The review report from reviewer #2:  
  
\*1: Is the paper relevant to ICDM?  
 [\_] No  
 [X] Yes  
  
\*2: How innovative is the paper?  
 [\_] 6 (Very innovative)  
 [X] 3 (Innovative)  
 [\_] -2 (Marginally)  
 [\_] -4 (Not very much)  
 [\_] -6 (Not at all)  
  
\*3: How would you rate the technical quality of the paper?  
 [\_] 6 (Very high)  
 [X] 3 (High)  
 [\_] -2 (Marginal)  
 [\_] -4 (Low)  
 [\_] -6 (Very low)  
  
\*4: How is the presentation?  
 [\_] 6 (Excellent)  
 [X] 3 (Good)  
 [\_] -2 (Marginal)  
 [\_] -4 (Below average)  
 [\_] -6 (Poor)  
  
\*5: Is the paper of interest to ICDM users and practitioners?  
 [X] 3 (Yes)  
 [\_] 2 (May be)  
 [\_] 1 (No)  
 [\_] 0 (Not applicable)  
  
\*6: What is your confidence in your review of this paper?  
 [\_] 2 (High)  
 [X] 1 (Medium)  
 [\_] 0 (Low)  
  
\*7: Overall recommendation  
 [\_] 6: must accept (in top 25% of ICDM accepted papers)  
 [X] 3: should accept (in top 80% of ICDM accepted papers)  
 [\_] -2: marginal (in bottom 20% of ICDM accepted papers)  
 [\_] -4: should reject (below acceptance bar)  
 [\_] -6: must reject (unacceptable: too weak, incomplete, or wrong)  
  
\*8: Summary of the paper's main contribution and impact  
 The paper presents a dynamic spatial-temporal prediction model for forecasting carbon emissions by addressing its need to shape sustainable policies and strategies. Given the dynamic inter-region correlations and complex temporal shifts in carbon emissions, the authors introduce a Dynamic Spatial-Temporal Graph Convolutional Recurrent Network (DSTGCRN), an integration of Graph Convolutional Network (GCN) and Recurrent Neural Network (RNN) to capture the evolving intricacies of carbon emissions data across 31 China's provinces from 2019 to 2022. This proposed design captures temporal dependencies using the Gated Recurrent Unit (GRU) and multi-head attention and models dynamic provincial correlations through an adaptive adjacency matrix. It uses the adaptive graph convolutional recurrent network (AGCRN) as a backbone to understand spatial-temporal patterns.  
  
\*9: Justification of your recommendation  
 This paper proposes a novel method to forecast carbon emissions, one of the leading contributors to global warming in the 21st century. Adopting AGCRN, which models multisource time series data, the authors refined its inherent limitations, mainly its static correlation. They effectively formulated the carbon emission prediction as a dynamic spatial-temporal time series prediction problem. Furthermore, the research's detailed analysis with visual representations of inter-provincial emissions dynamics, particularly the 3D graph, clearly explains how relationships evolve across different time steps. Several comprehensive experiments demonstrate that DSTGCRN significantly outperforms traditional and other spatial-temporal prediction models, highlighting the importance of the proposed methodology for accurate carbon emission prediction.  
  
\*10: Three strong points of this paper (please number each point)  
 1. The paper is well-written and presents the proposed algorithm clearly, making complex concepts understandable.  
2. The static correlation limitation of AGCRN has been well addressed by introducing dynamic embeddings in DSTGCRN. This approach effectively captures evolving inter-province carbon emission correlations over variable time steps, enhancing prediction accuracy.  
3. The ablation study effectively highlights the significant roles of dynamic embedding, Attention, and GRU in DSTGCRN, with the full model showcasing superior performance across metrics.  
  
\*11: Three weak points of this paper (please number each point)  
 1. The performance comparison would have been more effective if the paper included information about how the proposed method and baseline models vary in average runtime and memory cost.  
2. While the authors validated the DSTGCRN model on the Carbon Monitor dataset for China, it's unclear how well the model might adapt to datasets from a different target area.  
3. The paper discusses the integration of multiple modules, including GRU, multi-head attention, and AGCRN, along with applying feature engineering techniques to the datasets. However, the complexity of the model could pose challenges for its implementation in real-world applications or for other researchers to reproduce and validate the results without access to the source code.  
  
\*12: Is this submission among the best 10% of submissions that you reviewed for ICDM'23?  
 [\_] No  
 [X] Yes  
  
\*13: Are the datasets used in the study correctly identified and referenced?  
 [X] 3 Yes  
 [\_] 2 Partial  
 [\_] 1 No  
 [\_] 0 Not applicable  
  
\*14: If the authors use private data in the experiments, will they publish data for public access in the camera-ready version of the paper?  
 [\_] 3 Yes  
 [\_] 2 Partial  
 [\_] 1 No  
 [X] 0 Not applicable  
  
\*15: Are the competing methods used in the study correctly identified and referenced?  
 [X] 3 Yes  
 [\_] 2 Partial  
 [\_] 1 No  
 [\_] 0 Not applicable  
  
\*16: Will the authors publish their source code for public access in the camera-ready version of the paper?  
 [\_] 3 Yes  
 [\_] 2 Partial  
 [\_] 1 No  
 [X] 0 Not applicable  
  
\*17: Is the experimental design detailed enough to allow for reproducibility? (You can also include comments on reproducibility in the body of your review.)  
 [\_] 3 Yes  
 [X] 2 Partial  
 [\_] 1 No  
 [\_] 0 Not applicable  
  
\*18: If the paper is accepted, which format would you suggest?  
 [X] Regular Paper  
 [\_] Short Paper  
  
\*19: Detailed comments for the authors  
 The authors have clearly explained the motivation behind the research problem statement and backed up their proposed model's effectiveness with thorough experiments and results. It can be helpful to reproduce work if the source code is shared.