The Impact of Improving Throughput Efficiency of Coastal Ports Based on Machine Learning Methods on Sulfur Emissions

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Abstract. This article uses the LSTM long short-term memory model to predict the throughput of major coastal ports in China and remote sensing images of port night light, and explores the correlation between remote sensing images of port night light and sulfur emissions. Research has shown that the cargo throughput of major coastal ports in China increased at a rate of 5% from 2019 to 2029, which is significantly positively correlated with the growth of nighttime light data. The growth of nighttime light data is negatively correlated with the decrease in sulfur emissions in ports. This study can provide new ideas for the future green development of ports, thermal environment management.

Keywords: Port throughput, Night light remote sensing images, Sulfur emissions, LSTM,

1 Introduction

In the fabric of global economic activity, coastal ports are the threads that interweave the world's commerce and trade[1]. As the linchpins of international maritime transport, their throughput and efficiency are critical indicators of economic performance and environmental stewardship[2]. This study employs the Long Short-Term Memory (LSTM) models to predict the throughput of China's major coastal ports, offering insights into operational dynamics and environmental impacts[3]. The LSTM model, known for handling sequential data, is employed to analyze the temporal patterns in port activities, providing a window into energy consumption and sulfur emissions[4]. These models, when integrated with remote sensing data, offer a comprehensive approach to environmental monitoring and predictive analytics[5]. The predictive modeling of port operations is not just about throughput; it is also about understanding the environmental footprint of these maritime hubs[6]. The correlation between port activities and sulfur emissions is a significant aspect of this study, as it provides insights into the environmental impact of port operations[7]. This research aims to bridge the gap between operational efficiency and environmental sustainability, offering a roadmap for ports to achieve both[8]. The integration of machine learning with remote sensing technology is a testament to the interdisciplinary approach required to address complex environmental challenges[9]. By

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analyzing night-time imagery, this study uncovers the spatiotemporal patterns of port activities, which are indicative of energy use and potential sulfur emissions[10]. The findings of this research are expected to contribute to the development of sustainable port management practices, including green initiatives, thermal regulation, and low-carbon transportation strategies[11]. daidinggao The urgency of sustainable port management is highlighted by the growing environmental concerns associated with port activities[12]. This study aims to provide actionable insights for policymakers and port authorities, enabling them to make informed decisions that balance operational efficiency with environmental sustainability[13]. The data-driven strategies proposed in this research are expected to mitigate the environmental impacts of port operations while enhancing throughput and efficiency[14]. This study is structured as follows: The methodology section outlines the application of LSTM models and t integration with remote sensing data[15]. The results section presents the predictive analysis of port throughput and the correlation study between night-time lighting and sulfur emissions[16]. The discussion explores the broader implications for port sustainability and environmental policy[17]. The study concludes with a synthesis of findings and directions for future research[18]

2 Data

The port-level data is considered as the research object, Dalian, Yingkou, Qinhuangdao, Tianjin, Yantai, Qingdao, Rizhao, Lianyungang, Shanghai, Ningbo-Zhoushan, Fuzhou, Xiamen, Shantou, Guangzhou, Shenzhen, Zhuhai, Zhanjiang and Haikou, respectively. The original data, such as port throughput and relative indicators are published from 2005. In order to evade the effects of the COVID-19 epidemic, the sample period is selected from 2005 to 2019 to avoid uncessary estimation bias, where the data come from the National Bureau of Statistics (stats.gov.cn) and China port Statistical Yearlybook (govt.chinadaily.com). Notice that a small number of missing data is addressed via the linear interpolation approach.

Further, the vertical column density of SOX concentration in planetary boundary layer is obtained by the Ozone Monitoring Instrument, which has been carried by NASA's EOS-Aura satellite since Jul. 2004 (www.nasa.gov). As shown in Figure 1, the highest value around 14:00±0:15 BST from 13km to 24km is the most suitable for observing the long-term changes as the SOX concentration at each port. Here, the gridded data with the spatial resolution of $0.25° \times 0.25°$ are derived from SOX concentrations where the criterias for column harmonization are a zenith angle of less than 85°, a surface albedo of less than 30°, a cloudiness of less than 30°, and a trans-orbital position in the range [10, 50].

The data is sourced from the polar orbit satellite program of DMSP, the US Department of Defense. The existing DMSP is a three-axis attitude stabilization satellite that operates in a sun synchronous orbit at an altitude of approximately 830km, with a period of approximately 101 minutes and a scanning band width of 3000 km. The DMSP satellite adopts a dual satellite operation system, with two operational satellites operating simultaneously and crossing the equator at 05:36 and 10:52, providing a global cloud map every 6 hours. This data reflects the nighttime operation workload and port economic development of major coastal ports in China from 2005 to 2019

3 Method

Long short-term memory (LSTM)

With the continuous improvement and development of deep learning theory, the concept of time series is introduced, which not only pays attention to the processing of information at the current moment, but also realizes the connection of time information before and after, thereby improving the accuracy of analysis. For example, the recurrent neural network (RNN) introduces this concept into network construction, and its essential feature is that there are both internal feedback connections and feedforward connections between the processing units of the network layer. The model can perceive information from multiple time perspectives. Compared with the RNN model, the LSTM has better performance in longer sequences, mainly to solve the problems of gradient disappearance and gradient explosion during training of long sequences. This is helpful in LST prediction, it can reduce over-fitting and loss of prediction information and accuracy in the prediction process. LSTM introduces the cell state to memorize information, and adds three gates (input gate, forget gate, output gate) structure to realize the protection and control of LST。 The main formulas are expressed as follows.

Input gate: $j_t = \partial(W_i \cdot [m_{t-1}, l_t] + \alpha_i)$

Forget gate: $k_t = \partial\left(W_j \cdot [m_{t-1}, l_t] + \alpha_f\right)$

$\widetilde{C_t} = tanh(W_k \cdot [m_{t-1}, l_t] + \alpha_c)$

Output gate: $P_t = \partial\left(w_P \cdot [m_{t-1}, l_t] + \alpha_p\right)$

Long memory: $C_t = f_t \times C_{t-1} + j_t \times \widetilde{C_t}$

Short memory: $h_t = P_t \times tanh(C_t)$

where l, m are the input vector and output vector of LSTM, respectively; k is the forget gate, j is the input gate, p is the output gate; C is

the unit state of the LSTM neural network; ∂, tanh are the activations of sigmoid and tanh, respectively function; W and a denote the

weight and bias matrices, respectively.

4 Results and Analysis

Prediction of throughput of major ports in the country

This article selects the cargo throughput data of major ports in China from 2005 to 2019. Firstly, we used LSTM prediction model to predict the throughput data of major ports in China in 2019 using the throughput data of major ports in 2009 and 2014. And compare the accuracy of the results with the actual 2019 national major port data on the QGISv2.18 platform. The results show that the model has a prediction accuracy of 89.33% for changes in throughput along major coastal areas in China. This indicates that the model has good statistical accuracy and is suitable for predicting future throughput changes. Therefore, we can use the LSTM model to predict the changes in throughput of major ports in China in 2024 and 2029.We have calculated the changes in the throughput of major coastal ports in China in 2009, 2014, 2019, 24, and 29 years, and normalized the data to better present the trend of changes. Figure 1 shows that from 2009 to 2029, the cargo throughput of ports in China also showed a stable growth trend. From 2019 to 2024, the year-on-year growth rate of cargo throughput at major ports in China was around 3% -4%. From 2024 to 2029, the year-on-year growth rate of cargo throughput in all major ports was around 5%. Among them, ports such as Shanghai Port, Dalian Port, Ningbo Zhoushan Port, and Qingdao Port have shown the most obvious performance.

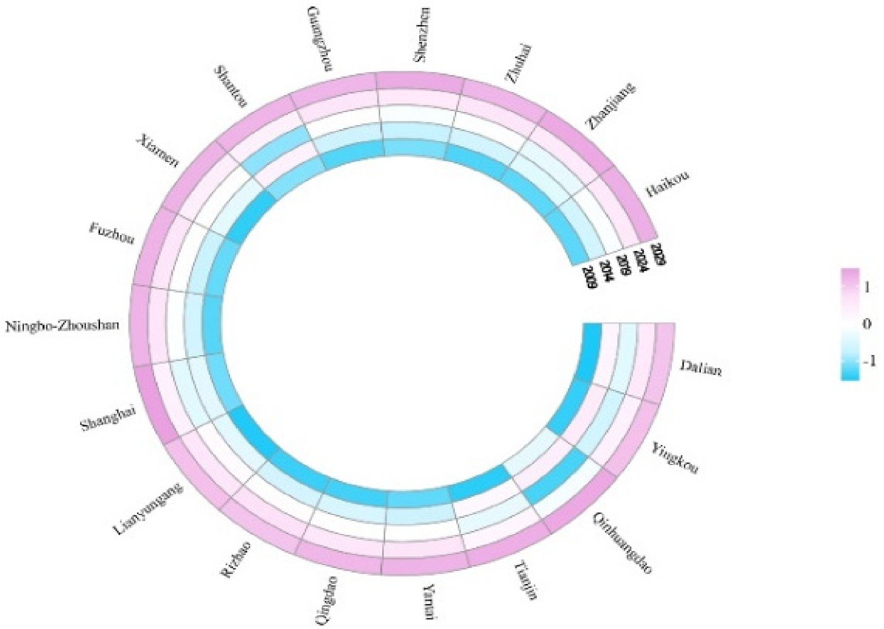

Fig. 1. 2009-2029 cargo throughput

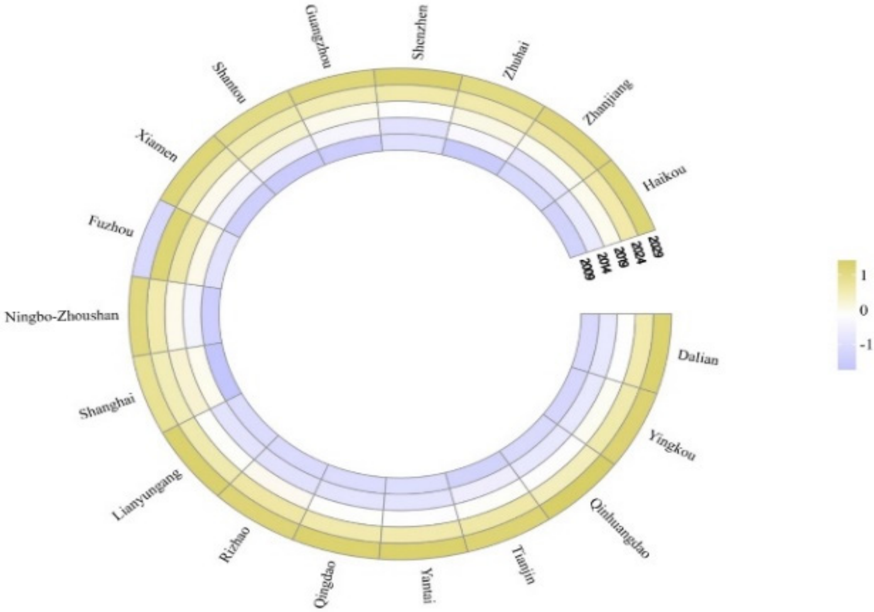

Fig. 2. 2009-2029 nighttime light data

Prediction of Night Light Remote Sensing Images

Using the previous method, we used the LSTM model to predict the DN values of nighttime light remote sensing images of major coastal ports in China. Predict DP values for 2019 using DN values from 2010 and 2015. And compare it with the actual DN value in 2019. The predicted result is 86.72% accurate compared to the actual value, indicating that the result is accurate. We have recorded the changes in the DN values of nighttime light remote sensing images of major coastal ports in China over 2009, 2014, 2019,2024, and 2029 years. Figure 2 shows that the DN value of nighttime light remote sensing in major coastal ports in China is gradually increasing. Among them, the Yangtze River Delta region, Shanghai Port, and Ningbo Zhoushan Port have the largest growth rates. The Bohai Rim region, Dalian Port, and Qingdao Port have the most significant growth rates.

We will fit the throughput data of major coastal ports in China from 2009 to 2029 and night light remote sensing images, and examine the positive and negative correlations between the two sets of data in the form of a circular graph. From Figure 3, we can see that the port throughput and nighttime lighting data are mainly positively correlated. We found that ports with larger scale and better economic development, such as Shanghai Port and Ningbo Zhoushan Port, have a strong correlation between port cargo throughput and nighttime light DN values. On the one hand, there are many construction and decoration equipment in the port, and the port is large in scale. On the other hand, the port economy is developed and there is a large amount of night work. There is a significant positive correlation between port cargo throughput and nighttime light DN values.

We will conduct inter group correlation analysis on the nighttime light data and SO2 emission data of national ports from 2005 to 2019, and then display their correlation through dynamic circular heat maps. Figure 4 shows SO2 emission data on the left and national nighttime lighting data on the right. Among them, the line connecting orange represents a positive correlation, while blue represents a negative correlation. We found that, except for Zhuhai, Zhanjiang, and Haikou ports, there was a negative correlation between SO2 emissions and nighttime light data emissions from major coastal ports in China from 2005 to 2019. Further observation of the changes in SO2 emissions data from major ports in the country on the left reveals that, except for Zhuhai, Zhanjiang, and Haikou ports, most other ports have shown a downward trend in SO2 emissions. Observing the nighttime light data of national ports on the right, it is found that there is generally an upward trend. The decrease in SO2 emissions is negatively correlated with the increase in port economic development, and the correlation is very obvious.

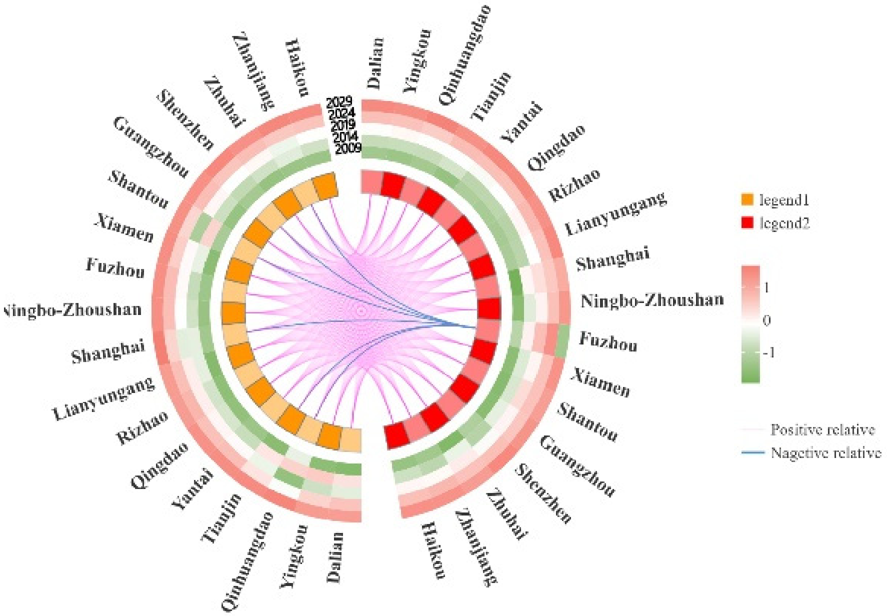

Fig. 3. The correlation between cargo throughput and nighttime lighting data in 2009-2029

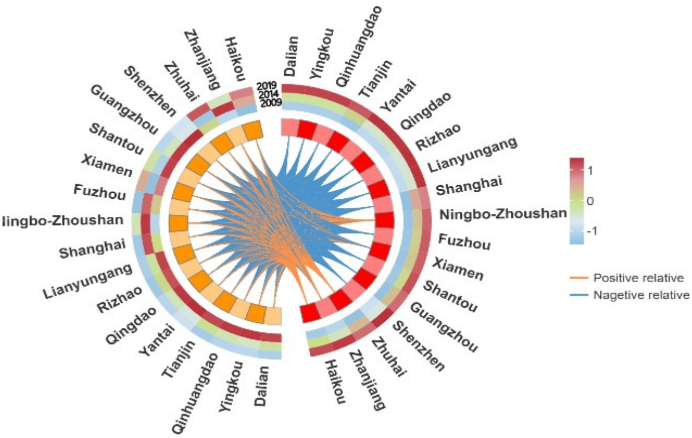

Fig. 4. Correlation between sulfur emissions and nighttime light data in 2009-2019

5 Conclusion

This article uses machine learning to predict the cargo throughput and nighttime light data of major ports in China, and explores the correlation between the improvement of port throughput in the future and the development of port economy, as well as SO2 emissions. Research has shown that with the development of global trade and economy, the cargo throughput of major ports in China will grow at a growth rate of about 5% in the coming years, which is positively correlated with the nighttime workload of ports and the development of port economy. Although sulfur emissions from major ports in China showed a trend of first increasing and then decreasing between 2005 and 2019, the decrease in sulfur emissions is negatively correlated with the increase in port throughput. This may provide new clues for the future development of port construction, environmental governance, and the mitigation of sulfur emissions.

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