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The review report from reviewer #1:

*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?
[X] 6 (Very high)
[_] 3 (High)
[_] -2 (Marginal)
[_] -4 (Low)
[_] -6 (Very low)

*4: How is the presentation?
[X] 6 (Excellent)
[_] 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?
[X] 2 (High)
[_] 1 (Medium)
[_] 0 (Low)

*7: Overall recommendation
[X] 6: must accept (in top 25% of ICDM accepted papers)
[_] 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
 This paper addresses the urgent need of accurate carbon emission forecasting and thus proposes a dynamic spatial-temporal model for China provincial carbon emission prediction. The proposed model can formulate carbon emission forecasting as a spatial-temporal time-series prediction problem to analyze the interaction between provincial carbon emissions. The two features of this model include leveraging the dynamic correlation among provinces, and capturing the dependency of carbon emissions with natural factors. Exhaustive experimental analysis justifies the effectiveness of the proposed model and the importance of the spatial-temporal setup in carbon emission prediction.

*9: Justification of your recommendation
 This study proposes a spatial-temporal model based on dynamic adjacency graph convolution and recurrent networks in the background of carbon emission prediction for Chinese provinces. The proposed model demonstrates its ability to capture dynamic correlations among provinces and carbon emission dependencies within each province over time. In the empirical evaluation, the excellent performance of the proposed model is demonstrated by comparing with traditional statistical and machine learning models in predicting carbon emissions of China's provinces.

*10: Three strong points of this paper (please number each point)
 1. This paper shows a successful application of spatial-temporal time-series models on carbon emission prediction.
2. The proposed model has a unique ability of capturing natural factors in carbon emission prediction.
3. The proposed model surpasses all baseline models and all variants in performance and robustness.

*11: Three weak points of this paper (please number each point)
 1. Some policy-related factors could be considered in the proposed carbon emission prediction model.
2. It is recommended to provide more precise results in the unit of provinces when comparing with other existing models.
3. In addition to the traditional models, some recent models should be introduced for model validation.

*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
 [X] 1 No
 [_] 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.)
 [X] 3 Yes
 [_] 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
 1. For the prediction of carbon emissions, it is suggested to consider some policy influencing factors, e.g., environmental regulation, carbon mission efficiency, and cost investment.
2. Section II provides a detailed literature review of this paper. However, some brief summaries should be given to explain the motivations of this work comparing to existing studies.
3. Does this work construct an independent model for each province? If so, it is better to show the results in the unit of provinces when comparing with other existing models.
4. There are some minor issues and typos, for example:
1) Please provide line numbers and page numbers.
2) In line 5 of P2, “take the interaction between provinces into consideration” should be “take into consideration the interaction between provinces”.
3) In line 2 of P7, “[47, VAR]” should be “(VAR)[47]”
4) What does each line represent in Fig. 2?
5) Please use a better reference format to avoid too many coauthors, like [45], [46].

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)
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*7: Overall recommendation
 [_] 6: must accept (in top 25% of ICDM accepted papers)
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 [_] -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?
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[_] 2 Partial
[_] 1 No
[X] 0 Not applicable

*15: Are the competing methods used in the study correctly identified and referenced?
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*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.

The review report from reviewer #3:

*1: Is the paper relevant to ICDM?
[_] No
[X] Yes

*2: How innovative is the paper?
[_] 6 (Very innovative)
[_] 3 (Innovative)
[_] -2 (Marginally)
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*3: How would you rate the technical quality of the paper?
[_] 6 (Very high)
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[X] -2 (Marginal)
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*4: How is the presentation?
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[X] 3 (Good)
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[X] 2 (May be)
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[_] -6: must reject (unacceptable: too weak, incomplete, or wrong)

*8: Summary of the paper's main contribution and impact
The paper introduces a novel approach for accurate carbon emissions forecasting, addressing the limitations of traditional methods. The proposed Dynamic Spatial-Temporal Graph Convolutional Recurrent Network (DSTGCRN) combines graph convolutional network (GCN) and recurrent neural network (RNN) structures to effectively model spatial-temporal correlations. By formulating carbon emission prediction as a spatial-temporal time-series problem and incorporating dynamic correlations between locations (provinces) over different time steps, the DSTGCRN was shown to outperform other baseline models. The research highlights the significance of the spatial-temporal setup for carbon emissions prediction, which can significantly contribute to global emissions reduction goals.

*9: Justification of your recommendation

While the paper clearly states the motivation and challenges, it is somewhat incremental in terms of novelty in its methodology as it simply builds upon the Adaptive Graph Convolutional Recurrent Network (AGCRN) framework. The experimental evaluation is also insufficient as it considers only one dataset for assessment, which makes it unclear how generalizable are their results. Comparing simpler baseline methods (e.g., VA, SVR, MLP, FC-LSTM) may not be sufficient to demonstrate the advantages of their complex deep learning model. To draw robust conclusions, the proposed model should be compared against a more diverse set of baseline methods. The clarity of how the hyper-parameters is tuned remains unclear. The complexity of the proposed model, compounded by the involvement of numerous parameters and the discretization of node embeddings for each time step, also raises concerns about its practicality and potential overfitting issues, which the authors had raised in their
introduction.

*10: Three strong points of this paper (please number each point)
1. The paper demonstrates a commendable clarity in presenting its motivation and challenges, which revolves around the crucial necessity for accurate carbon emissions forecasting to support global emissions reduction goals.
2. By effectively capturing intricate correlations and interactions between China's provinces, including the dynamic correlations over different time steps, the DSTGCRN demonstrates its ability to account for natural factors' influence on carbon emissions, such as weather and seasonal variations.
3. Results show significant improvement over other baseline methods.

*11: Three weak points of this paper (please number each point)
1. Incremental Contribution: The paper's main weakness lies in its incremental nature concerning novelty. While it introduces the Dynamic Spatial-Temporal Graph Convolutional Recurrent Network (DSTGCRN), the model's core elements heavily rely on the Adaptive Graph Convolutional Recurrent Network (AGCRN) backbone, with limited advancements beyond it. This lack of substantial novelty weakens the paper's overall contribution.
2. Limited Experimental Evaluation: Another weakness is the paper's limited experimental evaluation. It only considers a single dataset, providing insufficient comparative analysis against diverse baseline methods. The choice of simplistic baseline methods further hinders a comprehensive assessment of the model's true potential and performance.
3. Complex Model and Parameterization: In the introduction, the authors motivated their approach by stating the susceptibility of existing neural network approaches to overfitting. Yet the proposed DSTGCRN model exhibits substantial complexity, raising concerns about its practicality and generalization ability. With a significant number of parameters involved, there is a risk of overfitting and computational burden. These issues are not sufficiently discussed in the paper. Additionally, the discretization of node embeddings for each time step may exacerbate these challenges, potentially undermining the model's real-world applicability.

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[X] No
[_] Yes

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[X] 3 Yes
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[_] 2 Partial
[X] 1 No
[_] 0 Not applicable

*18: If the paper is accepted, which format would you suggest?
[_] Regular Paper
[X] Short Paper

*19: Detailed comments for the authors
The authors should take note of several shortcomings, as outlined in the following details:
1. The primary weakness of the paper lies in its lack of significant novelty, particularly in terms of its incremental approach. Although the introduction of the Dynamic Spatial-Temporal Graph Convolutional Recurrent Network (DSTGCRN) is notable, it's evident that the foundational elements of the model heavily rely on the Adaptive Graph Convolutional Recurrent Network (AGCRN) backbone. This reliance on existing architecture limits the extent of innovation presented in the paper, thereby diminishing its overall contribution to the field.
2. Another notable drawback pertains to the scope of the experimental evaluation conducted. The evaluation of the proposed DSTGCRN is confined to a single dataset, which substantially curtails the robustness of the findings. A more comprehensive analysis involving a diverse range of baseline methods is imperative to establish the comparative performance and potential advantages of the DSTGCRN model. Moreover, the selection of simplistic baseline methods further restricts the depth of the assessment, hindering a thorough understanding of the model's capabilities.
3. The complexity introduced by the DSTGCRN model raises practical concerns regarding its viability and generalizability. The substantial number of parameters utilized in the model design introduces a potential risk of overfitting and adds to the computational burden. Additionally, the discretization of node embeddings for each time step introduces another layer of complexity that could impede the model's applicability in real-world scenarios.
4. There are some typos: “Albation” in multiple places of Section V. F., “Sepcific” Table III, “etcs” in problem statement etc.