Reviewer #2:

The main research content of this paper focuses on the nonstationary relationship between drought losses and drought intensity, proposing nonstationary intensity-loss function based on the Logistic function.

We appreciate the brief summary of the paper. Considering that the intensity loss function plays a critical part in drought impact assessment. This paper presents an extension of the classic logistic function to account for temporal changes of drought losses.

If the authors can address the following issues, this manuscript has the potential to be accepted:

We are grateful to you for the insightful and constructive comments. Accordingly, we have conducted a thorough revision.

Below please find the point-by-point responses.

1. *The abstract provides a concise summary of the study; however, it could benefit from a more explicit mention of the key findings and their significance. Consider highlighting the specific improvements your model offers over existing approaches and the practical implications of these improvements.*

Thank you for your valuable suggestion. We have revised the abstract to explicitly highlight the key findings and their significance:

"While the stationary intensity loss function is fundamental to drought impact assessment, the relationship between drought loss and intensity can be nonstationary, i.e., changing as time progresses, owing to socio-economic developments. This paper addresses this critical gap by modelling nonstationary drought losses. Specifically, the time is explicitly formulated by linear and quadratic functions and then incorporated into the magnitude, shape and location parameters of the logistic function to derive in total six nonstationary intensity loss functions. To examine the effectiveness, a case study is designed for the drought-affected population by province in mainland China during the period from 2006 to 2023. The results highlight the existence of nonstationarity in that the drought-affected population exhibits significant correlation not only with standard precipitation index but also with time. The proposed nonstationary intensity loss functions are shown to outperform not only the classic logistic function but also the linear regression. They present effective characterizations of observed drought loss in different ways: 1) the nonstationary function with the flexible magnitude parameter fits the data by adjusting the maximum drought loss by year; 2) the nonstationary function with the flexible shape parameter works by modifying the growth rate of drought loss with intensity; and 3) the nonstationary function with the flexible location parameter acts by shifting the response curves along the axis by year. Among the nonstationary logistic functions, the function incorporating the linear function of time into the magnitude parameter generally outperform the others in terms of high coefficient of determination, low Bayesian information criterion and explicit physical meaning. Taken together, the nonstationary intensity loss functions developed in this paper can serve as an effective tool for drought management." (Page 2, Lines 21 to 36)

2. *In the introduction, this manuscript positions itself as addressing the nonstationarity of drought losses, it could benefit from a more explicit comparison with existing approaches. For instance, what specific limitations of traditional logistic functions or linear regression does this study overcome? The literature review could be expanded to include recent studies on the topic. This would provide a clearer picture of the current state of the field and where your work fits within it.*

Thank you very much for the constructive suggestion. Upon the classic logistic function, the developments of the nonstationary intensity-loss function are detailed in the methods:

"**2.3 Stationary and non-stationary formulations**

There are socio-economic factors contributing to temporal changes, i.e., nonstationarity, of the intensity loss function (AghaKouchak et al., 2021; Chiang et al., 2021; Long et al., 2020). Firstly, the exposure to drought can increase with time owing to increases of population, accumulations of wealth and developments of infrastructure. Secondly, the vulnerability under a given level of drought intensity may decrease with time considering engineering measures, such as constructions of water storage reservoirs and inter-basin water diversion projects. Thirdly, the resilience to drought can be improved by drought management measures such as sub-seasonal to seasonal hydroclimatic forecasting and forecast-informed reservoir operation. In general, the relationship between drought loss and intensity tends to evolve as time progresses due to socio-economic developments and deployments of engineering and non-engineering drought-coping strategies (Hou et al., 2019; Jonkman et al., 2008; Su et al., 2018).

Without considering temporal changes, there is a stationary logistic function $L_{A0k0c0}(\cdot)$:

$$L_{A0k0c0}(SPI_t) = \frac{A_0}{1 + e^{k_0(SPI_t - c_0)}} \tag{8}$$

To account for temporal change, the linear function that takes time t as an explanatory variable (Cheng et al., 2014; Xiong et al., 2015) can be formulated for the parameters A, k and c:

$$
\begin{cases} A_t = A_0 + A_1 \times t \\ k_t = k_0 + k_1 \times t \\ c_t = c_0 + c_1 \times t \end{cases} \tag{9}
$$

in which A_0, k_0 and c_0 are the intercepts while A_1, k_1 and c_1 are the slopes. The incorporation of Eq. (9) into Eq. (8) yields the following three equations:

$$
\begin{cases} L_{A1k0c0}(SPI_t) = \dfrac{A_0 + A_1 \times t}{1 + e^{k_0(SPI_t - c_0)}} \\ L_{A0k1c0}(SPI_t) = \dfrac{A_0}{1 + e^{(k_0 + k_1 \times t) \times (SPI_t - c_0)}} \\ L_{A0k0c1}(SPI_t) = \dfrac{A_0}{1 + e^{k_0(SPI_t - (c_0 + c_1 \times t))}} \end{cases} \tag{10}
$$

in which the logistic functions $L_{A0k1c0}(\cdot)$, $L_{A0k1c0}(SPI_t)$ and $L_{A0k0c1}(SPI_t)$ respectively have nonstationary magnitude, shape and location parameters.

Furthermore, the quadratic function can be used to accommodate possibly nonlinear changes:

$$
\begin{cases} A_t = A_0 + A_1 \times t + A_2 \times t^2 \\ k_t = k_0 + k_1 \times t + k_2 \times t^2 \\ c_t = c_0 + c_1 \times t + c_2 \times t^2 \end{cases} \tag{11}
$$

The incorporation of Eq. (11) into Eq. (8) yields another three equations:

$$
\begin{cases} L_{A2k0c0}(SPI_t) = \dfrac{A_0 + A_1 \times t + A_2 \times t^2}{1 + e^{k_0(SPI_t - c_0)}} \\ L_{A0k2c0}(SPI_t) = \dfrac{A_0}{1 + e^{(k_0 + k_1 \times t + k_2 \times t^2) \times (SPI_t - c_0)}} \\ L_{A0k0c2}(SPI_t) = \dfrac{A_0}{1 + e^{k_0(SPI_t - (c_0 + c_1 \times t + c_2 \times t^2))}} \end{cases} \tag{12}
$$

In Eq. (8), Eq. (10) and Eq. (12), the subscripts "Ax", "kx" and "cx" are respectively for the magnitude, shape and location parameters. As to "x", the values 0, 1 and 2 respectively indicate the non-involvement of time, the linear function of time and the quadratic function of time. As a result, the logistic function is non-stationary when x is 1 or 2. For example, $L_{A1k0c0}(SPI_t)$ represents the nonstationary logistic function involving the linear function of time for the magnitude parameter.

The fitting of the stationary and nonstationary functions is considered to be a nonlinear least-squares problem by searching for the set of parameters that minimize the sum of squares of residuals. It is performed by the curve_fit function in the SciPy optimization toolbox (Virtanen et al., 2020)." (Pages 6 to 8, Lines 136 to 161)

3. *The assumption of linear trends for the magnitude, shape, and location parameters may oversimplify the complex socio-economic influencing drought losses. It would*

strengthen the methodology to either justify this assumption or explore the feasibility of incorporating nonlinear trends.

Thank you for the constructive suggestion. As we have used both linear and quadratic functions to account for possible nonstationary relationships, we have elaborated on the results under both linear and quadratic functions:

"4.2 Decreasing drought-affected population

The stationary logistic function directly relates the drought-affected population to SPI (Figure 6), while the nonstationary logistic functions account for the dependency of drought-affected population on both SPI and time (Figures 7 and 8).

In Figure 6, it is shown that the mean drought-affected population is about 4 million. Yet, the maximum was up to 10 million in the year of 2010. Furthermore, the data point with the maximum drought-affected population happened to be with a SPI that is around 0, which is owing to that drought conditions depend not only on precipitation, but also on evapotranspiration, water storage and other hydroclimatic factors (Su et al., 2018; Yin et al., 2022a, b). In general, it is hard for the stationary logistic function A0k0c0 to capture the data points with lower SPI but smaller drought-affected population.

In Figure 7, the nonstationary logistic functions A1k0c0, A0k1c0 and A0k0c1 are visualized by the surface and wireframe plots. While the correlation between drought-affected population and time tends to be negative in Yunnan Province, it is observed that the nonstationary functions tend to capture not only the decrease of drought-affected population with SPI, but also the decrease of drought-affected population with time. Since the year with the maximum drought-affected population is in the early part of the study period, there is a remarkable increase in R^2. The three functions perform differently in capturing the observed data points:

1) The flexible magnitude parameter in A1k0c0 tends to fit the observed data by reducing the maximum drought loss by year (Figure 6a). As can be seen from the wireframe plot, the maximum drought loss evidently reduces from 2006 to 2023 while the shape and location of the curves remain the same.

2) The flexible shape parameter in A0k1c0 fits the observed data by changing the response surface, as shown in Figure 6b. Although it exhibits the highest R^2 and the lowest BIC, the fitted drought-affected population is shown to counterintuitively increase with SPI in 2021, 2022 and 2023. That is, more people could be subject to drought as precipitation increases in these three years. This wrong outcome is owing to the flexibility of the shape parameter. Specifically, the value of the shape parameter can be forced by the trend term to turn from positive to negative as time progresses. When the shape parameter is negative, the estimated drought impact would increase with the precipitation amount.

3) The flexible location parameter in A0k0c1 tends to fit the observation data by shifting the response curves by year, as shown in Figure 6c. Due to that the maximum drought-affected population is fixed from 2006 to 2023, it is observed

that the maximum affected population in 2010 is not effectively captured.

In Figure 8, the nonstationary logistic functions A2k0c0, A0k2c0 and A0k0c2 are also visualized by the surface and wireframe plots. Although the quadratic function leads to some improvements in R^2, the improvements are at the cost of the physical meaning of the results. From Figure 8a, it is observed that under a given SPI that is below 0, the drought-affected population initially increases but then decreases with time. From Figure 8b, it is observed that the response surface exhibits a complex shape that can be due to the fitting of sample-specific noise. The implication is that the data points are too limited to facilitate the fitting of quadratic function in A2k0c0, A0k2c0 and A0k0c2.

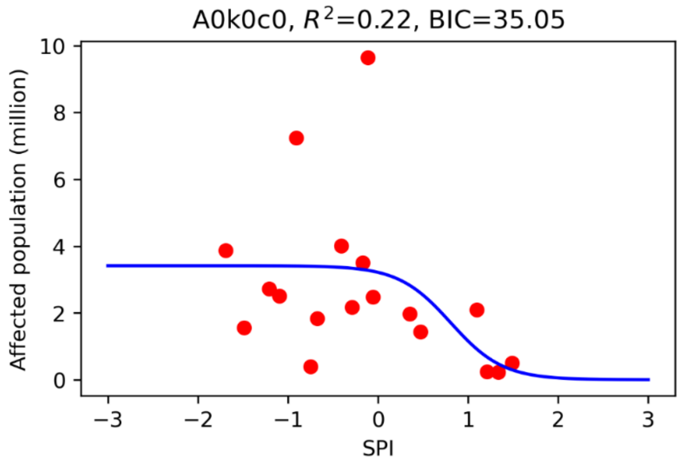

Figure 6. Illustration of the stationary logistic function A0k0c0 fitting the relationship between SPI and drought-affected population for Yunnan Province.

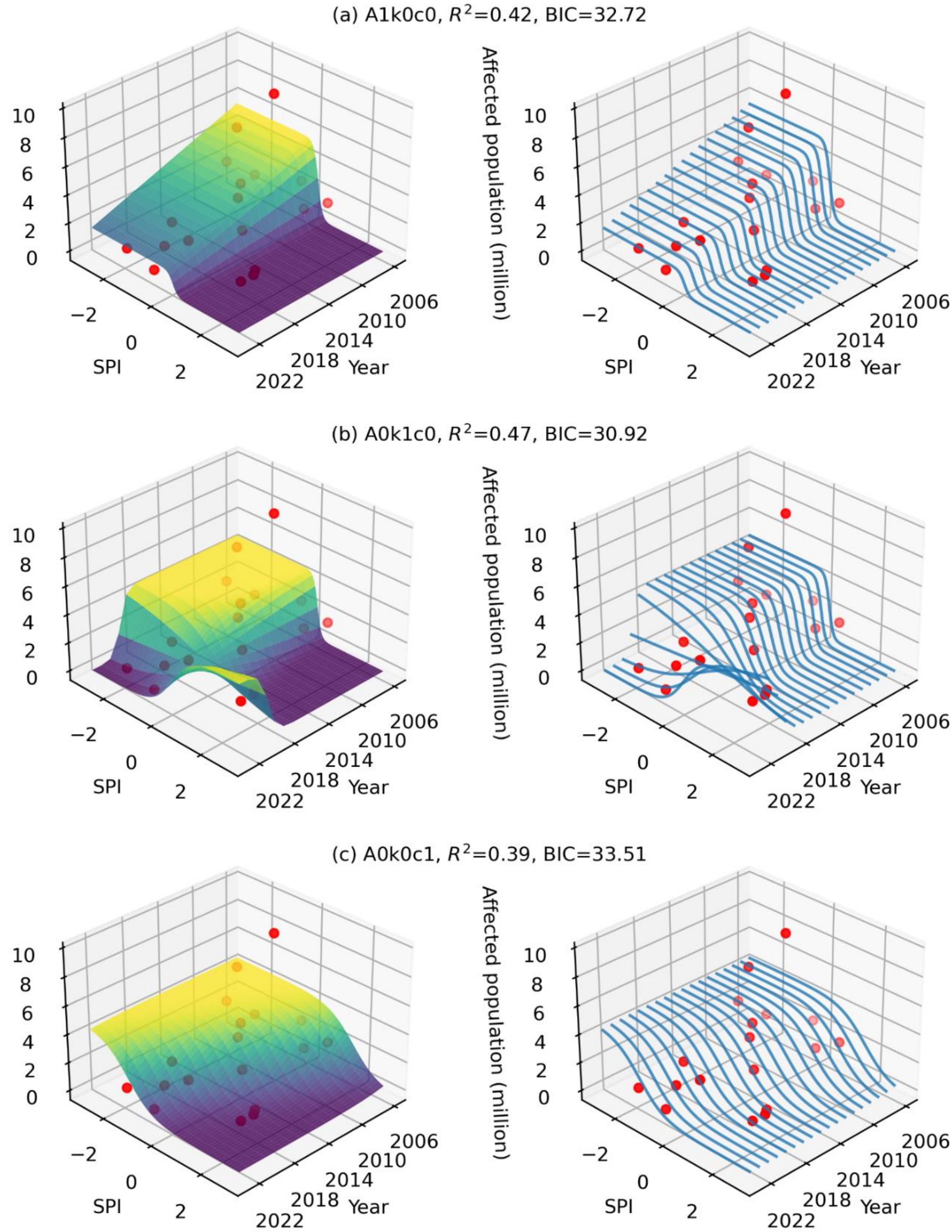

Figure 7. Surface plots (left) and wireframe plots (right) for the nonstationary logistic functions (a) A1k0c0, (b) A0k1c0 and (c) A0k0c1 relating the drought-affected population to SPI and time for Yunnan Province.

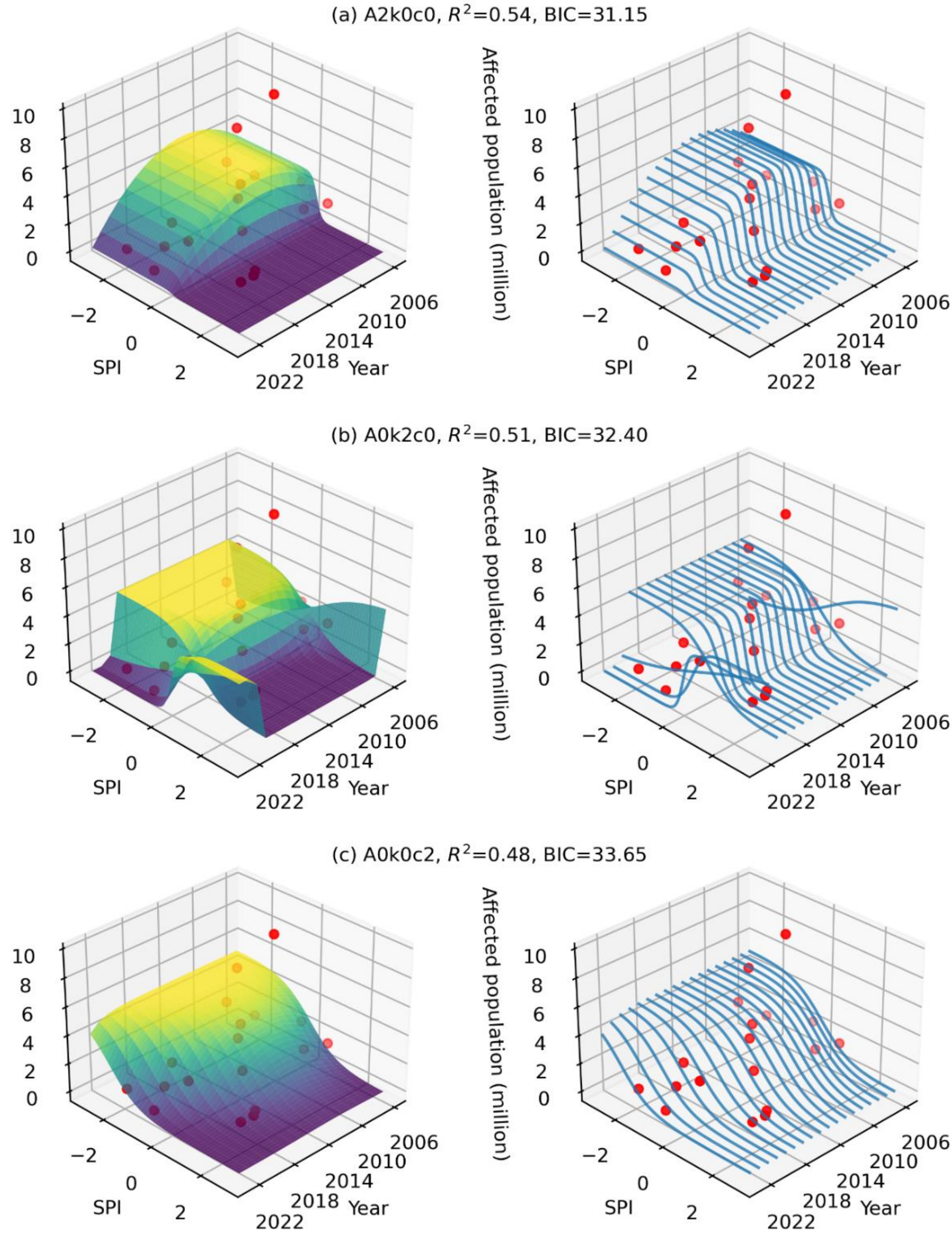

Figure 8. As for Figure 7, but for the nonstationary logistic functions (a) A2k0c0, (b) A0k2c0 and (c) A0k0c2.

4.3 Increasing drought-affected population

The stationary and nonstationary logistic functions are furthermore applied to Guangdong Province (Shao et al., 2020). Since the population of Guangdong is concentrated on the Pearl River Delta, recent years have witnessed serious water scarcity due to upstream reservoir impoundments and estuary saltwater intrusion (Weng et al., 2024).

From Figure 9, it is observed that there can be considerable drought-affected population when the precipitation is above average. The stationary logistic function A0k0c0 tends to capture the decrease of drought-affected population with SPI. Meanwhile, it is difficult for this function to capture the data points with high drought-affected population.

From Figure 10, it is seen that the three non-stationary logistic functions A1k0c0, A0k1c0 and A0k0c1 are more effective in characterising the dependency of drought-affected population on SPI and time. The linear function plays different parts in these three functions:

1) The linear magnitude parameter in A1k0c0 tends to fit the increase by enlarging the maximum drought loss by year. As shown in Figure 10a, it tends to capture the maximum drought-affected population of 1.50 million in 2020 and the second maximum drought-affected population of 1.24 million in 2021.

2) The linear shape parameter in A0k1c0 is observed to fit the observation data by changing the shape of response surface by year. As shown in Figure 10b, although the affected population in 2020 and 2021 is to some extent characterized, drought-affected population is seen to surprisingly increase with SPI in 2006. These results highlight the role that the shape parameter plays in determining the growth (reduction) rate.

3) The linear location parameter in A0k0c1 is shown to fit the observation data by fixing the maximum drought loss but shifting the response curves by year. As shown in Figure 10c, it tends to characterize the maximum and second maximum drought-affected population in recent years but does not seem to be as effective in characterizing drought-affected population in early years.

From Figure 11, it is observed that the three non-stationary logistic functions A2k0c0, A0k2c0 and A0k0c2 also tend to capture the drought-affected population. The result in Figure 11a is generally hard to interpret since the drought-affected population tends to initially decrease but then increase with time under a given SPI below zero. The results Figures 11b and 11c are respectively similar to those in Figures 10b and 10c. The implication is that the linear function in A0k1c0 and A0k0c1 can be as effective as the quadratic function in A0k0c2 and A0k0c2.

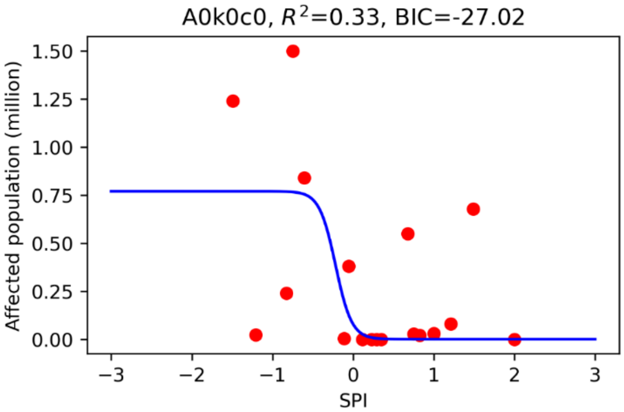

Figure 9. Illustration of the stationary logistic function A0k0c0 fitting the relationship between SPI and drought-affected population for Guangdong Province.

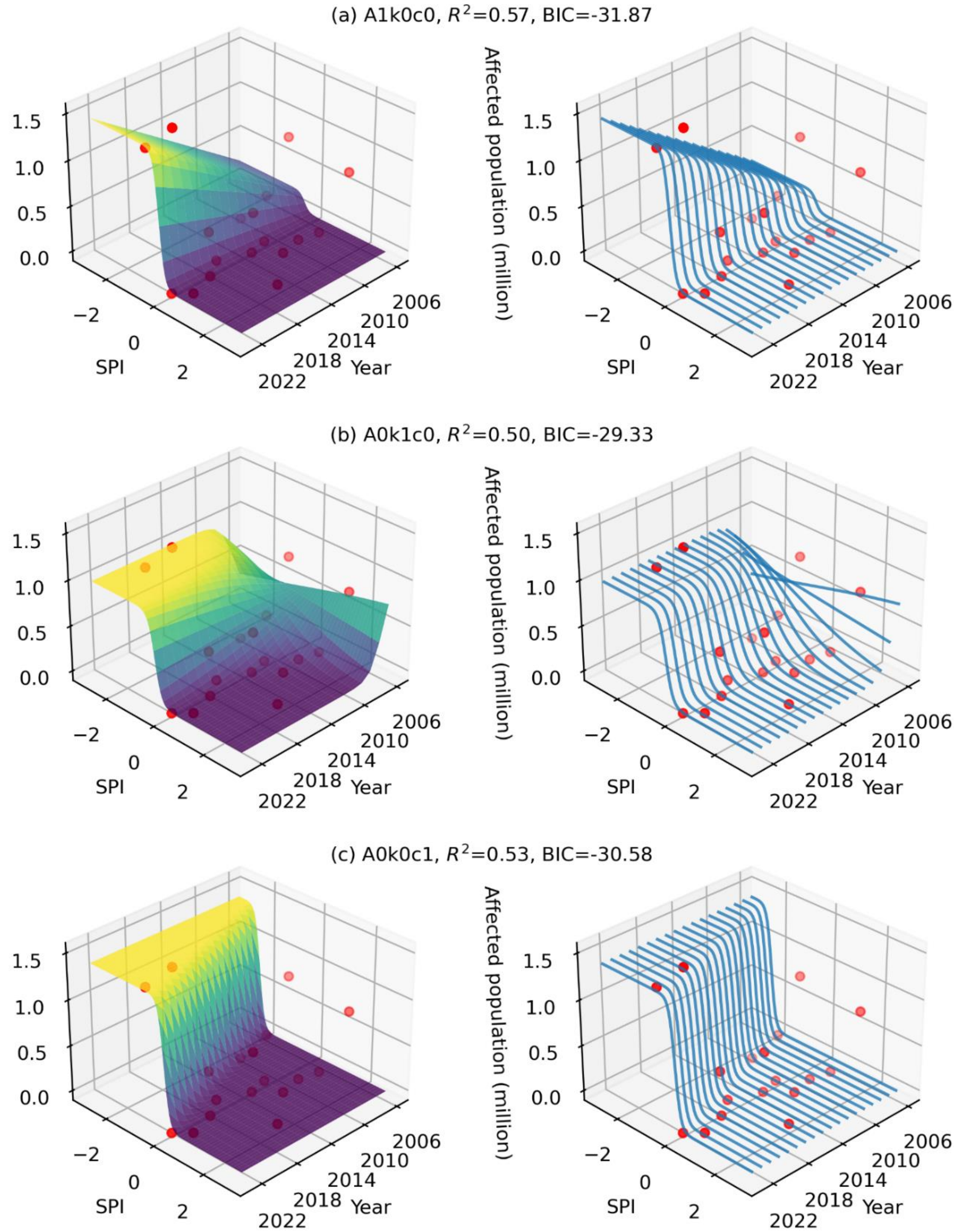

Figure 10. Surface plots (left) and wireframe plots (right) for the nonstationary logistic functions (a) A1k0c0, (b) A0k1c0 and (c) A0k0c1 relating the drought-affected population to SPI and time for Guangdong Province.

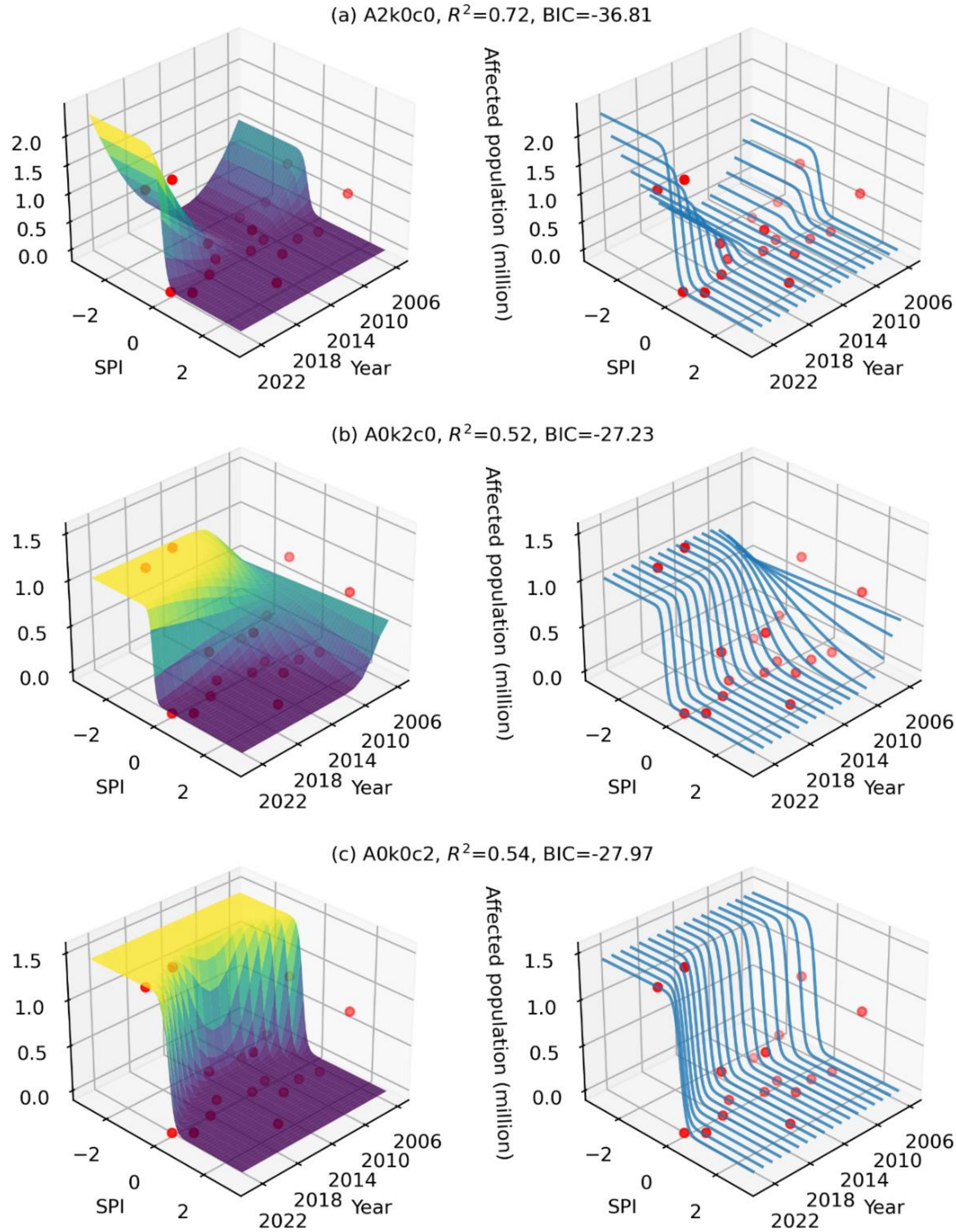

Figure 11. As for Figure 10, but for the nonstationary logistic functions (a) A2k0c0, (b) A0k2c0 and (c) A0k0c2.

” (Pages 13 to 21, Lines 248 to 328)

4. *This manuscript mentions that changes in the disaster-affected population are related to socio-economic development. However, further details on how specific*

socio-economic changes (e.g., population growth, infrastructure development) affect drought losses could be elaborated. This would help to better illustrate the importance of the study. For example, the author should be attempted to include socio-economic variables together with SPI as model inputs to further enhance the model's explanatory power, instead of just considering time as a covariate.

Thank you very much for the insightful suggestions. We agree on the importance of socio-economic variables. It is noted that as a critical explanatory variable, the time can be considered to be a proxy of socio-economic variables. The importance is illustrated in the methods:

"There are socio-economic factors contributing to temporal changes, i.e., nonstationarity, of the intensity loss function (AghaKouchak et al., 2021; Chiang et al., 2021; Long et al., 2020). Firstly, the exposure to drought can increase with time owing to increases of population, accumulations of wealth and developments of infrastructure. Secondly, the vulnerability under a given level of drought intensity may decrease with time considering engineering measures, such as constructions of water storage reservoirs and inter-basin water diversion projects. Thirdly, the resilience to drought can be improved by drought management measures such as sub-seasonal to seasonal hydroclimatic forecasting and forecast-informed reservoir operation. In general, the relationship between drought loss and intensity tends to evolve as time progresses due to socio-economic developments and deployments of engineering and non-engineering drought-coping strategies (Hou et al., 2019; Jonkman et al., 2008; Su et al., 2018)." (Page 6, Lines 137 to 145)

5. *The analysis effectively highlights differences between regions such as Yunnan and Guangdong. However, the underlying drivers of these variations (e.g., climate conditions, socio-economic factors) are insufficiently explored. Adding a discussion on the interaction between climate and socio-economic variables would enrich the interpretation.*

Thank you very much. For these two provinces, we have designed new experiments to test the robustness of the findings and the importance of drought indices:

"This paper has furthermore designed experiments to investigate the robustness of the nonstationary logistic functions using the drought indices SPEI and scPDSI (AghaKouchak et al., 2021; Apurv and Cai, 2021; Zhao et al., 2024b). The additional results are presented in the supplementary material. Specifically, as for SPEI, the correlation is presented in Figure S1 and the plots for Yunnan and Guangdong Provinces in Figures S2 to S7; as for scPDSI, the correlation is presented in Figure S8 and the plots for Yunnan and Guangdong Provinces in Figures S9 to S14. Overall, the results under SPEI and scPDSI conform to these under SPI. While the nonstationary plays an important part in the relationship between drought-affected population and drought conditions, it is highlighted that the nonstationary logistic functions are effective in characterising the dependency of drought-affected population on drought conditions and time. In the meantime, it is pointed out that different drought indices are of varying efficiency in characterizing the drought conditions. For example, the lower R^2 in Figure 6 is largely due to the correspondence of maximum drought-affected population with average precipitation in the year 2010; the R^2 evidently increases from 0.22 under SPI (Figure 6) to 0.42 under SPEI (Figure S2), and furthermore to 0.58 under scPDSI (Figure S9). This result highlight that drought conditions depend on precipitation and also on other hydroclimatic variables like evapotranspiration, recharge and runoff (Wells et al., 2004; Yin et al., 2022b)." (Pages 24 to 25, Lines 365 to 377)

6. *The discussion should not merely restate the results but should also delve deeper into the interpretation of these results in the context of existing literature. The discussion could better position the proposed nonstationary models within the broader literature on drought loss modeling. For instance, how do the findings align with or differ from previous studies, such as those using alternative loss functions or indices?*

Thank you very much for the constructive comment. The section of discussion has been improved by incorporating the results of additional experiments and the findings of peer studies:

"**5. Discussion**

This paper has furthermore designed experiments to investigate the robustness of the nonstationary logistic functions using the drought indices SPEI and scPDSI (AghaKouchak et al., 2021; Apurv and Cai, 2021; Zhao et al., 2024b). The additional results are presented in the supplementary material. Specifically, as for SPEI, the correlation is presented in Figure S1 and the plots for Yunnan and Guangdong Provinces in Figures S2 to S7; as for scPDSI, the correlation is presented in Figure S8 and the plots for Yunnan and Guangdong Provinces in Figures S9 to S14. Overall, the results under SPEI and scPDSI conform to these under SPI. While the nonstationary plays an important part in the relationship between drought-affected population and drought conditions, it is highlighted that the nonstationary logistic functions are effective in characterising the dependency of drought-affected population on drought conditions and time. In the meantime, it is pointed out that different drought indices are of varying efficiency in characterizing the drought conditions. For example, the lower R^2 in Figure 6 is largely due to the correspondence of maximum drought-affected population with average precipitation in the year 2010; the R^2 evidently increases from 0.22 under SPI (Figure 6) to 0.42 under SPEI (Figure S2), and furthermore to 0.58 under scPDSI (Figure S9). This result highlight that drought conditions depend on precipitation and also on other hydroclimatic variables like evapotranspiration, recharge and runoff (Wells et al., 2004; Yin et al., 2022b).

The nonstationary intensity loss functions developed in this paper complement existing studies on hydroclimatic processes of droughts (Garrido-Perez et al., 2024; Haile et al., 2020; Todisco et al., 2013). The frequency, duration and intensity are three important characteristics of drought (Baez-Villanueva et al., 2024; Entekhabi, 2023; Liu et al., 2024; Mishra and Singh, 2010; Yang et al., 2024). Given a threshold for the identification of drought events, the frequency is generally defined as the number of drought events in a certain period (one year for example), the duration as the timespan of a drought event and the intensity as the cumulative sum of the drought index (AghaKouchak et al., 2021; Chiang et al., 2021). Given that the SPI is derived for annual precipitation in this paper, the SPI values are expected to reflect the conditions of drought frequency, duration and intensity across different years. It is noted that the use of annual precipitation is mainly due to the fact that the drought-affected population by province is available at the annual timescale. It is possible that drought losses are available on an event scale. In that case, event-based analysis becomes feasible. That is, both drought loss and intensity can be quantified for each drought event; and then the effectiveness of the logistic function can be tested.

Focusing on drought indices such as SPI, PDSI, SPEI and SRI, previous studies have presented in-depth investigations about past changes and future projections of meteorological, hydrological, agricultural and socio-economic droughts (Apurv and Cai, 2021; Hao and Singh, 2015; Mishra and Singh, 2010). Under climate change, droughts are increasingly found to be interconnected with other extreme events including heatwaves (Yin et al., 2022a), tropical cyclones (Gao et al., 2024c), drought-flood abrupt alternation (Shi et al., 2021) and summer drought-flood coexistence (Wu et al., 2006). This paper proposes to time as a covariate to capture the overall trend of nonstationary drought losses. One remarkable feature of the proposed intensity loss function is the explicit estimation of drought loss under different combinations of drought indices and time. As the frequency and intensity of these compound disasters continue to increase, the socioeconomic losses are expected to rise in the future. The relationship between socioeconomic losses and other disaster indices can readily be investigated at local and regional scales. Given that the logistic function is already an established growth model in biosciences (Tsoularis and Wallace, 2002), it is expected that the proposed functions can be used to characterize the growth of drought loss with drought conditions characterized by different drought indices." (Pages 24 to 25, Lines 364 to 400)

7. *The conclusion summarizes the advantages of the proposed nonstationary models. However, emphasizing the methodological contributions and their potential for advancing drought impact assessment frameworks would make the conclusion more impactful.*

Thank you very much. The section of conclusions has been improved:

"**6 Conclusions**

This paper has presented nonstationary intensity loss functions for drought impact assessment. On the one hand, the classic logistic function that has three parameters, i.e., magnitude, shape and location, presents a stationary formulation of the growth of drought losses with drought conditions. On the other hand, the incorporations of time as linear and quadratic functions into the magnitude, shape and location parameters facilitate in total six nonstationary logistic functions. A case study is presented for the drought-affected population by province in China during the period from 2006 to 2023. The results highlight that despite the fact that drought-affected population can either decrease or increase with time, the joint use of both SPI and time as explainable variables leads to effective characterization of drought-affected population. In comparison with the stationary logistic function, the effectiveness of the nonstationary logistic functions is indicated not only by higher R^2, which indicates reasonable proportion of total explained variation, but also by lower BIC, which suggests low risk of overfitting. Among the nonstationary logistic functions, the function incorporating the linear function of time into the magnitude parameter generally outperform the others in terms of higher R^2, lower BIC and clearer physical meanings. In conclusion, the nonstationary intensity loss functions developed in this paper can improve our understanding and respond to drought risks in an era of rapid socio-economic and environmental change. Future research could further enhance this framework by incorporating additional socio-economic variables, to refine the model's predictive capabilities and support targeted mitigation strategies." (Page 26, Lines 401 to 415)

8. *Figures 6 and 7 provide valuable insights, but the 3D surface plots may not be intuitive for all readers. Supplementary 2D plots or contour maps could improve accessibility while maintaining scientific rigor.*

Thank you very much for the valuable suggestion. We have generated 2D heatmaps for the 3D surface plots and presented them in the supplementary material:

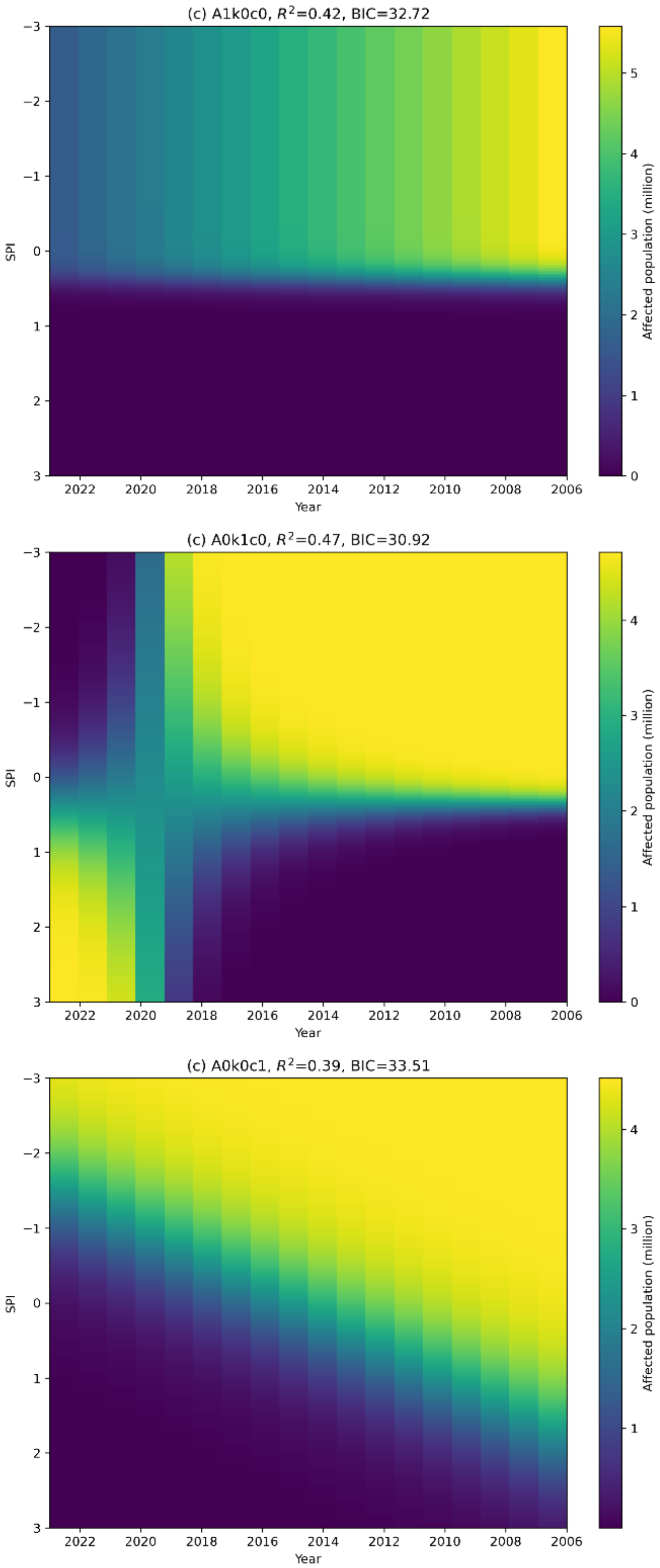

Figure S17. 2D heatmaps for for the nonstationary logistic functions (a) A1k0c0, (b) A0k1c0 and (c) A0k0c1 relating the drought-affected population to time and SPI for Yunnan Province.

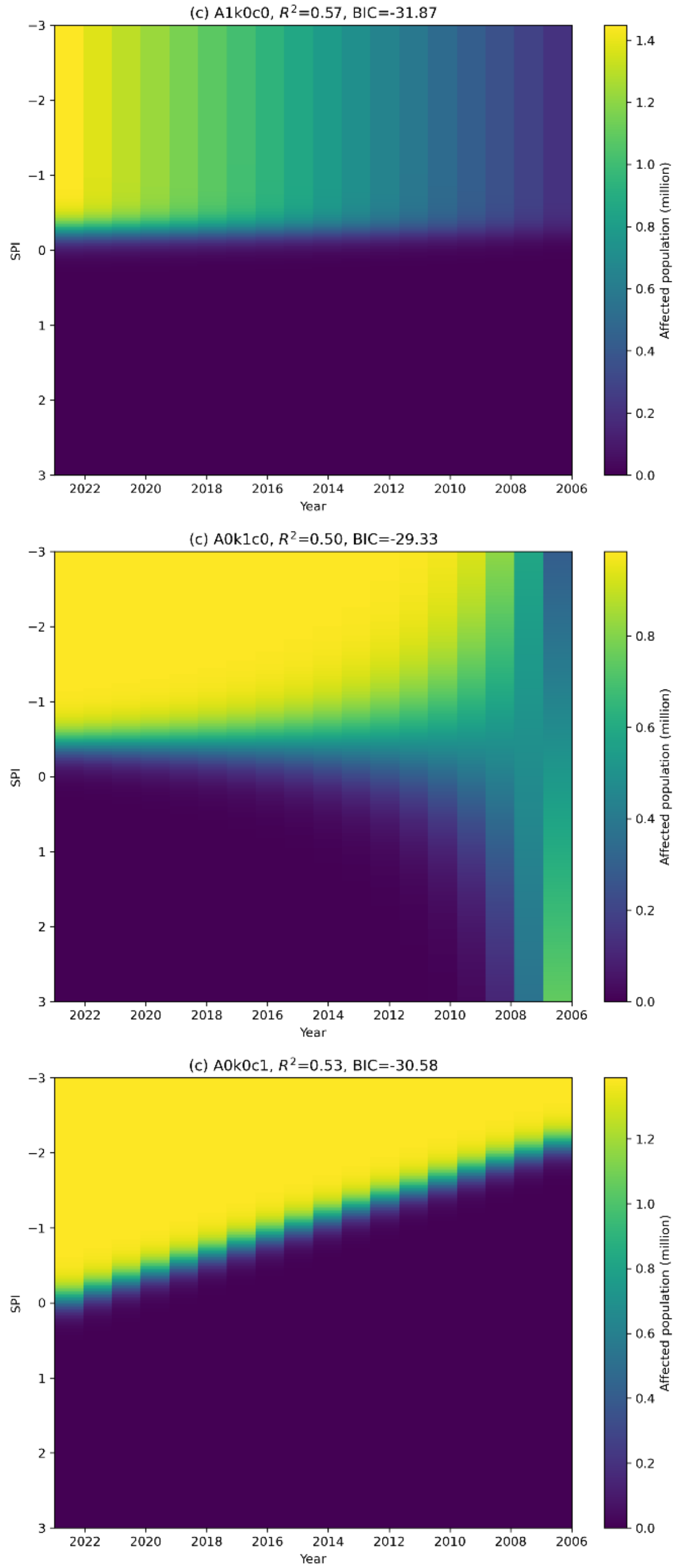

Figure S18. As for Figure S17, but for Guangdong Province.