CNF-based Prediction of COVID-19 Transmission without Considering NPIs

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Abstract

Natural factors and non-pharmaceutical interventions (NPIs) have effect on COVID-19 transmission, but it's difficult to separate these two factors. The Compound natural factor (CNF) model is proposed to deal with this problem. In this model, the weight of single natural factors (SNFs) could be expressed the coupling relationship (CR) among them. Then, CR is iteratively optimized by Elitism-based compact genetic algorithms (ECGAs). Considering optimal coupling relationship of SNFs, CNF has a strong correlation (r=0.56) with the COVID-19 infection rate. However, CNF does not have much correlation with mortality (r=-0.25) and recovery rate (r=-0.46), due to slight change of weather in hospitals. Therefore, a linear weighted CNF model is constructed to forecast the impending infection rate. As a result, NPIs effect have been eliminated in the predicted infection rate by the CNF model, which is only the result of climate change. If China ignored NPIs, COVID-19 virus would transmit in the CNF forecast way as climate changes. This model built on Chinese cases provides a new perspective to forecast the global infection rate which is only under the intervention of natural factors.

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Key Points:

- Weighted Compound Natural Factor (CNF) has potential to predict COVID-19 infection rate, which is only the result of weather change.
- Cosidering coupling relationship among SNFs acting on COVID-19, CNF is much better parameter than SNFs.
- CNF parameter has strong correlation with COVID-19 transmission.
- CNF parameter does not have higher correlation with COVID-19 mortality and recovery rate.

Abstract

Natural factors and non-pharmaceutical interventions (NPIs) have effect on COVID-19 transmission, but it's difficult to separate these two factors. The Compound natural factor (CNF) model is proposed to deal with this problem. In this model, the weight of single natural factors (SNFs) could be expressed the coupling relationship (CR) among them. Then, CR is iteratively optimized by Elitism-based compact genetic algorithms (ECGAs). Considering optimal coupling relationship of SNFs, CNF has a strong correlation (r=0.56) with the COVID-19 infection rate. However, CNF does not have much correlation with mortality (r=-0.25) and recovery rate (r=-0.46), due to slight change of weather in hospitals. Therefore, a linear weighted CNF model is constructed to forecast the impending infection rate. As a result, NPIs effect have been eliminated in the predicted infection rate by the CNF model, which is only the result of climate change. If China ignored NPIs, COVID-19 virus would transmit in the CNF forecast way as climate changes. This model built on Chinese cases provides a new perspective to forecast the global infection rate which is only under the intervention of natural factors.

Plain language summary

The World Health Organization declared COVID-19 a pandemic on March 11, 2020. NATURE and SCIENCE published articles affirming the positive effect of Non-pharmaceutical interventions (NPIs) on mitigating the pandemic in China but still the possibility cannot be ruled out that the decrease is partially attributable to other unknown climatic factors. This paper only considers the natural factors and ignore the effect of NPIs. In this regards, single natural factors (SNFs), such as temperature, humidity, wind speed, aerosol, visibility have poor correlation with COVID-19 transmission. Owing to that, compound natural factor (CNF) is proposed to draw the combined effect with virus spread. Through assigning optimal weight values to SNFs, a coupling relationship (CR) is expressed among them. As a result, CNF has a higher correlation (r=0.56) with the COVID-19 infection rate. With a simple computer code to predict future infection rate, it is confirmed that reduction in CNF value could, along with the weather change, help delay the spread of virus. Both NPIs and reduction in CNF value could help delay the transmission of COVID-19, but how to separate these two factors? Modeling results suggest that benefit of NPIs has been eliminated in the CNF predicted infection rate.

1 Introduction

On March 11, 2020, the World Health Organization declared COVID-19 a pandemic. Non-pharmaceutical interventions (NPIs) helped China decrease a 67-fold COVID-19 cases (Lai et al., 2020), but still the possibility cannot be ruled out that the decrease is partially attributable to other unknown climatic factors, e.g. temperature and absolute humidity. Many countries hope that the spread of COVID-19 is likely constrained by climate, as the SARS in 2003. Some studies show temperature could have significant relationship to COVID-19 transmission, and there might be an optimal temperature for the viral transmission (Wang, Mao et al., 2020; Wang, Tang et al., 2020), and solar radiation threats the virus survival (Ahmadi et al., 2020). However, some studies do not support the hypothesis that high temperature and UV radiation can be conductive in the reduction of COVID-19 transmissibility. It might be premature to count on warmer weather to control COVID-19 (Yao et al., 2020; Zhu et al., 2020). Other climatic factors are also researched, such as humidity (Luo et al., 2020; Ma et al., 2020), aerosol (Sima et al., 2020; Wang, Du, 2020), wind speed (Islam et al., 2020; Ahmadi et al., 2020). Previous studies supported an epidemiological hypothesis that dry environments facilitate the survival and spread of droplet-mediated viral diseases, and humid environments see attenuated viral transmission (Barreca et al., 2012; Shaman et al., 2011). Next, reference (Wang, Tang et al., 2020; Ahmadi et al., 2020) show high humidity reduces the transmission of COVID-19. However, reference (Luo et al., 2020) concludes that the role of absolute humidity in transmission of COVID-19 has not yet been established. In addition, COVID-19 may transmit through aerosol (Wang, Du et al., 2020; Liu et al., 2020), whereas there are also important reasons to suspect it plays a role in the high transmissibility of virus (Sima et al., 2020). Further, a study shows that an outbreak at low wind speed is remarkable (Islam et al., 2020), but this result is nullified by another study (Oliveiros et al., 2020).

Why these studies show diverged results? It is still not clear that how climate play its part in the transmissibility of COVID-19. The spreading mechanism of virus is very complex, coupling certain factors. NATURE and SCIENCE published articles affirming the positive effect of pre-emptive implementation of NPIs on mitigating the pandemic (Lai et al., 2020; Tian et al., 2020). Considering the impact of natural factors on virus transmission along and excluding the NPIs, it is still insignificant method to do independent analysis on the part of considering single natural factors (SNFs) and to ignore their coupling relationship (CR). However, there are few studies in this field. One of the potential solutions is weighted ensemble method, which is popular in Meteorology (Yoo et al., 2020), Socioeconomics (Boyce et al., 2020), Climatology (Strobach et al., 2020). Therefore, the main contribution of this paper is the weighted Composite Natural Factor (CNF)-based prediction of the COVID-19 infection rate (Tellis et al., 2020), mortality (Ma et al., 2020), and recovery rate.

2 Model Description

In this study, for experimental purpose 27 provincial capitals and 4 metropolitan cities of China are considered, wherein 3 epidemic parameters (EPs) and 7 single natural factors (SNFs) data from February 1st to March 31st, 2020 are collected. EPs contain daily infection rate, mortality, and recovery rate. SNFs include meteorological data, vegetation, and aerosol data. Meteorological data contains temperature, humidity, visibility, wind speed, and barometric pressure. After the normalization process, the February data are taken as model input (Fig.1). First the correlation between SNFs and EPs is calculated. However, EPs of COVID-19 are the result of the combined actions of multiple natural factors, and each factor has different influence. So, separate weight value should be assigned on the basis of its influence. This Compound Natural Factor (CNF) is represented by the letter $\boldsymbol{C}$, as shown in formula (1).

$$\boldsymbol{C} = w_T \times \boldsymbol{T} + w_H \times \boldsymbol{H} + w_V \times \boldsymbol{V} + w_B \times \boldsymbol{B} + w_W \times \boldsymbol{W} + w_A \times \boldsymbol{A} + w_v \times \boldsymbol{v} \tag{1}$$

Where $\boldsymbol{W} = \{w_T, w_H, w_V, w_B, w_W, w_A, w_v\}$ respectively correspond to the weight values of 7 different natural factors, and satisfy the constraints of formula (2). Vector $\boldsymbol{T}$, $\boldsymbol{H}$, $\boldsymbol{V}$, $\boldsymbol{B}$, $\boldsymbol{W}$, $\boldsymbol{A}$, $\boldsymbol{v}$ corresponds to the temperature, humidity, visibility, barometric pressure, wind speed, aerosol, and vegetation factor, respectively. Vector $\boldsymbol{G}$, $\boldsymbol{D}$, $\boldsymbol{R}$ corresponds to infection rate, mortality, and recovery rate, respectively.

$$w_T + w_H + w_V + w_B + w_W + w_A + w_v = 1 \tag{2}$$

But how to determine the weight values of different natural factors? First, the initial weight vector $\boldsymbol{W}$ is generated randomly, and be substituted into the formula (1) to get the compound natural factor of vector $\boldsymbol{C}$. Then the correlation coefficients $R_{\boldsymbol{C-G}}$, $R_{\boldsymbol{C-D}}$, $R_{\boldsymbol{C-R}}$ of vector $\boldsymbol{C}$ and vector $\boldsymbol{G}$, $\boldsymbol{D}$, $\boldsymbol{R}$ is calculated, respectively. Further, the Elitism-based compact genetic algorithms (ECGA) (Chang et al., 2003) is used to iteratively optimize $\boldsymbol{W}$ to obtain an accurate weight vector $\boldsymbol{W}_t$, where t represents the number of iterations. Finally, the exact linear models of vector $\boldsymbol{C}$ and vector $\boldsymbol{G}$, $\boldsymbol{D}$, $\boldsymbol{R}$ is calculated, respectively, as shown in formula (3).

$$\begin{cases} \boldsymbol{G} = f(\boldsymbol{C}) \\ \boldsymbol{D} = f(\boldsymbol{C}) \\ \boldsymbol{R} = f(\boldsymbol{C}) \end{cases} \tag{3}$$

Assuming that social intervention elements are not considered. If the temperature, humidity, visibility, barometric pressure, wind speed, and aerosol can be predicted by meteorologist, these predicted SNFs and the weight vector $\boldsymbol{W}_t$ are simultaneously substituted into the formula (1). Then, the predicted vector $\boldsymbol{C}$ can be calculated. Further, predicted vector $\boldsymbol{C}$ is substituted into the formula (3), the future infection rate $\boldsymbol{G}$, mortality $\boldsymbol{D}$, and recovery rate $\boldsymbol{R}$ is predicted, respectively. Finally, the actual March data is compared with the March prediction results to evaluate the accuracy of CNF model build on the February data.

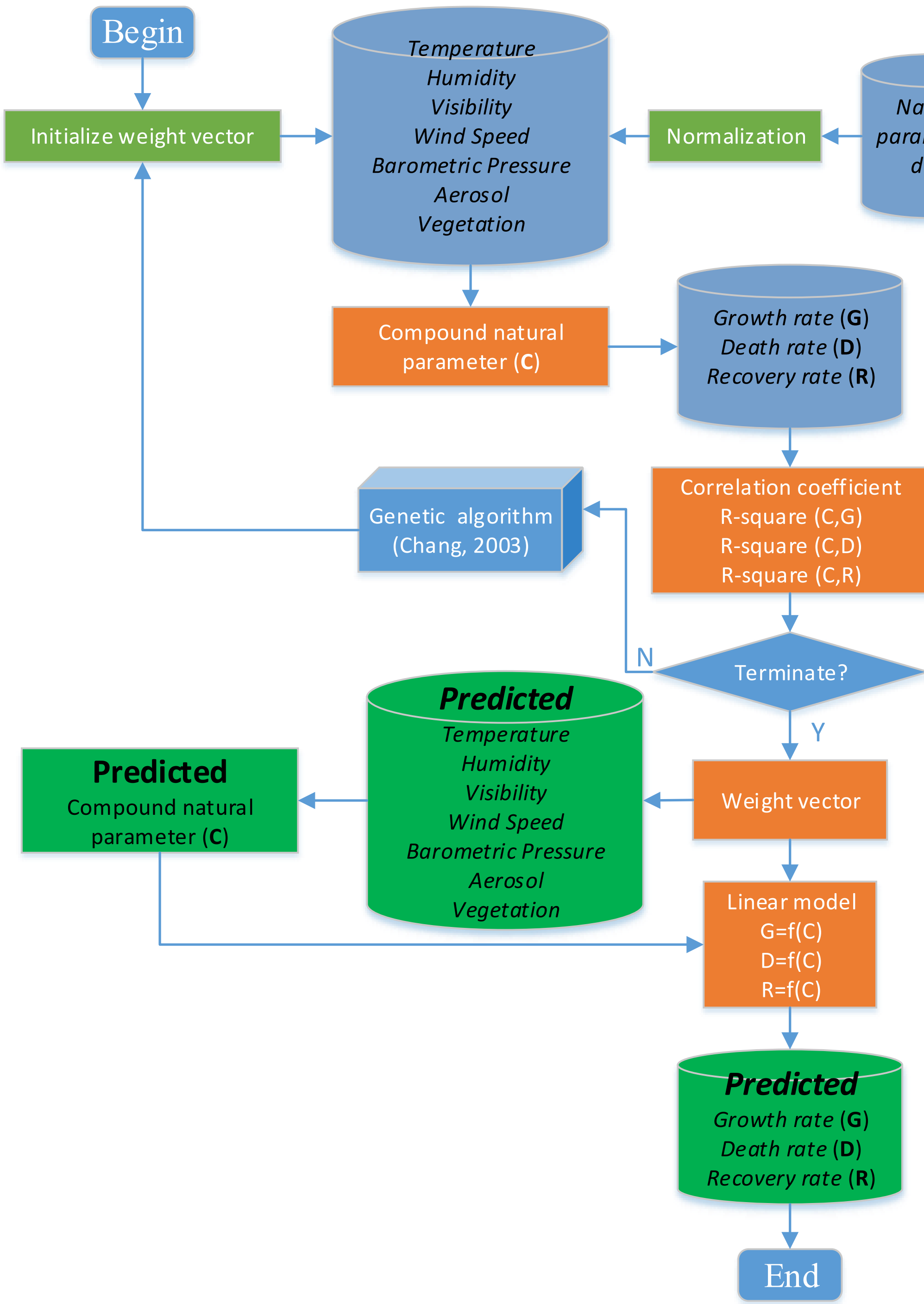


Figure 1. CNF model

4 Coupling relationship among SNFs acting on COVID-19 transmission

Single natural factors (SNFs) are weakly correlated with the infection rate (Fig.3a), but compound natural factor (CNF) weighted by SNFs has a higher correlation (r=0.56). This shows that CNF is a better parameter than SNFs to analyze the correlation between climate and COVID-19 transmission. The CNF dedicated by 7 SNFs, wherein the humidity has assigned the largest weight (0.5), followed by temperature (0.26), and other SNFs contribute less (Fig.3b). The weight value of SNFs reveals the coupling relationship (CR) among different SNFs when acting on COVID-19 transmission. Besides, during the independent correlation analysis of SNFs with infection rate (Fig.3a), humidity also owns the largest r value (0.27), followed by temperature (r=0.19). It shows that the unbiased correlation between SNFs and infection rate is consistent with its coupling relationship (CR) in CNF. To get a more realistic CR, the ECGA algorithm (Chang et al., 2003) is employed to optimize the initial CR, which converges after nearly 5000 iterations (Fig.3c). Meanwhile, r value of CNF and infection rate also converges to 0.56 (Fig.3d). As we all know, COVID-19 transmission is a synthesized process. There are many SNFs that act on this process. Some of which contribute to the virus, and some others hinder the virus. It's necessary to consider the CR between different SNFs rather than do objective analysis of SNFs on virus transmission. Although it's not enough for the weighted linear model to uncover CR among SNFs in the real word, CNF is much better parameter than SNFs on COVID-19.

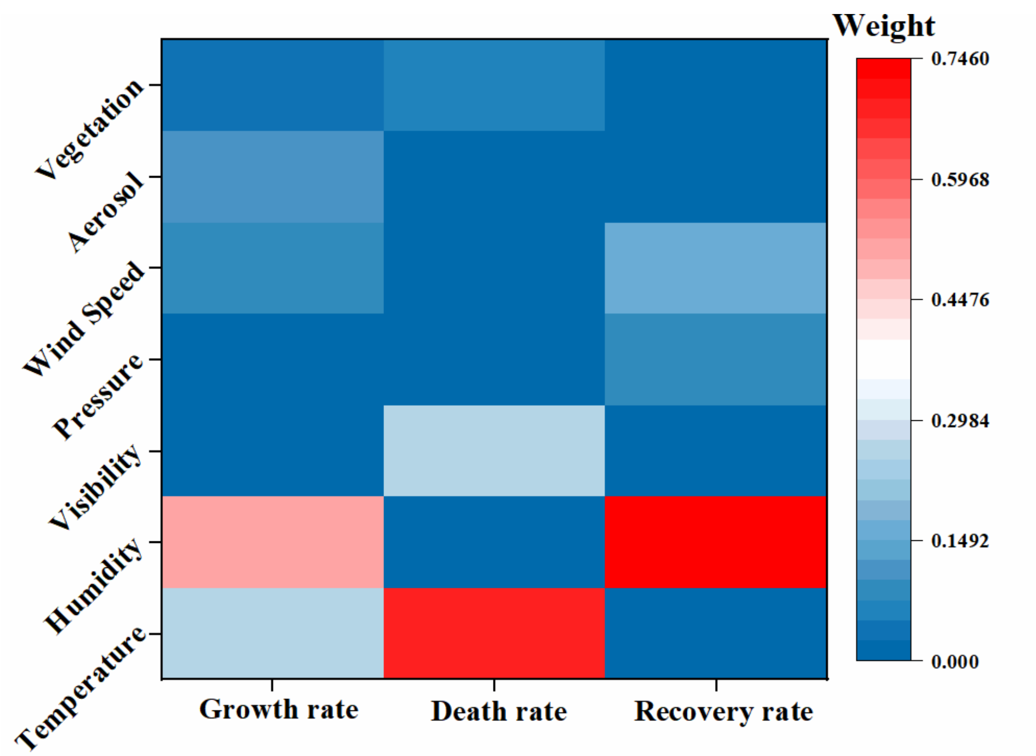


Figure 2. Single natural factors (SNFs) and growth (infection) rate, death rate, recovery rate. Among 7 SNFs, humidity has the greatest influence on the infection rate (positive) and recovery rate (negative), but it's irrelevant to mortality. Temperature affects mortality (negative) the most.

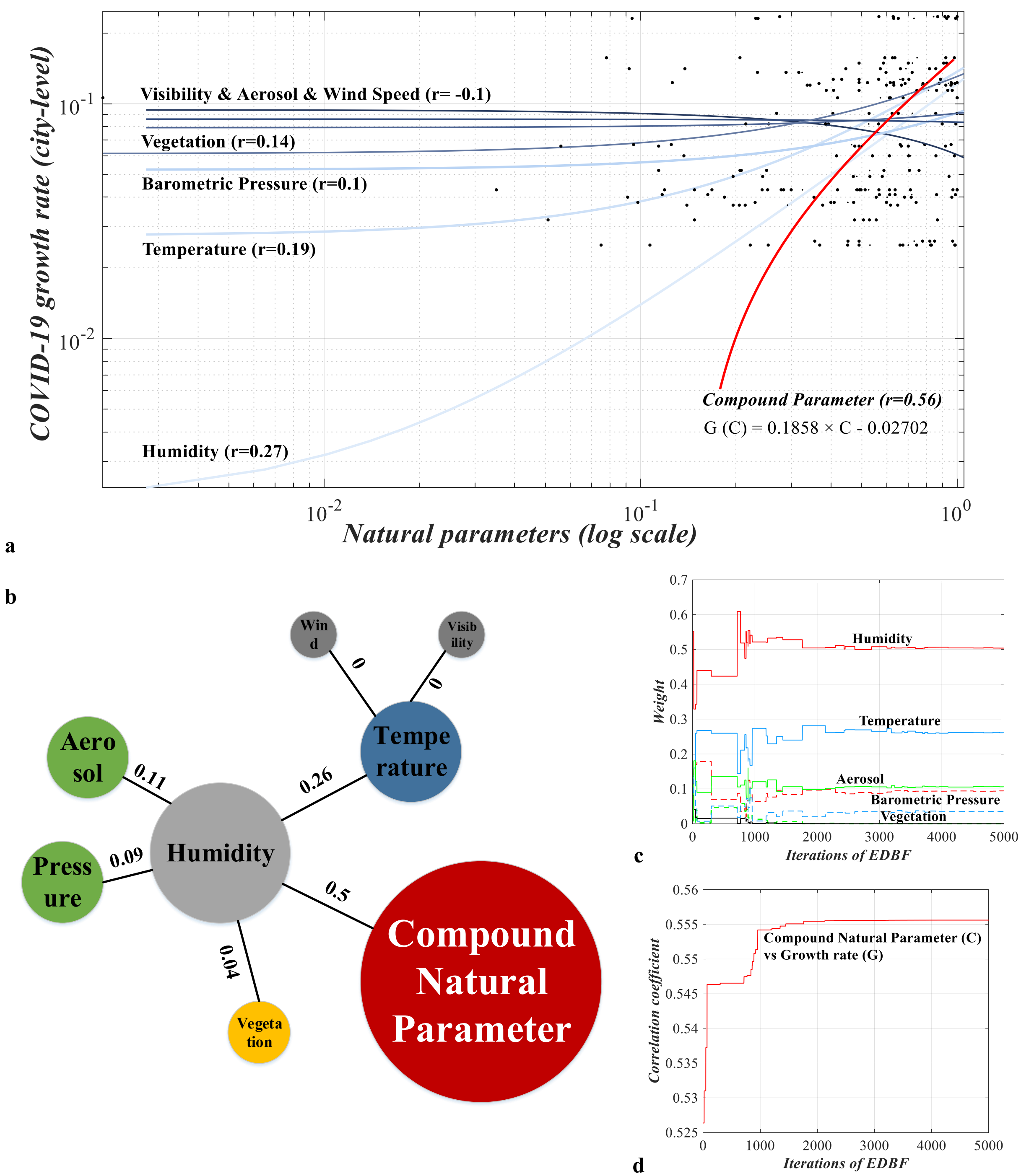


Figure 3. Compound natural factor (CNF) and infection rate. (a) CNF has a strong positive correlation with COVID-19 infection rate (r > 0.5), and 7 single natural factors (SNFs) are weakly correlated with infection rate (| r |<0.3). r is the correlation coefficient, and values of 7 SNFs are all normalized. **(b)** In the weighted CNF, the weight of humidity is 0.5, temperature (0.26), aerosol (0.11) and barometric pressure (0.09), vegetation (0.04), wind speed and visibility do not contribute to CNF. The linear model of infection rate G and CNF C is $G(C) = 0.1858 \times C - 0.02702$. (**c**) Weight values of 7 SNFs gradually converge to be stable with 5000 iterations of

ECGA. **(d)** r value of CNF C and infection rate G increases to 0.56 with nearly 5000 iterations of ECGA.

5 CNF based prediction of infection rate

The linear model of infection rate G and CNF is $G(C) = 0.1858 \times C - 0.02702$ (Fig.3a), which is modeled on February SNFs and infection rate data. Due to the lagging effect of NPIs and incubation period of the virus, the NPIs began in February, but significant effects on virus control appeared in March. Therefore, if CNF model is created on February data, the predicted result in March is still the infection rate without the significant benefit of NPIs (Fig.5a). Forecast infection rate in March is reduced by an average of 1.7% compared to the February data, an average 6.4% higher than the actual March data (0.3%). 6.4% can be used to estimate the benefit of non-pharmaceutical interventions in February to contain COVID-19 in March. 1.7% can be used to evaluate the impact of climate change in March on the COVID-19 transmission in February (Fig.4). Even the climate change slightly suppressed the COVID-19, virus would transmit in the CNF predicted way in March if China ignored NPIs (Fig.5a).

After deleting the effect of NPIs to virus transmission, the climate change in March is analyzed. In the previous independent analysis of the correlation between SNFs and infection rate in February, humidity has the largest r value (r=0.27, positive), but it has a negative correlation with the infection rate in March (Fig.5b). Therefore, it's insignificant to do independent analysis on SNFs and to ignore coupling relationship among them. However, both CNF and infection rate in March is lower than February (Fig.5c), consistent with previous positive correlation (r=0.56) conclusion (Fig.3a). Therefore, CNF is a better parameter than SNFs to analyze the correlation between climate and COVID-19 transmission. Before analyzing effect of the climate change on COVID-19, the benefit of NPIs to virus transmission should be first eliminated, and the coupling relationship between different SNFs shouldn't be ignored.

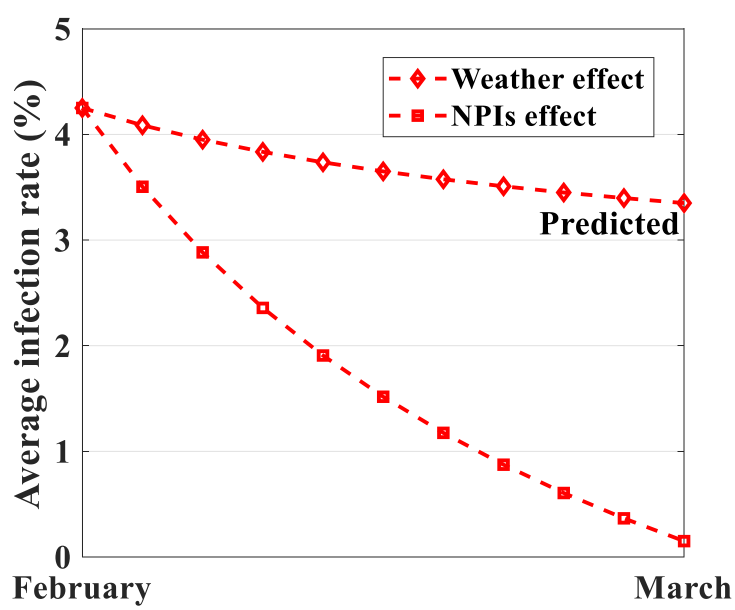


Figure 4. Effects of NPIs (6.4%) and climate (1.7%) to average infection rate.

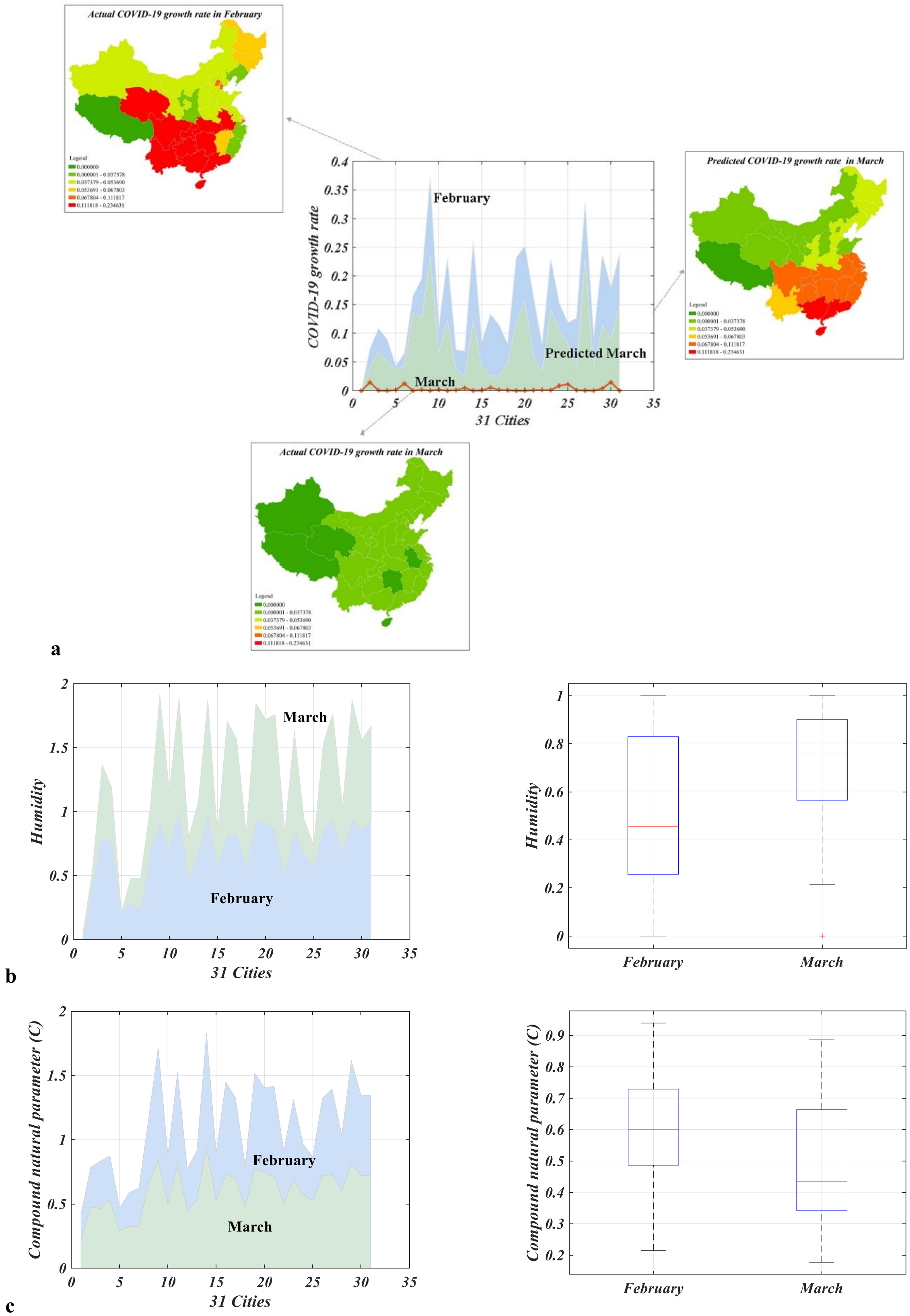


Figure 5. CNF-based prediction of infection rate in March. (a) Predicted infection rate in March doesn't have significant benefit of NPIs. That is to say, if China ignored NPIs, COVID-19

virus would transmit in the CNF predicted way as climate changes. (**b**) Humidity in March is higher than February, but infection rate in March is lower than February, contradictory to previous positive correlation (r=0.27) conclusion. Therefore, it's insignificant to do independent analysis on SNFs and ignore their coupling relationship. (**c**) Both CNF and infection rate in March are lower than February, consistent with previous positive correlation (r=0.56) conclusion. Therefore, CNF is a better parameter than SNFs to analyze the correlation between climate and COVID-19 transmission.

6 Climate does not have much correlation with mortality and recovery rate

Both CNF and SNFs have weak correlation with COVID-19 mortality ($|r|<0.3$). r is the correlation coefficient, and values of 7 SNFs are all normalized (Fig.6a). In the weighted CNF, the weight of temperature is 0.68, followed by visibility (0.26) and vegetation (0.11), humidity, wind speed, barometric pressure and aerosol do not contribute to CNF (Fig.6b). The linear model of mortality D and CNF C is $D(C) = -0.0007755 \times C + 0.0007352$. Weight values of 7 SNFs gradually converge to be stable with nearly 15000 iterations of ECGA (Fig.6c). r value of CNF and mortality increases to -0.25 with nearly 15000 iterations of ECGA (Fig.6d). Then, CNF modeled on February data is employed to predict mortality in March. However, the predicted result has a poor agreement with actual mortality in March (Fig.7a), In addition, both CNF and mortality in March is lower than February (Fig.7b), contradictory to previous negative correlation (r=-0.25) conclusion (Fig.6a). Therefore, climate does not have much correlation with COVID-19 mortality. The main reason is that climate change in the hospital is not obvious, and majority of death are reported from hospitals after their diagnosis.

Similarly, majority of recoveries are also reported from hospitals with little climate change until they were cured. Therefore, climate change maybe doesn't have much correlation with COVID-19 recovery rate. Based on our analysis, CNF has a slight negative correlation with recovery rate ($0.3< |r| < 0.5$), and 7 single natural factors (SNFs) are weakly correlated with the recovery rate ($|r| <0.3$) (Fig.8a). In the weighted CNF, the weight of humidity is 0.75, wind speed is succeeding (0.16), barometric pressure (0.09), vegetation, temperature, aerosol, and visibility do not contribute to CNF (Fig.8b). The linear model of recovery rate R and CNF C is $R(C) = -0.008462 \times C + 0.03565$. Weight values of 7 SNFs gradually converge to be stable with nearly 15000 iterations of ECGA (Fig.8c). r value of CNF C and recovery rate R increases to -0.46 with nearly 15000 iterations of ECGA (Fig.8d). Further, predicted recovery rate by CNF in March well matches with actual data (Fig.9a). However, both CNF and recovery rate in March is lower than February (Fig.9b), contradictory to previous negative correlation (r=-0.46) conclusion (Fig.9a). Therefore, climate actually does not have much correlation with COVID-19 recovery rate.

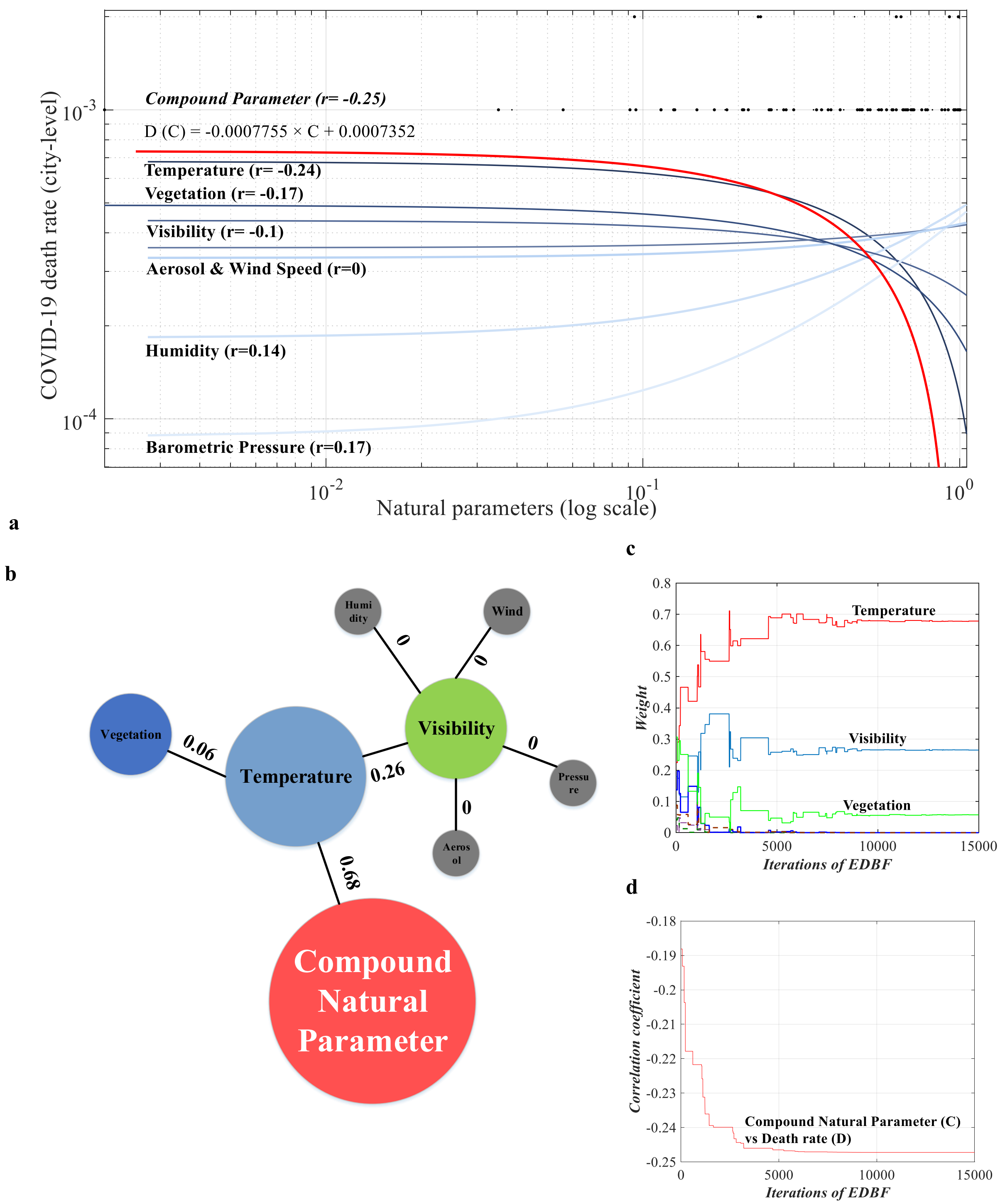
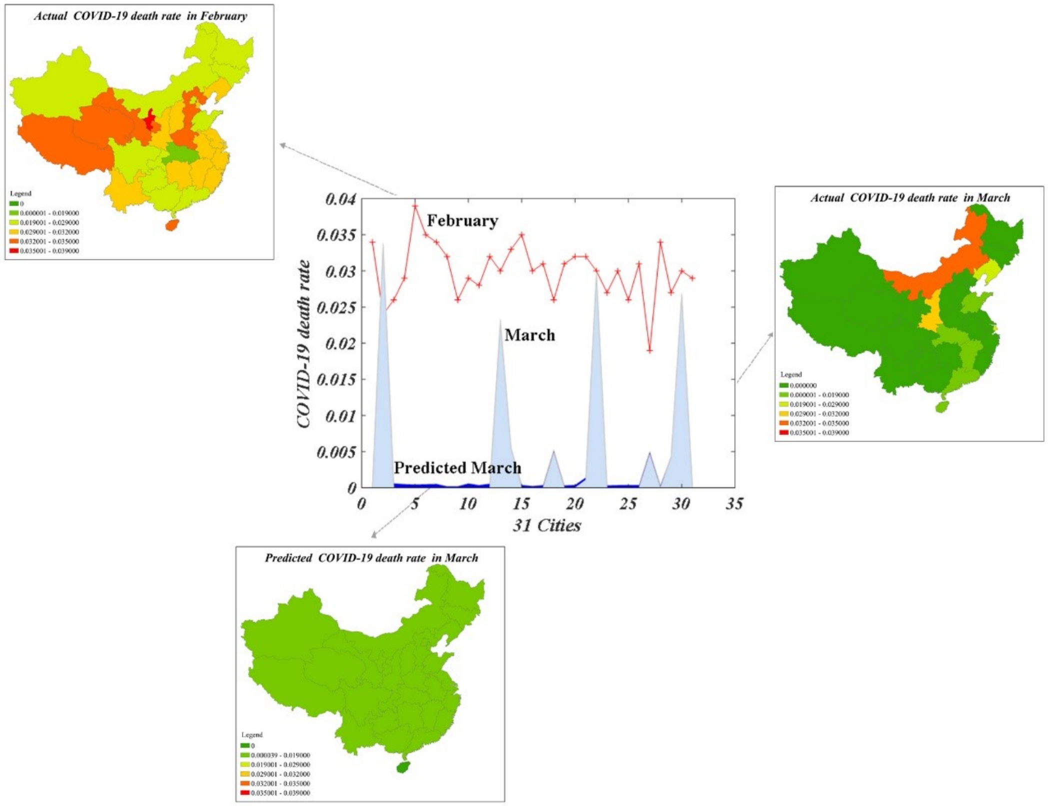
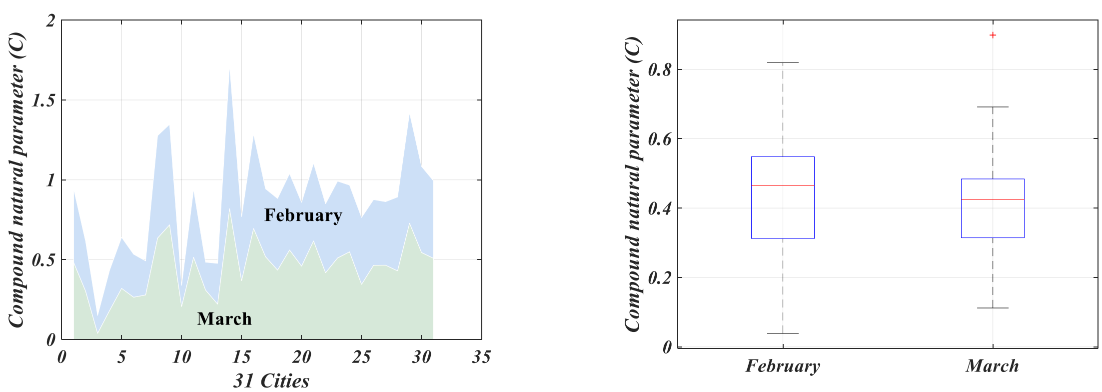


Figure 6. Compound natural factor (CNF) and mortality. (a) Both CNF and SNFs have weak correlation with COVID-19 mortality (| r | <0.3). r is the correlation coefficient, and values of 7 SNFs are all normalized. (**b)** In the weighted CNF, the weight of temperature is 0.68, followed by visibility (0.26) and vegetation (0.11), humidity, wind speed, barometric pressure and aerosol do not contribute to CNF. The linear model of mortality *D* and CNF *C* is $D(C) = -0.0007755 \times C + 0.0007352$. (**c)** Weight values of 7 SNFs gradually converge to be stable with nearly 15000

iterations of ECGA. (**d)** r value of CNF and mortality increases to -0.25 with nearly 15000 iterations of ECGA.



a



b

Figure 7. CNF-based prediction of mortality in March. (a) CNF is weakly correlated with mortality (|r|<0.3) in February. The distribution pattern of predicted mortality in March not only mismatch the February, but also makes a poor agreement with actual mortality in March. (**b**) Both CNF and mortality in March is lower than February, contradictory to previous negative correlation (r=-0.25) conclusion. Therefore, climate does not have much correlation with COVID-19 mortality.

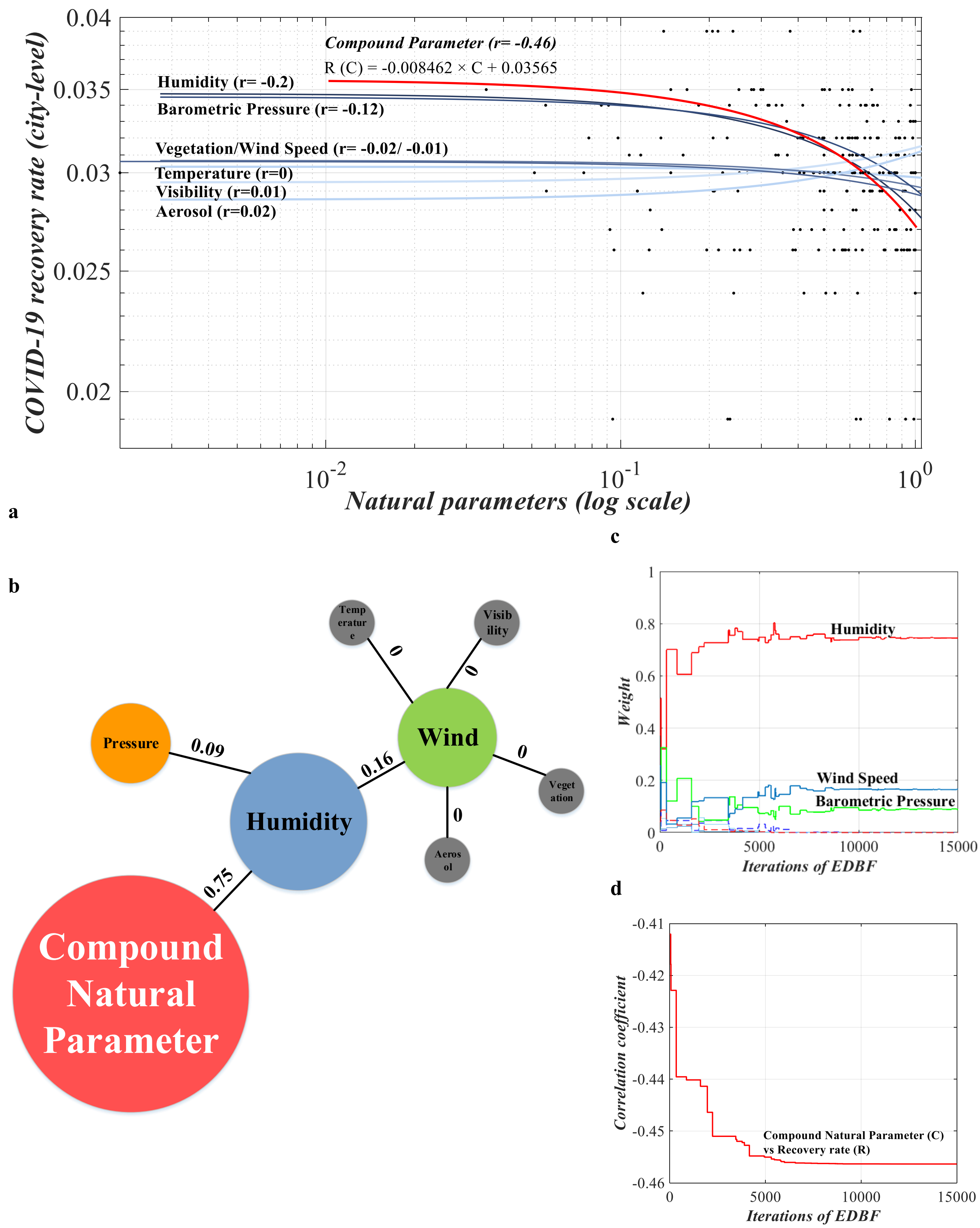


Figure 8. Compound natural factor (CNF) and the recovery rate. (a) CNF has a medium negative correlation with COVID-19 recovery rate (0.3< |r| < 0.5), and 7 single natural factors (SNFs) are weakly correlated with the recovery rate (|r| <0.3). r is the correlation coefficient, and values of 7 SNFs are all normalized. **(b)** In the weighted CNF, the weight of humidity is 0.75, wind

speed is succeeding (0.16), barometric pressure (0.09), vegetation, temperature, aerosol, and visibility do not contribute to CNF. The linear model of recovery rate R and CNF C is $R(C) = -0.008462 \times C + 0.03565$. (**c**) Weight values of 7 SNFs gradually converge to be stable with nearly 15000 iterations of ECGA. (**d**) r value of CNF C and recovery rate R increases to -0.46 with nearly 15000 iterations of ECGA.

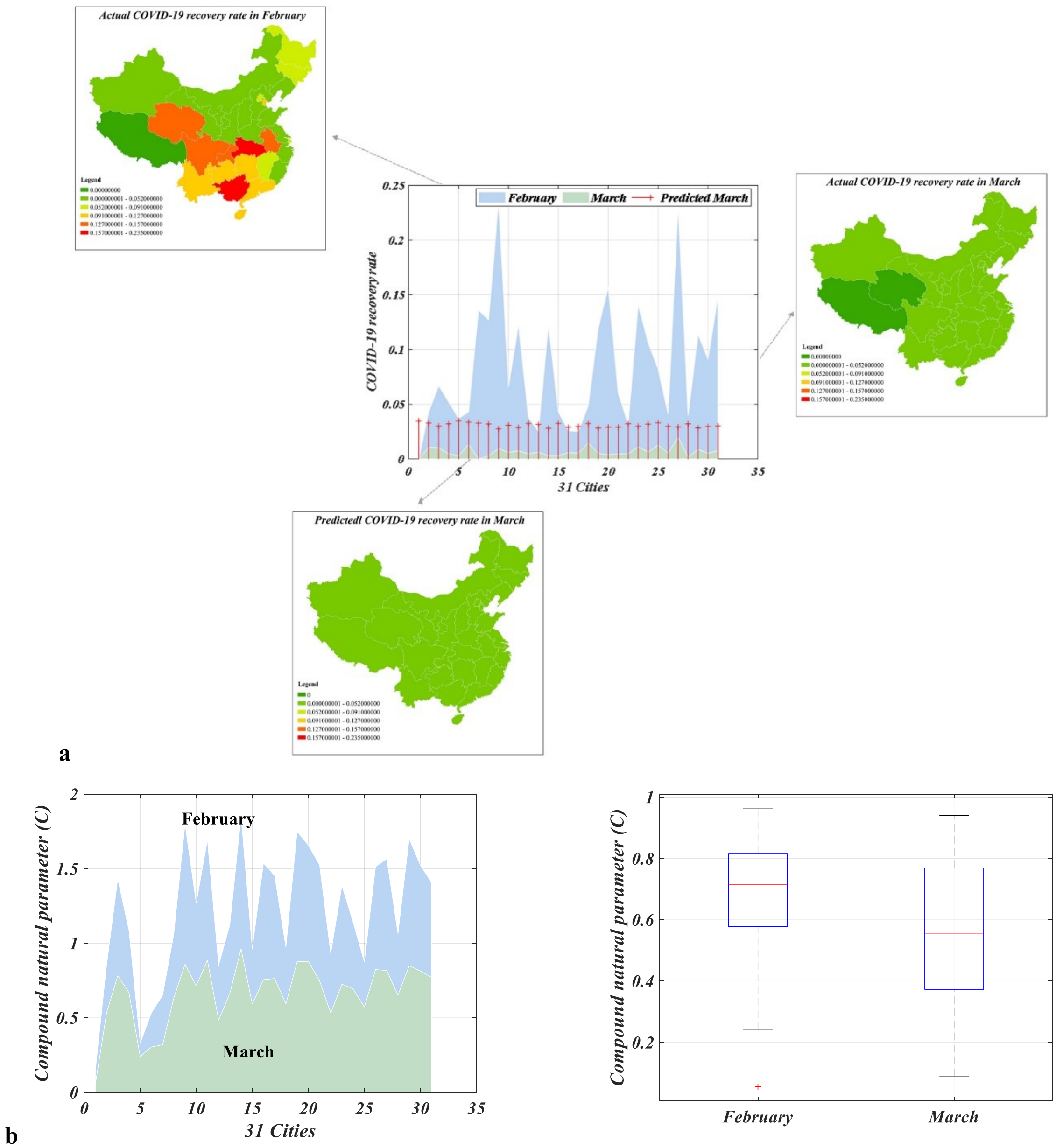


Figure 9. CNF-based prediction of recovery rate in March. (a) Predicted recovery rate in March matches actual March data well. (**b**) Both CNF and recovery rate in March are less than February, contradictory to previous negative correlation (r=-0.46) conclusion. Therefore, climate does not have much correlation with COVID-19 recovery rate.

7 Conclusions

Both climate change and non-pharmaceutical interventions (NPIs) effect on COVID-19 transmission, but it's difficult to separate these two effects (Lai et al., 2020). The proposed CNF model could deal with the problem. In this model, the weight of SNFs could be expressed the coupling relationship (CR) among them. Then CR is iteratively optimized by Elitism-based compact genetic algorithms (ECGA) (Chang et al., 2003). Due to assigning weight to CR, CNF parameter has a strong correlation with the COVID-19 infection rate, a linear CNF model is constructed to predict the impending infection rate. Interestingly, benefit of NPIs has been eliminated in the predicted infection rate by CNF model. Because Chinese NPIs began in February, but significant benefit to contain the virus didn't appear until in March (Tellis et al., 2020). Therefore, the forecast infection rate by CNF model is only the result of climate change. However, climate change has little correlation with mortality (recovery rate), because most of deaths (recoveries) are reported from inside the hospitals with minor climate change until they were died (cured). Therefore, the CNF model built by Chinese case provides a new perspective to forecast the global infection rate which is only under the intervention of climate change.

Acknowledgments

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