Nonlinear Network of Inter-city Air Pollution and Its Linkage Network in the Middle Yangtze River Urban Agglomeration

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Abstract

Based on daily Air Quality Index (AQI) data from January 1, 2015 to December 15, 2015 for the Yangtze River Middle Reaches Urban Agglomeration, this paper employs a nonlinear Granger causality test method within the VAR model framework to scientifically identify the nonlinear transmission relationships of air pollution among cities in this region, and utilizes social network analysis to comprehensively reveal the structural characteristics of their linkage network. The study finds that significant nonlinear transmission relationships of air pollution exist among cities in the Yangtze River Middle Reaches Urban Agglomeration, forming a complex linkage network. In the robustness network (R-Network), 11 cities—including Huangshi, Jingmen, Nanchang, Pingxiang, Huanggang, Jingzhou, Yichang, Zhuzhou, Changde, Xiaogan, and Ezhou —occupy core positions, while the remaining 16 cities are situated at the network periphery. In the maximum likelihood network (ML-Network), 18 cities including Huangshi and Jingmen are positioned at the network core, thereby expanding the scope of the core area for joint prevention and control. Based on these findings, this paper argues that improving joint prevention and control of air pollution should commence with the robustness network, focusing on core cities, and subsequently construct a joint prevention and control mechanism encompassing all cities in the Yangtze River Middle Reaches based on the maximum likelihood network.

Nonlinear Transmission of Inter-Urban Air Pollution and Its Co-Movement Network in the Middle Reaches of the Yangtze River Megalopolis

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Abstract: This paper employs daily Air Quality Index (AQI) data from January 1 to December 15, 2015, for the middle reaches of the Yangtze River megalopolis to scientifically identify nonlinear transmission relationships in inter-urban air pollution within a VAR model framework using nonlinear Granger causality tests. Social network analysis methods are then applied to comprehensively reveal the structural characteristics of this co-movement network. The findings indicate that significant nonlinear transmission relationships exist among cities in the middle reaches of the Yangtze River megalopolis, forming a complex co-movement network. In the robustness network (R-Network), 11 cities—Huangshi, Jingmen, Nanchang, Pingxiang, Huanggang, Jingzhou, Yichang, Zhuzhou, Changde, Xiaogan, and Ezhou—occupy core positions, while the remaining 16 cities are situated at the periphery. In the maximum likelihood network (ML-Network), 18 cities including Huangshi and Jingmen occupy core positions, expanding the scope of joint prevention and control. Based on these conclusions, effective air pollution joint prevention and control should begin with the robustness network, focusing on core cities, and subsequently establish a joint mechanism covering all cities in the middle reaches of the Yangtze River megalopolis based on the maximum likelihood network.

Keywords: AQI; Middle Reaches of the Yangtze River Megalopolis; Spatial Transmission; Co-Movement Network; Nonlinear Granger Causality Test

Recent scientific research confirms that China has become one of the world' s most severely air-polluted regions (van Donkelaar et al., 2010). As urban areas continue to expand and cities develop contiguously, inter-urban air pollution interactions have become increasingly pronounced due to the dual effects of atmospheric circulation and atmospheric chemistry. Regional air pollution problems characterized by PM10 and PM2.5 have grown increasingly prominent, with the middle reaches of the Yangtze River megalopolis representing one of China' s more severely polluted areas. According to daily AQI data released by the Ministry of Environmental Protection from January 1 to December 15, 2015, the 27 prefecture-level cities in this region experienced an average of 77 days failing to meet air quality standards. Wuhan, Ezhou, Jingzhou, Jingmen, Xiaogan, and Huanggang ranked 1st through 6th in terms of non-compliant days, with Wuhan recording the highest number at 157 days (45.0% of the period). Yichang experienced the most days of heavy or worse pollution, reaching 31 days (8.9% of the period).

The regional nature of air pollution means it no longer occurs in isolation. Under natural conditions such as atmospheric circulation, air pollution often transmits between cities, where one city' s pollution may trigger or exacerbate another city' s pollution levels. In other words, urban air pollution is no longer an isolated phenomenon occurring in individual cities but rather establishes an endogenous inter-causal relationship. This transmission effect poses significant challenges to current environmental management models. Since China's environmental management and pollution control primarily operate along administrative boundaries, the contradiction between administrative-based management models and the regional characteristics of air pollution continues to intensify. The "fragmented" approach focusing on individual cities has become inadequate for addressing increasingly severe regional air pollution problems (Bai, Shi & Liu, 2014), necessitating the breakdown of administrative restrictions and the adoption of joint prevention and control measures to form pollution control synergies.

China has begun actively exploring effective pathways for regional air pollution joint prevention and control mechanisms (Wang et al., 2012; Chai et al., 2013), with inter-city joint prevention and control gradually becoming the "new normal" for air pollution control and achieving certain positive progress. However, under the influence of atmospheric circulation and economic development factors, inter-urban air pollution interactions extend beyond the transport, transformation, and coupling of primary pollutants between geographically close cities. Certain pollutants, especially those forming PM2.5, can cross urban and even provincial administrative boundaries to achieve long-distance transport (Xue et al., 2014). In other words, inter-urban air pollution influences have transcended purely geographical distance and proximity effects, with spatial transmission potentially occurring between more distant cities. Given the contiguous development of cities in the middle reaches of the Yangtze River megalopolis, pollution transmission among multiple cities forms a multi-threaded complex network, undoubtedly increasing the difficulty of joint prevention and control.

Current research on spatial transmission of air pollution involves three main branches: First, numerical simulation of cross-city air pollution transport based on different air quality models in environmental science (Xue et al., 2014; An et al., 2012; Hu et al., 2011; Yang et al., 2012; Qin et al., 2015; Jiang et al., 2015). Second, characterization of spatial distribution and spatial correlation features of air pollution based on spatial statistical techniques in geographical sciences (van Donkelaar et al., 2010; Li et al., 2012; Gao, 2008; Ma & Zhang, 2014a, b; Gao et al., 2014; Wang et al., 2014). Third, application of time series statistics and econometric techniques to describe temporal variation patterns of air pollution and reveal inter-urban pollution interactions (Yang et al., 2015; Wang et al., 2014; Hu et al., 2015; Ren et al., 2013; Li & Teng, 2014; Wu &

Guan, 2013). Despite partially revealing cross-boundary transport and mutual influences of air pollution in specific cities or characterizing spatial correlation and agglomeration features from a spatial perspective, existing studies have not considered nonlinear transmission characteristics of air pollution due to methodological and data limitations, nor have they revealed the structural features of the co-movement network of urban air pollution spatial transmission, reducing their policy guidance significance.

Compared with existing research, this paper employs time series data analysis methods, focusing on the middle reaches of the Yangtze River megalopolis and utilizing 2015 AQI daily data released by the Ministry of Environmental Protection. Within a VAR model framework, we employ nonlinear Granger causality testing methods proposed by Baek & Brock (1992), Hiemstra & Jones (1994), and Diks & Panchenko (2006) to effectively identify spatial transmission effects of air pollution. Social network analysis (SNA) methods are then applied to reveal network structural characteristics of inter-urban air pollution spatial transmission from both robustness and maximum likelihood network perspectives. The paper is organized as follows: Section 2 presents methods and data; Section 3 examines nonlinear transmission effects of air pollution among cities in the middle reaches of the Yangtze River megalopolis; Section 4 proposes implementation approaches for joint prevention and control based on the transmission network; and the final section presents conclusions and policy recommendations.

Methods and Data

Identification of Nonlinear Transmission Relationships in Inter-Urban Air Pollution

Currently, Granger causality testing based on VAR models has been applied to identify inter-urban air pollution transmission relationships (Wu & Guan, 2013; Chen & Cheng, 2014). This method treats all variables as endogenous without requiring excessive prior constraints on variable relationships, making it broadly theoretical in nature, while providing information on whether one set of variables helps improve prediction of another set. However, Granger' s (1969) original test only examines linear relationships between variables, potentially leading to significant bias by ignoring actual nonlinear causal relationships. As Granger & Newbold (1986) noted, the real world consists almost entirely of nonlinear relationships, with nonlinear models representing the correct direction for simulating reality. To overcome limitations of traditional linear Granger causality testing, Baek & Brock (1992), Hiemstra & Jones (1994), and Diks & Panchenko (2006) developed test methods based on nonlinear statistics. These methods filter out linear "predictability" between series based on linear Granger causality models and extract corresponding information from residuals to analyze nonlinear Granger causality.

1. Linear Granger Causality Test Proposed by Granger (1969) and extended by Sims (1972), this statistical test reflects whether one variable helps predict another, addressing whether historical information from one time series can improve prediction of another series' current value and testing whether one variable temporally "precedes" another. If a variable' s lagged values do not help improve prediction of another variable based on its own lagged values, the former is not considered a Granger cause of the latter; otherwise, it is. For operational simplicity, Granger causality testing between two time series can be conducted within the VAR model framework proposed by Sims (1980), derived from equations (1) and (2).

$$X_t = \alpha_0 + \sum_{i=1}^{\theta_1} \alpha_i X_{t-i} + \sum_{j=1}^{\theta_2} \beta_j Y_{t-j} + \varepsilon_{1t}$$

$$Y_t = \delta_0 + \sum_{i=1}^{\theta_3} \delta_i X_{t-i} + \sum_{j=1}^{\theta_4} \phi_j Y_{t-j} + \varepsilon_{2t}$$

where X_t and Y_t are two time series variables; α, β, δ, and ϕ are parameters to be estimated; ε_1 and ε_2 are residual series; and θ_1, θ_2, θ_3, and θ_4 are lag orders. To measure linear Granger causality at specific lag orders, T-statistics can be used to test the null hypothesis "$H_0 : \sum \beta_j = 0$" in equation (1), indicating that past values of Y_t do not help predict future values of X_t, or to test "$H_0 : \sum \phi_j = 0$" in equation (2), indicating that past values of X_t do not help predict future values of Y_t. If the null hypothesis in (1) is rejected, Y is considered a Granger cause of X, meaning Y has a spillover effect on X. Similarly, if the null hypothesis in (2) is rejected, X is considered a Granger cause of Y, indicating a spillover effect from X to Y.

2. BDS Test Before conducting nonlinear Granger testing, it is necessary to test time series for nonlinearity, typically using the BDS method. This method tests whether a time series is independently and identically distributed based on estimators of spatial probabilities across time. The BDS test removes linear relationships through the VAR model in equations (1) and (2) to obtain residual series ε_1 and ε_2, which are then tested for independent and identical distribution. If the null hypothesis of independent and identical distribution is rejected, the residual series may contain nonlinearity, making nonlinear Granger causality testing more appropriate. Given an m-dimensional time series Z_t with observations $(z_t, z_{t+1}, ..., z_{t+m-1})$, the cross-temporal spatial probability estimator correlation integral is defined as:

$$C_{m,T}(d) = \frac{2}{(T-m+1)(T-m)} \sum_{s<t} I(Z_t^m, Z_s^m, d)$$

where $I(Z_t^m, Z_s^m, d)$ is an indicator function equal to 1 when $\|Z_t^m - Z_s^m\| \le d$ and 0 otherwise. $\|Z_t^m - Z_s^m\|$ represents the Euclidean distance between two series Z_t^m, d is the bandwidth, T is the total sample size, and series Z_t can be divided into T_m m-dimensional subsamples with $Z_t^m = (z_t, z_{t+1}, ..., z_{t+m-1})$ and $Z_s^m = (z_s, z_{s+1}, ..., z_{s+m-1})$.

The BDS test statistic is then defined as:

$$W_{m,T}(d) = \sqrt{T-m+1}\frac{C_{m,T}(d) - C_{1,T}(d)^m}{\sigma_m(d)}$$

where $\sigma_m(d)$ is the standard deviation of the m-dimensional sample. The BDS statistic $W_m(T,d)$ asymptotically follows a standard normal distribution. If the BDS statistic rejects the null hypothesis, it indicates the presence of nonlinear relationships in the series.

3. Nonlinear Granger Causality Test Diks & Panchenko (2006) improved upon the nonparametric statistical test methods of Baek & Brock (1992) and Hiemstra & Jones (1994). This approach filters out linear “predictability” between series based on linear Granger causality models and extracts corresponding information from residuals to analyze nonlinear Granger causality. Considering X_t and Y_t as two time series variables, define the m-dimensional leading vector of X_t as X_t^{Lx} and the Lx-period lag vector and Ly-period lag vector of Y_t as X_{t-Lx}^{Lx} and Y_{t-Ly}^{Ly}, respectively, as shown in equation (5):

$$X_t^{Lx} = (X_{t-Lx+1}, ..., X_t), \quad X_{t-Lx}^{Lx} = (X_{t-Lx}, ..., X_{t-1}), \quad Y_{t-Ly}^{Ly} = (Y_{t-Ly+1}, ..., Y_t)$$

For given values $m, Lx, Ly > 1$ and arbitrarily small constant $d > 0$, Y is not a strict nonlinear Granger cause of X if it satisfies the conditional probability in equation (6), where $Pr(\cdot)$ denotes probability and $\|\cdot\|$ denotes the maximum norm, with $s, t = \max(Lx, Ly) + 1, ..., T - m + 1$. If the conditional probability on the right side of equation (6) for series X_t is unaffected by whether series Y_t is included as a condition, it indicates that Y does not Granger-cause X. The conditional probability in (6) can also be expressed as equation (7):

Assuming X_t and Y_t are strictly stationary and satisfy mixing conditions (Denker & Keller, 1983), Diks & Panchenko (2006) constructed a T-statistic with asymptotic normal distribution based on the null hypothesis that “Y_t is not a strict Granger cause of X_t” , as shown in equation (8):

$$T_n(m, Lx, Ly, d) = \frac{\sqrt{n}\left[CI_{m+Lx,Ly,d,n} - CI_{Lx,Ly,d,n} \cdot CI_{m+Lx,d,n}/CI_{Lx,d,n}\right]}{\sigma(m, Lx, Ly, d)}$$

where $n = T + 1 - m - \max(Lx, Ly)$ and $\sigma^2(\cdot)$ is the asymptotic variance of the modified test statistic. The statistic in equation (8) can be used to test the two estimated residual series ($\varepsilon_{1,t}, \varepsilon_{2,t}$) from the VAR models in equations (1) and (2). If the null hypothesis of non-causality is rejected, the causal relationship between the two series must be nonlinear.

Characterizing Co-Movement Network Structure Features–Social Network Analysis Methods

1. Characterizing Overall Network Features In social network analysis, overall network features are typically measured by network density and connectivity indicators. Network density is defined as the ratio of actual connections to maximum possible connections in the entire network (Carrington & Scott, 2005), describing the quantity and intimacy of relationships among member nodes. More relationships yield greater network density, indicating stronger overall network influence on individual node attributes. Network connectedness reflects the network' s robustness and vulnerability (Krackhardt & David, 1994). If relationships among nodes connect the system into an integrated whole where any two nodes have direct or indirect paths, the network exhibits good connectivity. If many network lines pass through a particular node, the network becomes highly dependent on that node; removing it may cause network collapse, indicating an unstable structure with low connectivity. Connectivity is typically measured by connectedness, network hierarchy, and network efficiency. Connectedness measures reachability–more paths between two points yield greater connectedness. Network hierarchy indicates the degree of asymmetric reachability among nodes, reflecting their dominant positions. Network efficiency measures redundant lines in a known network structure (Liu, 2014). Lower network efficiency in air pollution spatial correlation indicates more spillover channels and multiple superimposed spillover effects, making the network more stable.

2. Characterizing Individual Network Features Individual network analysis answers how much "power" individuals or organizations have in their social networks, or what central positions they occupy. In a directed graph, each point' s degree can be divided into in-degree centrality and out-degree centrality. A point' s in-degree counts other points directing ties to it (direct relationships received), while out-degree counts ties it directly sends. Beyond out-degree and in-degree, individual network features are typically measured by three centrality indicators: degree centrality, betweenness centrality, and closeness centrality. Degree centrality measures an individual' s "power" in the entire network–its ability to develop direct relationships with other points. Higher degree centrality indicates a more central position and greater capacity to control the overall situation. Betweenness and closeness centrality measure an actor' s ability to control interactions among other actors, depending on relationships with all network actors rather than just direct node connections. For betweenness centrality, a point with high betweenness lies on many shortest paths between other point pairs, indicating strong control over other nodes' activities and a central network position. Low betweenness centrality means weak control and a peripheral position. For closeness centrality, measurement uses the inverse of the sum of shortest distances from a point to all other network points. A point with short distances to all others can transmit information more easily and may occupy the network center, indicating high closeness centrality. The actor farthest from the center is weakest in information resources and influence.

Sample Data

This study selects 27 prefecture-level cities in the middle reaches of the Yangtze River megalopolis as samples, specifically: Wuhan, Huangshi, Ezhou, Huanggang, Xiaogan, Xianning, Yichang, Jingmen, Jingzhou, Changsha, Zhuzhou, Xiangtan, Yueyang, Yiyang, Changde, Hengyang, Loudi, Nanchang, Jiujiang, Jingdezhen, Yingtan, Xinyu, Yichun, Pingxiang, Shangrao, Fuzhou, and Ji' an. We use the Air Quality Index (AQI) as the indicator for urban environmental pollution. According to the "Technical Regulation on Ambient Air Quality Index (AQI) (Trial)" (HJ633-2012) issued by the Ministry of Environmental Protection on February 29, 2012, AQI is a dimensionless index quantitatively describing air quality conditions, comprehensively considering multiple pollutants including sulfur dioxide (SO), nitrogen dioxide (NO), particulate matter with diameter less than 10 m (PM10), particulate matter with diameter less than 2.5 m (PM2.5), carbon monoxide (CO), and ozone (O). Higher AQI values indicate more severe air pollution, while lower values indicate better air quality. All data are sourced from daily AQI reports published by the National Environmental Protection Department Data Center, covering 349 days from January 1 to December 15, 2015, yielding a total of 349 × 27 = 9,423 sample observations.

Nonlinear Transmission Effects of Inter-Urban Air Pollution in the Middle Reaches of the Yangtze River Megalopolis

Objective Facts of Air Pollution in the Middle Reaches of the Yangtze River Megalopolis

Using 349-day mean AQI data for 27 prefecture-level cities in the middle reaches of the Yangtze River megalopolis that implemented new air quality standards, we conducted spatial visualization of pollution conditions using Kriging interpolation in ArcGIS, as shown in Figure 1 [Figure 1: see original paper]. The visualization reveals a trend of air pollution gradually spreading from a northwestern center toward the southeast. Figure 2 [Figure 2: see original paper] shows significant differences in air quality among the 27 cities. Wuhan, Jingzhou, and Jingmen in Hubei Province had average AQI values exceeding 100, reaching the light pollution level. Most cities in Hunan Province had AQI values around 80, while cities in Jiangxi Province generally had better air quality, with Yichun showing the best performance at an average AQI of 57.9. Figure 3 [Figure 3:

see original paper] displays the fluctuating trends of air pollution across the 27 cities, with a fitted AQI trend line showing a U-shaped pattern—more severe in spring and winter, significantly improved in summer and autumn. Monthly analysis (Figure 4 [Figure 4: see original paper]) indicates that the region experienced light pollution in January and February 2015, with the worst air quality in January (average AQI of 129.3) and the best in June (average AQI of 60.9).

Nonlinear Transmission Effects and Co-Movement Network Structure

1. Unit Root Test Nonlinear Granger causality testing applies to stationary time series (Yang & Zhao, 2014), as the presence of unit roots may cause the F-statistic to no longer follow standard limiting distributions, potentially leading to erroneous conclusions (Ohanian, 1988; Sims et al., 1990; Toda & Phillips, 1993a). Therefore, stationarity must be tested before nonlinear Granger causality testing. We employ the ADF unit root test for all series, with results shown in Table 1 . The ADF test results indicate that at the 1% significance level, T-statistics are all smaller than critical values, rejecting the null hypothesis of unit roots. Thus, the level series are all stationary, allowing us to proceed with nonlinearity testing and nonlinear Granger causality testing based on AQI indices for the 27 cities.

2. BDS Test Before analyzing inter-urban air pollution transmission relationships, it is necessary to conduct nonlinearity tests to examine whether significant nonlinear characteristics exist during pollution transmission (Yang et al., 2013). This study employs the mainstream BDS test method (Brock et al., 1996) to examine nonlinear trends between pairwise AQI series for the 27 cities. First, we construct VAR models for each city pair to determine mutual influence relationships and filter out linear dependence components. Then, we conduct nonlinear BDS tests on the filtered residual series. The test results (not reported due to space limitations) reject the null hypothesis of linear relationships at the 5% significance level for all pairwise city combinations, indicating significant nonlinear relationships between cities. Consequently, we employ nonlinear Granger causality testing to examine urban air pollution transmission effects.

3. Structural Features of Inter-Urban Air Pollution Transmission Networks Traditional linear Granger causality testing is highly sensitive to lag order selection, typically using VAR models with AIC, SIC, LR, FPE, and HQ criteria to select optimal lag orders. Although no unified rules currently exist for optimal lag order selection in nonlinear Granger causality testing (Francis et al., 2010; Diks & Panchenko, 2006), this provides new perspectives for comprehensively understanding inter-urban air pollution transmission relationships. We argue that if test results across all lag orders accept the null hypothesis of "no nonlinear Granger causality," then no spillover relationship exists. If at least one test across all lag orders significantly rejects the null hypothesis, we cannot exclude the possibility of spillover relationships. The association network formed based on this possible spillover relationship is defined as the "maximum likelihood network" (ML-Network). If test results across all lag orders significantly reject the null hypothesis, a "robust" spillover relationship exists, and the association network formed based on this robust relationship is defined as the "robust network" (R-Network).

(1) Robustness Network Analysis

Based on nonlinear Granger causality testing, we identified robust relationships among the 27 cities (Table 2). If nonlinear transmission relationships exist for lags 1-4, it is recorded as "1" ; otherwise, "0."

Overall R-Network Structure. Using the robust transmission relationships identified through nonlinear Granger causality testing, we visualized the R-Network using Ucinet' s Netdraw tool (Figure 5 [Figure 5: see original paper]). The visualization reveals that air pollution transmission in the middle reaches of the Yangtze River megalopolis presents a complex, multi-threaded network structure with no city isolated from the network. One city' s air pollution can be explained and predicted by another' s, connecting all cities and posing severe challenges for policy formulation. As the saying goes, "He who does not consider the whole cannot manage a part." The nonlinear transmission network requires a holistic, integrated perspective for joint prevention and control. The robust network contains 259 transmission relationships, with a theoretical maximum of 702, yielding a network density of 0.369, indicating relatively high connectivity. Network connectedness equals 1, demonstrating strong network cohesion and accessibility with universal pollution transmission effects. Network hierarchy is 0.145, showing that transmission effects are not strictly hierarchical, with nonlinear relationships existing among cities with different pollution levels. Network efficiency is 0.462, indicating numerous redundant connections and multiple superimposed nonlinear transmission relationships, making the network relatively stable.

Individual R-Network Structure. To examine each city' s position and role in the robust network, we analyze three centrality indicators: degree centrality, closeness centrality, and betweenness centrality (Table 3). Degree centrality results show a mean of 57.3 across 27 cities, with the top six being Zhuzhou, Huangshi, Nanchang, Jingmen, Hengyang, and Changde. Zhuzhou and Huangshi both achieve degree centrality of 84.6, indicating numerous nonlinear transmission relationships with other cities, likely due to close energy exchanges. Mean out-degree is 9.6, with top cities being Huangshi, Jingmen, Jingzhou, Yichang, Nanchang, and Zhuzhou, showing strong spillover effects and "leading" roles. Top in-degree cities are Xiaogan, Zhuzhou, Changsha, Hengyang, Loudi, and Changde, indicating strong influence from other cities and "following" positions. Closeness centrality results show a mean of 70.7, with top cities Zhuzhou, Huangshi, Nanchang, Jingmen, Hengyang, and Changde demonstrating faster internal connections with other cities and central actor roles. Yueyang, Yiyang, Shangrao, Yingtan, Xianning, and Ezhou rank lowest, playing peripheral roles. Betweenness centrality shows a mean of 1.8, with Huangshi, Nanchang, Fuzhou, Xiaogan, Hengyang, and Ji' an ranking 1-6, accounting for 45.7% of total betweenness centrality. These cities exhibit strong control over inter-urban pollution transmission, serving as intermediaries in the robust network. Shangrao, Yueyang, Yiyang, Xianning, and Yingtan have betweenness centrality below 0.5, indicating no control function and dependence on higher-betweenness cities.

R-Network Core-Periphery Analysis. Based on robust transmission relationships, we measured coreness using Ucinet software. Cities with coreness above the mean occupy core positions, while others are peripheral. Table 4 shows that Huangshi, Jingmen, Nanchang, Pingxiang, Huanggang, Jingzhou, Yichang, Zhuzhou, Changde, Xiaogan, and Ezhou (11 cities) occupy core positions in the robust network, while other cities are peripheral. Therefore, the first phase of joint prevention and control should establish mechanisms covering these 11 core cities while considering 16 peripheral cities including Xinyu and Fuzhou.

(2) Maximum Likelihood Network Analysis

Overall ML-Network Structure. Based on maximum likelihood transmission relationships (Table 5), we visualized the ML-Network using Ucinet 6.0' s Netdraw tool (Figure 6 [Figure 6: see original paper]). Compared with the robust network, the maximum likelihood network shows more nonlinear transmission relationships and more extensive, universal connections. Each city' s air pollution depends on both its own factors and other cities' pollution, with no city isolated. In other words, no city can "remain unaffected" when facing the maximum likelihood network. The ML-Network contains 547 relationships, with a theoretical maximum of 702, yielding a network density of 0.779, indicating widespread and extensive spatial transmission relationships. Network connectedness is 1, showing strong cohesion and accessibility with widespread transmission effects. Network hierarchy is 0, indicating no strictly hierarchical structure, high symmetry in reachability, and few subordinate or peripheral cities, meaning spatial spillovers exist even between distant cities. Network efficiency is 0.092, indicating numerous redundant connections and strong stability.

Individual ML-Network Structure. To examine each city' s position in the maximum likelihood network, we analyze the same three centrality indicators (Table 6). Degree centrality shows a mean of 91.5, with top cities Zhuzhou, Huangshi, Fuzhou, Ji' an, Yingtan, and Xinyu. Zhuzhou and Huangshi achieve degree centrality of 100, indicating numerous nonlinear transmission relationships. Mean out-degree is 20.3, with top cities Huangshi, Jingmen, Zhuzhou, Changde, Nanchang, and Xinyu showing strong spillover effects and leading roles. Top in-degree cities are Hengyang, Changde, Loudi, Jiujiang, Ji' an, and Xiaogan, indicating strong influence and following positions. Closeness centrality shows a mean of 92.7, with top cities Zhuzhou, Huangshi, Fuzhou, Ji' an, Yingtan, and Xinyu demonstrating faster connections and central actor roles. Shangrao, Yueyang, Yiyang, Yingtan, Wuhan, Ezhou, and Xianning rank lowest, playing peripheral roles. Betweenness centrality shows a mean of 0.342, with Zhuzhou, Huangshi, Ji' an, Nanchang, Huanggang, and Xiaogan ranking 1-6, accounting for 36.0% of total betweenness centrality. These cities exhibit strong control over transmission, serving as intermediaries. Shangrao, Yueyang, and Yiyang have betweenness centrality below 0.1, indicating no control function.

ML-Network Core-Periphery Analysis. Based on maximum likelihood transmission relationships, we measured coreness for the ML-Network. Table 7 shows that 18 cities including Huangshi and Jingmen have above-mean coreness, occupying core positions, while nine cities including Yingtan and Wuhan are peripheral. Compared with the robust network, the ML-Network has more core cities, suggesting that joint prevention and control mechanisms should cover more core cities while considering a few peripheral cities.

Joint Prevention and Control of Air Pollution Based on Inter-Urban Transmission Networks

Coordinated air pollution governance must consider not only pollution levels but also each city' s core-periphery position in the transmission network, requiring reexamination from a "pollution level—network position" synergy perspective. Based on 2015 AQI means and core-periphery positions in both networks, we construct a two-dimensional analytical framework.

Joint Prevention and Control Based on the Robustness Network

Using the mean AQI from January 1 to December 15, 2015, we classify cities as "low-pollution" or "high-pollution," and using mean coreness from the robust network, we classify them as "core" or "peripheral," creating four categories (Figure 7 [Figure 7: see original paper]):

- **HH Type**: High pollution and robust network core position, including Yichang, Jingzhou, Huangshi, Ezhou, Xiaogan, Jingmen, Huanggang, and Pingxiang (8 cities).
- **LH Type**: High pollution but robust network peripheral position, including Wuhan, Xianning, Changsha, Xiangtan, Yiyang, and Loudi (6 cities).
- **HL Type**: Low pollution but robust network core position, including Zhuzhou, Changde, and Nanchang (3 cities).
- **LL Type**: Low pollution and peripheral position, including Yueyang, Hengyang, Jiujiang, Xinyu, Yingtan, Ji' an, Yichun, Fuzhou, Shangrao, and Jingdezhen (10 cities).

For HH cities, high pollution levels and core positions create relatively greater governance pressure, providing intrinsic motivation for strict environmental measures. These cities should formulate regulations based on economic development stages, industrial structure, and energy consumption patterns, focusing on reducing pollution levels while serving as priorities in joint prevention and control mechanisms. For HL cities, despite low pollution, their core positions should leverage advanced experiences in energy conservation and emission reduction, actively extending these through the robust network' s transmission structure. For LH cities, although peripheral, their severe pollution requires efforts to reduce local emissions while accounting for transmission effects from core cities. For LL cities, despite currently good air quality and peripheral positions, no city can remain unaffected in a network structure. Individual efforts may show short-term effects but long-term impacts from other cities' transmission necessitate active roles in joint mechanisms for sustainable green development.

Joint Prevention and Control Based on the Maximum Likelihood Network

- **HH Type**: High pollution and ML-Network core position, including Yichang, Jingzhou, Huangshi, Ezhou, Xiaogan, Jingmen, Huanggang, Changsha, Xiangtan, and Pingxiang (10 cities).
- **LH Type**: High pollution but ML-Network peripheral position, including Wuhan, Xianning, Yiyang, and Loudi (4 cities).
- **HL Type**: Low pollution but ML-Network core position, including Zhuzhou, Changde, Hengyang, Nanchang, Jiujiang, Xinyu, Ji' an, and Fuzhou (8 cities).
- **LL Type**: Low pollution and peripheral position, including Yueyang, Yingtan, Yichun, Shangrao, and Jingdezhen (5 cities).

For these four categories, governance strategies can reference those for the robust network, but note that the ML-Network framework has 18 core cities and only 9 peripheral cities. Therefore, joint prevention and control mechanisms based on the ML-Network should cover a broader scope, establishing truly cross-provincial, cross-city mechanisms encompassing all 27 cities to effectively improve air quality.

Conclusions and Policy Recommendations

Based on 2015 Chinese urban AQI daily data for 27 cities in the middle reaches of the Yangtze River megalopolis, this paper employs nonlinear Granger causality testing to identify nonlinear transmission effects and uses social network analysis to reveal network structural features from both robustness and maximum likelihood perspectives. The findings show significant nonlinear transmission relationships among the 27 cities, forming a complex co-movement network with good accessibility. In the robust network, 11 cities including Zhuzhou, Huangshi, Nanchang, Jingmen, Hengyang, and Changde occupy core positions. The ML-Network density reaches 0.779, with mean degree centrality and closeness centrality of 91.5 and 92.7 respectively (reaching 100 for some cities), and mean betweenness centrality of 0.342. Eighteen cities including Zhuzhou, Huangshi, and Fuzhou occupy core positions, with enhanced pairwise nonlinear transmission relationships not requiring intermediary cities. These conclusions provide empirical evidence for joint prevention and control. As the saying goes, "He who does not consider the whole cannot manage a part." Facing nonlinear transmission, we must adopt a global perspective— "viewing China from the world, viewing city clusters from the nation, and viewing cities from city clusters" —to reexamine air pollution issues and accelerate construction of multi-level, cross-regional joint prevention and control systems for coordinated governance and air quality improvement.

The State Council' s April 2015 "Development Plan for the Middle Reaches of the Yangtze River Megalopolis" emphasizes strengthening joint environmental pollution prevention, improving ecological compensation mechanisms, and implementing coordinated environmental supervision to establish cross-regional ecological civilization construction mechanisms. However, numerous challenges remain. Since no city can "remain unaffected" in the spatial transmission network, successful joint prevention and control requires: First, each of the 27 cities must "govern itself well" by utilizing energy-saving technologies and industrial structure adjustments. Second, organizational guarantees require a top-down authority, such as the "APEC Blue"and "Parade Blue"during the APEC meeting and military parade, achieved when Vice Premier Zhang Gaoli headed the joint prevention and control group to coordinate all parties. Without such coordination, multi-city games will result in no city willing to make greater pollution control efforts, reducing expected outcomes. Third, assessment mechanisms should accelerate establishment of ecological civilization performance evaluation and accountability systems based on joint prevention and control, gradually implementing performance-oriented environmental management evaluation to change previous inefficient, extensive management models emphasizing input over output, construction over effectiveness, and effects over benefits. Future research must deeply explore individual behaviors and game relationships within joint prevention and control mechanisms to ensure effectiveness. Additionally, while joint prevention and control emphasizes spatial coordination and "connection," it remains a "symptomatic treatment." The fundamental path to ensuring thorough air quality improvement lies in accelerating transformation of production and lifestyle patterns and achieving green development—green development is the ultimate choice for air pollution control and air quality improvement.

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Note: Figure translations are in progress. See original paper for figures.