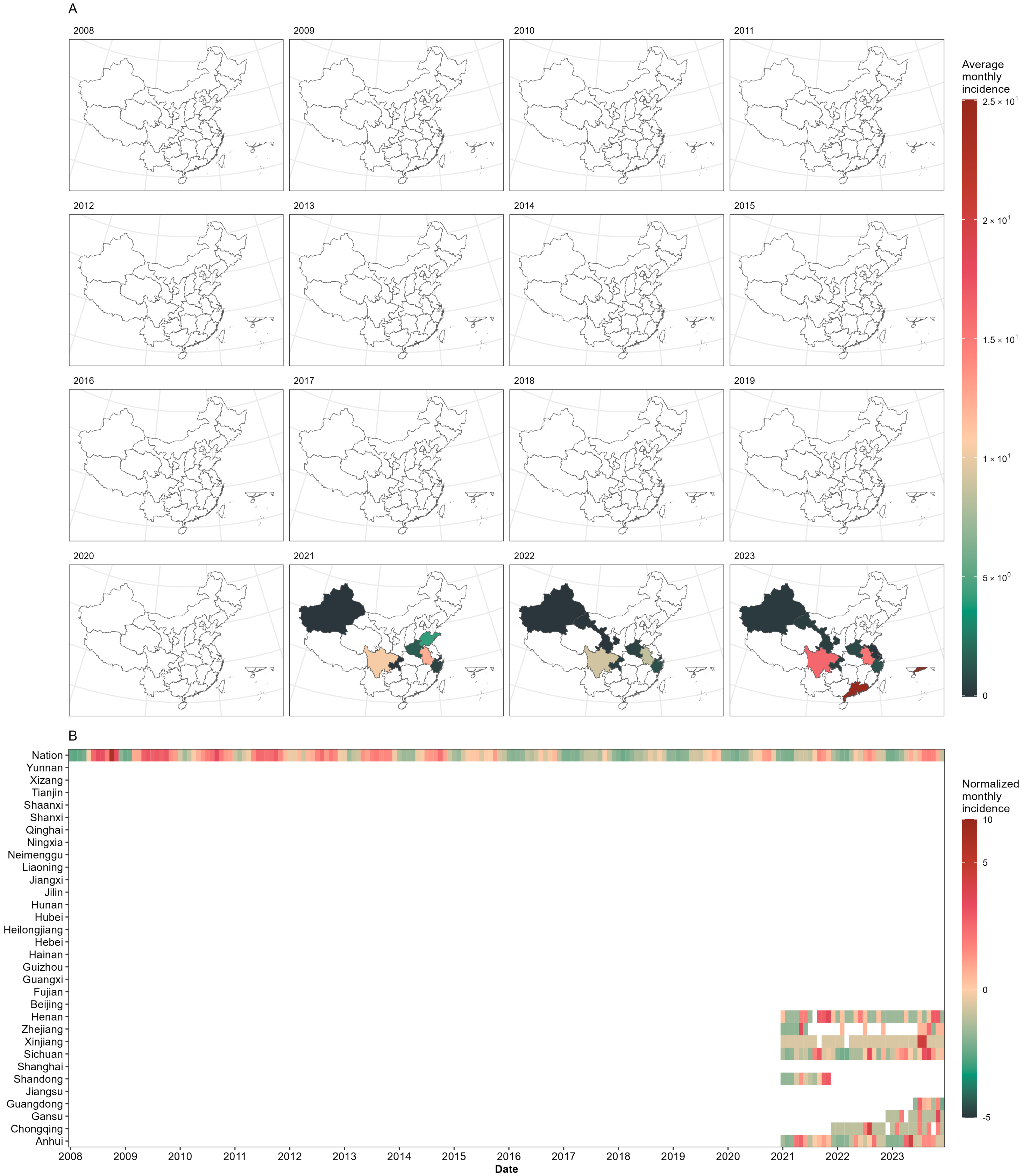
Supplementary Fig. 45. Temporal variation in the monthly incidence of malaria in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



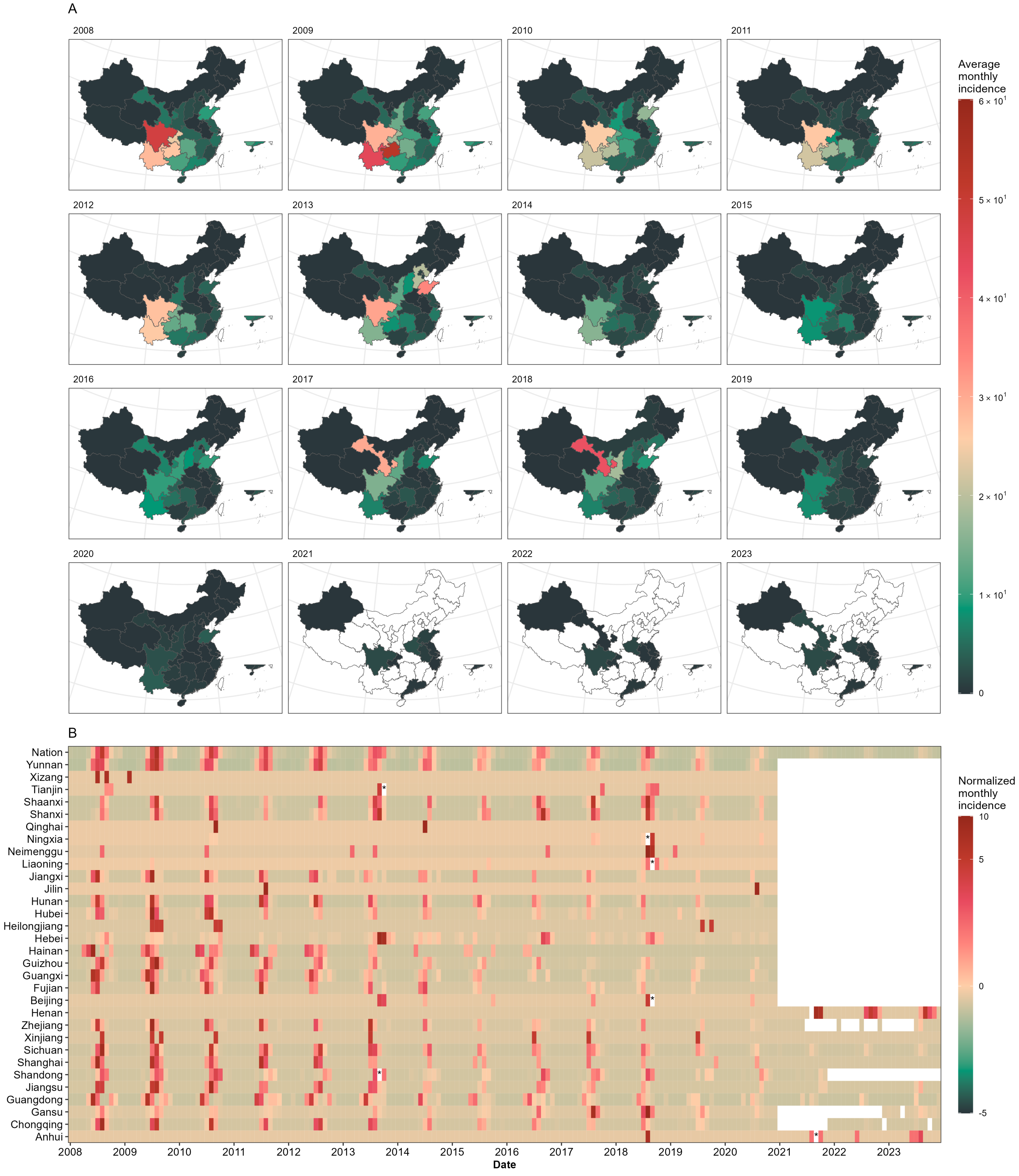
Supplementary Fig. 46. Temporal variation in the monthly incidence of echinococcosis in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



Supplementary Fig. 47. Temporal variation in the monthly incidence of typhus in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.



Supplementary Fig. 48. Temporal variation in the monthly incidence of Japanese encephalitis (JE) in China from January 2008 to December 2023.

(A) The spatial distribution of cases in China; **(B)** Temporal variation in the monthly incidence bwtween different provinces. The heatmap represents normalized monthly incidence data for each province, with color intensity corresponding to the normalized monthly incidence. * Normalized monthly incidence > 10.