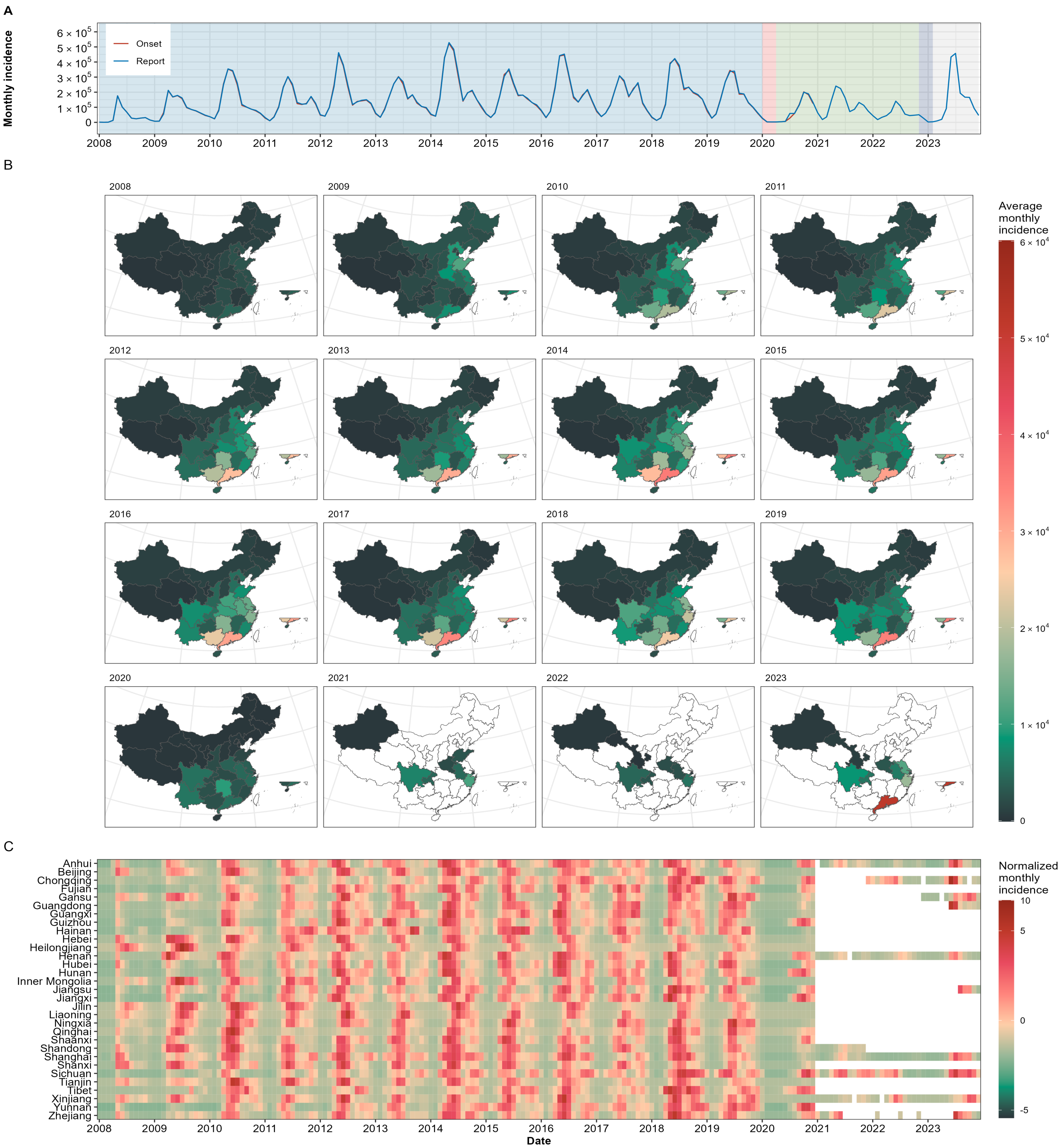
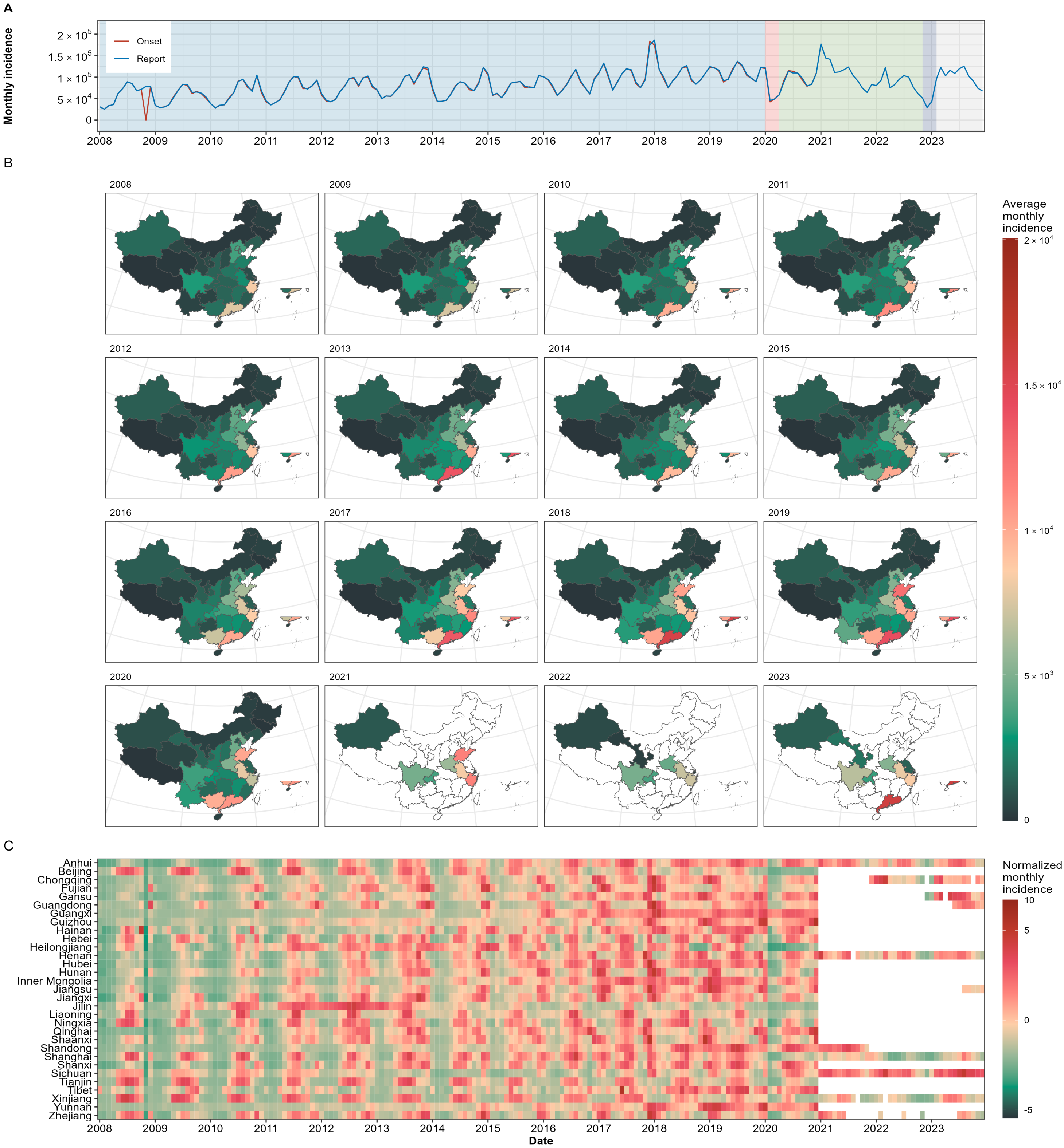
Supplementary Appendix 1:

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



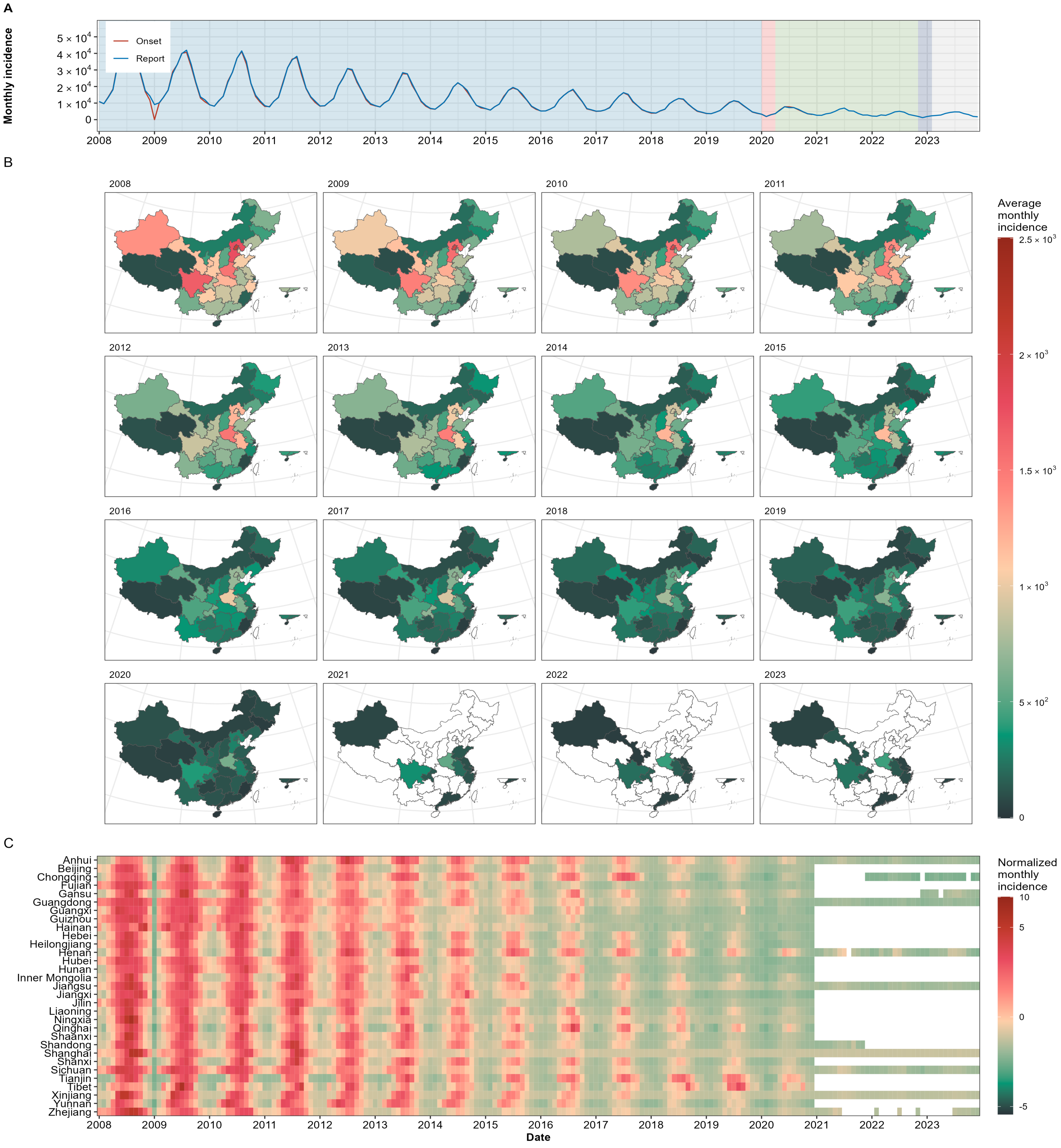
Supplementary Fig. 1. Temporal variation in monthly incidence of hand, foot, and mouth disease (HFMD) from January 2008 to December 2023 in China.

(A) The incidence of hand, foot, and mouth disease (HFMD) in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



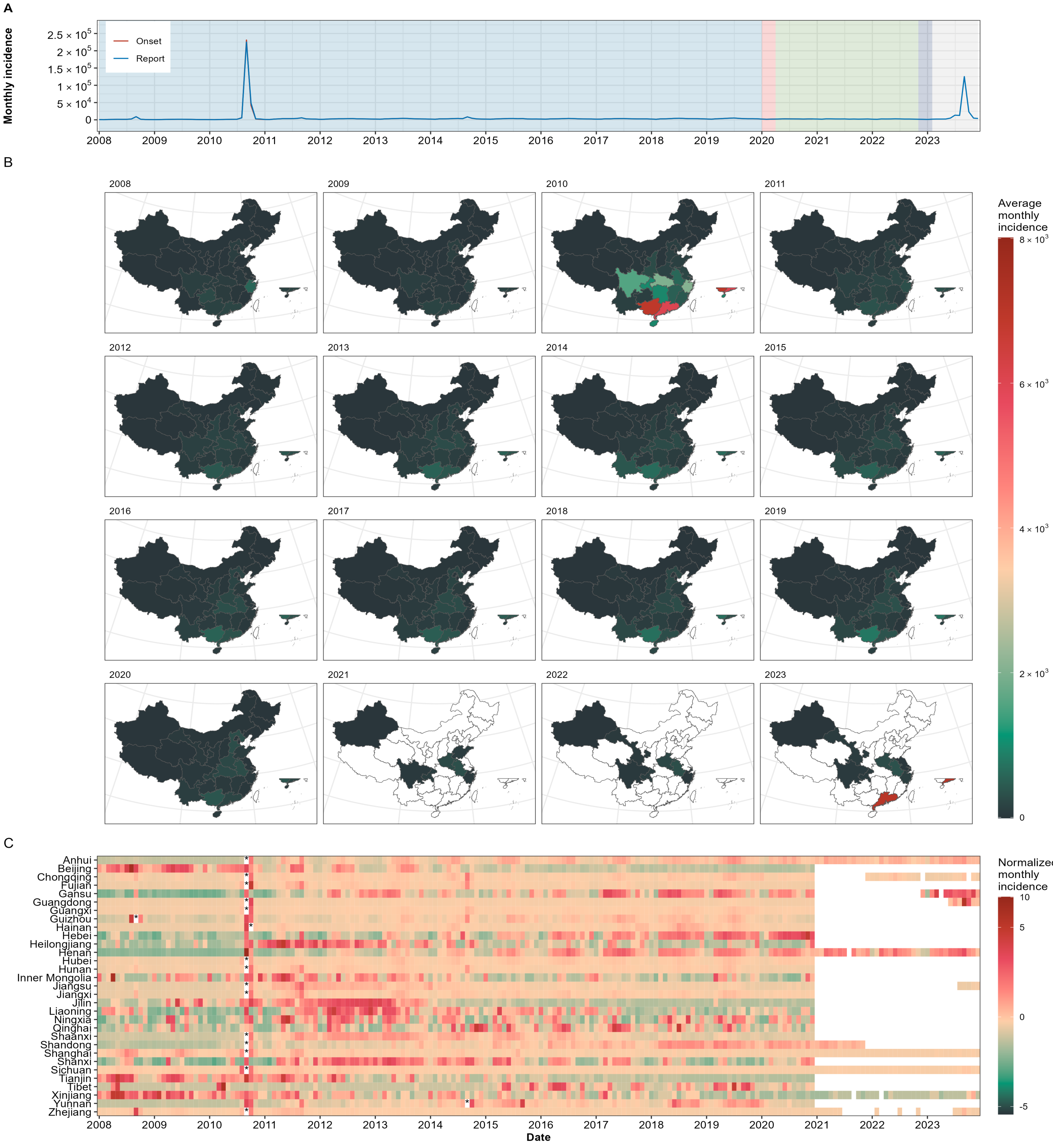
Supplementary Fig. 2. Temporal variation in monthly incidence of infectious diarrhea from January 2008 to December 2023 in China.

(A) The incidence of infectious diarrhea in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



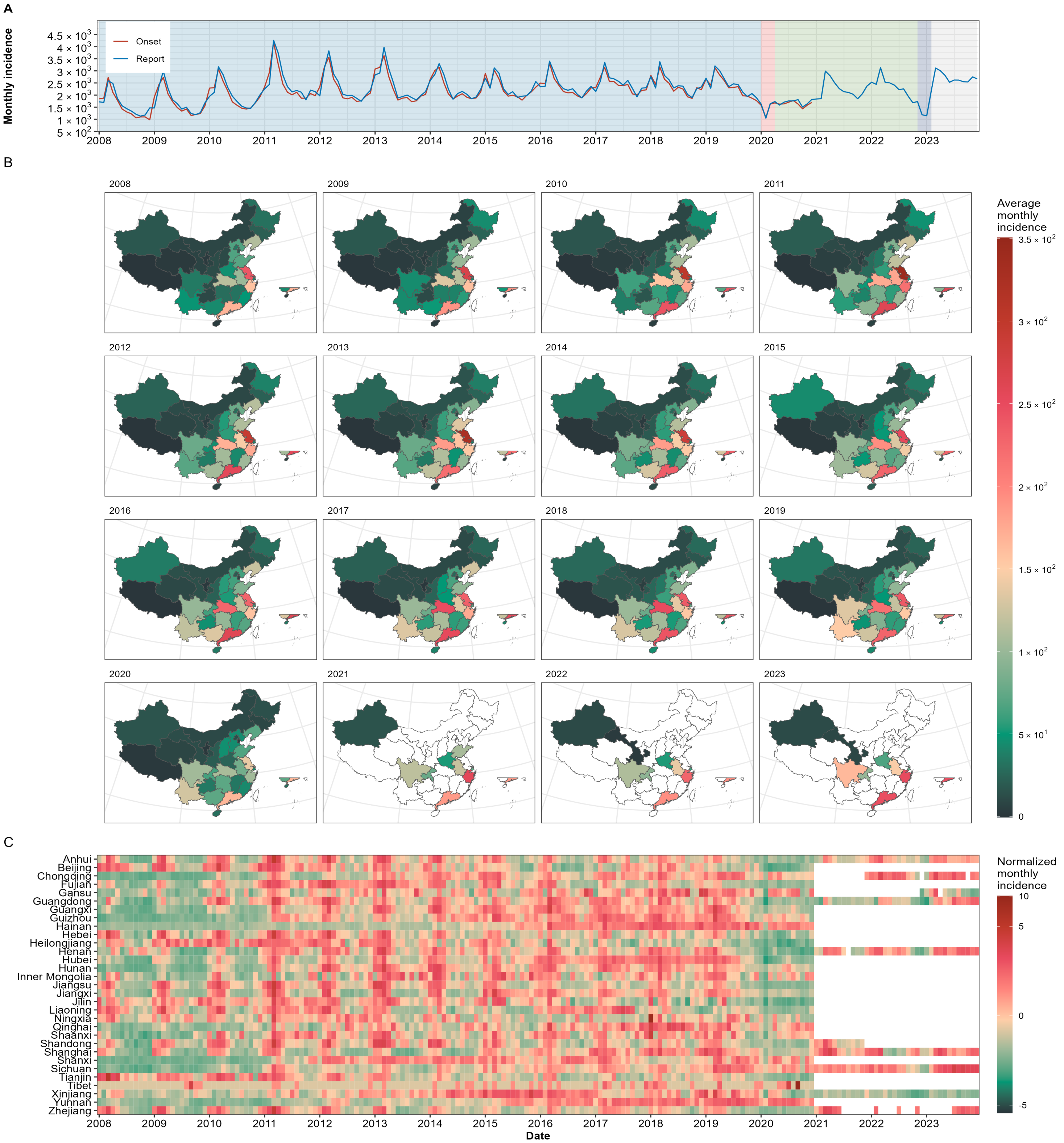
Supplementary Fig. 3. Temporal variation in monthly incidence of dysentery from January 2008 to December 2023 in China.

(A) The incidence of dysentery in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



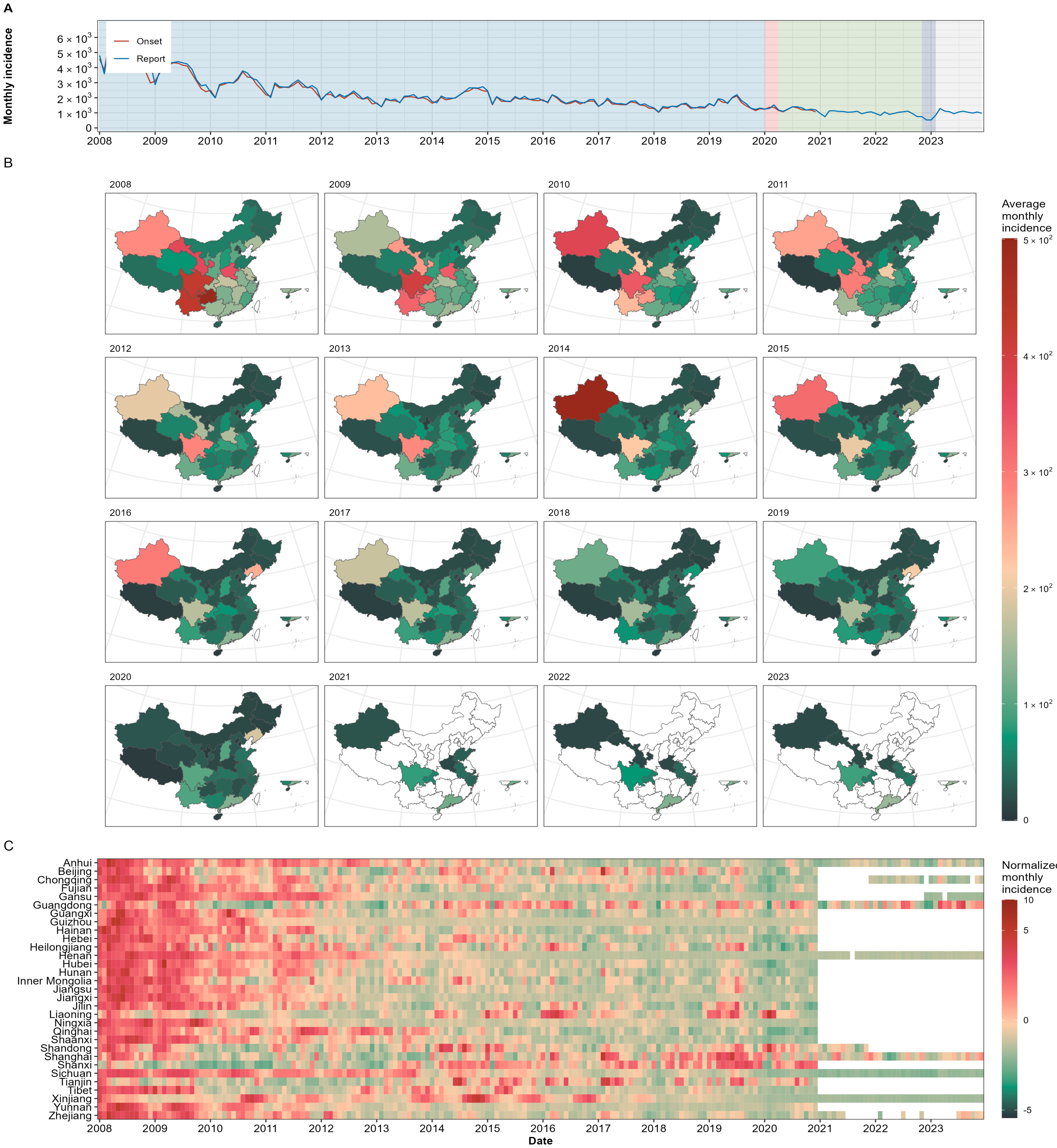
Supplementary Fig. 4. Temporal variation in monthly incidence of acute hemorrhagic conjunctivitis (AHC) from January 2008 to December 2023 in China.

(A) The incidence of acute hemorrhagic conjunctivitis (AHC) in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



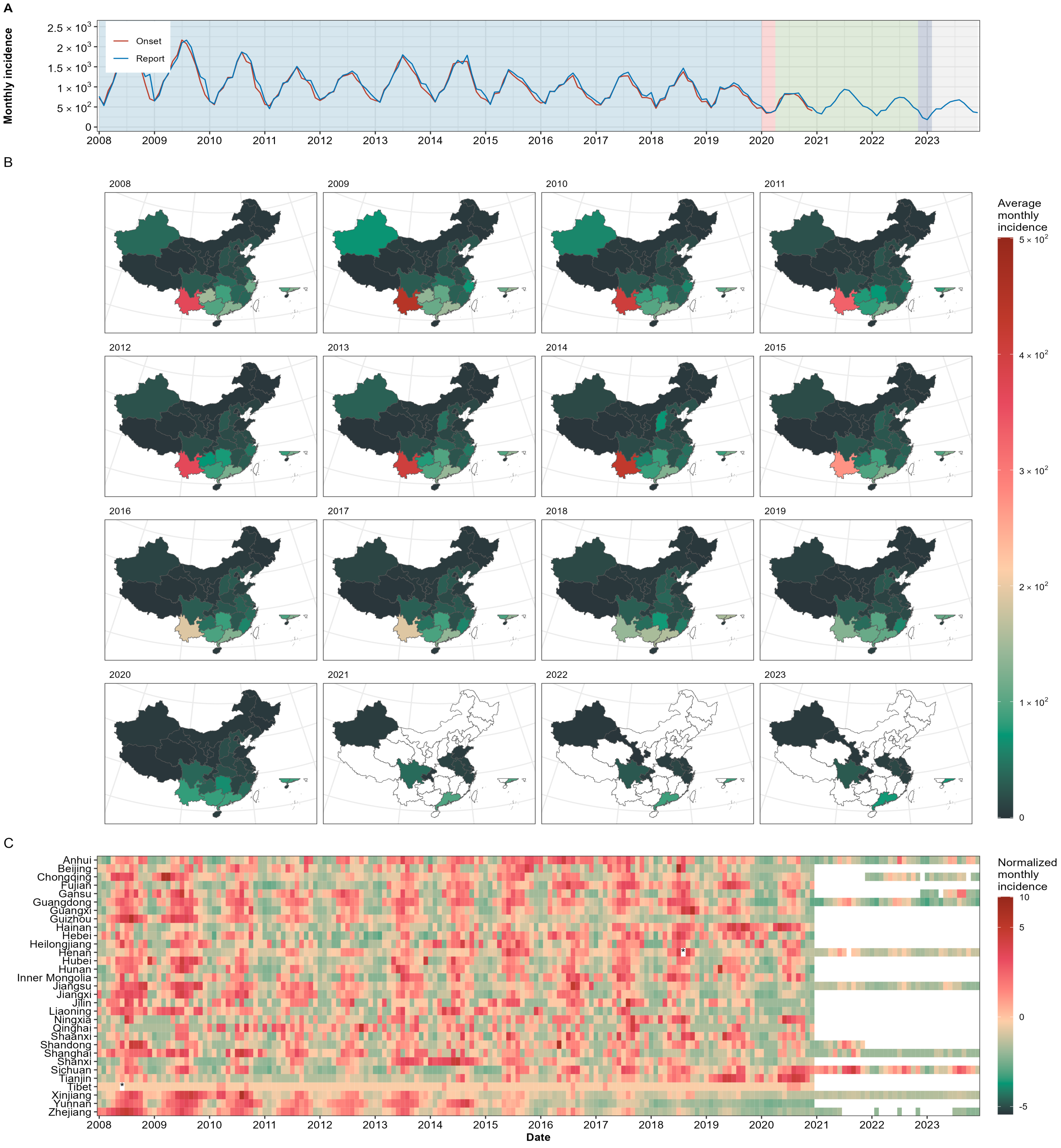
Supplementary Fig. 5. Temporal variation in monthly incidence of hepatitis E from January 2008 to December 2023 in China.

(A) The incidence of hepatitis E in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



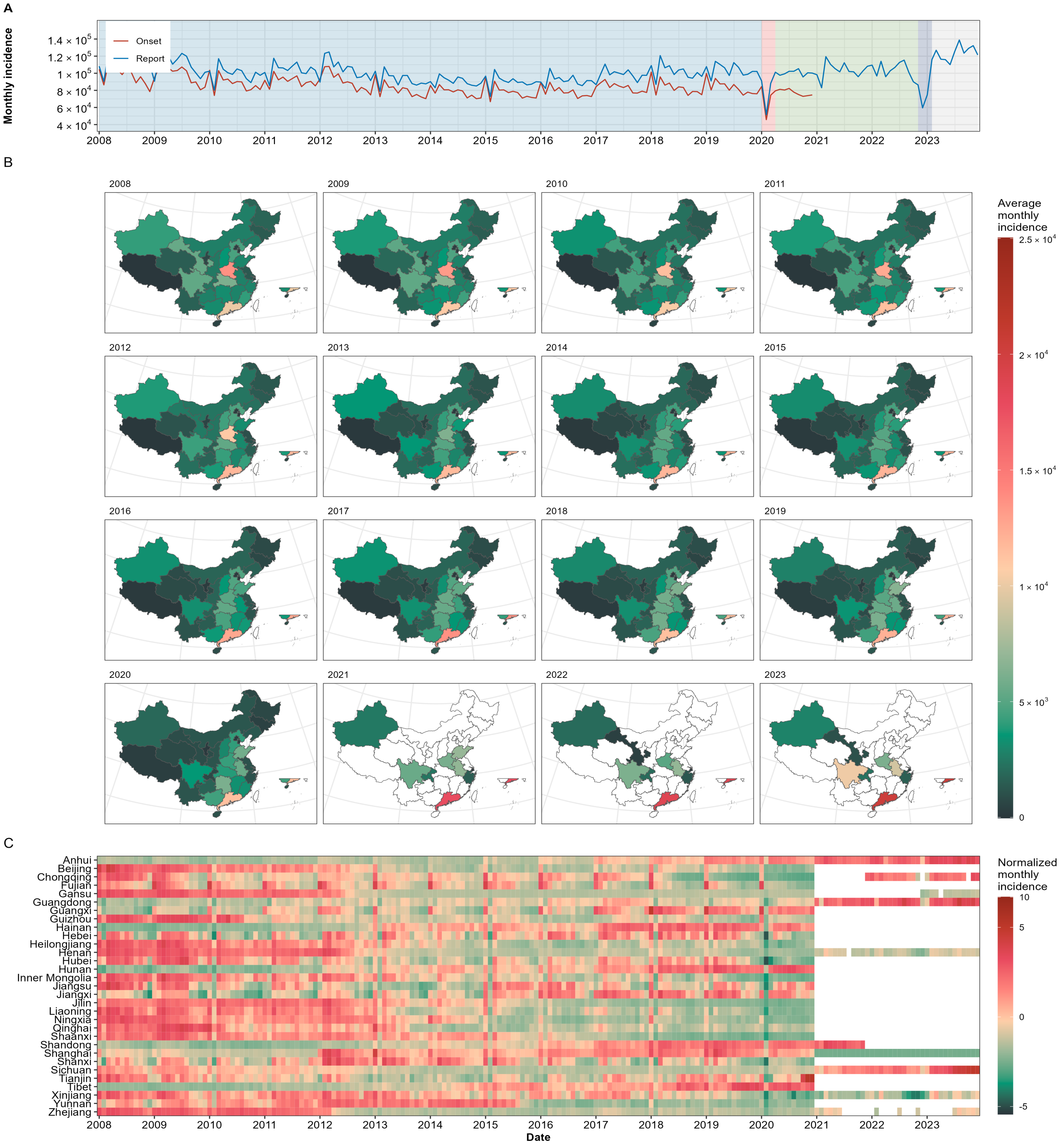
Supplementary Fig. 6. Temporal variation in monthly incidence of hepatitis A from January 2008 to December 2023 in China.

(A) The incidence of hepatitis A in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



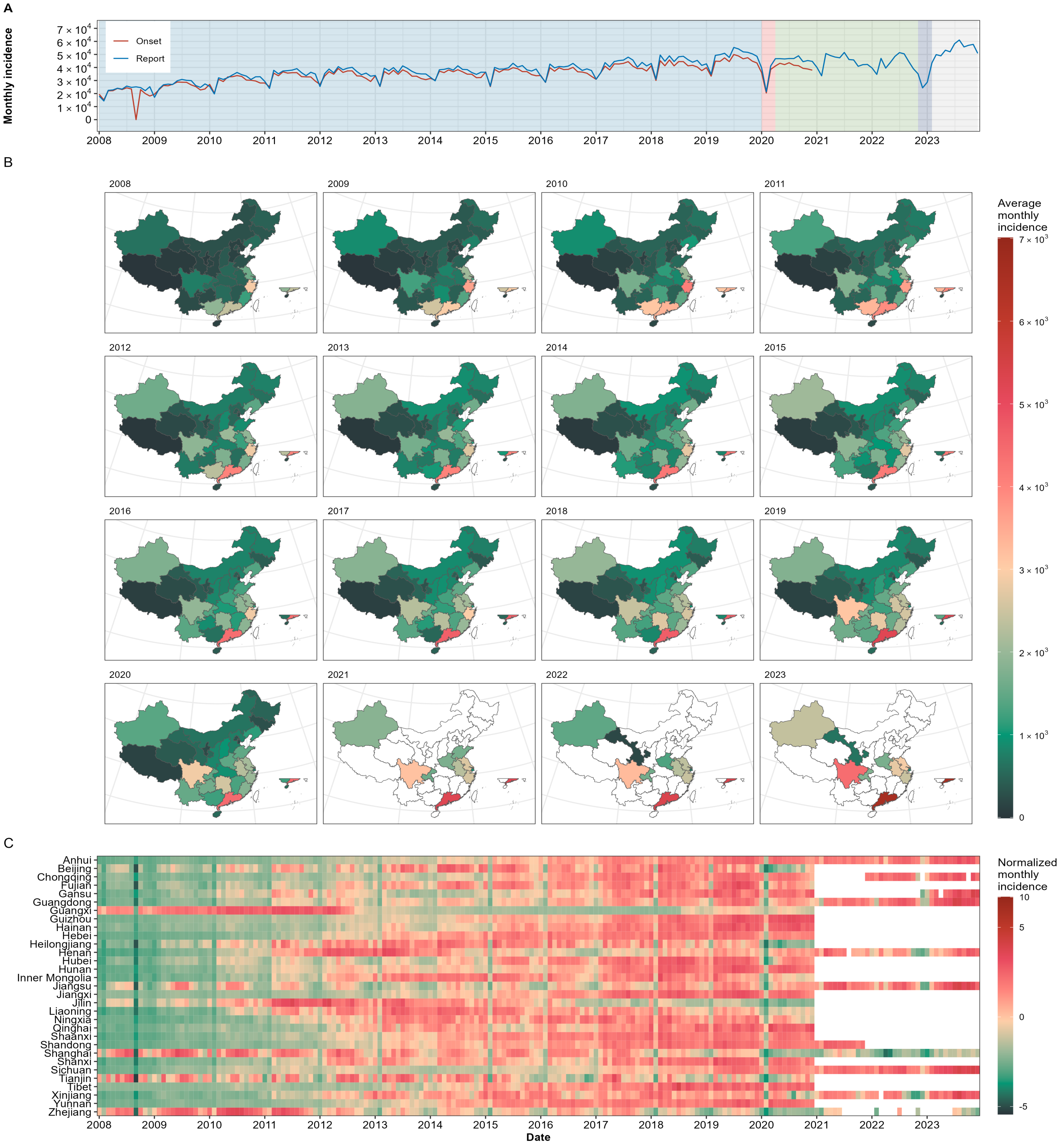
Supplementary Fig. 7. Temporal variation in monthly incidence of enteric fever from January 2008 to December 2023 in China.

(A) The incidence of enteric fever in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



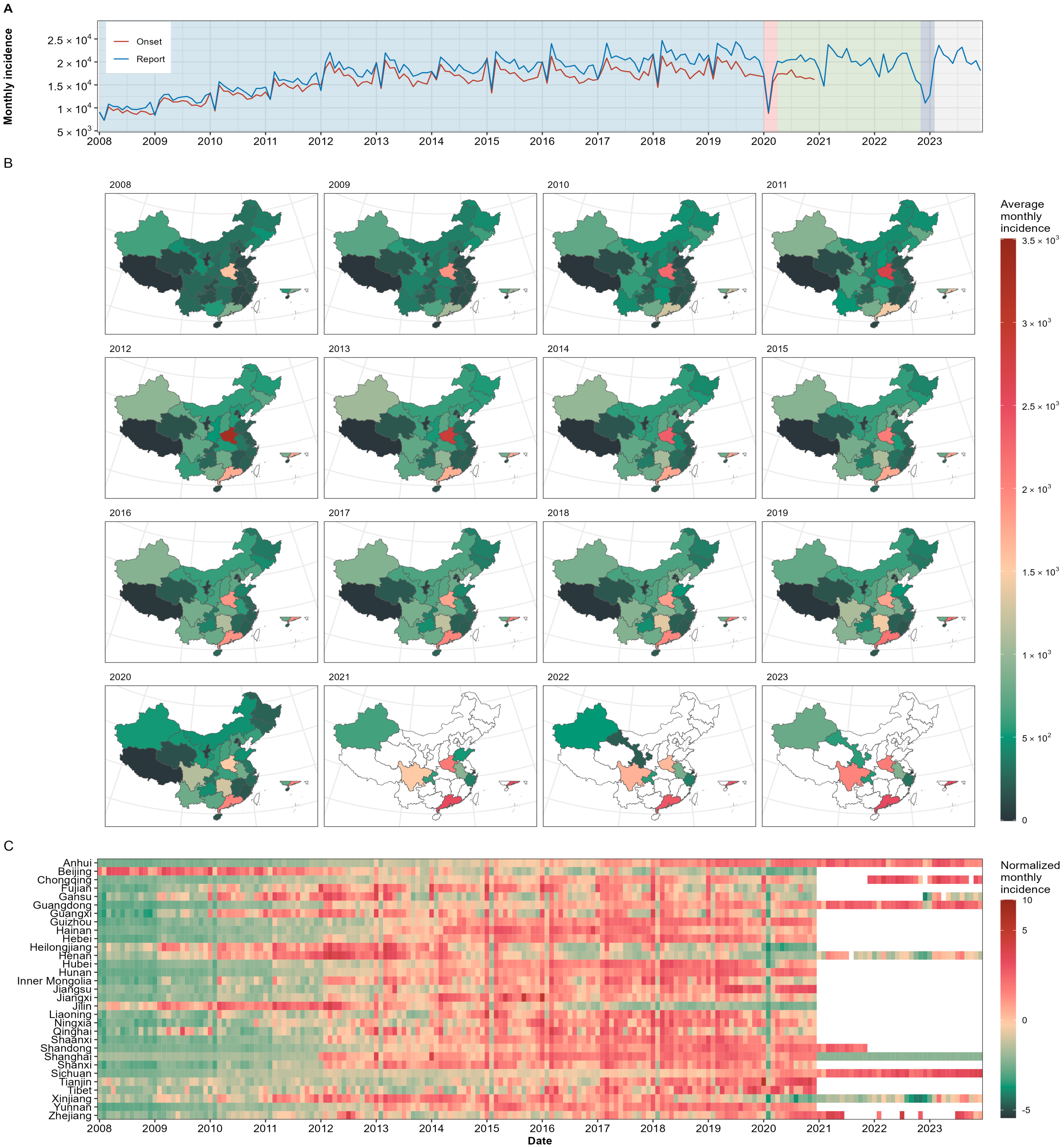
Supplementary Fig. 8. Temporal variation in monthly incidence of hepatitis B from January 2008 to December 2023 in China.

(A) The incidence of hepatitis B in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



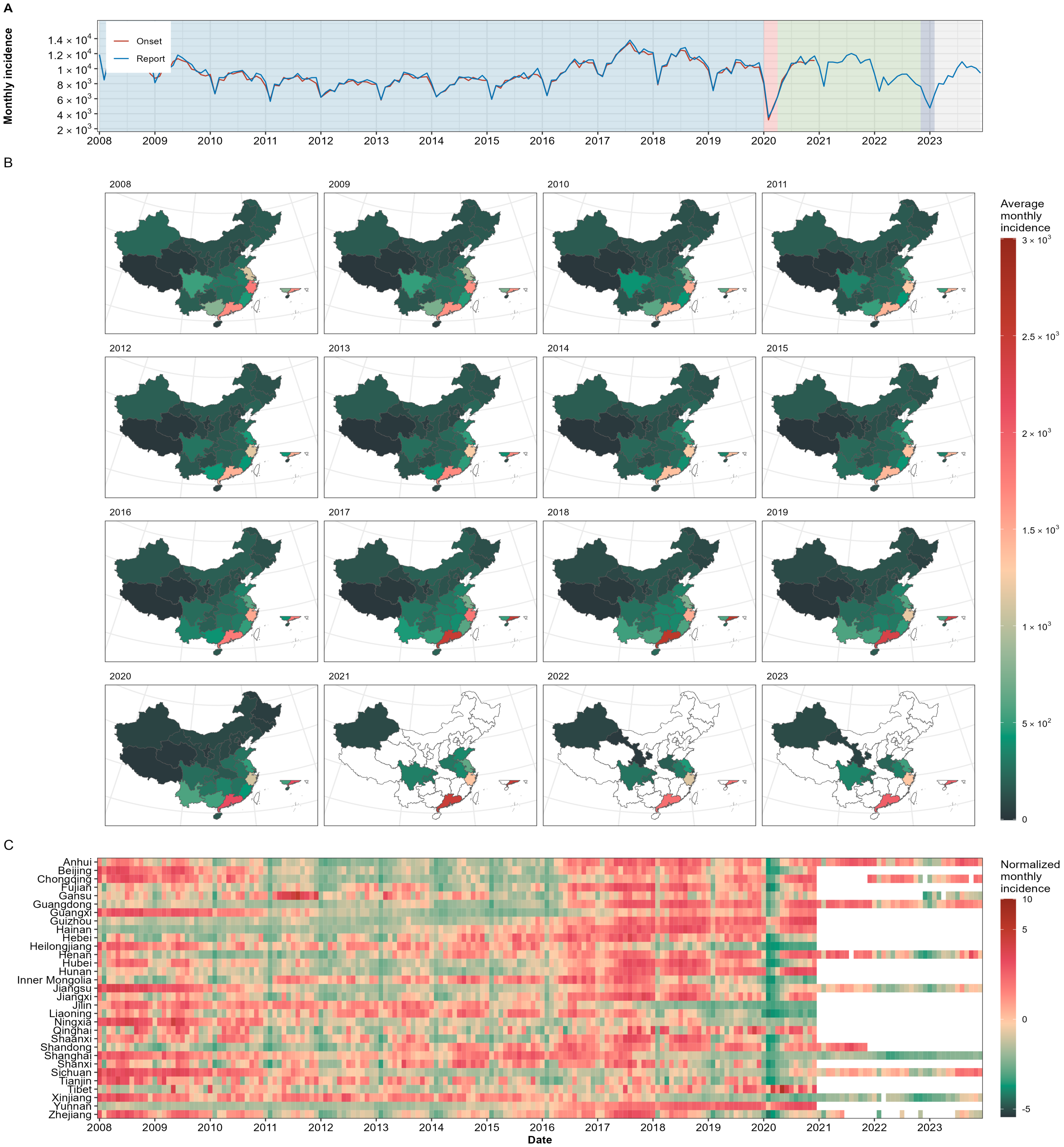
Supplementary Fig. 9. Temporal variation in monthly incidence of syphilis from January 2008 to December 2023 in China.

(A) The incidence of syphilis in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



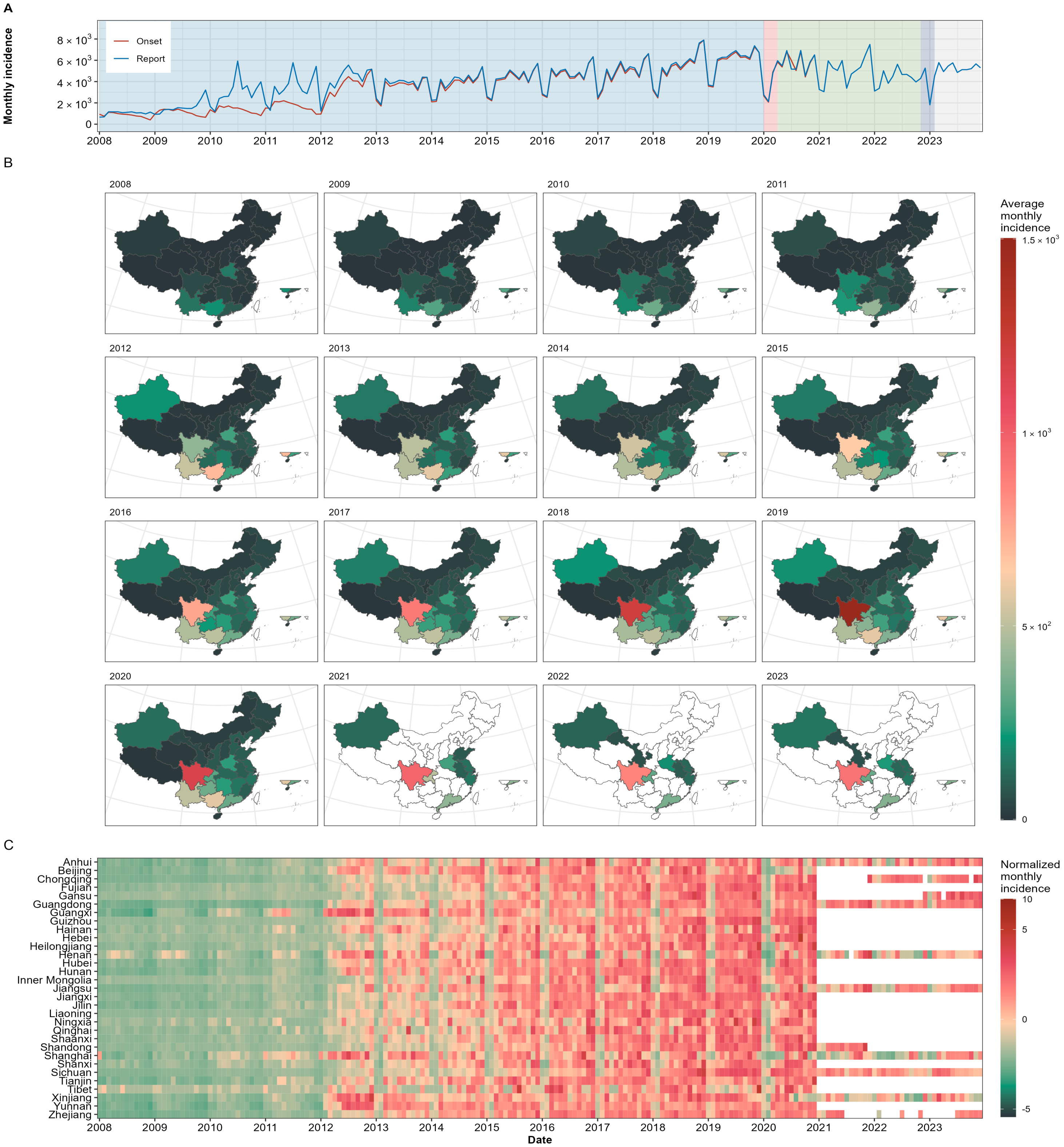
Supplementary Fig. 10. Temporal variation in monthly incidence of hepatitis C from January 2008 to December 2023 in China.

(A) The incidence of hepatitis C in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



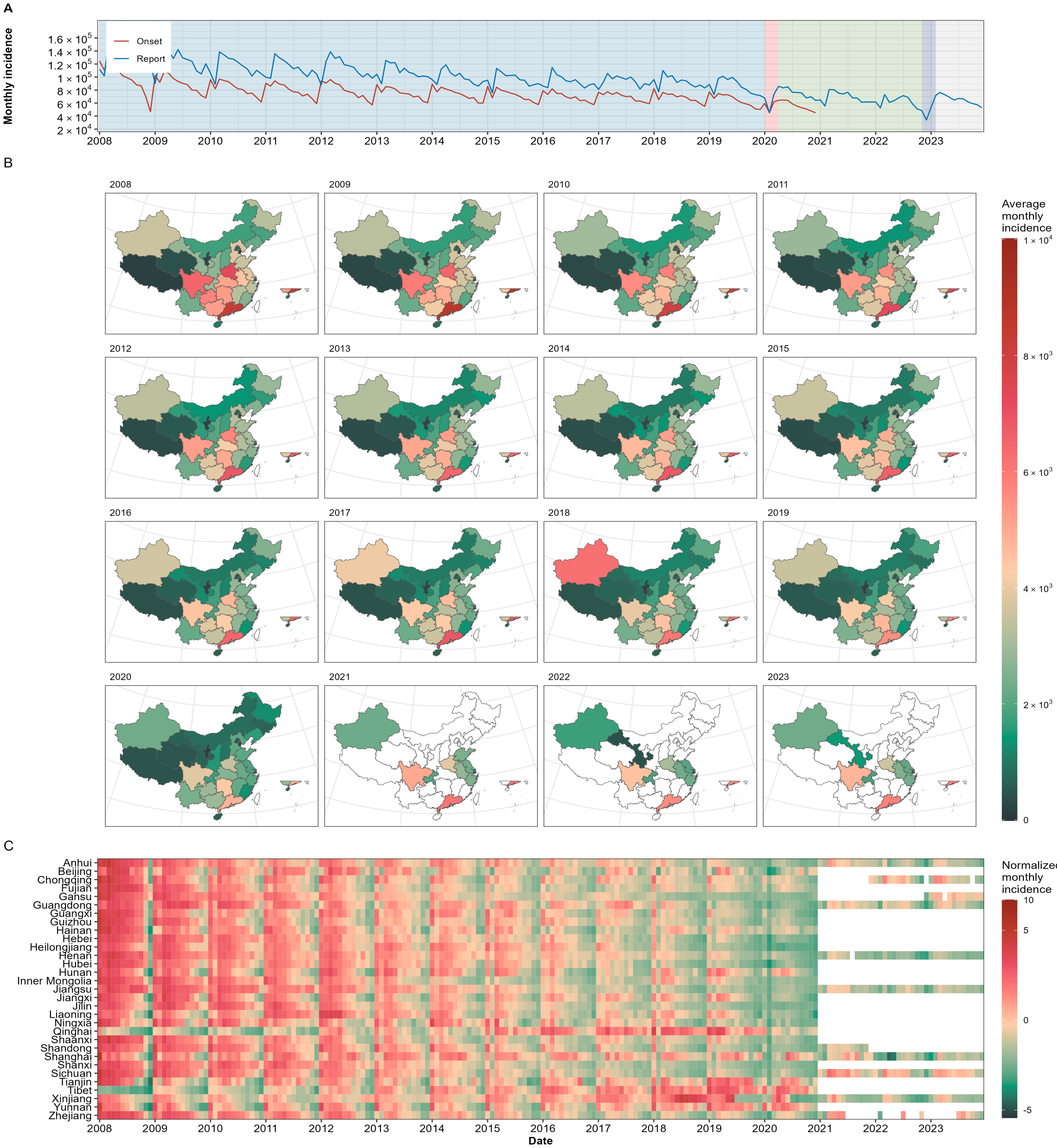
Supplementary Fig. 11. Temporal variation in monthly incidence of gonorrhea from January 2008 to December 2023 in China.

(A) The incidence of gonorrhea in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



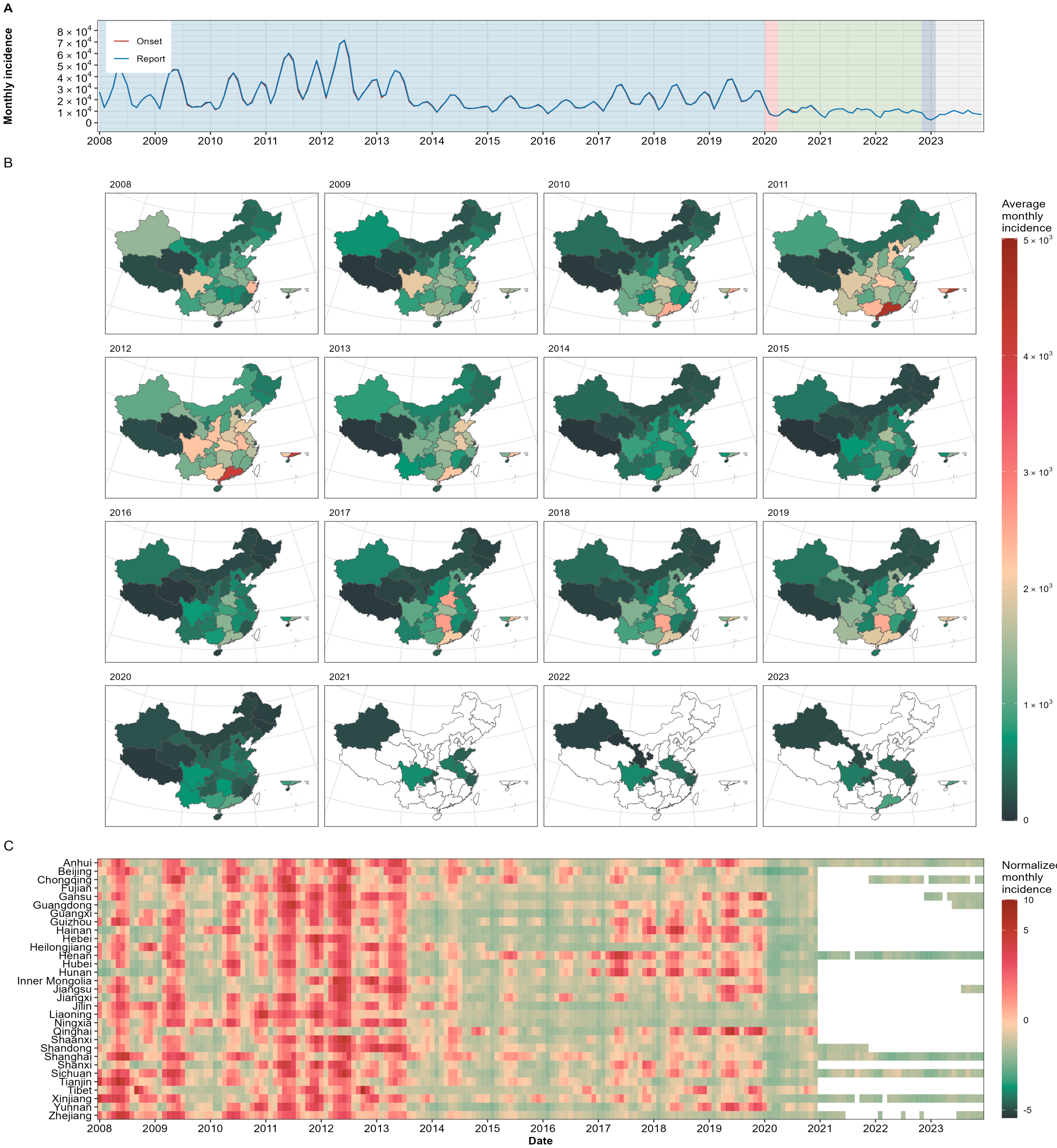
Supplementary Fig. 12. Temporal variation in monthly incidence of acquired immunodeficiency syndrome (AIDS) from January 2008 to December 2023 in China.

(A) The incidence of acquired immunodeficiency syndrome (AIDS) in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



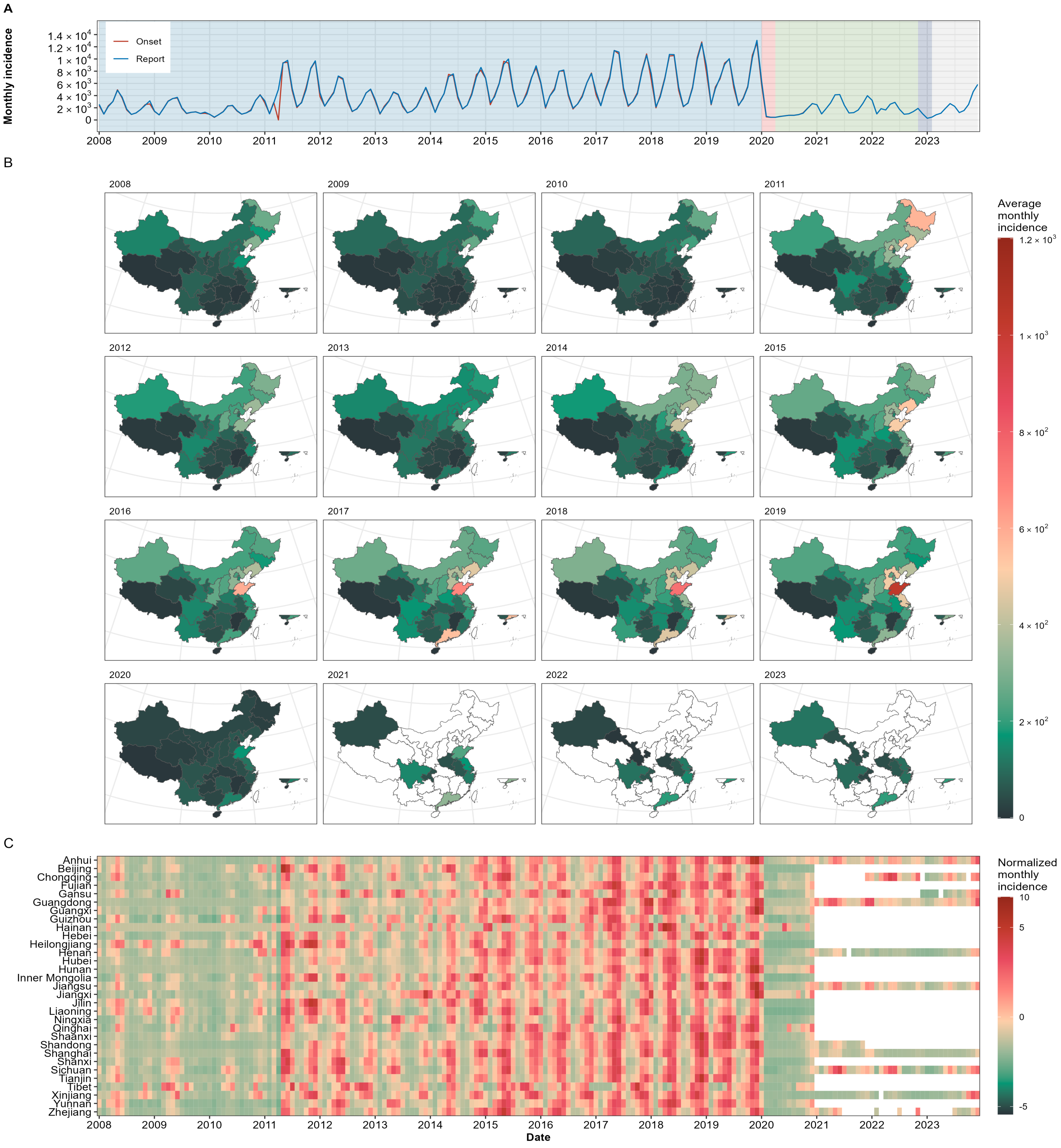
Supplementary Fig. 13. Temporal variation in monthly incidence of tuberculosis from January 2008 to December 2023 in China.

(A) The incidence of tuberculosis in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



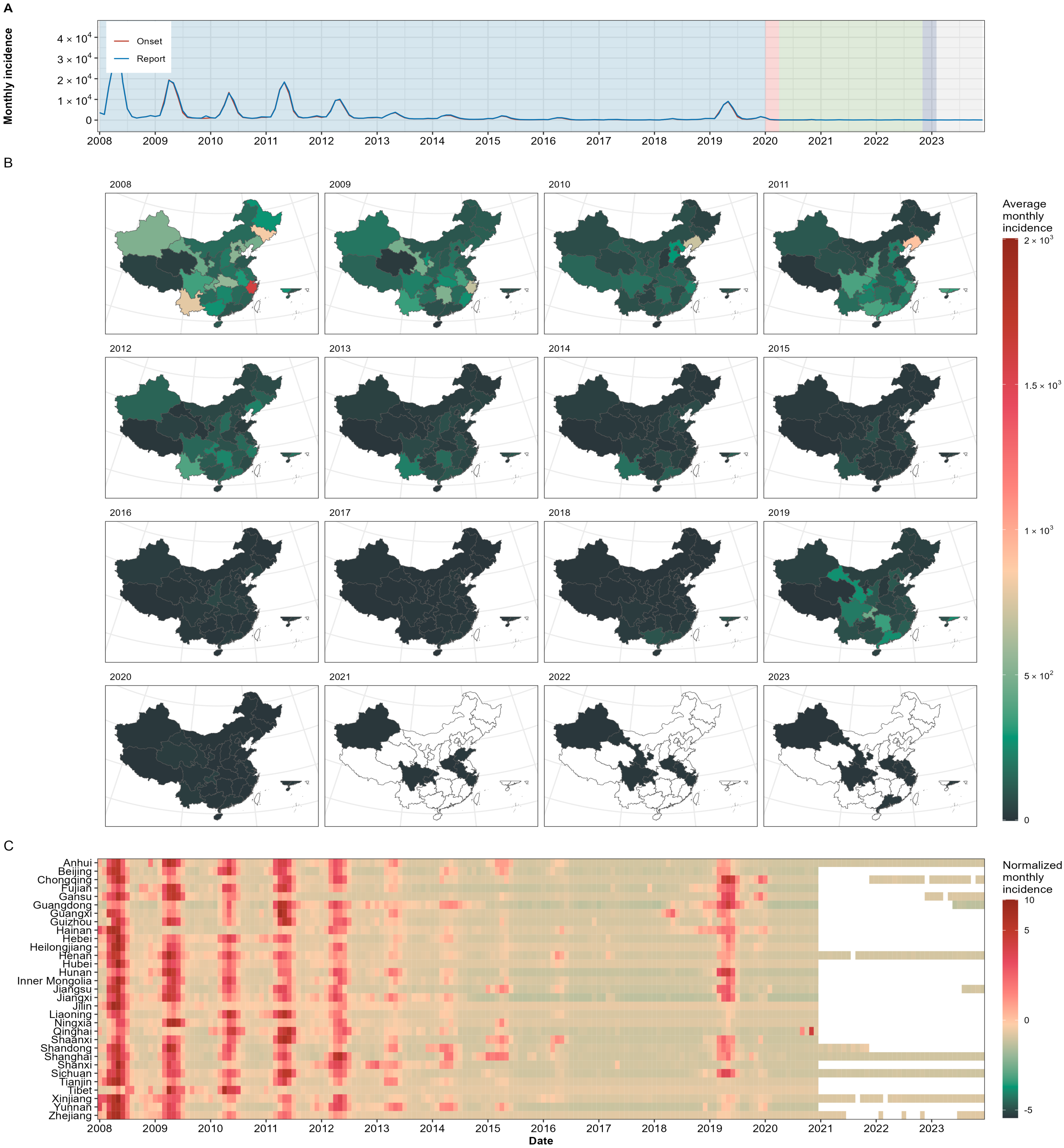
Supplementary Fig. 14. Temporal variation in monthly incidence of mumps from January 2008 to December 2023 in China.

(A) The incidence of mumps in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



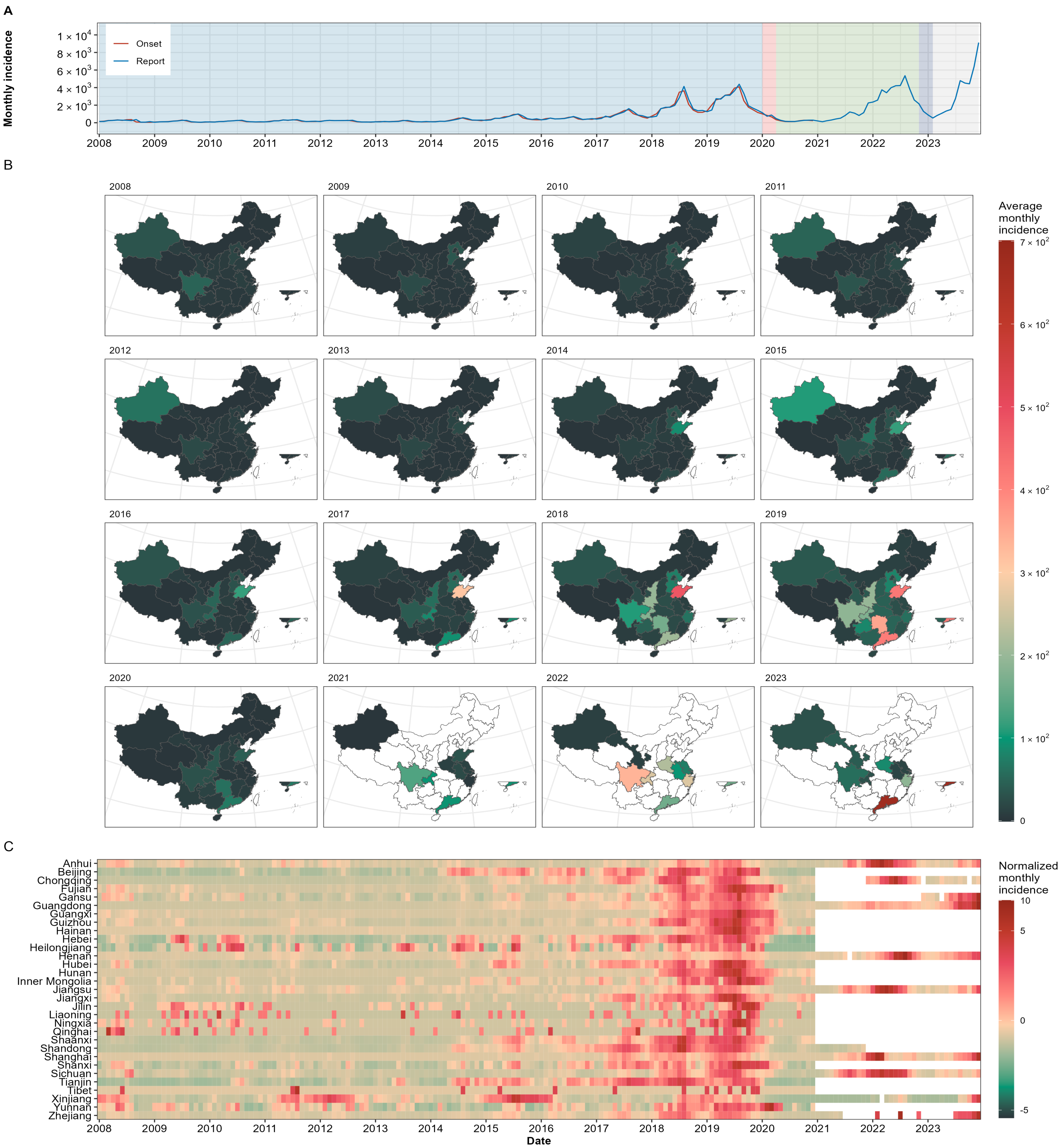
Supplementary Fig. 15. Temporal variation in monthly incidence of scarlet fever from January 2008 to December 2023 in China.

(A) The incidence of scarlet fever in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



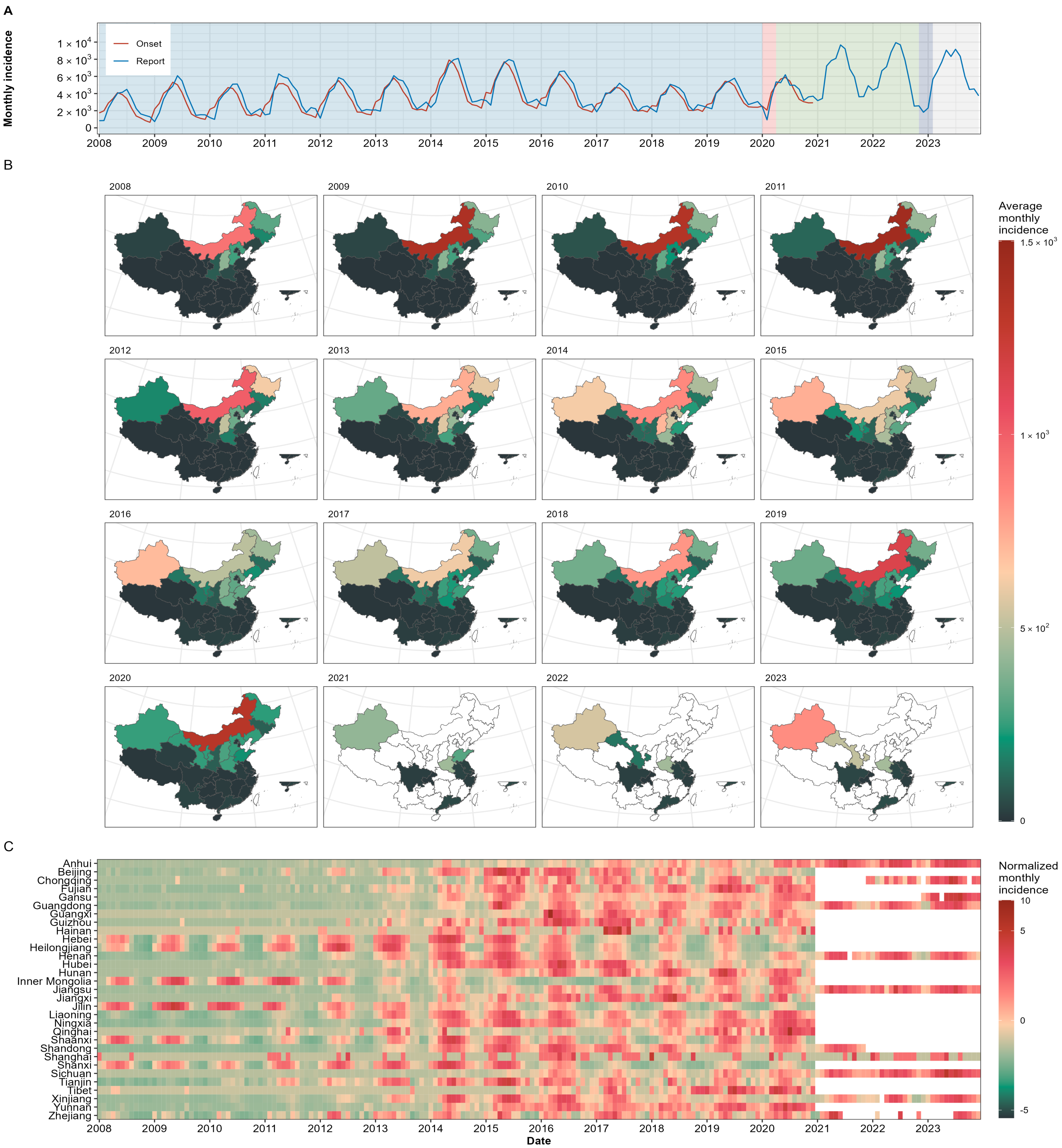
Supplementary Fig. 16. Temporal variation in monthly incidence of rubella from January 2008 to December 2023 in China.

(A) The incidence of rubella in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



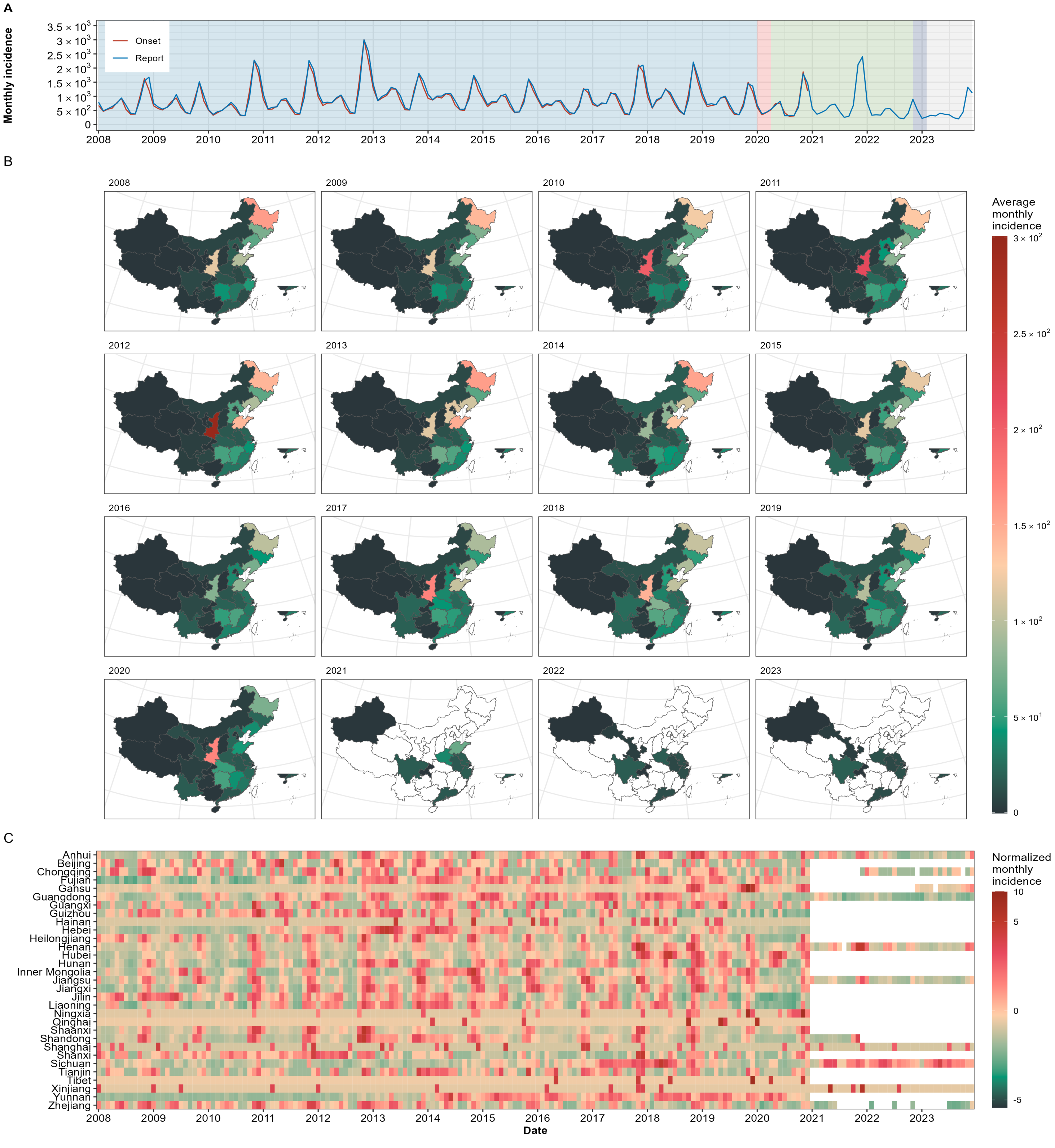
Supplementary Fig. 17. Temporal variation in monthly incidence of pertussis from January 2008 to December 2023 in China.

(A) The incidence of pertussis in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



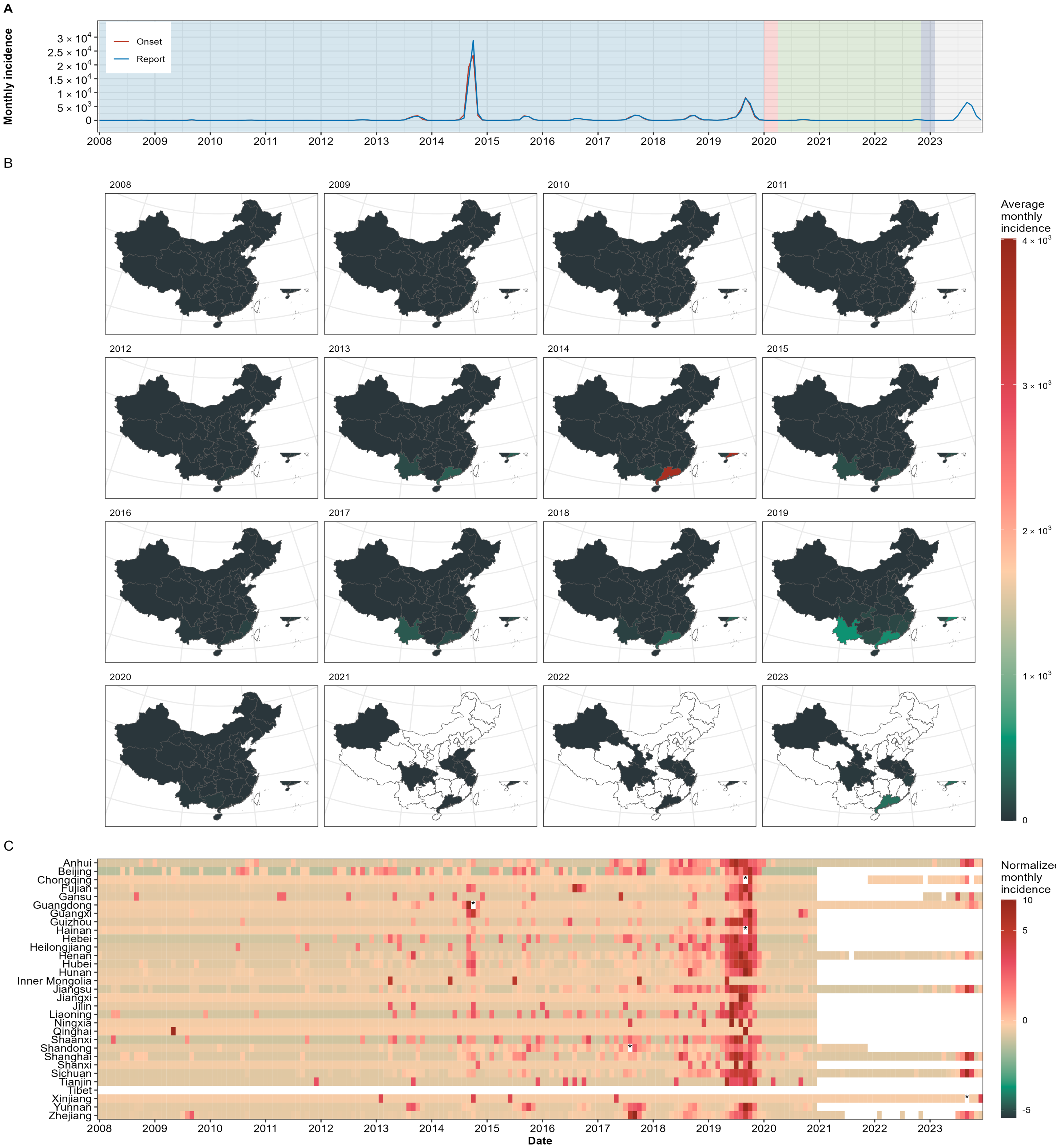
Supplementary Fig. 18. Temporal variation in monthly incidence of brucellosis from January 2008 to December 2023 in China.

(A) The incidence of brucellosis in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



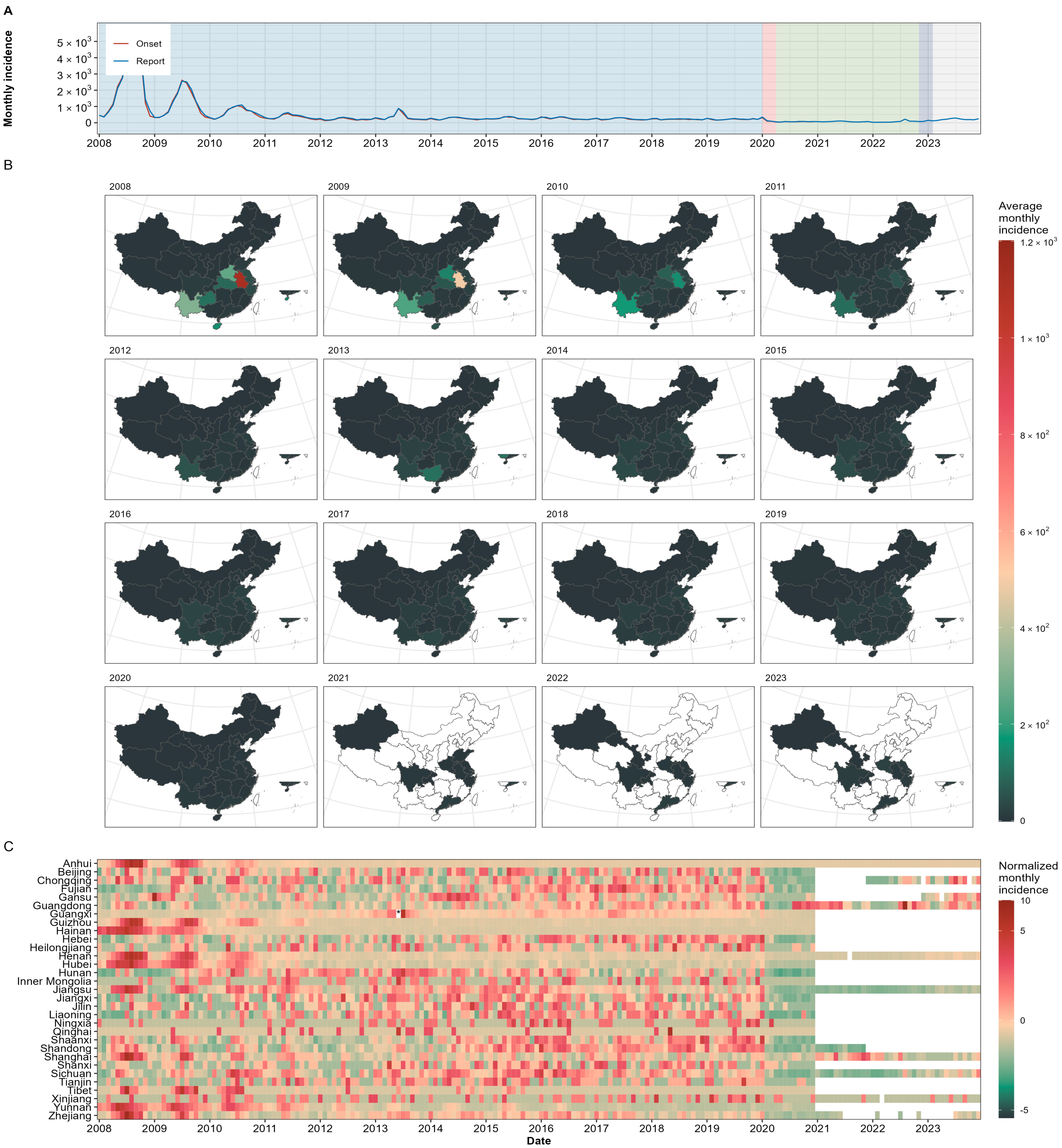
Supplementary Fig. 19. Temporal variation in monthly incidence of hemorrhagic fever with renal syndrome (HFRS) from January 2008 to December 2023 in China.

(A) The incidence of hemorrhagic fever with renal syndrome (HFRS) in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



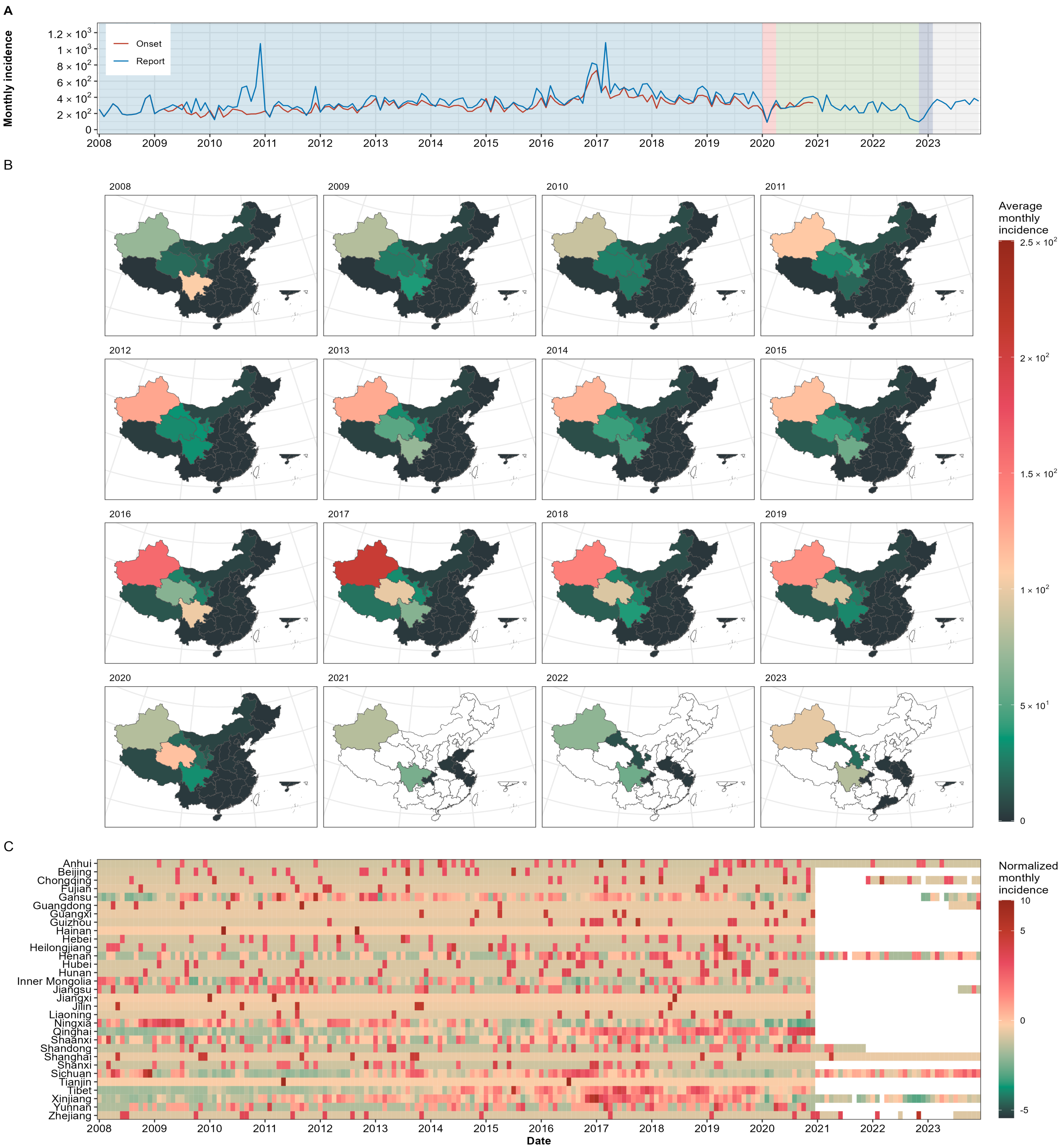
Supplementary Fig. 20. Temporal variation in monthly incidence of dengue fever from January 2008 to December 2023 in China.

(A) The incidence of dengue fever in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



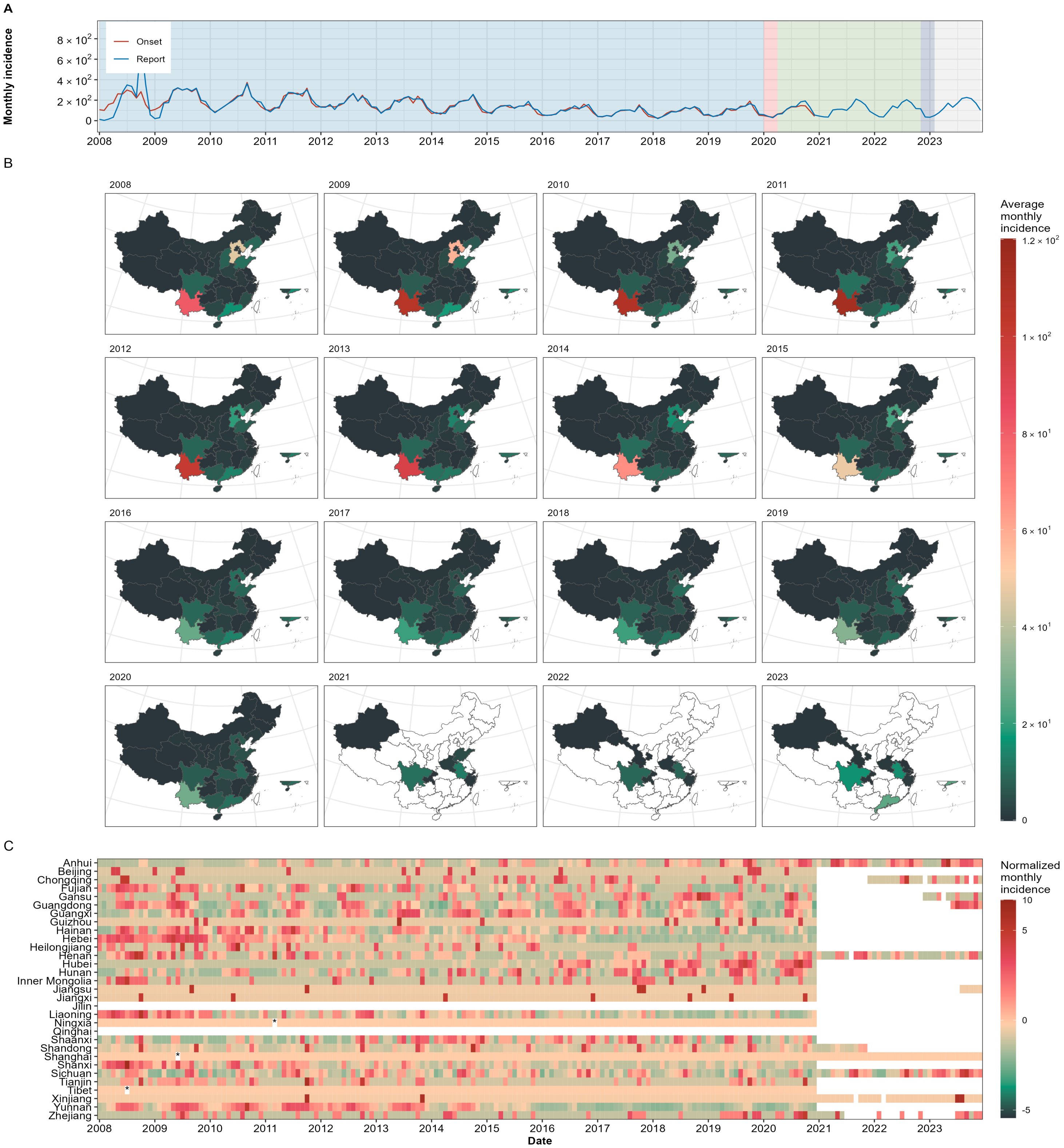
Supplementary Fig. 21. Temporal variation in monthly incidence of malaria from January 2008 to December 2023 in China.

(A) The incidence of malaria in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



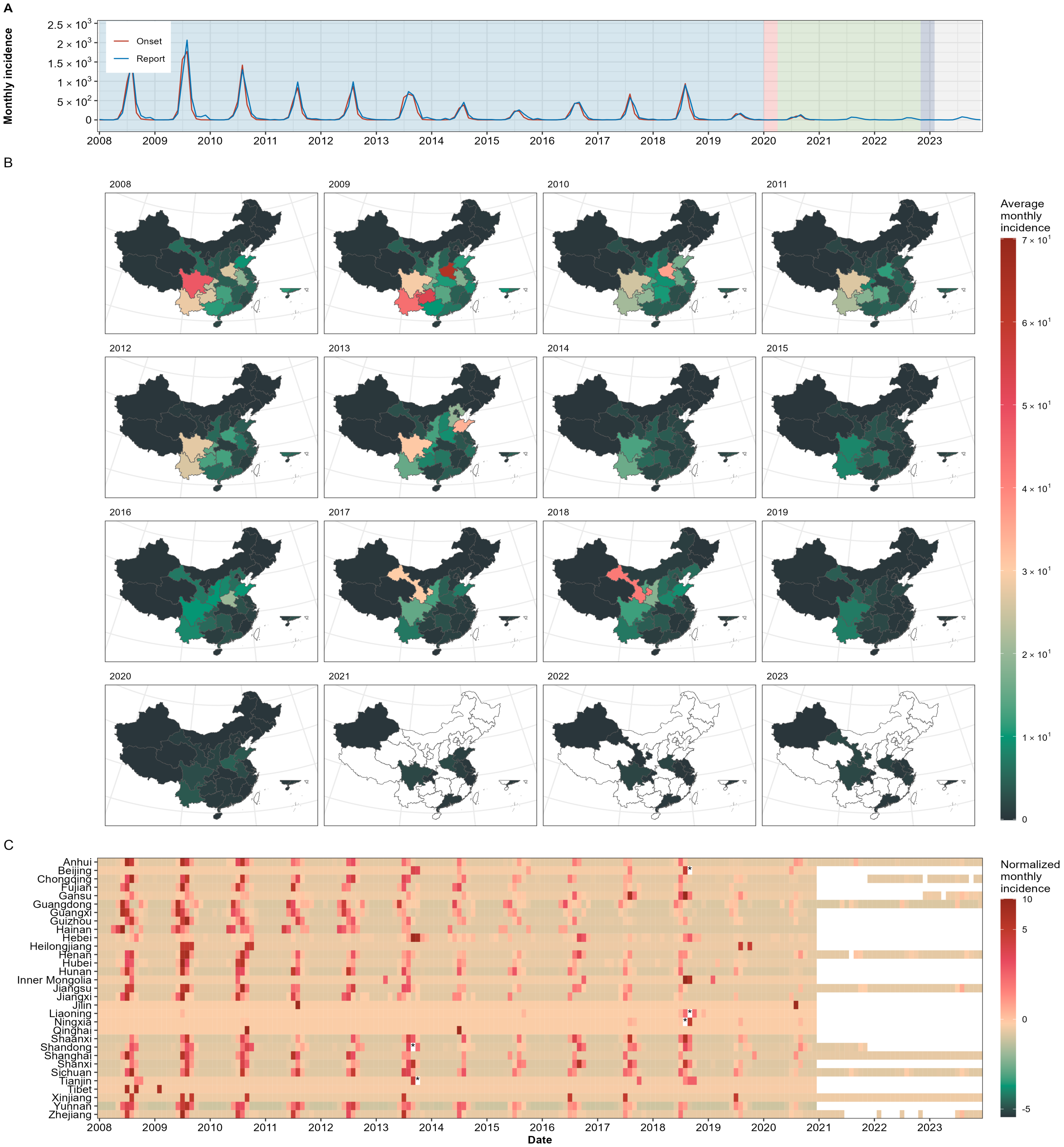
Supplementary Fig. 22. Temporal variation in monthly incidence of echinococcosis from January 2008 to December 2023 in China.

(A) The incidence of echinococcosis in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



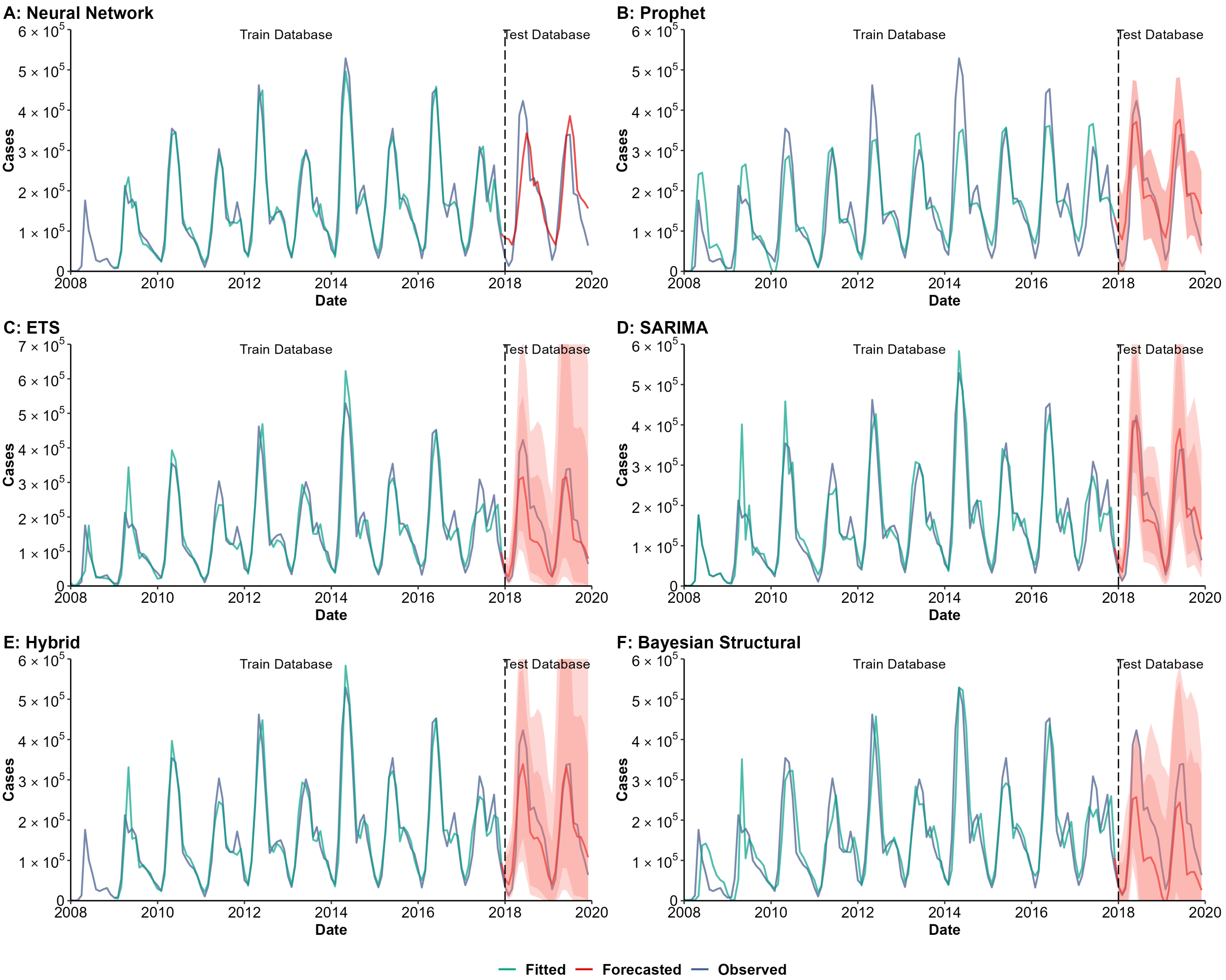
Supplementary Fig. 23. Temporal variation in monthly incidence of typhus from January 2008 to December 2023 in China.

(A) The incidence of typhus in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



Supplementary Fig. 24. Temporal variation in monthly incidence of Japanese encephalitis (JE) from January 2008 to December 2023 in China.

(A) The incidence of Japanese encephalitis (JE) in China from January 2008 to December 2023; **(B)** The spatial distribution of cases in China; **(C)** Temporal variation in monthly incidence among different provinces. The heatmap represents the normalized monthly incidence data of each province, and the color intensity corresponds to the normalized monthly incidence. Provincial data in panel **(B)** and **(C)** before January 2020 sourced from the Chinese Public Health Science Data Center, and data after January 2020 sourced from the provincial Notifiable Infectious Diseases Reports. * Normalized monthly incidence > 10.



G : SMAPE of Models

Method	Train	Test	All
Neural Network	13.19	39.54	17.98
ETS	22.63	35.13	24.71
SARIMA	18.83	33.32	21.24
Hybrid*	15.83	31.71	18.71
Bayesian Structural	34.59	64.98	39.65
Prophet	37.35	42.58	38.22

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	23323.90	72265.71	37344.47
ETS	40788.11	63677.84	45411.48
SARIMA	41585.44	53910.58	43880.70
Hybrid*	33188.04	48221.11	36386.27
Bayesian Structural	55537.49	98552.75	64723.40
Prophet	54513.95	62646.47	55951.52

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.30	1.10	0.43
ETS	0.47	1.07	0.56
SARIMA	0.44	0.71	0.49
Hybrid*	0.37	0.83	0.46
Bayesian Structural	0.67	1.80	0.85
Prophet	0.65	1.07	0.83

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

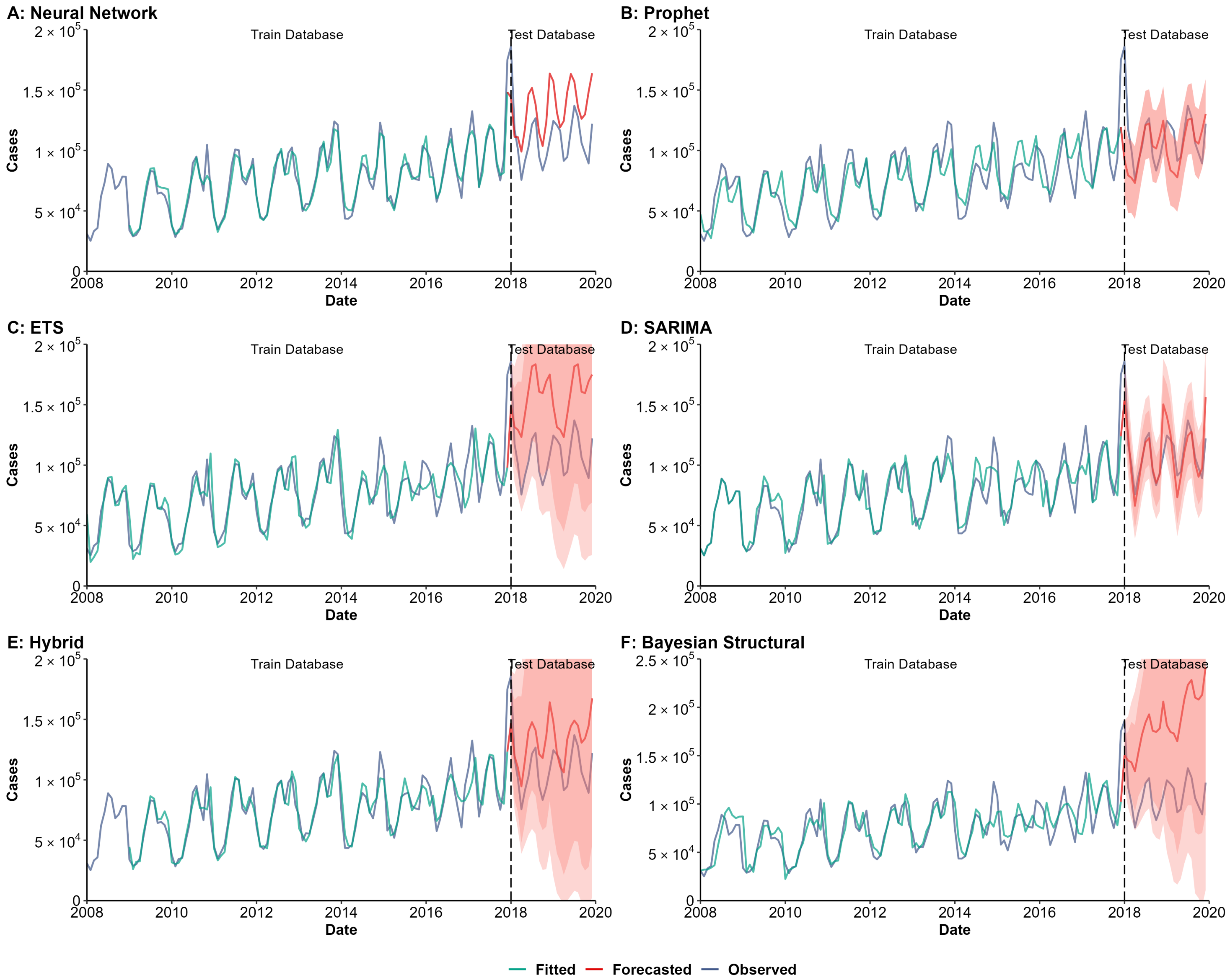
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.96	0.65	0.90
ETS	0.88	0.81	0.86
SARIMA	0.88	0.81	0.87
Hybrid*	0.92	0.89	0.90
Bayesian Structural	0.78	0.81	0.71
Prophet	0.78	0.79	0.77

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

Supplementary Fig. 25. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	6.56	23.06	9.56
ETS	13.26	36.59	17.15
SARIMA	10.37	9.05	10.15
Hybrid*	9.41	21.78	11.66
Bayesian Structural	15.32	52.15	21.46
Prophet	15.23	15.68	15.31

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	6990.88	32511.72	15237.14
ETS	14680.65	52087.60	25135.38
SARIMA	12083.49	15076.35	12631.64
Hybrid*	10773.19	30462.76	16238.32
Bayesian Structural	16986.54	80925.42	36495.74
Prophet	15073.91	26207.03	17430.44

*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
ETS	0.66	4.02	1.17
SARIMA	0.59	0.50	0.56
Hybrid*	0.49	1.80	0.83
Bayesian Structural	0.80	6.24	1.79
Prophet	0.76	1.54	1.06

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

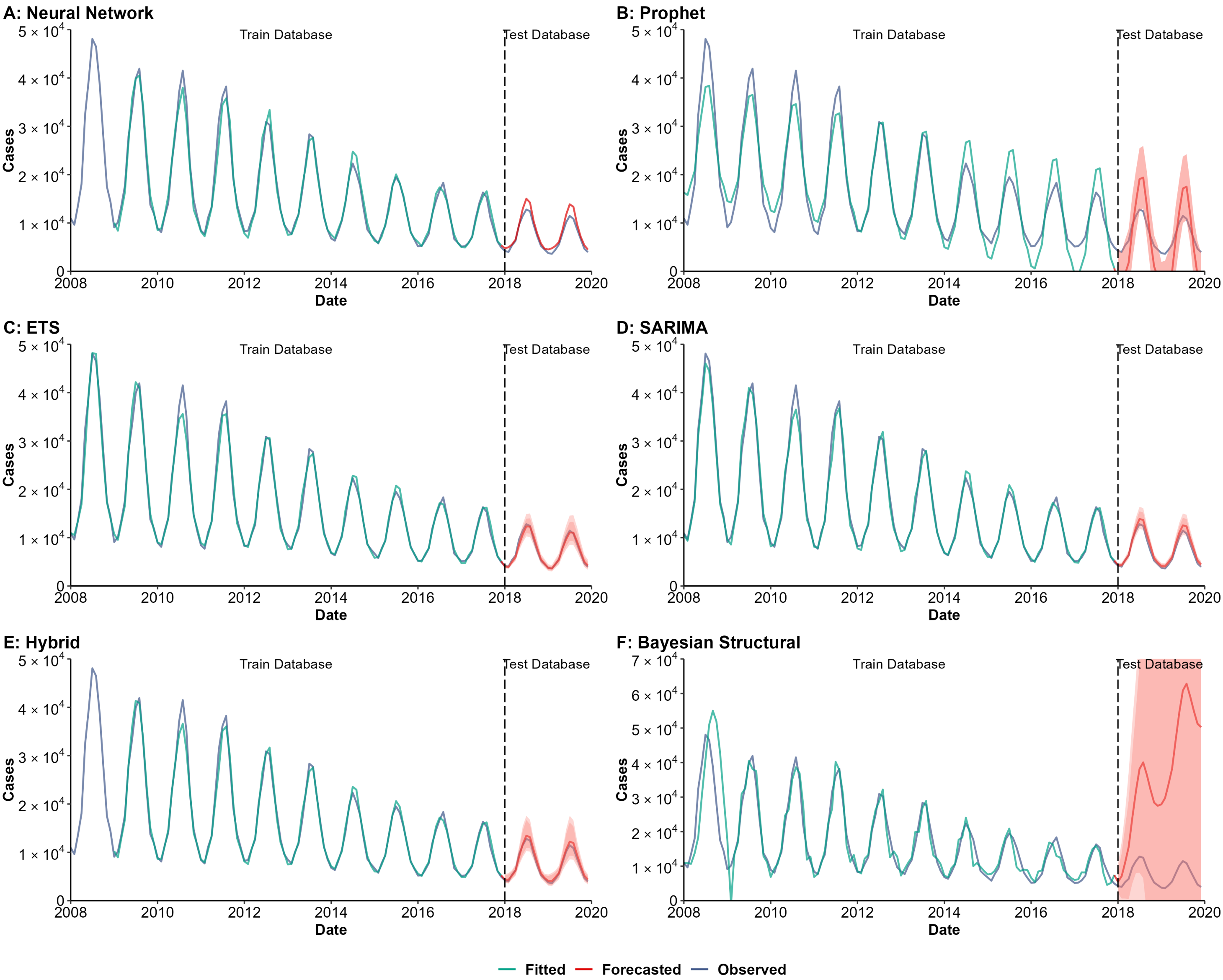
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.93	0.22	0.79
ETS	0.69	0.06	0.61
SARIMA	0.79	0.63	0.81
Hybrid*	0.83	0.26	0.74
Bayesian Structural	0.59	0.02	0.47
Prophet	0.67	0.05	0.63

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

Supplementary Fig. 26. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	5.97	12.00	7.07
ETS	4.49	4.43	4.48
SARIMA	4.92	8.70	5.55
Hybrid*	4.52	6.38	4.86
Bayesian Structural	17.83	123.02	35.36
Prophet	25.50	108.09	39.26

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	1339.95	1163.71	1309.68
ETS	1258.85	417.50	1161.74
SARIMA	1202.91	776.69	1142.97
Hybrid*	1132.16	520.12	1047.81
Bayesian Structural	4875.02	32607.31	14036.06
Prophet	3405.75	5433.71	3819.27

*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
ETS	0.20	0.24	0.21
SARIMA	0.22	0.43	0.23
Hybrid*	0.20	0.31	0.22
Bayesian Structural	0.71	6.98	1.66
Prophet	0.68	1.26	0.79

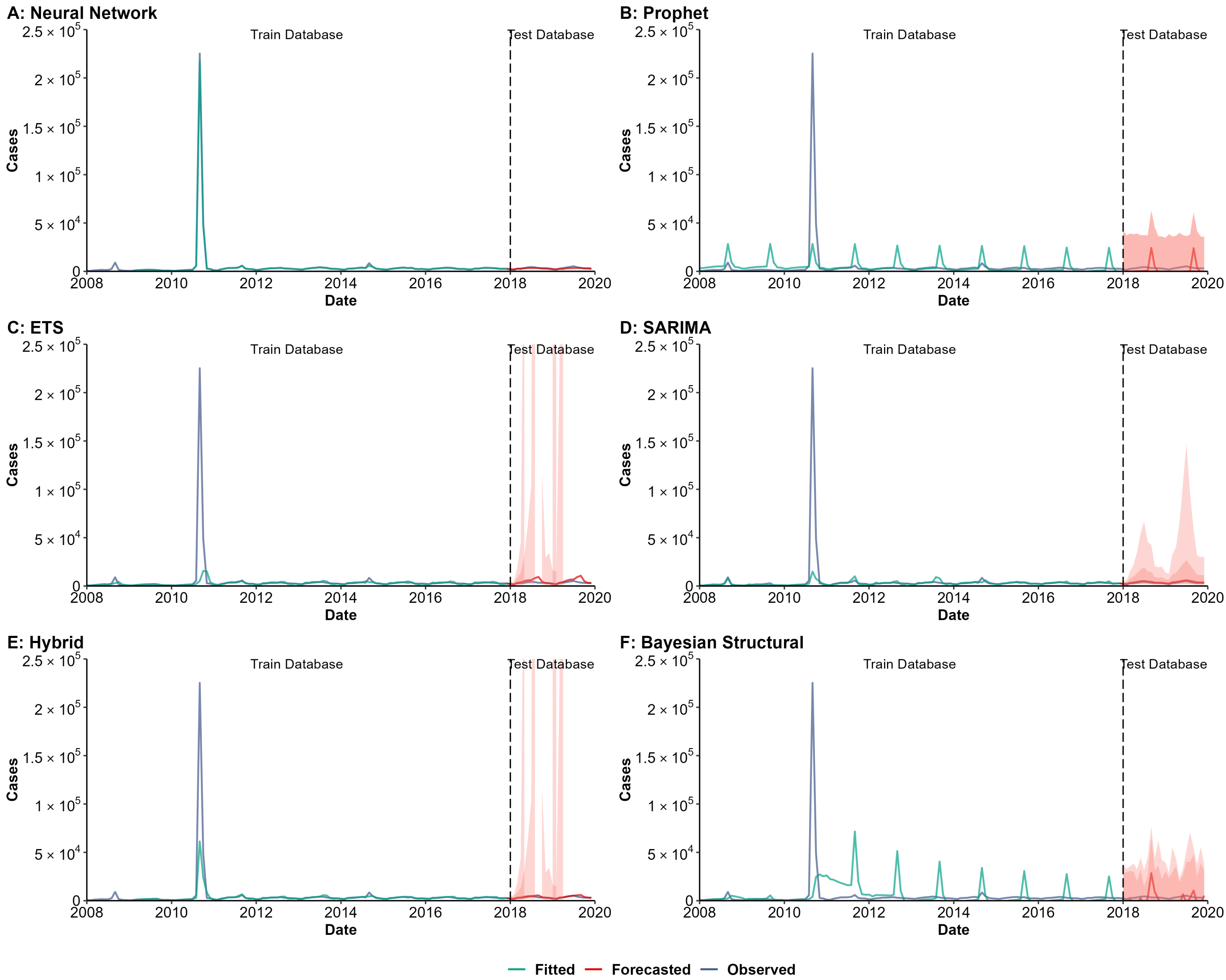
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.98	0.98	0.98
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
Prophet	0.89	0.97	0.87

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

Supplementary Fig. 27. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	2.33	15.99	4.83
ETS	23.46	32.23	24.92
SARIMA	20.55	18.79	20.26
Hybrid*	14.04	14.44	14.11
Bayesian Structural	119.92	145.03	124.11
Prophet	87.88	175.25	102.44

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	845.24	682.80	817.89
ETS	20369.45	2571.36	18624.28
SARIMA	19596.50	750.74	17891.70
Hybrid*	16051.37	837.24	14511.11
Bayesian Structural	23230.53	7742.52	21440.75
Prophet	19461.24	7003.92	17994.23

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.04	2.03	0.06
ETS	0.64	1.23	2.94
SARIMA	2.39	1.38	2.31
Hybrid*	0.46	0.92	1.30
Bayesian Structural	1.82	0.81	1.37
Prophet	1.26	1.13	1.25

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

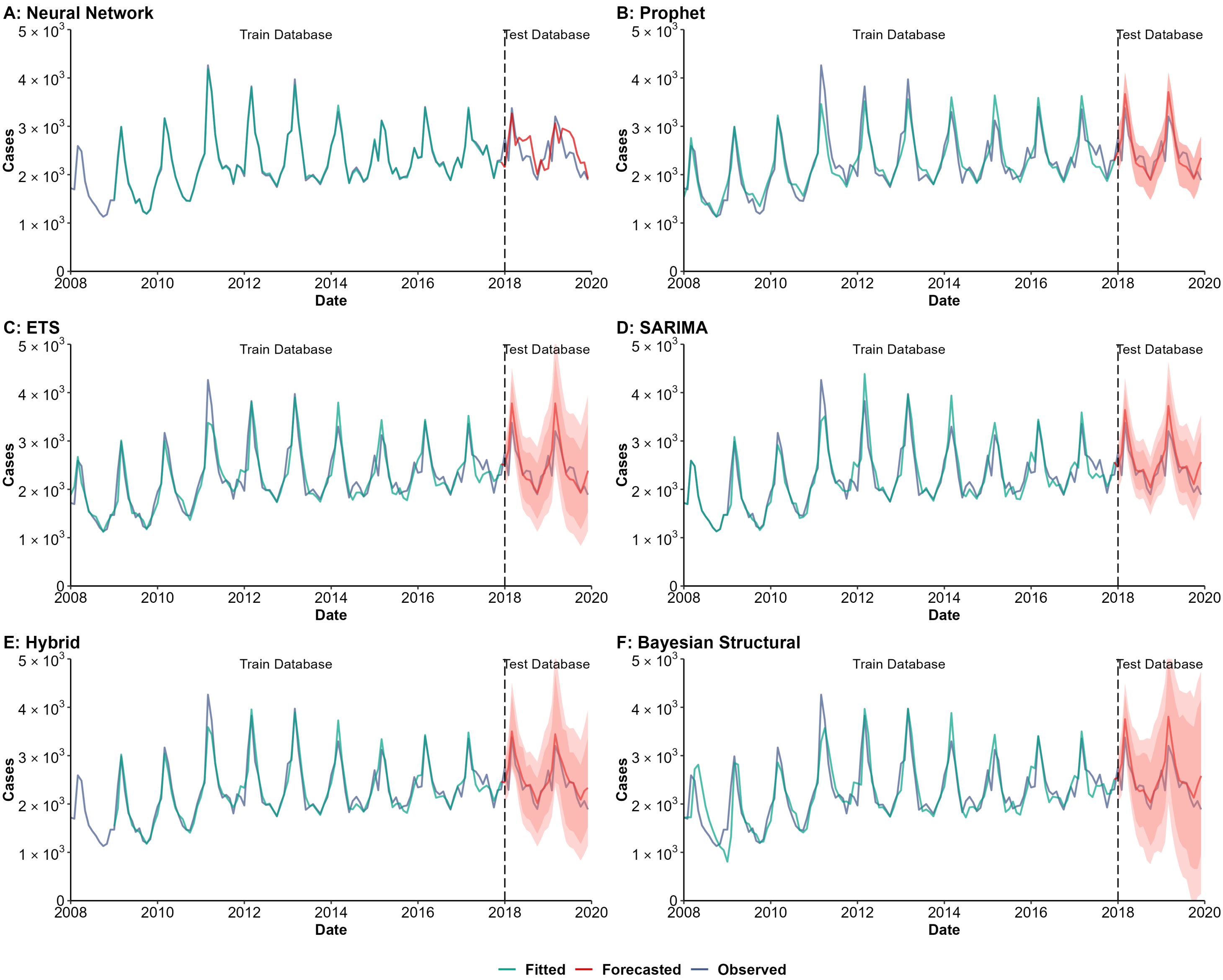
J : R_Squared of Models

Method	Train	Test	All
Neural Network	1.00	0.70	1.00
ETS	0.06	0.48	0.04
SARIMA	0.37	0.91	0.34
Hybrid*	0.95	0.67	0.94
Bayesian Structural	0.00	0.02	0.00
Prophet	0.11	0.01	0.10

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

Supplementary Fig. 28. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	0.99	12.28	3.04
ETS	6.96	7.91	7.12
SARIMA	6.43	8.26	6.73
Hybrid*	5.13	7.15	5.49
Bayesian Structural	10.03	8.68	9.81
Prophet	7.37	7.85	7.45

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	31.67	346.22	150.38
ETS	222.24	275.29	231.92
SARIMA	230.76	273.79	238.47
Hybrid*	168.61	222.28	179.57
Bayesian Structural	308.89	301.30	307.64
Prophet	222.36	254.26	227.99

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.07	1.15	0.23
ETS	0.48	0.65	0.55
SARIMA	0.47	0.71	0.51
Hybrid*	0.36	0.72	0.44
Bayesian Structural	0.66	0.75	0.70
Prophet	0.51	0.66	0.58

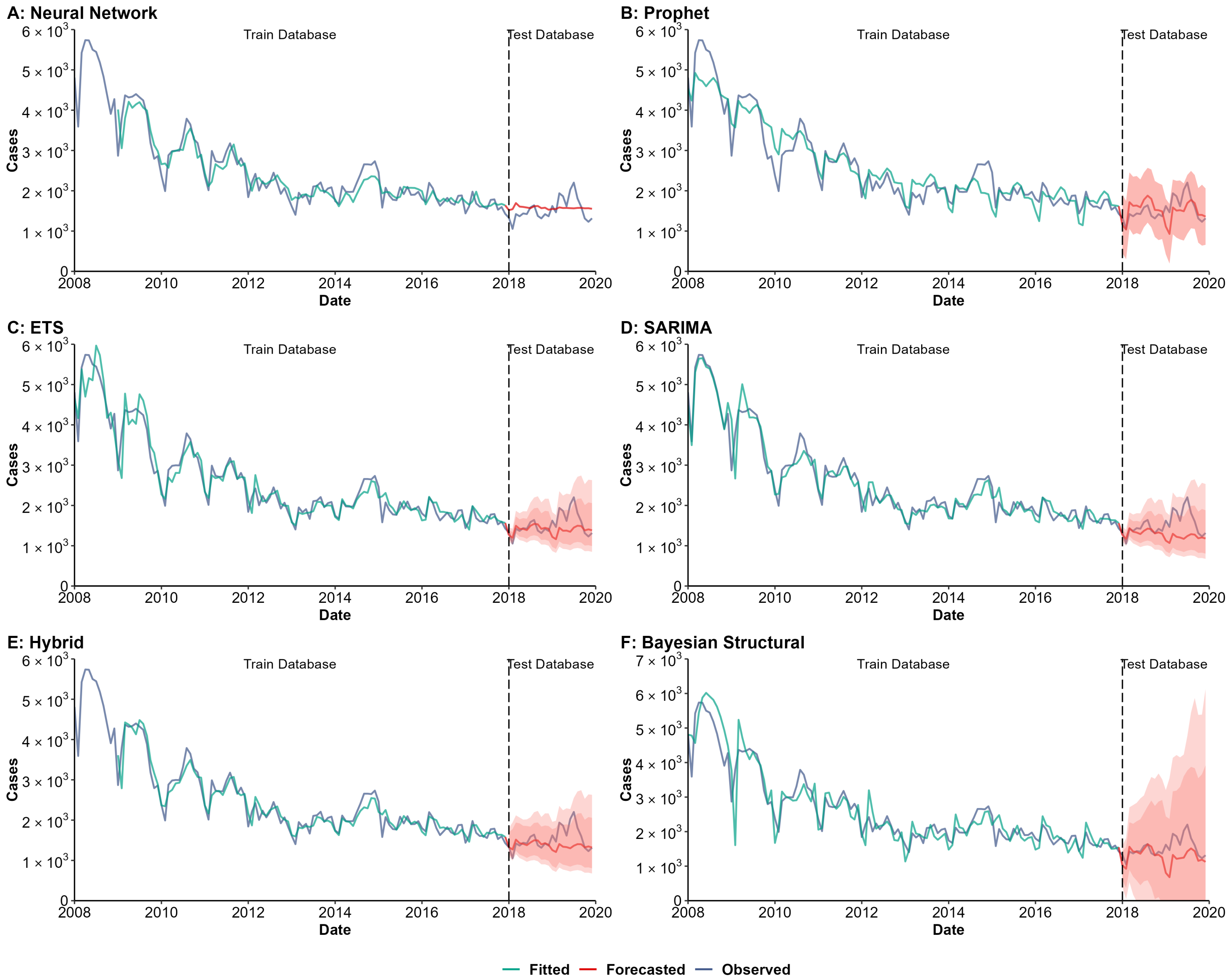
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	1.00	0.38	0.93
ETS	0.86	0.75	0.84
SARIMA	0.86	0.74	0.85
Hybrid*	0.91	0.78	0.89
Bayesian Structural	0.76	0.72	0.75
Prophet	0.86	0.75	0.84

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

Supplementary Fig. 29. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	8.38	14.48	9.49
ETS	6.94	13.53	8.04
SARIMA	6.80	18.57	8.76
Hybrid*	6.46	14.06	7.85
Bayesian Structural	10.83	20.47	12.44
Prophet	10.68	15.57	11.50

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	263.42	271.41	264.89
ETS	264.65	293.40	269.65
SARIMA	252.16	388.66	279.58
Hybrid*	209.55	316.97	232.80
Bayesian Structural	408.83	398.95	407.20
Prophet	360.64	288.37	349.64

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

I : MASE of Models

Method	Train	Test	All
Neural Network	1.29	8.67	1.56
ETS	0.71	2.74	0.86
SARIMA	0.73	3.81	0.91
Hybrid*	0.65	3.48	1.03
Bayesian Structural	1.05	1.78	0.88
Prophet	1.02	1.50	1.47

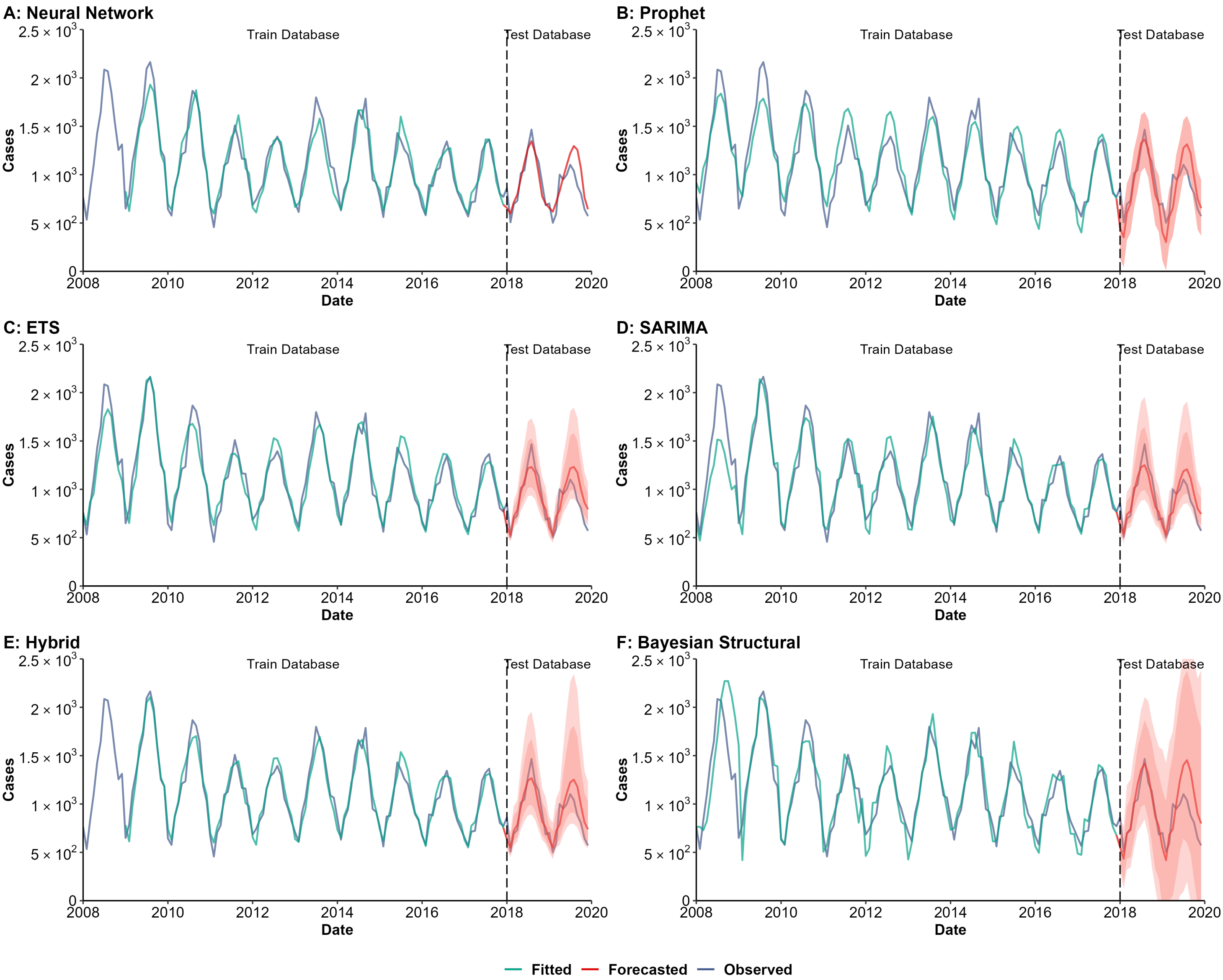
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.87	0.00	0.87
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
Prophet	0.88	0.13	0.89

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

Supplementary Fig. 30. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	8.48	12.72	9.25
ETS	8.21	13.65	9.12
SARIMA	9.43	12.75	9.98
Hybrid*	6.86	13.23	8.02
Bayesian Structural	12.74	17.62	13.56
Prophet	12.04	18.88	13.18

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	118.27	142.29	122.99
ETS	114.56	146.43	120.45
SARIMA	148.46	131.32	145.75
Hybrid*	91.41	138.18	101.53
Bayesian Structural	205.33	203.74	205.07
Prophet	157.24	180.16	161.29

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.57	0.90	0.62
ETS	0.48	1.05	0.59
SARIMA	0.61	0.96	0.65
Hybrid*	0.42	0.97	0.52
Bayesian Structural	0.74	0.96	0.72
Prophet	0.71	0.85	0.77

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

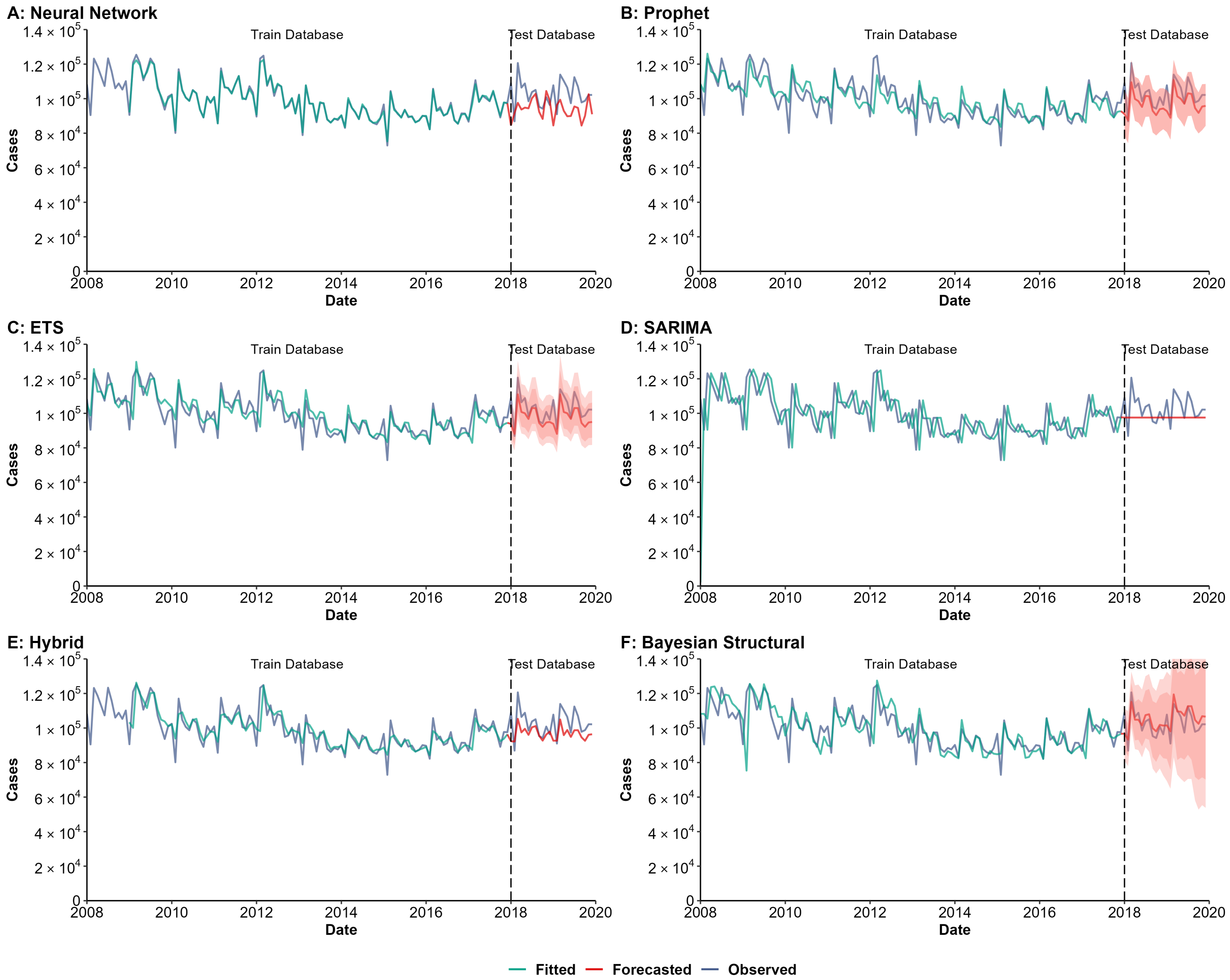
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.90	0.72	0.88
ETS	0.91	0.67	0.90
SARIMA	0.86	0.73	0.86
Hybrid*	0.94	0.71	0.92
Bayesian Structural	0.78	0.65	0.77
Prophet	0.83	0.71	0.82

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

Supplementary Fig. 31. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	0.71	10.58	2.50
ETS	4.23	5.29	4.41
SARIMA	9.86	7.33	9.44
Hybrid*	3.76	6.81	4.31
Bayesian Structural	5.35	4.52	5.22
Prophet	4.53	5.88	4.76

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	1041.08	12656.05	5478.10
ETS	6186.51	6740.76	6282.28
SARIMA	15019.03	9396.49	14236.98
Hybrid*	5523.44	8479.68	6167.26
Bayesian Structural	8381.15	5365.91	7958.34
Prophet	6389.18	7366.71	6562.22

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.10	1.62	0.35
ETS	0.51	0.98	0.78
SARIMA	0.99	Inf	1.16
Hybrid*	0.46	1.72	1.02
Bayesian Structural	0.65	0.91	0.83
Prophet	0.55	1.11	0.88

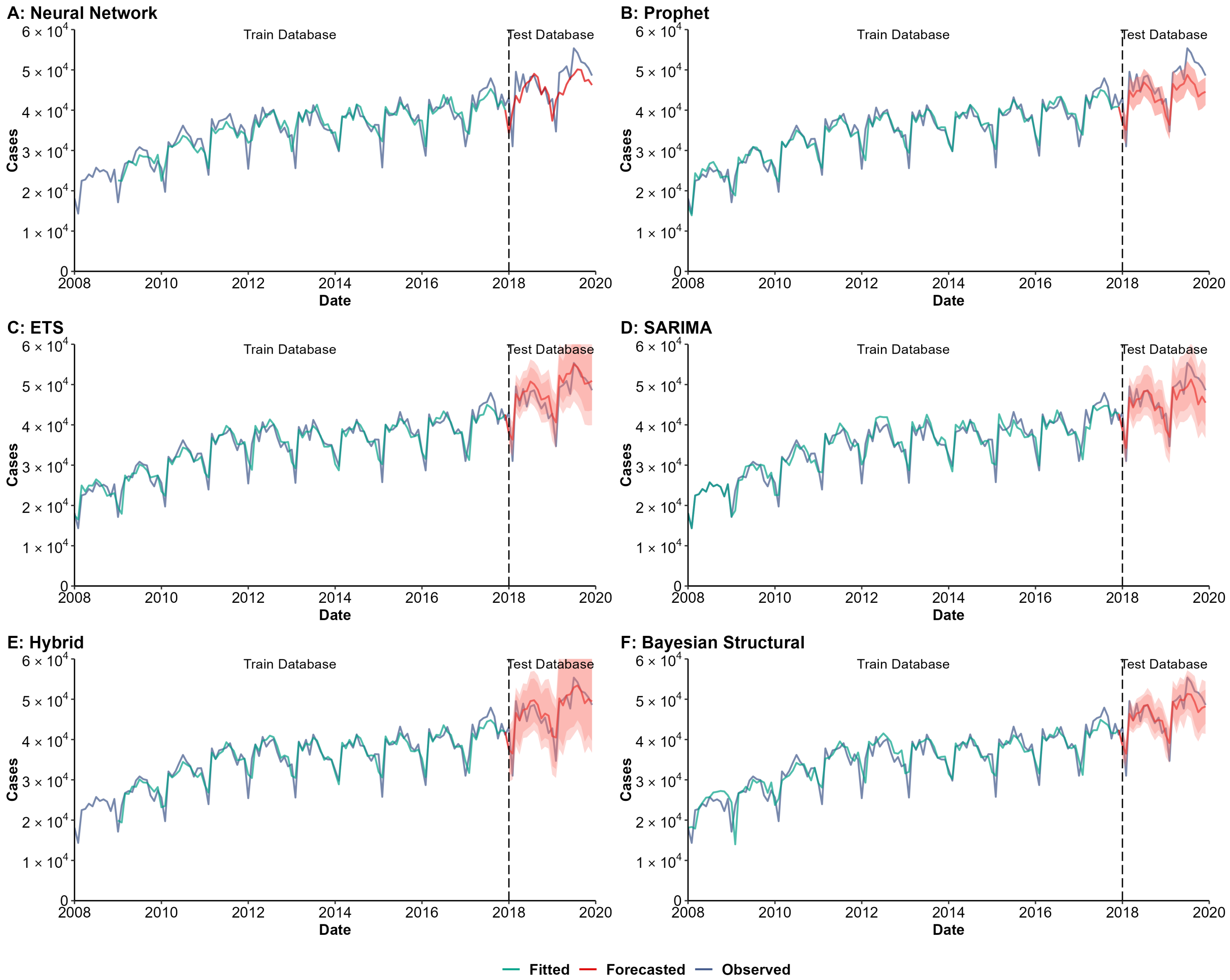
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.99	0.02	0.75
ETS	0.70	0.71	0.67
SARIMA	0.10		0.09
Hybrid*	0.73	0.48	0.65
Bayesian Structural	0.54	0.58	0.55
Prophet	0.67	0.67	0.64

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

Supplementary Fig. 32. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	5.13	8.48	5.74
ETS	4.45	5.26	4.59
SARIMA	4.30	5.40	4.48
Hybrid*	4.18	4.90	4.31
Bayesian Structural	5.85	4.86	5.68
Prophet	4.08	8.16	4.76

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	2280.48	4523.55	2824.09
ETS	1865.68	2960.59	2088.41
SARIMA	1943.45	2973.30	2149.63
Hybrid*	1821.54	2743.41	2020.68
Bayesian Structural	2469.89	2717.47	2512.84
Prophet	1755.91	4295.93	2375.96

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.79	1.65	0.94
ETS	0.45	0.98	0.70
SARIMA	0.57	0.84	0.62
Hybrid*	0.44	0.94	0.69
Bayesian Structural	0.58	0.99	0.87
Prophet	0.42	1.68	0.75

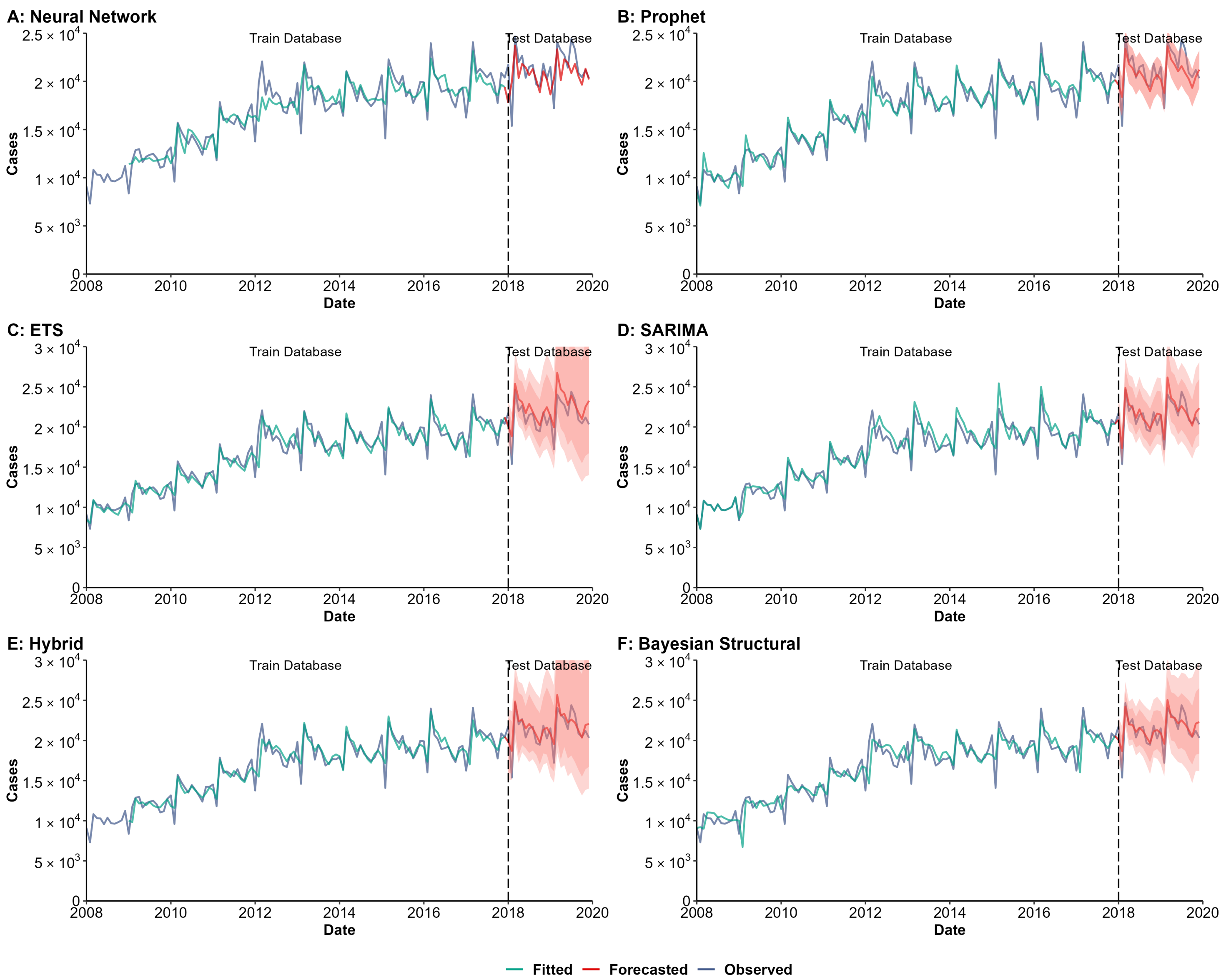
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

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

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

Supplementary Fig. 33. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	5.75	6.82	5.95
ETS	4.87	6.22	5.09
SARIMA	4.61	4.11	4.53
Hybrid*	4.41	4.63	4.45
Bayesian Structural	6.26	4.42	5.96
Prophet	4.50	5.35	4.64

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	1313.61	1921.85	1443.39
ETS	1062.89	1602.86	1170.31
SARIMA	1076.37	1059.44	1073.56
Hybrid*	1026.21	1245.38	1069.41
Bayesian Structural	1336.63	1208.47	1316.14
Prophet	1008.31	1367.16	1076.46

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.99	0.87	0.96
ETS	0.48	0.82	0.68
SARIMA	0.61	0.49	0.59
Hybrid*	0.43	0.68	0.66
Bayesian Structural	0.59	0.73	0.94
Prophet	0.44	0.92	0.66

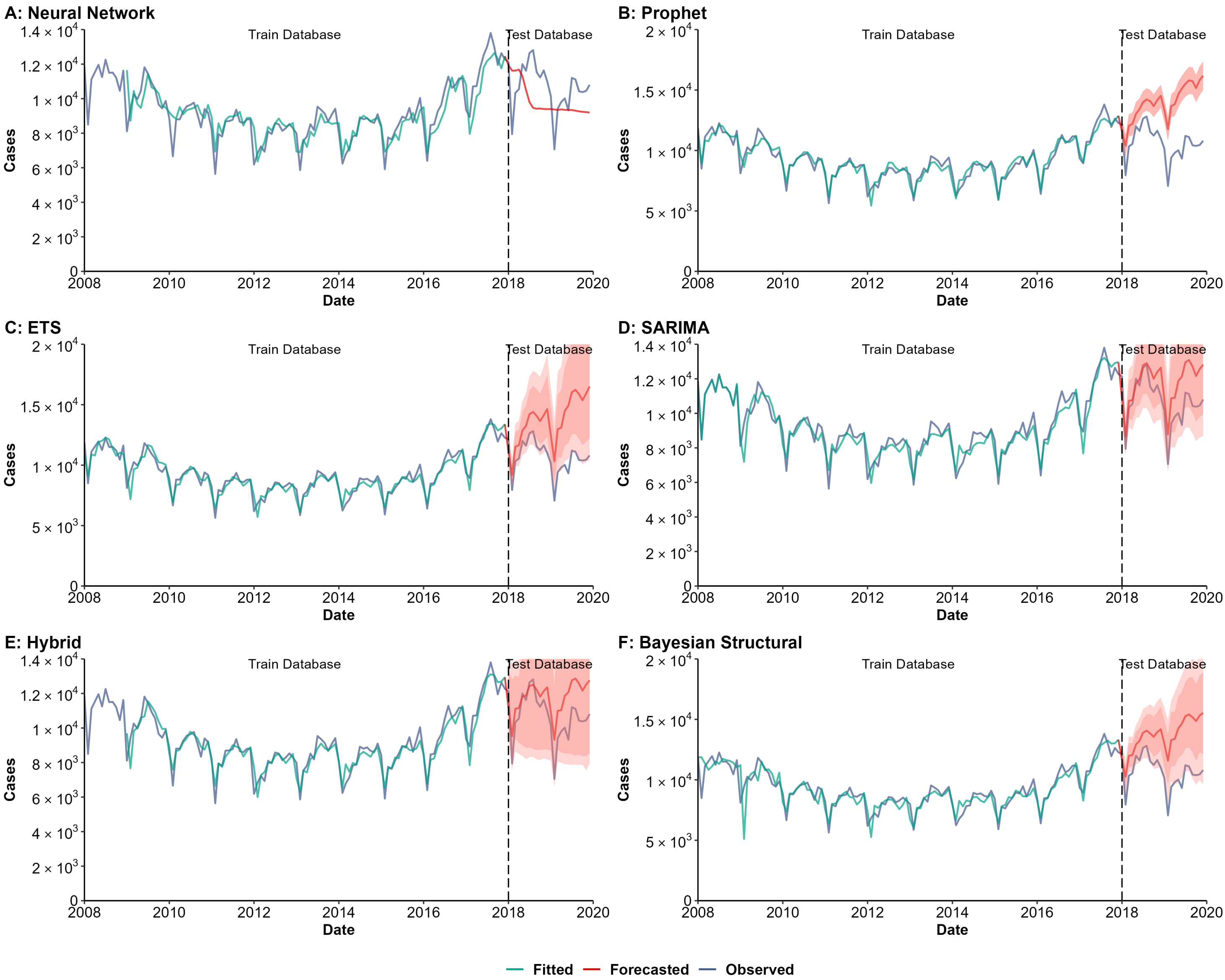
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.83	0.24	0.82
ETS	0.92	0.67	0.92
SARIMA	0.93	0.77	0.94
Hybrid*	0.90	0.68	0.90
Bayesian Structural	0.88	0.70	0.89
Prophet	0.93	0.69	0.93

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

Supplementary Fig. 34. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	6.22	14.29	7.68
ETS	4.49	25.52	8.00
SARIMA	4.50	11.09	5.60
Hybrid*	4.29	11.46	5.59
Bayesian Structural	5.78	25.16	9.01
Prophet	4.06	27.09	7.90

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	768.47	1741.24	1017.07
ETS	527.64	3552.64	1528.25
SARIMA	531.86	1435.89	761.16
Hybrid*	512.80	1436.89	768.47
Bayesian Structural	803.90	3352.88	1553.12
Prophet	472.92	3665.31	1557.39

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.92	11.29	1.38
ETS	0.52	3.43	1.25
SARIMA	0.58	1.58	0.76
Hybrid*	0.52	2.07	0.90
Bayesian Structural	0.67	4.99	1.37
Prophet	0.47	5.13	1.37

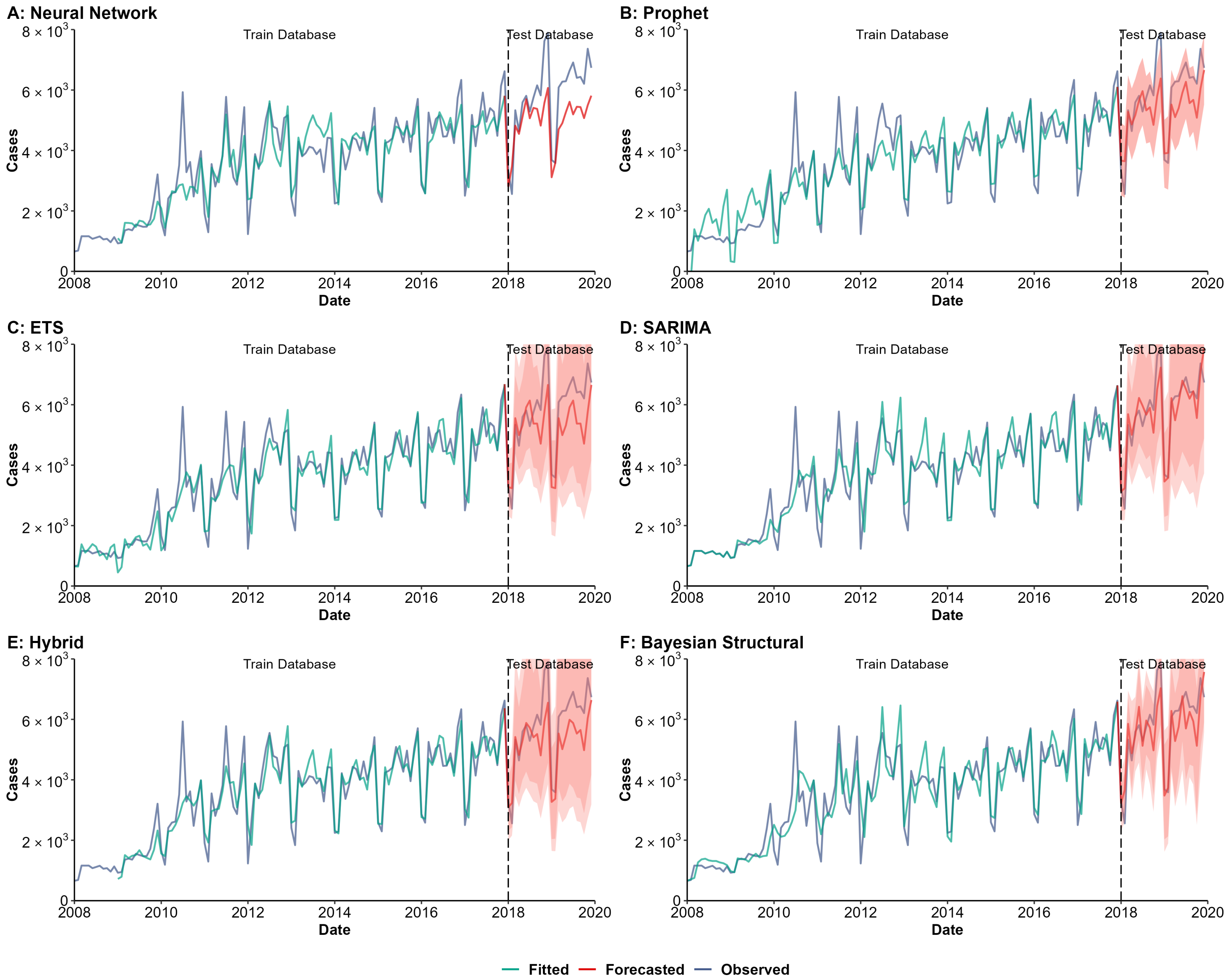
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.76	0.00	0.63
ETS	0.90	0.17	0.64
SARIMA	0.91	0.52	0.83
Hybrid*	0.90	0.51	0.82
Bayesian Structural	0.78	0.13	0.59
Prophet	0.92	0.09	0.60

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

Supplementary Fig. 35. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	12.69	16.54	13.39
ETS	11.58	13.62	11.92
SARIMA	10.56	7.26	10.01
Hybrid*	10.25	12.17	10.60
Bayesian Structural	13.89	9.71	13.19
Prophet	19.54	12.87	18.43

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	596.10	1073.93	707.41
ETS	495.77	906.91	584.73
SARIMA	551.30	518.54	545.98
Hybrid*	495.91	817.70	568.14
Bayesian Structural	612.22	659.41	620.33
Prophet	584.61	845.66	635.61

*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
ETS	0.42	0.96	0.59
SARIMA	0.54	0.45	0.51
Hybrid*	0.39	0.92	0.58
Bayesian Structural	0.53	0.51	0.58
Prophet	0.55	1.11	0.70

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

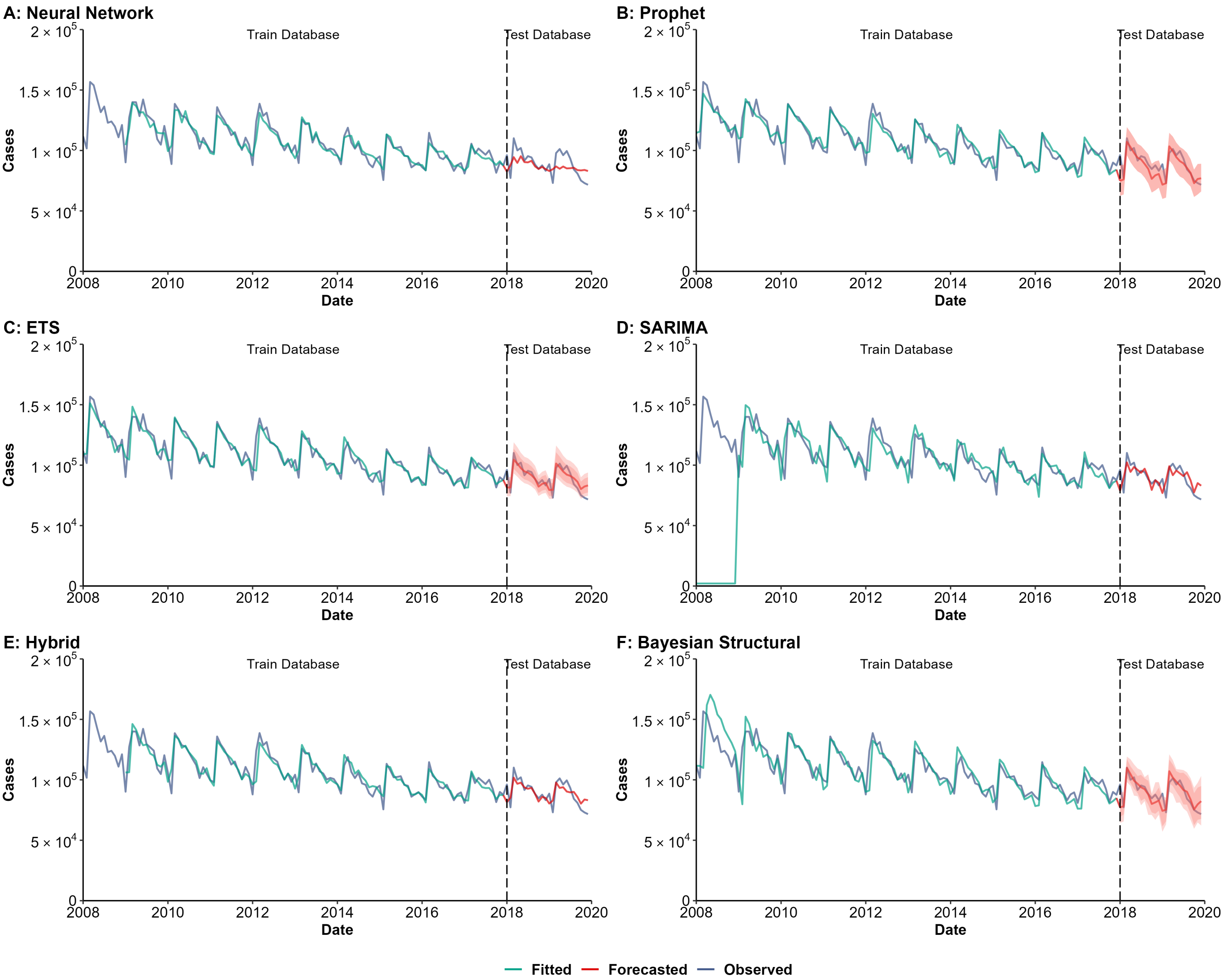
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.81	0.81	0.82
ETS	0.90	0.73	0.90
SARIMA	0.87	0.85	0.90
Hybrid*	0.87	0.83	0.88
Bayesian Structural	0.84	0.78	0.87
Prophet	0.86	0.80	0.87

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

Supplementary Fig. 36. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	3.61	8.56	4.51
ETS	3.73	5.55	4.03
SARIMA	24.50	7.31	21.64
Hybrid*	3.85	6.24	4.28
Bayesian Structural	6.34	5.22	6.16
Prophet	4.17	5.62	4.41

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	5048.30	9072.43	5984.72
ETS	5942.67	5897.21	5935.12
SARIMA	40903.93	7918.45	37479.69
Hybrid*	5951.85	6656.23	6085.99
Bayesian Structural	10818.75	6471.70	10223.42
Prophet	6199.41	6882.93	6318.47

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.66	3.25	0.87
ETS	0.43	1.10	0.67
SARIMA	2.03	0.99	1.90
Hybrid*	0.46	1.33	0.73
Bayesian Structural	0.76	0.72	0.79
Prophet	0.48	0.79	0.71

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

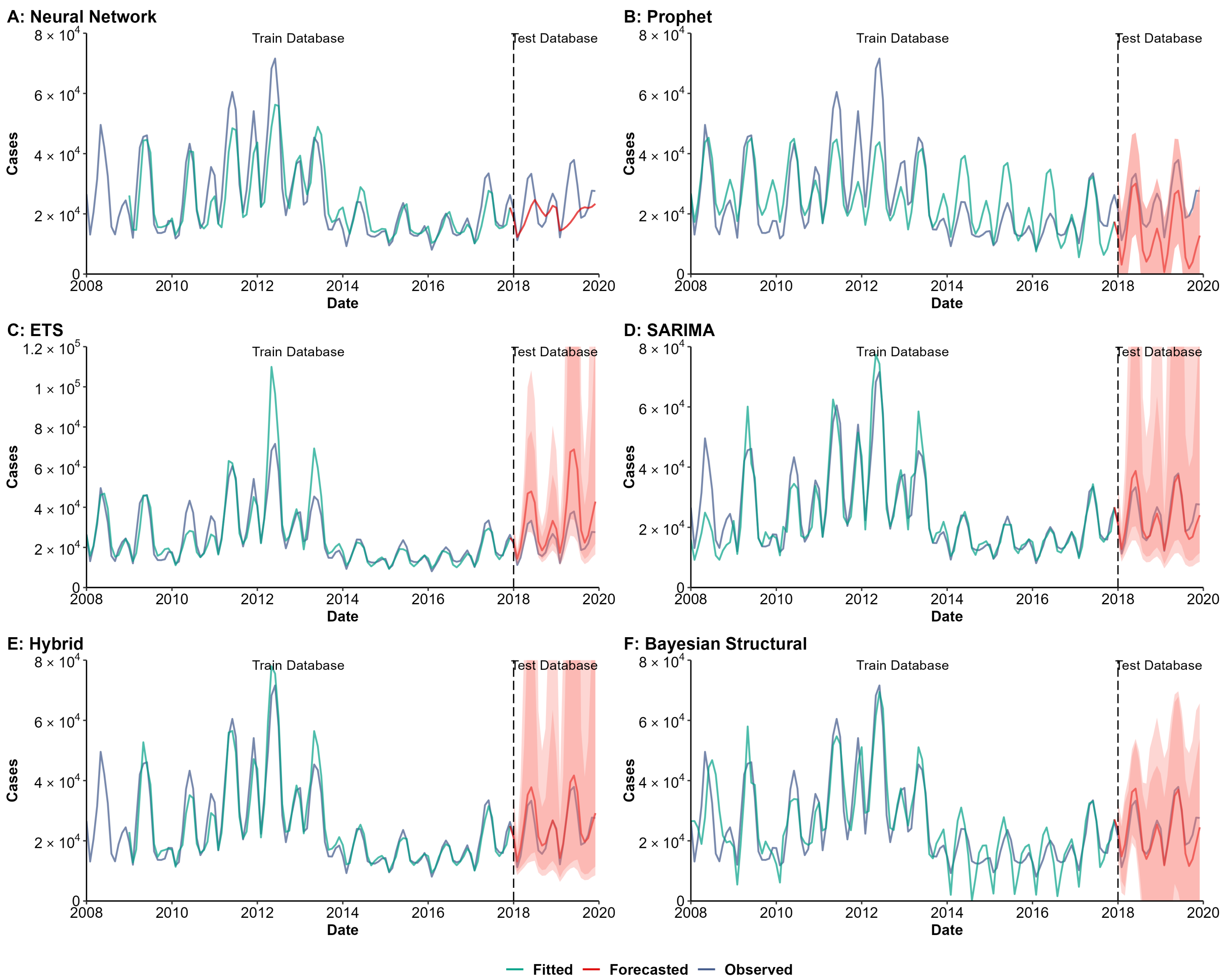
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.90	0.37	0.87
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
Prophet	0.87	0.68	0.87

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

Supplementary Fig. 37. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	17.22	24.96	18.62
ETS	12.95	31.97	16.12
SARIMA	14.06	11.14	13.58
Hybrid*	10.19	10.15	10.18
Bayesian Structural	27.89	14.49	25.65
Prophet	27.47	73.75	35.18

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	6262.36	7883.47	6586.85
ETS	6868.39	13611.02	8377.88
SARIMA	5460.31	3226.85	5155.70
Hybrid*	3679.01	3132.44	3585.83
Bayesian Structural	6631.07	3784.71	6247.39
Prophet	8652.71	11406.85	9169.36

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.85	2.96	1.01
ETS	0.58	1.09	0.67
SARIMA	0.51	0.46	0.50
Hybrid*	0.42	0.42	0.43
Bayesian Structural	0.77	0.49	0.65
Prophet	1.01	1.59	1.12

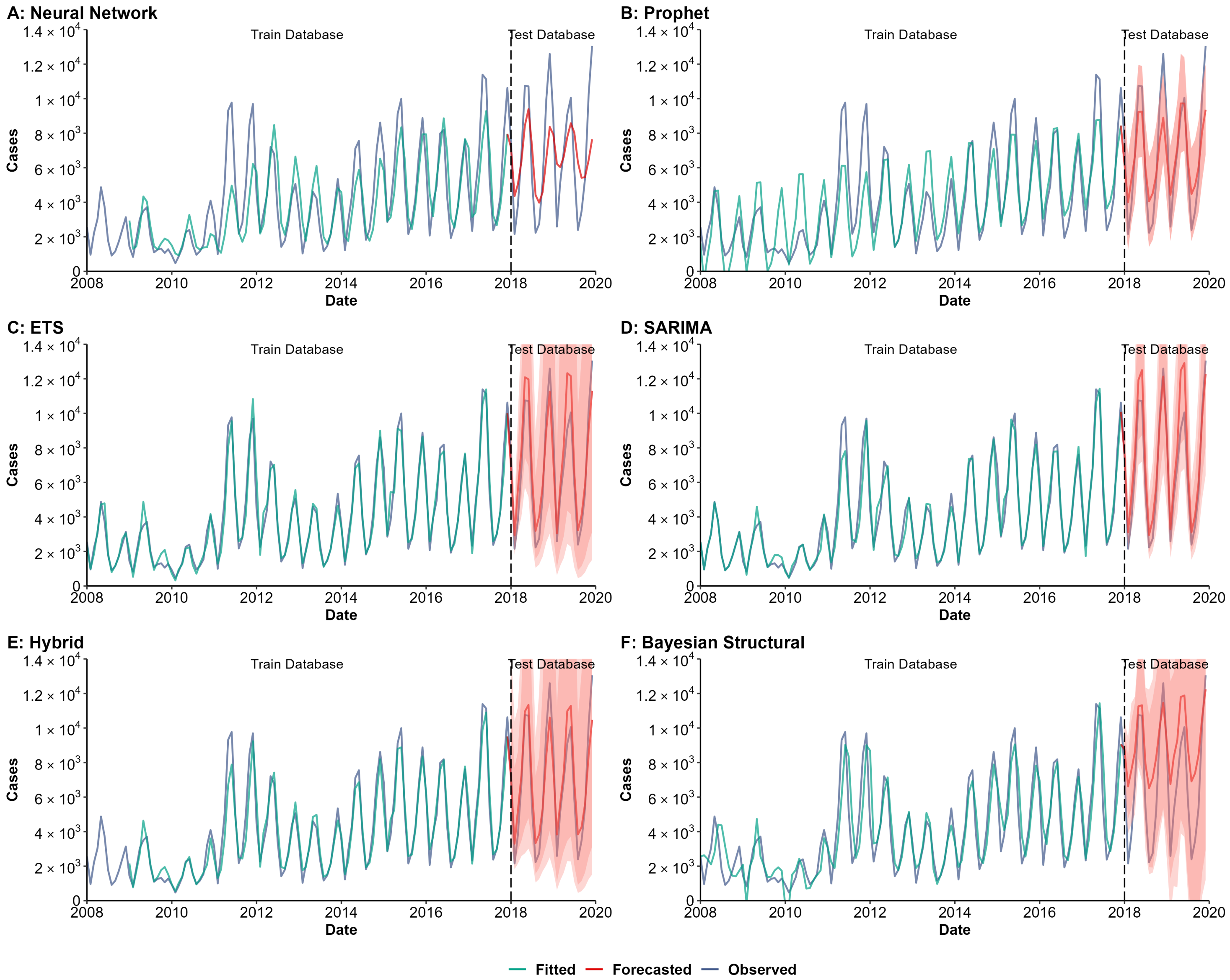
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.80	0.11	0.75
ETS	0.86	0.87	0.80
SARIMA	0.86	0.82	0.86
Hybrid*	0.93	0.91	0.93
Bayesian Structural	0.78	0.78	0.78
Prophet	0.59	0.76	0.51

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

Supplementary Fig. 38. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	29.94	32.57	30.42
ETS	10.94	18.43	12.19
SARIMA	10.42	16.31	11.40
Hybrid*	13.07	18.71	14.09
Bayesian Structural	28.96	40.55	30.89
Prophet	37.36	25.23	35.34

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	1559.38	2412.97	1745.90
ETS	507.57	1307.01	706.68
SARIMA	572.96	1233.43	726.04
Hybrid*	680.15	1231.46	808.84
Bayesian Structural	1171.60	2831.52	1574.84
Prophet	1374.52	1738.25	1441.53

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.84	1.62	0.97
ETS	0.21	0.41	0.26
SARIMA	0.24	0.32	0.26
Hybrid*	0.28	0.44	0.34
Bayesian Structural	0.52	1.52	0.78
Prophet	0.63	0.89	0.69

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

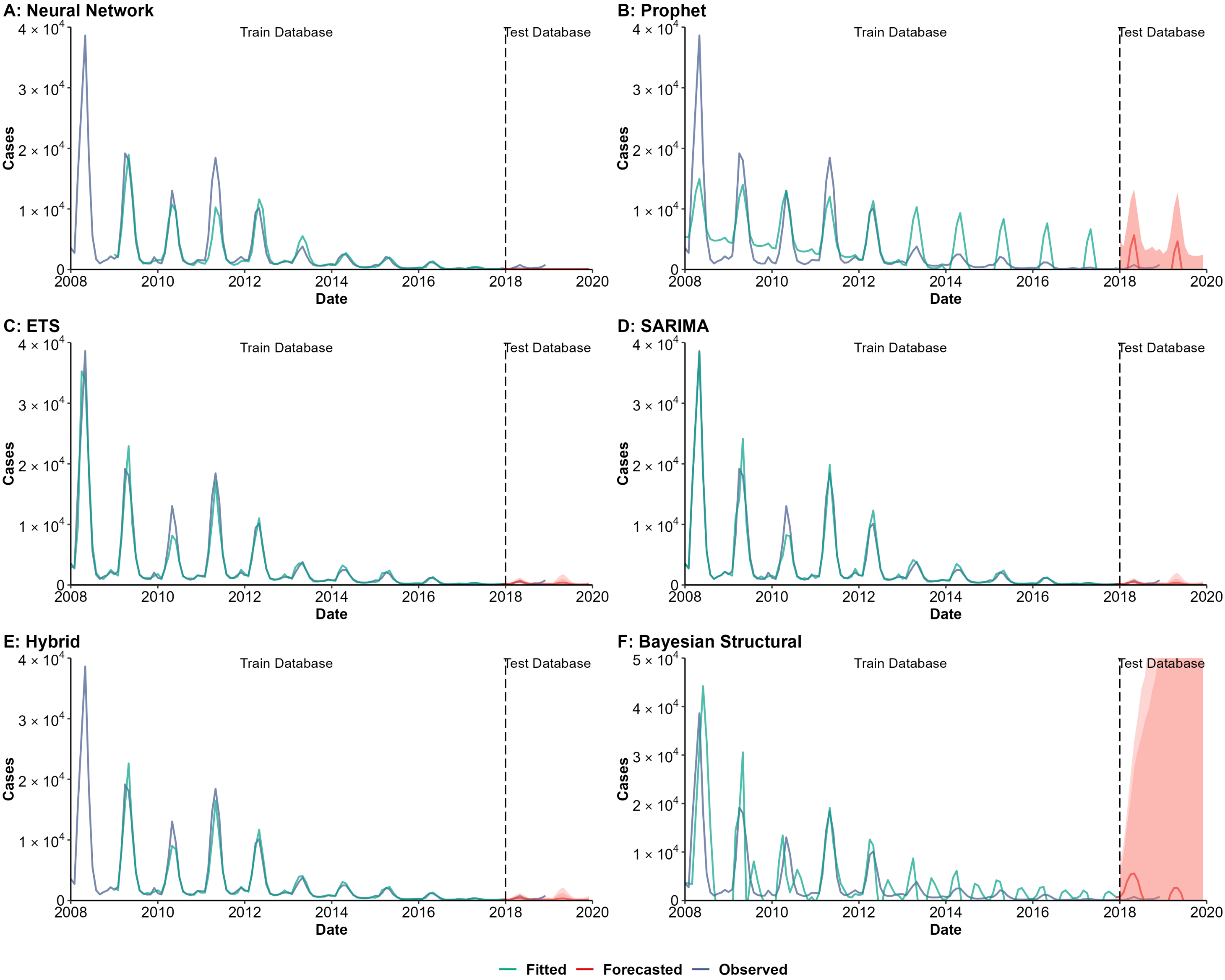
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.67	0.61	0.67
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
Prophet	0.73	0.88	0.77

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

Supplementary Fig. 39. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	22.14	87.34	28.66
ETS	15.04	58.21	18.96
SARIMA	14.79	62.87	19.16
Hybrid*	13.87	62.14	18.70
Bayesian Structural	111.03	176.40	116.97
Prophet	98.40	184.97	106.27

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	1574.38	316.31	1496.94
ETS	1409.08	234.49	1345.36
SARIMA	1058.88	243.11	1012.26
Hybrid*	962.14	246.44	916.09
Bayesian Structural	5302.93	3056.49	5139.45
Prophet	3850.75	3883.99	3853.78

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.59	12.59	0.61
ETS	0.33	2.10	0.35
SARIMA	0.23	2.55	0.24
Hybrid*	0.33	2.99	0.34
Bayesian Structural	1.80	2.26	0.96
Prophet	1.43	2.00	1.49

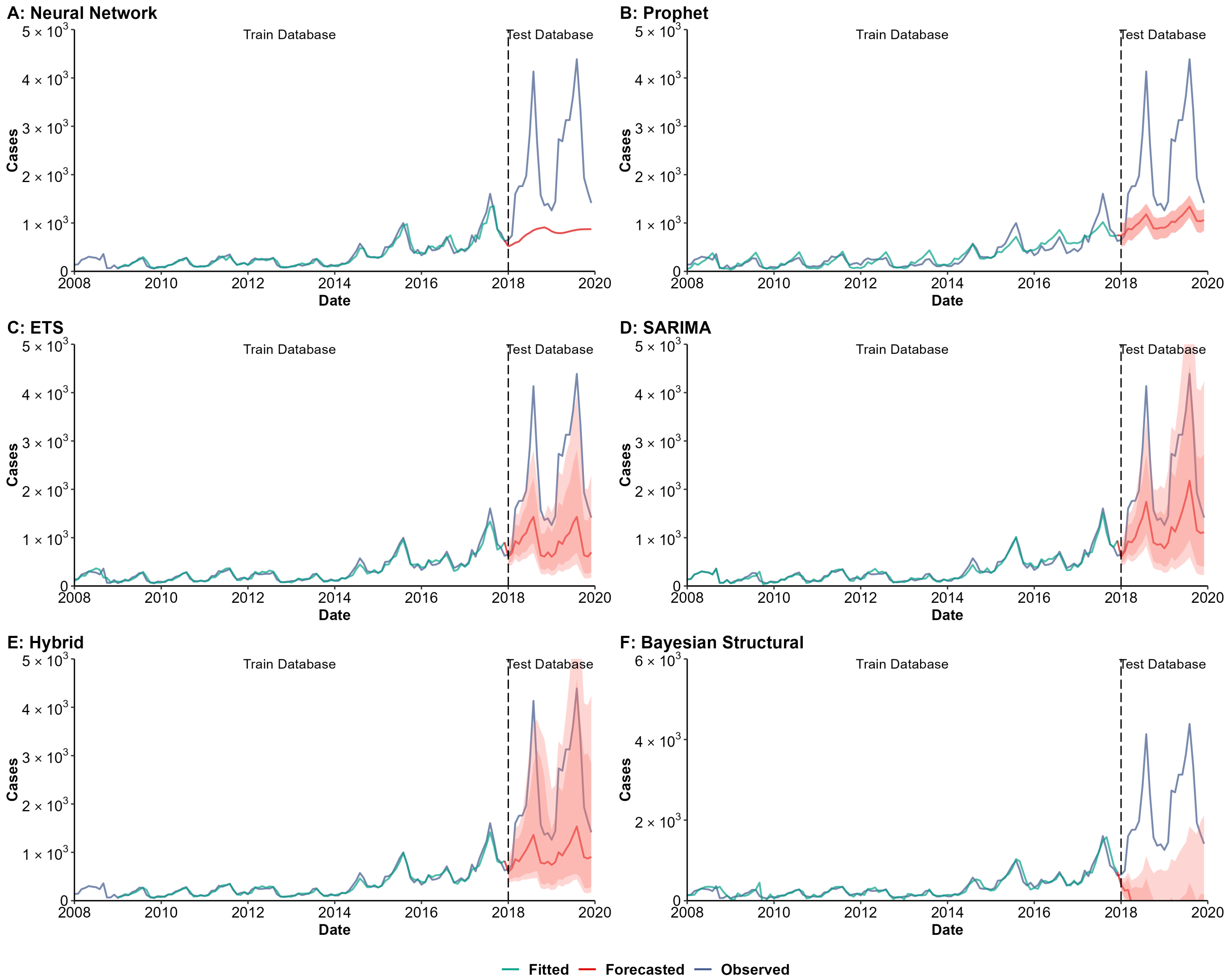
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.86	0.29	0.86
ETS	0.94	0.20	0.94
SARIMA	0.97	0.20	0.97
Hybrid*	0.95	0.23	0.95
Bayesian Structural	0.51	0.02	0.51
Prophet	0.56	0.26	0.53

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

Supplementary Fig. 40. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	12.75	83.99	25.70
ETS	14.60	76.57	24.93
SARIMA	13.86	54.60	20.65
Hybrid*	11.44	69.55	22.00
Bayesian Structural	23.53	187.05	50.78
Prophet	29.54	65.67	35.56

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	70.07	1720.43	736.33
ETS	62.62	1523.42	624.56
SARIMA	59.63	1221.93	501.81
Hybrid*	50.95	1470.03	628.52
Bayesian Structural	90.84	4006.62	1637.80
Prophet	118.75	1489.20	617.55

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.67	55.29	5.05
ETS	0.55	7.91	3.05
SARIMA	0.54	4.87	2.14
Hybrid*	0.44	8.94	3.26
Bayesian Structural	0.78	19.78	6.38
Prophet	1.14	17.72	4.23

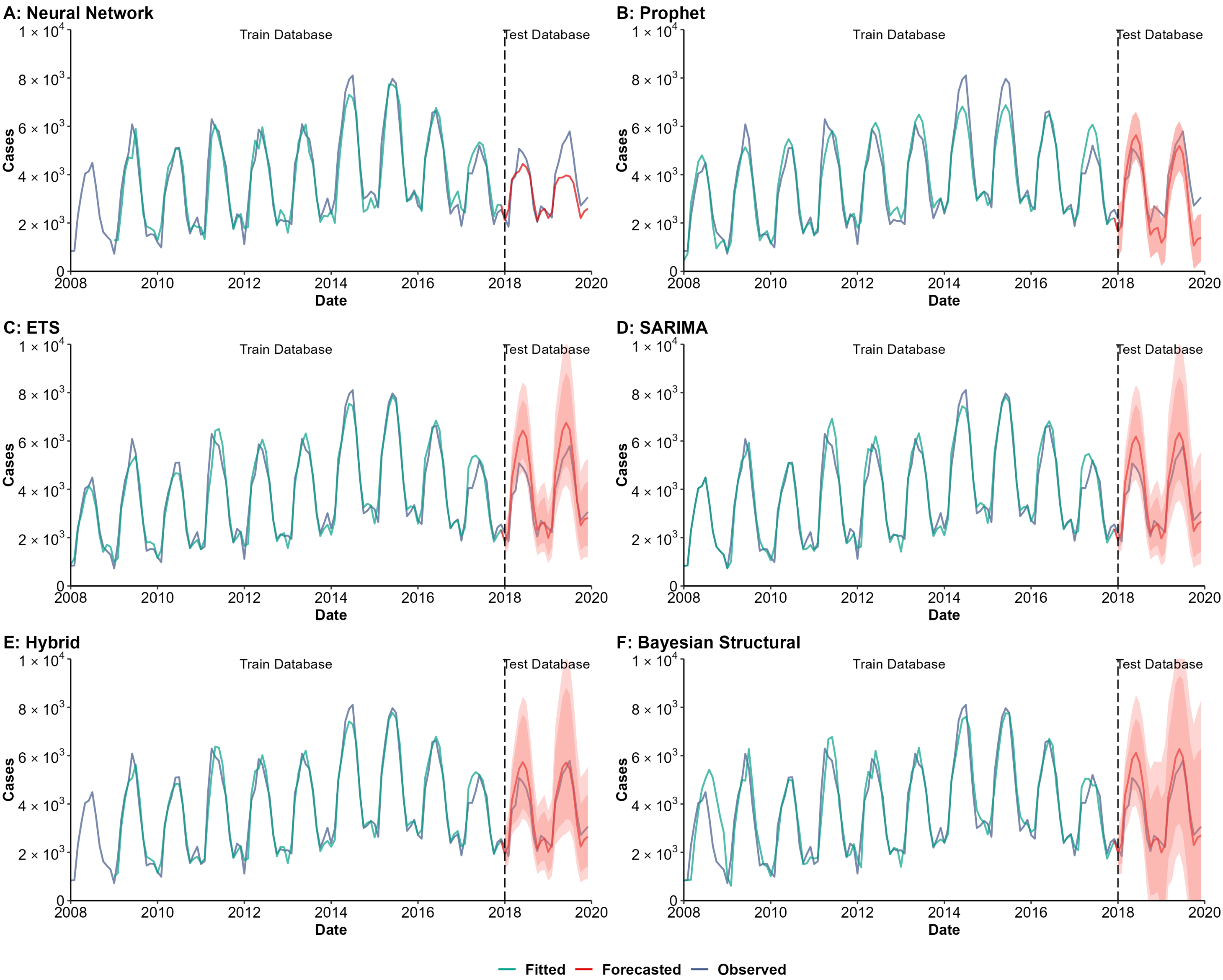
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.94	0.18	0.55
ETS	0.95	0.77	0.76
SARIMA	0.95	0.91	0.89
Hybrid*	0.97	0.92	0.79
Bayesian Structural	0.90	0.09	0.39
Prophet	0.81	0.84	0.75

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

Supplementary Fig. 41. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	12.14	14.48	12.56
ETS	9.62	15.38	10.58
SARIMA	9.00	13.31	9.72
Hybrid*	8.87	10.70	9.20
Bayesian Structural	15.36	12.61	14.90
Prophet	11.07	28.19	13.92

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	476.32	721.75	529.47
ETS	402.21	796.37	490.42
SARIMA	427.34	619.30	464.87
Hybrid*	383.89	431.13	392.90
Bayesian Structural	683.38	583.40	667.76
Prophet	509.86	879.70	587.89

*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
ETS	0.37	0.78	0.46
SARIMA	0.37	0.66	0.42
Hybrid*	0.35	0.54	0.40
Bayesian Structural	0.58	0.63	0.60
Prophet	0.47	0.96	0.58

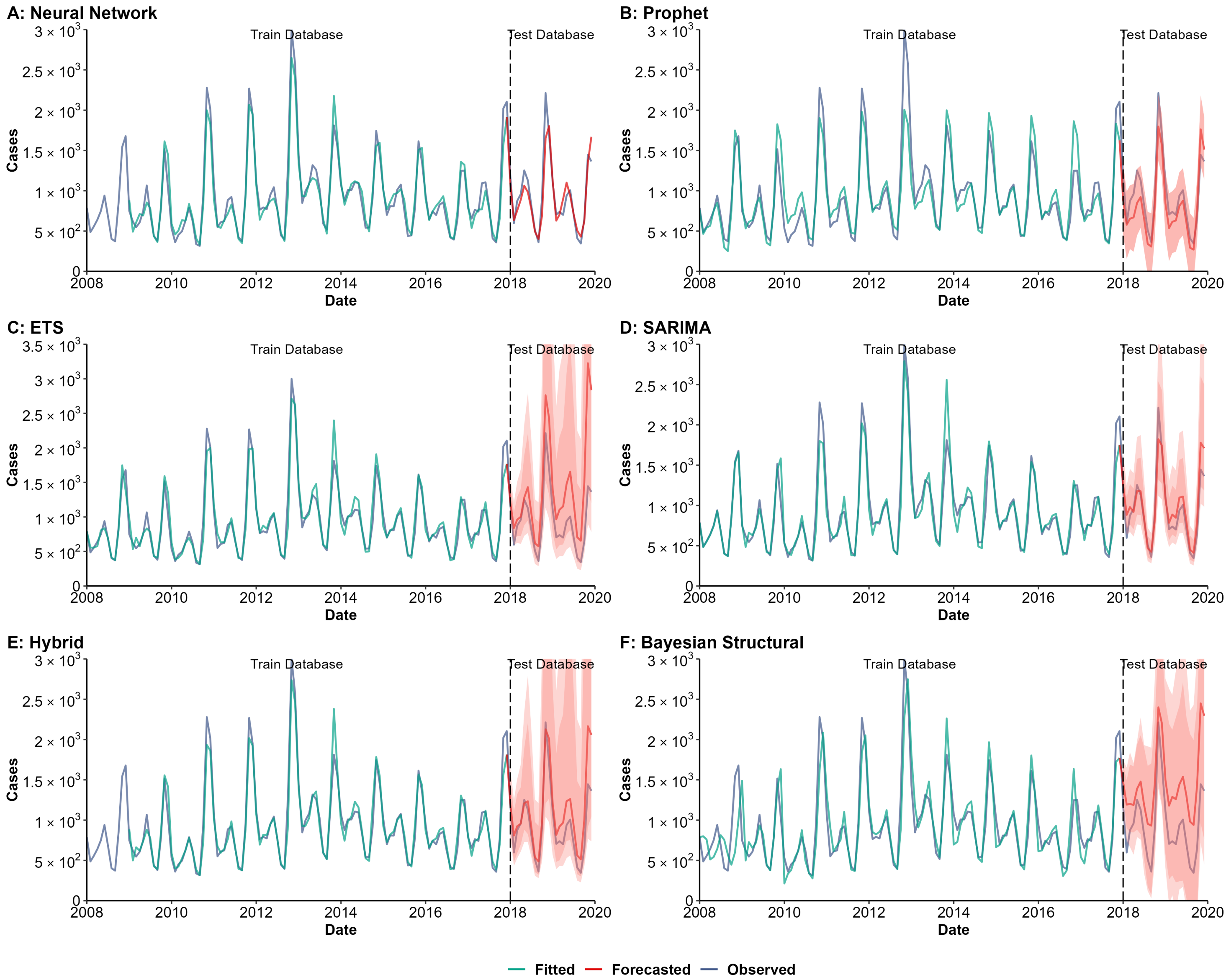
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.93	0.81	0.91
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
Prophet	0.92	0.82	0.89

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

Supplementary Fig. 42. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	9.74	12.02	10.15
ETS	9.05	37.05	13.72
SARIMA	8.90	12.89	9.57
Hybrid*	7.92	19.72	10.07
Bayesian Structural	16.77	47.16	21.84
Prophet	14.22	21.09	15.37

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	129.17	165.65	136.53
ETS	138.60	611.14	279.75
SARIMA	151.85	162.02	153.59
Hybrid*	127.49	266.81	162.00
Bayesian Structural	235.53	541.45	308.37
Prophet	207.85	204.60	207.31

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.32	0.41	0.33
ETS	0.29	0.98	0.45
SARIMA	0.29	0.44	0.31
Hybrid*	0.26	0.60	0.32
Bayesian Structural	0.50	1.77	0.65
Prophet	0.45	0.61	0.48

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

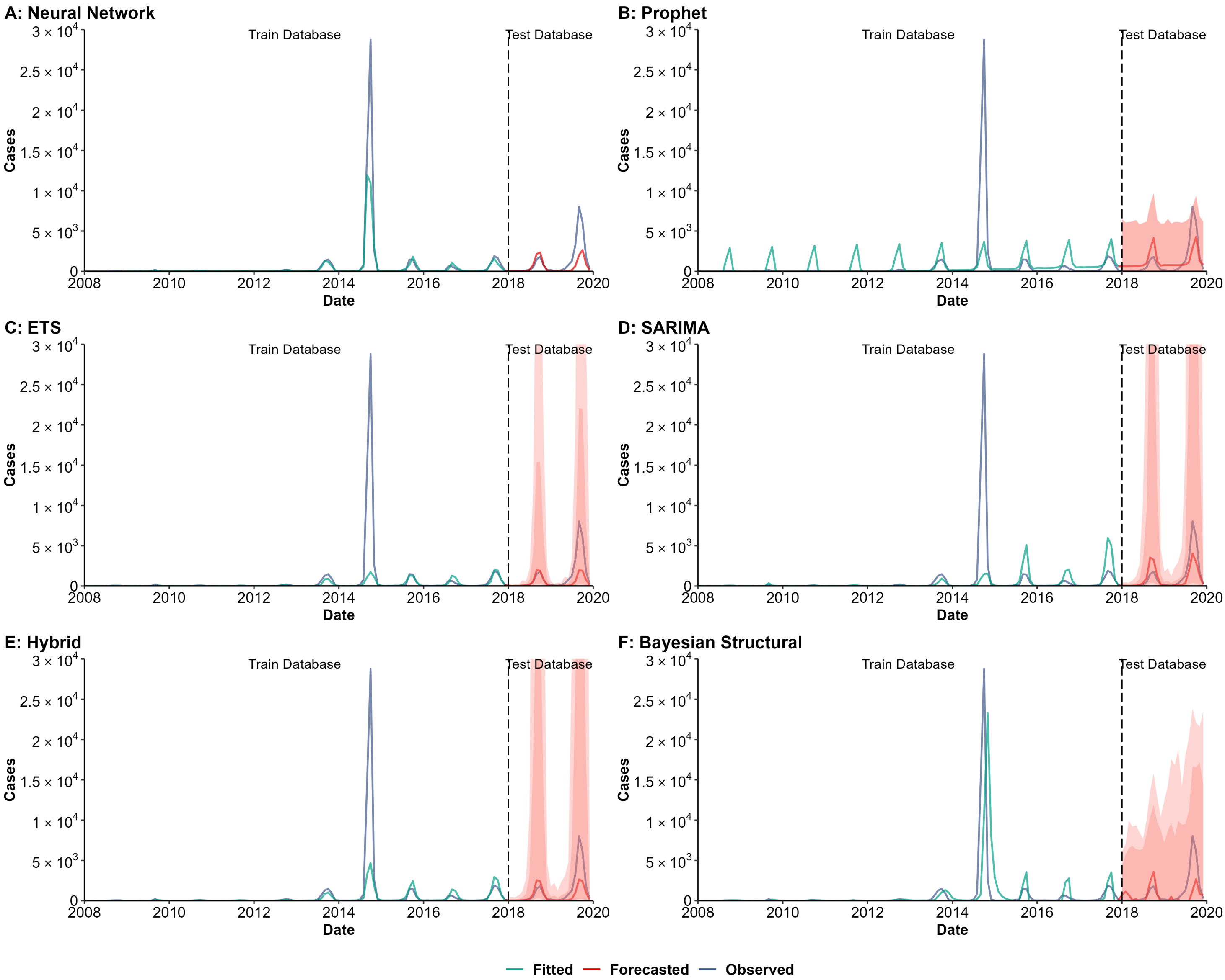
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.94	0.86	0.93
ETS	0.92	0.70	0.76
SARIMA	0.91	0.88	0.90
Hybrid*	0.94	0.84	0.89
Bayesian Structural	0.78	0.79	0.67
Prophet	0.82	0.87	0.82

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

Supplementary Fig. 43. 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.



G : SMAPE of Models

Method	Train	Test	All
Neural Network	32.55	80.31	41.23
ETS	60.01	73.88	62.32
SARIMA	64.04	57.21	62.90
Hybrid*	48.62	69.78	52.47
Bayesian Structural	116.22	137.74	119.80
Prophet	150.99	109.97	144.15

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	1740.62	1564.42	1709.94
ETS	2773.70	1648.69	2619.97
SARIMA	2873.25	1225.84	2670.22
Hybrid*	2582.23	1474.07	2418.81
Bayesian Structural	2967.59	1848.96	2812.22
Prophet	2733.37	1408.61	2560.63

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.74	1.70	0.96
ETS	0.71	2.17	2.92
SARIMA	1.98	1.02	1.69
Hybrid*	0.65	1.60	1.73
Bayesian Structural	1.29	1.34	1.17
Prophet	1.50	1.58	1.52

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

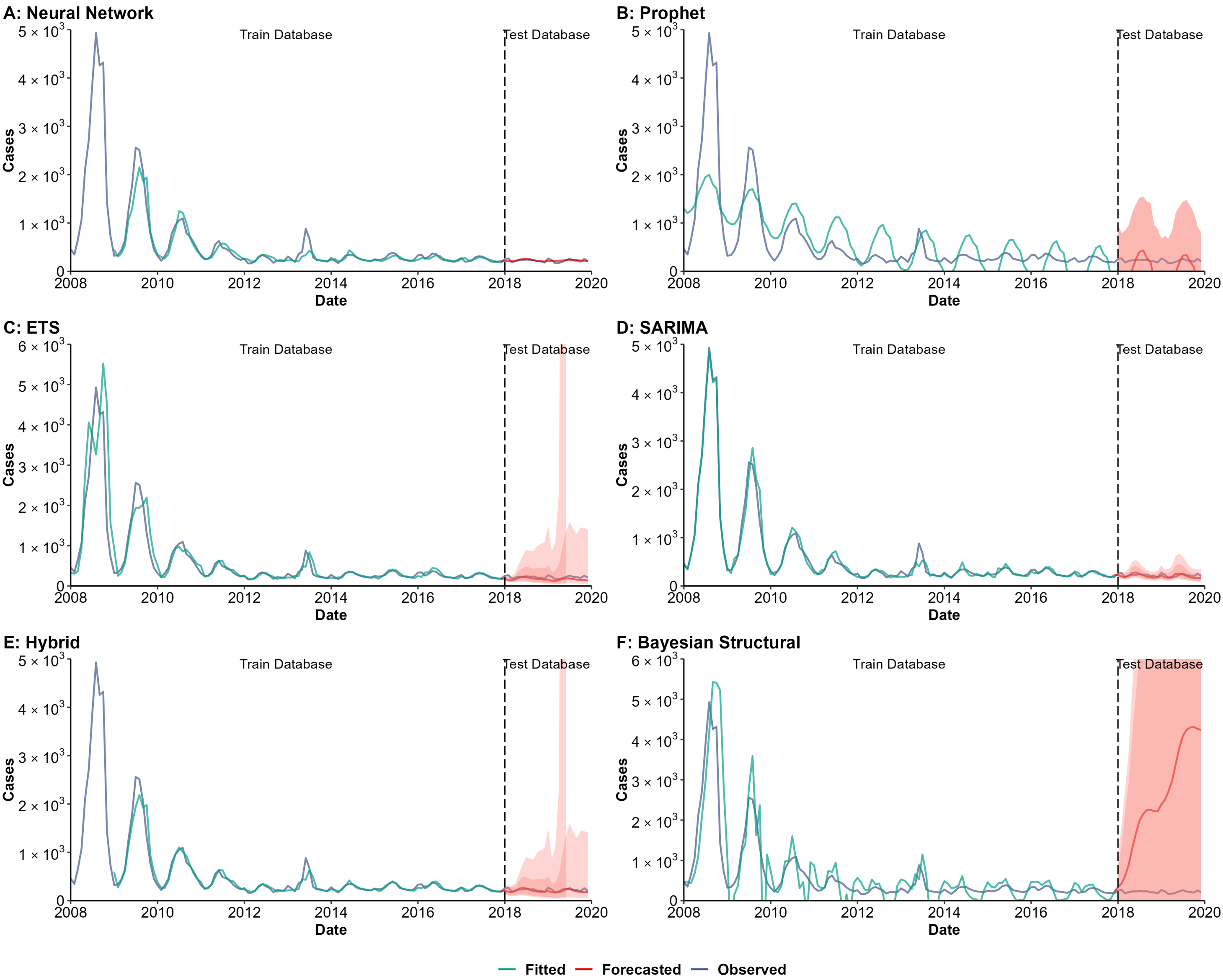
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.86	0.58	0.84
ETS	0.28	0.59	0.29
SARIMA	0.06	0.66	0.11
Hybrid*	0.60	0.62	0.57
Bayesian Structural	0.17	0.21	0.17
Prophet	0.14	0.53	0.17

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

Supplementary Fig. 44. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	15.18	10.57	14.34
ETS	17.98	27.30	19.53
SARIMA	12.43	15.32	12.91
Hybrid*	11.52	13.11	11.81
Bayesian Structural	68.73	153.70	82.89
Prophet	81.68	126.76	89.20

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	143.37	28.45	130.25
ETS	404.63	61.48	370.23
SARIMA	108.42	39.92	100.31
Hybrid*	118.88	36.39	108.65
Bayesian Structural	595.78	2665.33	1216.47
Prophet	594.28	401.53	566.73

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.91	3.19	0.96
ETS	0.91	3.48	0.88
SARIMA	0.33	1.53	0.36
Hybrid*	0.56	1.62	0.67
Bayesian Structural	2.00	13.03	1.88
Prophet	2.32	2.27	2.63

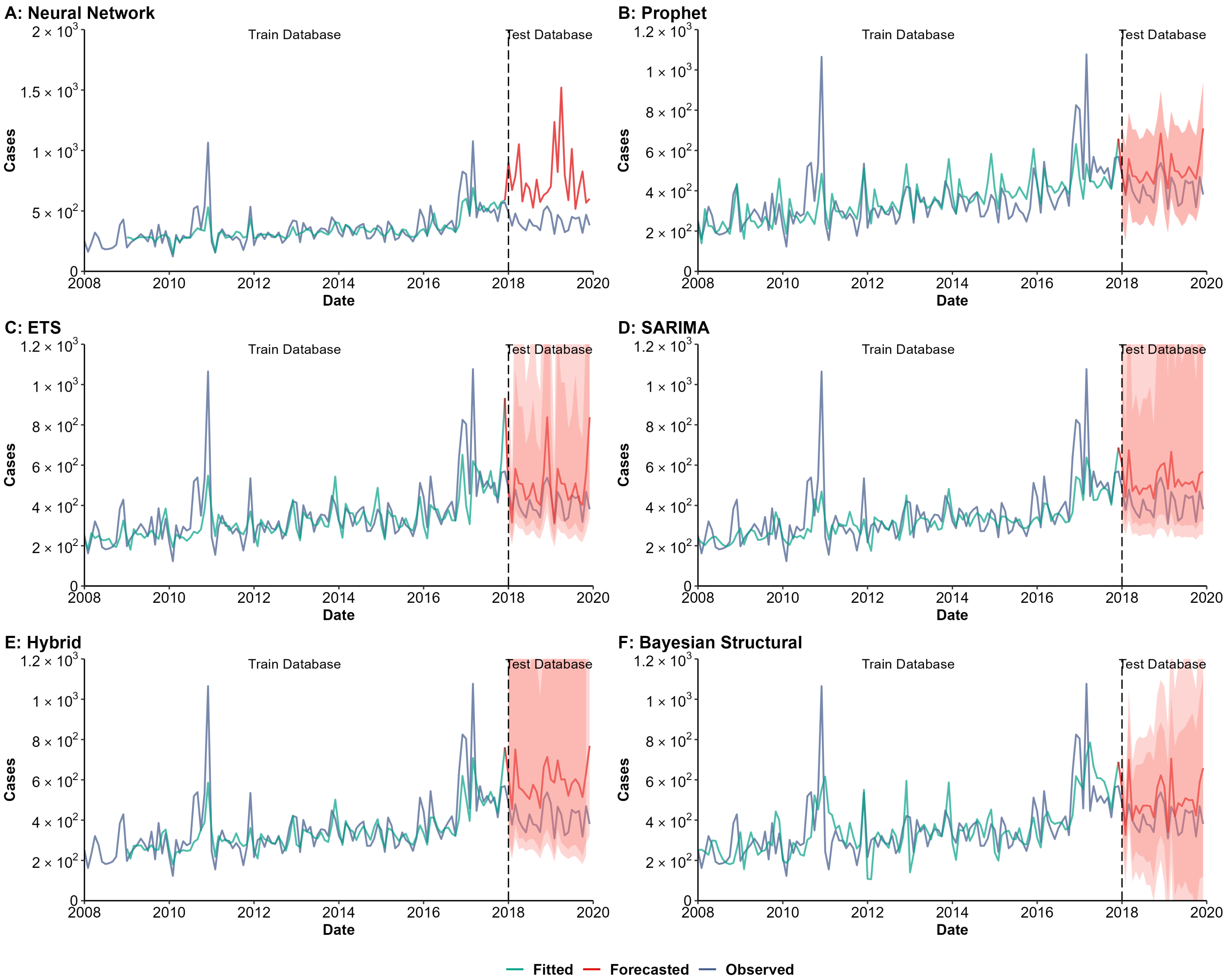
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.89	0.09	0.90
ETS	0.82	0.14	0.82
SARIMA	0.98	0.11	0.98
Hybrid*	0.92	0.13	0.92
Bayesian Structural	0.69	0.01	0.26
Prophet	0.52	0.05	0.49

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

Supplementary Fig. 45. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	14.39	56.86	22.11
ETS	18.03	20.39	18.42
SARIMA	19.26	25.02	20.22
Hybrid*	15.36	36.33	19.18
Bayesian Structural	23.15	20.69	22.74
Prophet	19.67	20.28	19.77

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	95.96	433.61	204.25
ETS	109.02	139.10	114.58
SARIMA	110.36	125.18	112.96
Hybrid*	96.63	193.75	120.27
Bayesian Structural	119.46	117.68	119.17
Prophet	112.35	113.36	112.52

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

I : MASE of Models

Method	Train	Test	All
Neural Network	1.31	1.35	1.32
ETS	0.68	0.82	0.95
SARIMA	1.51	1.54	1.52
Hybrid*	0.58	2.09	1.34
Bayesian Structural	0.83	0.82	1.06
Prophet	0.73	1.25	1.00

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

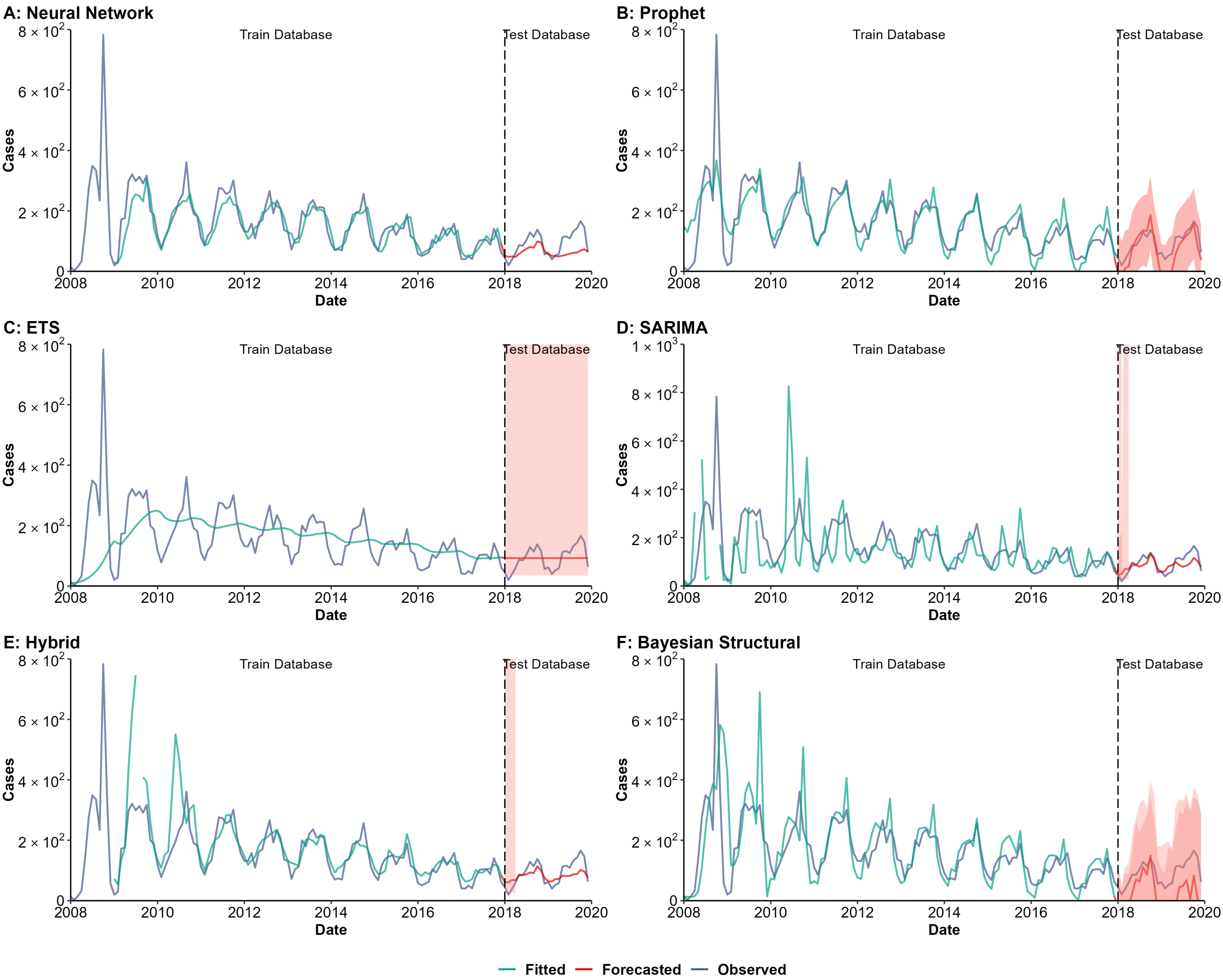
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.66	0.00	0.17
ETS	0.50	0.25	0.42
SARIMA	0.52	0.51	0.40
Hybrid*	0.64	0.34	0.40
Bayesian Structural	0.42	0.45	0.41
Prophet	0.44	0.30	0.40

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

Supplementary Fig. 46. 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 : SMAPE of Models

Method	Train	Test	All
Neural Network	19.06	40.05	22.88
ETS	43.26	42.22	43.09
SARIMA	42.25	28.28	39.85
Hybrid*	23.23	30.53	24.57
Bayesian Structural	39.33	131.59	54.71
Prophet	32.34	74.13	39.31

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	38.50	43.52	39.46
ETS	103.91	40.12	96.26
SARIMA	116.52	27.73	106.68
Hybrid*	78.30	30.21	71.94
Bayesian Structural	99.99	85.32	97.70
Prophet	61.06	40.85	58.18

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

I : MASE of Models

Method	Train	Test	All
Neural Network	1.09	5.40	1.30
ETS	1.42	37811.26	16.10
SARIMA	0.92	1.59	0.94
Hybrid*	1.19	3.31	1.19
Bayesian Structural	1.26	1.83	1.03
Prophet	0.82	0.99	0.95

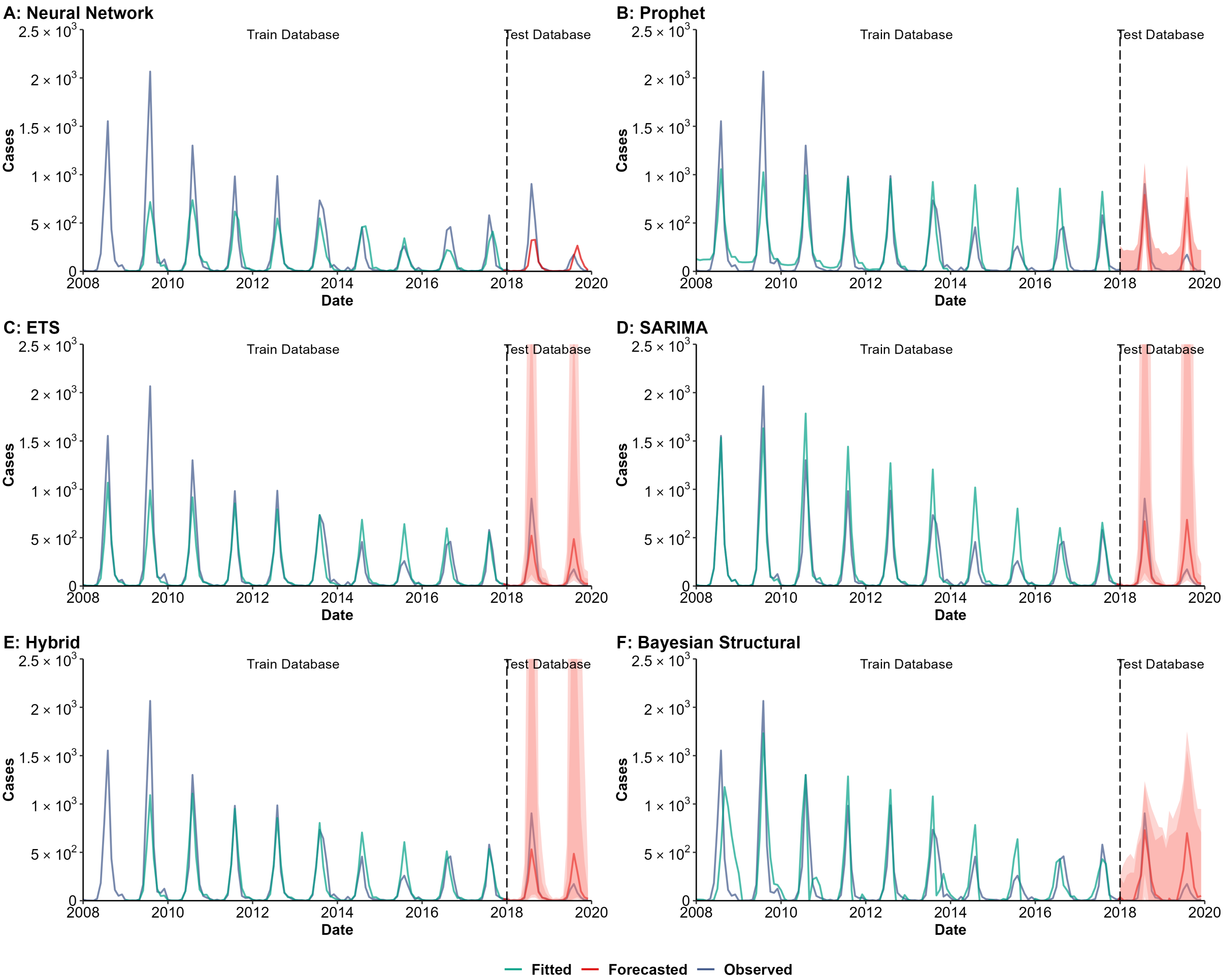
*Hybrid: Combined SARIMA, ETS, STL and Neural Network model

J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.75	0.38	0.74
ETS	0.05	0.29	0.09
SARIMA	0.11	0.64	0.14
Hybrid*	0.57	0.80	0.59
Bayesian Structural	0.40	0.54	0.44
Prophet	0.63	0.80	0.65

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

Supplementary Fig. 47. 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.



G : SMAPE of Models

Method	Train	Test	All
Neural Network	56.47	71.44	59.20
ETS	45.10	66.28	48.63
SARIMA	50.29	66.36	52.97
Hybrid*	46.67	61.37	49.34
Bayesian Structural	120.67	116.21	119.93
Prophet	114.71	165.91	123.24

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

H : RMSE of Models

Method	Train	Test	All
Neural Network	186.43	142.46	179.24
ETS	155.98	123.15	151.00
SARIMA	147.68	137.83	146.09
Hybrid*	138.15	120.42	135.10
Bayesian Structural	239.91	150.99	227.51
Prophet	173.93	180.99	175.13

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

I : MASE of Models

Method	Train	Test	All
Neural Network	0.89	1.25	0.94
ETS	0.40	0.70	0.51
SARIMA	0.36	0.57	0.38
Hybrid*	0.39	0.69	0.46
Bayesian Structural	0.88	0.64	0.70
Prophet	0.66	0.93	0.71

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

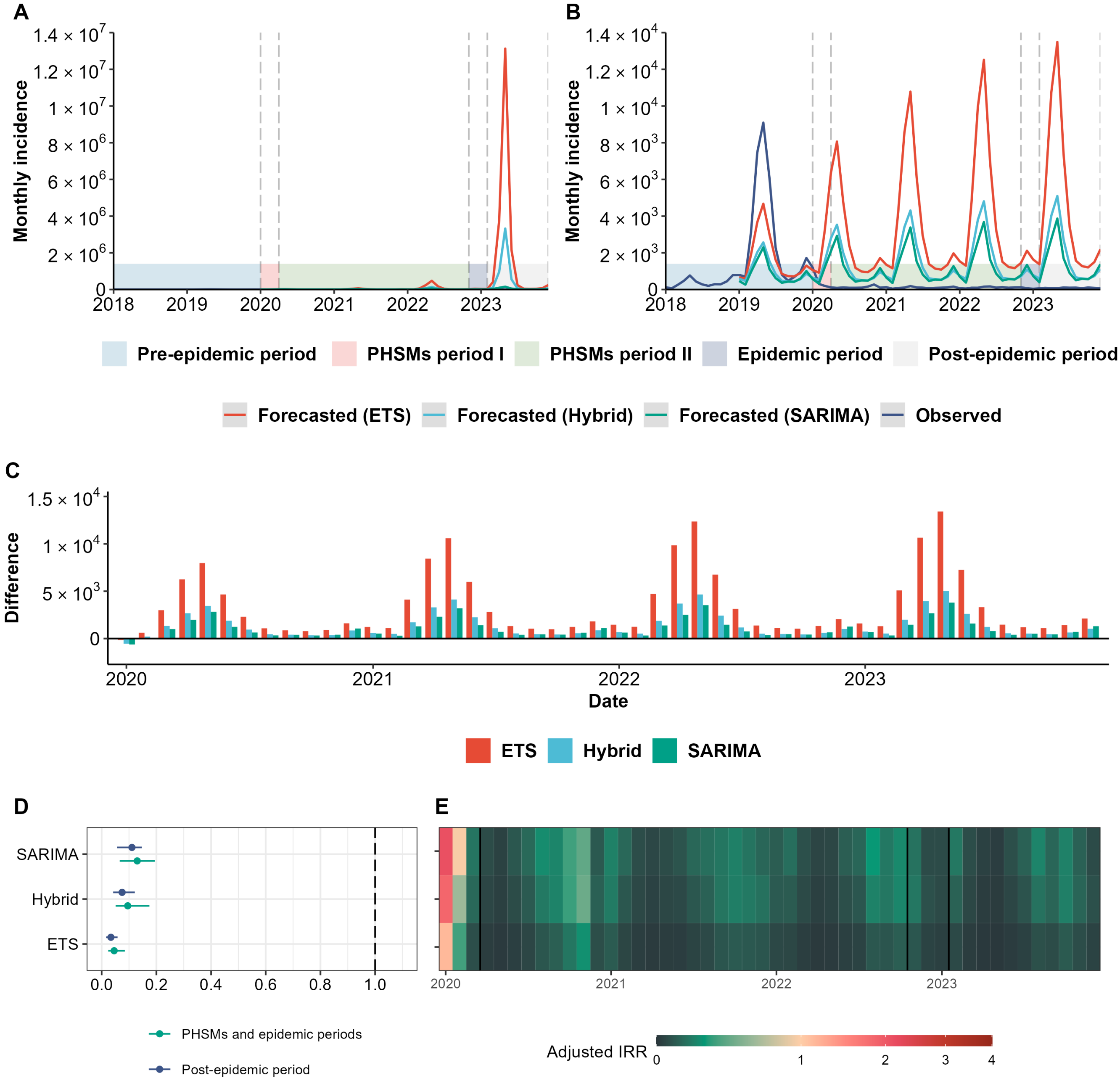
J : R_Squared of Models

Method	Train	Test	All
Neural Network	0.74	0.64	0.73
ETS	0.82	0.64	0.81
SARIMA	0.85	0.60	0.83
Hybrid*	0.82	0.66	0.81
Bayesian Structural	0.56	0.61	0.57
Prophet	0.72	0.63	0.69

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

Supplementary Fig. 48. 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. 49. Training and comparing variant time series models for rubella. **(A)** The forecasted number of rubella cases in the China from 2020 to 2023 trained on 2008-2019 data. **(B)** The forecasted number of rubella cases in the China from 2019 to 2023 trained on 2008-2018 data. **(C)** The difference between the forecasted incidence and the observed incidence of rubella in the China from 2020 to 2023, based on the model trained on 2008-2018 data. **(D)** The adjusted incidence relative ratio (IRR) distribution of rubella during different period which split by October 2022. **(E)** The changes of adjusted IRR of rubella during different period.