# Spatiotemporal dynamics and center of gravity shifts in China's cold chain logistics infrastructure

Weiwei Gong[a], Yuhang Wang[b], Langya Zhou[a], Cheng Chen[a], Lingyun Zhou[*a]
[a]Transportation & Economics Research Institute, China Academy of Railway Sciences Corporation Limited, Beijing 100081, China; [b]Postgraduate Department of China Academy of Railway Sciences, Beijing 100081, China

## ABSTRACT

This study employs the LISA-SDE Hybrid Modeling Approach to analyze the distribution and dynamics of cold chain logistics enterprises across China from 2018 to 2022, focusing on enterprise numbers, storage capacities, and vehicle fleets. Results from the LISA analysis indicates strong, persistent spatial clustering in regions such as Gansu and Qinghai, with Gansu maintaining high LISA indices from 0.798 in 2018 to 0.789 in 2022 and consistently low p-values below 0.005. The Standard Deviation Ellipse analysis reveals a significant geographic center shift northward by approximately 21 kilometers between 2018 and 2019 and an increase in the spatial extent of logistics facilities, as evidenced by the expansion of the ellipse area from 228.417 square units in 2018 to 231.006 square units in 2021. These findings highlight the dynamic evolution of China's cold chain logistics infrastructure, underscoring significant advancements in spatial distribution and strategic clustering, which are crucial for informing infrastructure development and policy-making aimed at modernizing the system by 2035.

**Keywords:** Cold chain logistics, LISA-SDE modeling, spatiotemporal dynamics, center of gravity shift, logistics infrastructure

## 1. INTRODUCTION

Logistics is essential for linking production and consumption stages and driving national economic development. Cold chain logistics ensures food safety and enhances agricultural product quality, making it a key focus area. The "14th Five-Year Plan for Modern Logistics Development" and the 2024 No.1 Central Document emphasize building a modern cold chain logistics system. By 2035, China aims to have a world-class system in facilities, technology, and service quality. The Chinese cold chain logistics market has grown rapidly, with an annual growth rate over 15%. By 2030, agricultural product output is projected to reach 1.546 billion tons, with the cold chain market reaching 416 million tons. However, uneven geographical distribution of facilities limits service coverage and exacerbates regional development disparities.

Cold chain logistics plays a critical role in managing temperature-sensitive products like medicines, vaccines, and food, underscored by numerous recent advancements: Multi-criteria decision-making has been utilized to optimize supplier selection[1]. Additional research has focused on the real-time management of logistics systems, the impacts of government subsidies, and maintaining product quality throughout the distribution chain[2,3]. These studies collectively highlight the importance of advancing cold chain logistics to improve efficiency, safety, and sustainability. Research on China's cold chain logistics infrastructure reveals significant spatiotemporal dynamics and shifts in the center of gravity, mainly due to urbanization, economic growth, and ecological management[4]. These shifts, including the northwest movement of the logistics center, impact grain production and the distribution of logistics resources[5]. Studies also highlight the evolution of logistics centers, like Shanghai in the Yangtze River Delta, affecting the regional distribution of industries[6]. Analyzing these trends is crucial for understanding the changes in China's logistics landscape and guiding sustainable development policies[7]. Recent research has examined China's cold chain logistics, focusing on shifts in its center of gravity. Studies reveal a northwestward shift[8], attributed to urbanization, ecological management, and economic growth[9]. Understanding these dynamics is crucial for sustainable development. Studies across diverse fields explore gravity center changes including analyzing vertical deformations, shifting in cultivated land and a method for inertial measurement[10]. Studies focus on cervical spine loads[11], and compare carbon emissions comparing and spatial-temporal changes in production-

[*]s04062599@sina.com

International Conference on Optics, Electronics, and Communication Engineering (OECE 2024), edited by Yang Yue, Proc. of SPIE Vol. 13395, 133953D · © 2024 SPIE · 0277-786X · Published under a Creative Commons Attribution CC-BY 3.0 License · doi: 10.1117/12.3049994

living-ecological space[12]. These studies underscore the importance of understanding gravity center changes across various domains.

This paper investigates the spatiotemporal dynamics and shifts in China's cold chain logistics infrastructure using a LISA-SDE Hybrid Modeling Approach. It highlights the importance of cold chain logistics in national economic development and food safety. By integrating Local Indicators of Spatial Association (LISA) and Standard Deviation Ellipse (SDE), the study analyzes spatial distribution and shifts from 2018 to 2022. Using data on enterprises, storage capacities, and logistics vehicle fleets across 30 regions, the paper aims to reveal patterns of spatial clustering and geographical shifts to guide strategic planning and policy-making for improving China's cold chain logistics system.

## 2. MATERIALS AND METHODS

The cold chain logistics industry in China is an all-encompassing system that covers the logistics of temperature-sensitive products such as food and pharmaceuticals from production to consumption. The data for this study were sourced from the website http://www.lenglianwuliu.org.cn/home.html, focusing on the "National Cold Chain Logistics Enterprise Distribution Map" for the years 2018 to 2020. This distribution map is compiled under the guidance of the China Cold Chain Alliance, in collaboration with government agencies, academic institutions, expert committees, and leading enterprises. It aims to provide a comprehensive overview of the current state and development trends within the cold chain logistics industry, serving as a valuable reference for government policy-making and corporate development strategies. The compilation of the "National Cold Chain Logistics Enterprise Distribution Map" statistical analysis report strives for scientific classification, detailed data accuracy, ease of reference, and quantitative regional analysis. The statistical standards for the distribution map adhere to the "Cold Storage Identification" classifications and the "Three Nos and Eight Determinants" standards set by the China Cold Chain Alliance, focusing on the collection of operational cold chain facilities from key enterprises nationwide.

### 2.1 Data structure

This study utilizes comprehensive datasets spanning from 2018 to 2022, detailing the landscape of cold chain logistics enterprises across 30 distinct regions in China. It encapsulates an increasing trend in the number of enterprises, from 1,667 in 2018 to 2,227 in 2022, alongside a significant expansion in storage capacity, which escalated from approximately 43.07 million cubic meters to 56.86 million cubic meters over the five years. The datasets also document the vehicles dedicated to cold chain logistics, showing fluctuations over the years, peaking at 44,346 in 2021 before slightly decreasing to 42,612 in 2022. This rich compilation of data, including the total number of enterprises, storage capacities, and logistics vehicles, provides a foundational basis for analyzing the growth and spatial distribution of the cold chain logistics sector within the country. The structure of the data is illustrated in Table 1, while specific data for the year 2022 is presented in Table 1.

Table 1. Dataset descriptions.

| Year | Area | Storage | Capital | Latitude | Longitude |
|---|---|---|---|---|---|
| 2022 | Anhui | 1427272 | Hefei | 31.8639 | 117.2808 |
| 2022 | Beijing | 2228301 | Beijing | 39.9042 | 116.4074 |
| 2022 | Tianjin | 2199085 | Tianjin | 39.3434 | 117.3616 |
| ... | ... | ... | ... | ... | ... |
| 2022 | Zhejiang | 1881118 | Hangzhou | 30.2741 | 120.1551 |

### 2.2 Methods

This study proposes a new method, the LISA-SDE Hybrid Modeling Approach, which combines the Local Indicators of Spatial Association (LISA) and the Standard Deviation Ellipse (SDE) algorithms. This approach aims to reveal the complex patterns of spatial distribution and spatiotemporal changes in China's cold chain logistics infrastructure. By integrating the local clustering characteristics identified by LISA with the global perspective provided by SDE, it offers a more detailed and comprehensive framework for analyzing the spatial and temporal dynamics of the infrastructure. This method facilitates a deeper understanding of the clustering trends and migration paths of cold chain logistics infrastructure, thereby providing valuable insights for industry planning and policy-making.

The core formula of LISA is based on the Moran's I statistic but applies a local evaluation for each observation point. The LISA statistic for a spatial unit $i$ can be expressed as:

$$I_i = \frac{n}{\sum_j \varpi_{ij}} \bullet \frac{(x_i - \bar{x})\sum_j \varpi_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{1}$$

where, $n$ is the total number of spatial units; $x_i$ and $x_j$ represent the attribute values of spatial units $i$ and $j$, such as the number or capacity of cold chain logistics facilities; $\bar{x}$ is the mean of the attribute values across all spatial units.

The Spatial Weight Matrix $\omega$ is an $n \times n$ matrix, where $n$ is the number of spatial units. The elements $\varpi_{ij}$ of the matrix represent the spatial weight between unit $i$ and $j$. There are various methods to determine these weights, including the following common definitions:

$$\varpi_{ij} = \frac{1}{\alpha_{ij}^{\beta}} \tag{2}$$

To ensure analytical consistency across the study, weights within $\omega$ are normalized such that each unit's weight sum aligns to unity:

$$\varpi_{ij}^{'} = \frac{\varpi_{ij}}{\sum_j \varpi_{ij}} \tag{3}$$

The Standard Deviation Ellipse (SDE) algorithm is a spatial statistical method used to understand the spatial characteristics and distribution patterns of geographic phenomena. It is particularly useful for depicting the central tendency, dispersion, and orientation of spatial data points. The SDE is often applied to analyze geographical data to identify directional trends and the spatial extent of datasets. In the application of Standard Deviation Ellipse (SDE) analysis to the distribution issue of cold chain logistics infrastructure, the following steps and analytical parameters are meticulously delineated:

The geographical coordinates data is collected for cold chain logistics facilities, encompassing the longitude ($x_i$) and latitude ($y_i$) of warehouses, distribution centers, and other relevant entities. Aggregated attribute data is pertinent to spatial locations, such as storage capacities and service ranges, to further analyze the functional efficacy and efficiency of the cold chain logistics infrastructure.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4}$$

The covariance of the $x$ and $y$ coordinates is to be calculated to understand the directional relationship between them. This calculation helps in determining the rotation angle of the ellipse, aligning it with the direction of maximum variance in the data.

$$Cov(x, y) = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \tag{5}$$

The standard deviation ($\sigma_i$, $\sigma_j$)is calculated relative to the mean center. to decide the lengths of the SDE's major and minor axes, reflecting the dispersion degree of the facilities in the principal distribution direction.

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2}, \sigma_y = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{6}$$

Spatiotemporal Fusion Analysis, as part of the LISA-SDE workflow, is a critical step for integrating spatial and temporal analysis results to understand the dynamics of cold chain logistics infrastructure. This step combines the detailed local clustering insights obtained from the LISA analysis with the broader spatial distribution patterns identified through SDE analysis. The objective is to provide a comprehensive view of how the spatial characteristics and clustering behaviors of cold chain logistics infrastructure evolve over time.

**Combining Local and Global Insights:** The integration begins by overlaying the LISA results, which highlight spatial hotspots and cold spots indicating areas of significant local clustering, with the SDE results that describe the overall spatial trends and distributions. This overlay allows for the examination of how local clustering patterns fit within the broader distribution of cold chain logistics infrastructure.

**Temporal Dimension:** By conducting LISA and SDE analyses at different time points within the specified study period, we can capture the dynamic changes in spatial patterns. This temporal analysis helps in identifying trends such as the movement of hotspots, changes in the concentration of infrastructure, or shifts in the central tendency of distributions.

# 3. RESULTS

To implement the LISA algorithm using Python, the libraries required for this task include Geopandas, Pandas, Shapely, libpysal, esda and matplotlib. Then Python script conducts a Local Indicators of Spatial Association analysis to identify significant spatial clusters within cold chain logistics storage data for the year 2018 across different regions in China. Initially, the script loads the data from an Excel file into a Pandas DataFrame, which is then converted into a GeoDataFrame with geometry derived from the longitude and latitude columns, setting the coordinate reference system to WGS 84. It proceeds to align the point data with the spatial context of China by loading a shapefile of the country's boundary and transforming the GeoDataFrame's CRS to match. Subsequently, a spatial weights matrix is constructed using the K-nearest neighbors method, facilitating the computation of the LISA statistics. The analysis results, including the local Moran's I values and their significance (p-values), are appended to the GeoDataFrame. Points with significant local spatial autocorrelation (p-value < 0.05) are highlighted, illustrating clusters where storage capacities are either significantly higher or lower than the average. The visualization, created using matplotlib, displays these significant clusters against the backdrop of China's geographical outline, with significant clusters marked distinctly.

## 3.1 LISA calculation results

Gansu, Xinjiang, Beijing, Ningxia, and Qinghai consistently exhibit significant clustering throughout the five-year period. This persistent presence of significant clusters suggests a robust pattern of high-value concentration, which is statistically non-random and indicates a stable geographical advantage or targeted developmental policies fostering these clusters. In contrast, Hebei shows a lack of consistent clustering, with significant clusters only detected in 2019. The absence of clustering in other years (2018, 2020, 2021, 2022) suggests either a potential fluctuation in the factors driving spatial aggregation or less effective regional policies in sustaining significant clustering.

Local Indicators of Spatial Association (LISA) indices and their corresponding p-values for six key regions in China—Beijing, Gansu, Ningxia, Qinghai, Xinjiang, and Hebei—from 2018 to 2022. These statistics are instrumental in identifying significant spatial clusters of storage capacities.

**Gansu** stands out with high LISA indices, such as 0.798 in 2018, decreasing slightly to 0.789 in 2022, coupled with consistently low p-values, peaking at 0.004 in 2018 and bottoming out at 0.003 in 2022. This pattern underscores a strong and statistically significant cluster of high values throughout the period.

**Qinghai** also exhibits a similar trend of significant positive clustering, with its LISA indices progressively increasing from 0.904 in 2018 to 0.948 in 2022. The p-values remain low, moving from 0.018 in 2018 to 0.007 in 2022, highlighting persistent and statistically significant hotspots.

**Ningxia** and **Xinjiang** show robust clustering with indices like 0.775 and 0.758 in 2018, respectively, and maintaining strong indices over the years, with Ningxia reaching 0.880 and Xinjiang 0.604 in 2022, both reflecting substantial spatial clustering with very low p-values.

In contrast, **Hebei** demonstrates fluctuating LISA indices, beginning at -0.265 in 2018 and moving to a slightly positive 0.079 in 2022. Its p-values, such as 0.077 in 2018 and 0.067 in 2022, indicate a weaker and less consistent pattern of spatial clustering.

Displaying the results of LISA analysis on a map from 2018 to 2022, using different color codes to represent different LISA I values. Significantly spatially autocorrelated points with a *p*-value less than 0.05 are filtered out and highlighted with red asterisks to emphasize the distribution characteristics of hotspots and coldspots in geographical space. Since the results for 2021 and 2022 are very similar, they are displayed in a single figure, as shown in Figure 1.

The following trends and characteristics can be observed: there is a slight upward trend in the annual average LISA I values, increasing from 0.19 in 2018 to 0.21 in 2022, indicating a possible annual strengthening of spatial associations between regions. The number of significantly clustered points peaked in 2019 at 7, thereafter stabilizing at around 6, suggesting that although overall spatial association strength may be increasing, the number of significantly high or low value clustering areas remains relatively stable. Furthermore, the standard deviation has been increasing annually, rising from 0.40 in 2018 to 0.45 in 2022, reflecting an increasing disparity in LISA I values between regions, which may indicate an exacerbation of regional development imbalances.

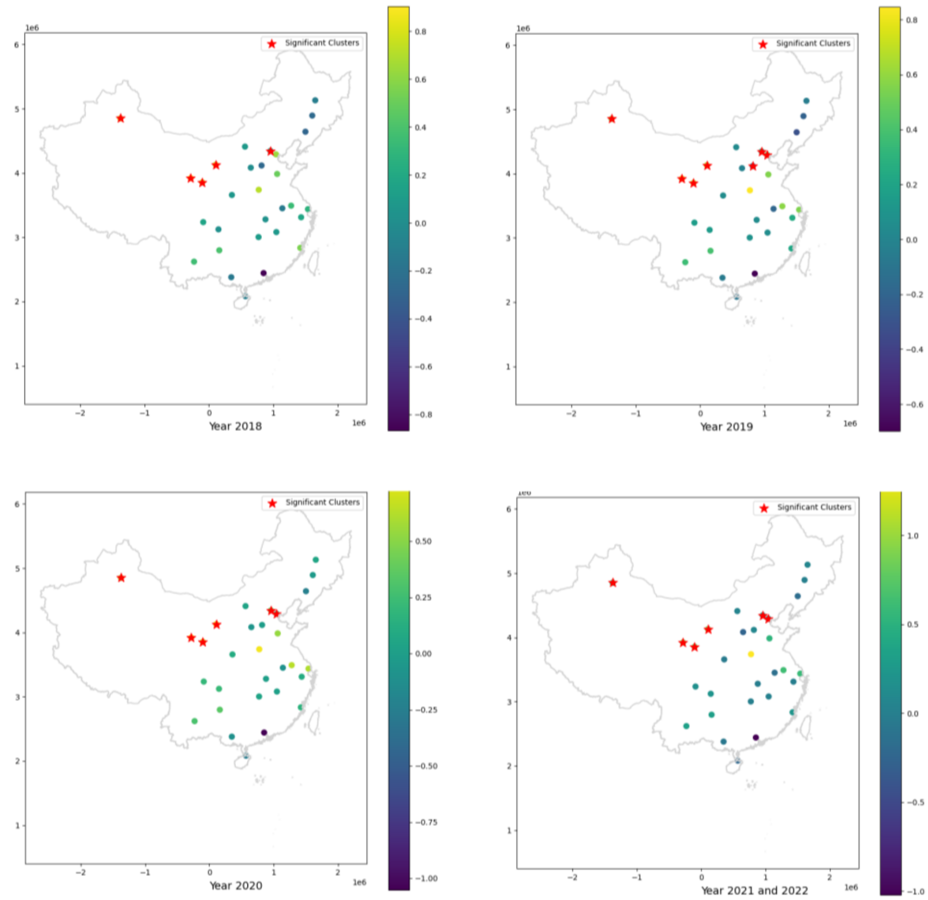


Figure 1. LISA analysis result map from year 2018 to 2022.

### 3.2 SDE calculation results

As consumer demand for fresh, high-quality agricultural products and food increases, coupled with the rise of e-commerce and online food purchases, cold storage facilities have become crucial for ensuring product quality and extending shelf life. Supported by local policies, the continuous construction and upgrading of cold chain infrastructure nationwide are essential. Given that each degree of latitude corresponds to approximately 111 kilometers, the fluctuation in the north-south direction is only about 21.37 kilometers. Moreover, the rotation angle of the ellipses incrementally increased annually, suggesting a slight rotational shift in the distribution of the data, see Figure 2.

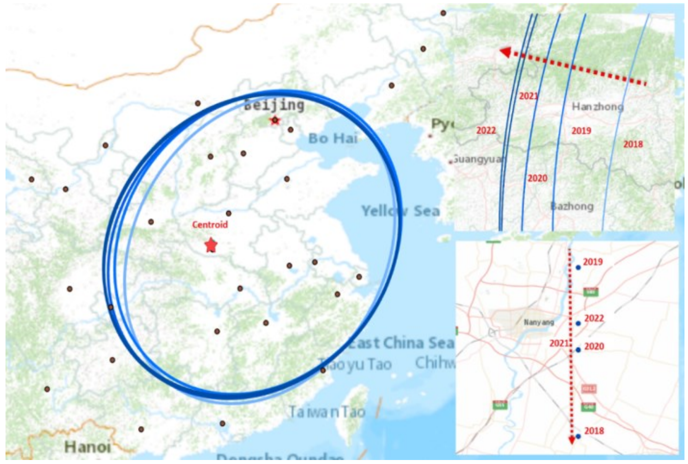


Figure 2. DEA analysis result map from year 2018 to 2022.

Analysis of the standard deviation ellipse area from 2018 to 2022 reveals a trend in the spatial range of the data. In 2018, the area of the ellipse was 228.417243 square units. In 2019, the area slightly decreased to 223.274615 square units, indicating a minor contraction from the previous year. By 2020, the area returned to its 2018 level, at 228.417243 square units, suggesting a recovery in the distribution of data after the contraction seen in the previous year. In 2021, the ellipse area increased further, reaching a peak of 231.006092 square units, indicating an expansion in the data's spatial distribution. Although the area slightly decreased in 2022 to 230.489557 square units, it remained above the initial value of 2018, overall showing a gradual expansion in the data's spatial range over these years.

## 4. CONCLUSIONS

This study pioneers the integration of Local Indicators of Spatial Association with the Standard Deviational Ellipse analysis, innovatively analyzing the distribution dynamics and spatial changes of cold chain logistics enterprises in China from 2018 to 2022. This novel LISA-SDE hybrid modeling approach not only enhances understanding of spatial clustering phenomena and geographic center shifts but also improves the precision and depth of the analysis. Through this methodology, intense spatial clustering in regions such as Gansu and Qinghai has been revealed, along with a notable northward shift of approximately 21 kilometers in the geographic center of infrastructure within a short span, accompanied by an expansion in the spatial extent of logistics facilities. These innovative findings underscore the dynamic evolution and optimization importance of China's cold chain logistics infrastructure, providing a scientific basis for the modernization of the cold chain logistics system. The methods and results of this research offer new perspectives for guiding the development and policy-making of infrastructure, particularly in enhancing system modernization and service efficiency. It is recommended that government and industry decision-makers fully leverage this innovative approach in planning and decision-making, optimizing the layout and technological application of the cold chain logistics network to support an efficient and sustainable logistics service system. Furthermore, as the demand for high-quality living continues to increase, optimizing and innovating cold chain logistics infrastructure becomes a crucial task in supporting the construction of a modernized economic system.

## ACKNOWLEDGMENT

This article was supported by China National Railway Group Co., Ltd. under the Science and Technology Research and Development Program (Project No. L2022X001); and the China Academy of Railway Sciences Corporation Limited under the Scientific Research Project (Project No. 2023YJ313). My sincere thanks go to all the individuals and organizations that contributed to the success of this study.

## REFERENCES


[1] Wen, Z., Liao, H., Ren, R., Bai, C., Zavadskas, E. K., Antucheviciene, J. and Al-Barakati, A., "Cold chain logistics management of medicine with an integrated multi-criteria decision-making method," International Journal of Environmental Research and Public Health, (2019).

[2] Liu, G., Hu, J., Yang, Y., Xia, S. and Lim, M., "Vehicle routing problem in cold chain logistics: a joint distribution model with carbon trading mechanisms," Resources Conservation and Recycling, (2020).

[3] Huang, X., Xie, R. and Huang, L., "Real-time emergency management mode of cold chain logistics for agricultural products under the background of "Internet+"," J. Intell. Fuzzy Syst., (2020).

[4] Li, D., Yang, J., Hu, T., Wang, G., Cushman, S. A., Wang, X., Kollányi, L., Su, R., Yuan, L., Li, B., Wu, Y. and Bai, T., "The seeds of ecological recovery in urbanization—spatiotemporal evolution of ecological resiliency of Dianchi Lake Basin, China," Ecological Indicators, 153, (2023).

[5] Yu, D., Hu, S., Tong, L. and Xia, C., "Spatiotemporal dynamics of cultivated land and its influences on grain production potential in Hunan Province, China," Land, 9(12), 510 (2020). https://doi.org/10.3390/land9120510

[6] Qiao, X., Liu, H., Liu, Y., Gong, P., Li, P. and Li, L., "Analysis of spatial and temporal evolution and drivers of cropland in the economic zone of the northern slope of Tianshan mountain," Environmental Research Communications, 5(10), (2023). https://doi.org/10.1088/2515-7620/ad0026

[7] Mehmood, K., Tischbein, B., Flörke, M. and Usman, M., "Spatiotemporal analysis of groundwater storage changes, controlling factors, and management options over the transboundary Indus basin," Water, 14(20), 3254 (2022). https://doi.org/10.3390/w14203254

[8] Liu, L., Zhang, C., Luo, W., Chen, S., Yang, F. and Liu, J., "New remote sensing image fusion for exploring spatiotemporal evolution of urban land use and land cover," Journal of Applied Remote Sensing, 16(3), 034527 (2022). https://doi.org/10.1117/1.JRS.16.034527

[9] Mu, N., Wang, Y. and Tian, P., "Spatio-temporal distribution characteristics of the cooperation between logistics industry and economy in Southwest China," International Journal of Computational Intelligence Systems, 15(7), (2022). https://doi.org/10.1007/s44196-021-00062-5

[10] Barrett, J. M., McKinnon, C. D., Dickerson, C. R., Laing, A. C. and Callaghan, J. P., "Posture and Helmet configuration effects on joint reaction loads in the middle cervical spine," Aerospace Medicine and Human Performance, 93(3), 220-227 (2022).

[11] Wang, J., You, K., Qi, L. and Ren, H., "Gravity center change of carbon emissions in Chinese residential building sector: differences between urban and rural area," Energy Reports, 8, 2404-2413 (2022).

[12] Xu, H., Zhang, F., Li, W., Shi, J. and Johnson, B. A., "Spatial-temporal pattern of change in production-living-ecological space of Nanchong City from 2000 to 2020 and underlying factors," Environmental Monitoring and Assessment, 195(4), 212 (2023).