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COMMENTARY

Spatial-temporal large models: A super hub linking multiple scientific areas with artificial intelligence

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Intelligent spatial-temporal data analysis, leveraging data such as multivariate time series and geographic information, provides researchers with powerful tools to uncover multiscale patterns and enhance decision-making processes. As artificial intelligence advances, intelligent spatial-temporal algorithms have found extensive applications across various disciplines, such as geosciences, biology, and public health.[1] Compared to traditional methods, these algorithms are data driven, making them well suited for addressing the complexities of modeling real-world systems. However, their reliance on substantial domain-specific expertise limits their broader applicability. Recently, significant advancements have been made in spatial-temporal large models. Trained on large-scale data, these models exhibit a vast parameter scale, superior generalization capabilities, and multitasking advantages over previous methods. Their high versatility and scalability position them as promising super hubs for multidisciplinary research, integrating knowledge, intelligent algorithms, and research communities from different fields. Nevertheless, achieving this vision will require overcoming numerous critical challenges, offering an expansive and profound space for future exploration.

CHALLENGES OF APPLYING INTELLIGENT SPATIAL-TEMPORAL DATA ANALYSIS IN SCIENTIFIC RESEARCH

In this section, we highlight the challenges of applying intelligent spatial-temporal data analysis across various scientific fields (Figure 1, left).

Abstracting data modalities from complex disciplinary knowledge and formulating tasks require research teams to possess expertise in both artificial

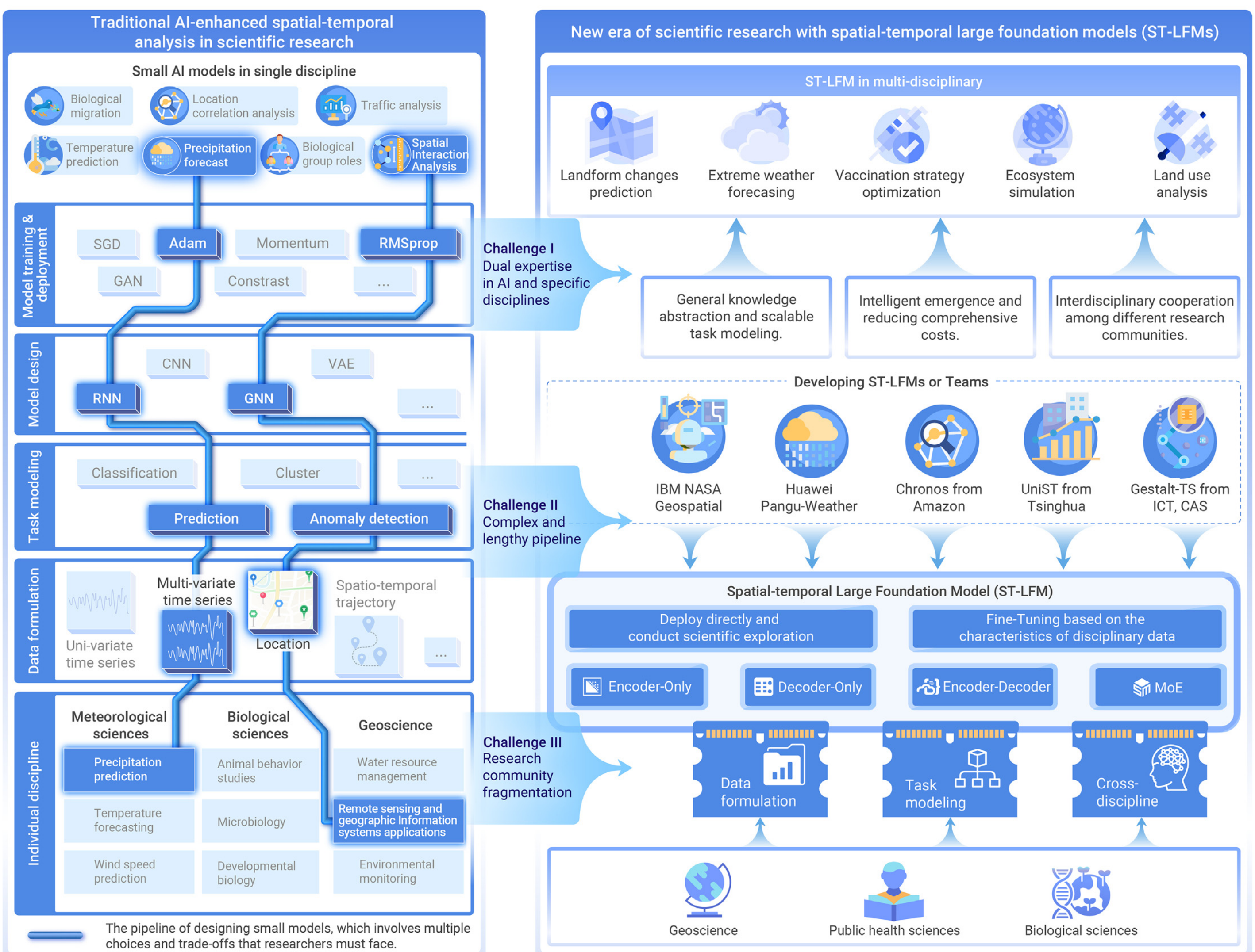

Figure 1. Spatial-temporal large models: A super hub linking multiple scientific areas with artificial intelligence Left: challenges of traditional artificial intelligence-enhanced spatial-temporal analysis in individual disciplines, including the need for dual expertise, complex pipelines, and community fragmentation. Right: how spatial-temporal large models address these challenges, ushering in a new era where artificial intelligence acts as a central hub connecting various scientific domains.

intelligence and specific disciplines. Unlike domains such as computer vision, which benefit from well-established frameworks, spatial-temporal data analysis lacks a similarly robust foundational network. The design of classic spatial-temporal data analysis algorithms relies heavily on domain-specific knowledge, and is generally effective only within specific domains. Furthermore, disciplinary knowledge is often highly theoretical, whereas intelligent analysis algorithms are driven primarily by experimental approaches. As a result, researchers skilled in both areas are exceedingly rare, posing a significant barrier to the integration and development of intelligent spatial-temporal analysis technologies in scientific research.

Integrating intelligent spatial-temporal data analysis into scientific research is a complex and time-consuming process. This pipeline involves multiple critical steps: data collection and processing, model design, training and optimization, and, ultimately, model deployment and inference. For instance, designing an effective model structure requires researchers to select appropriate backbones based on the characteristics of the data. Advanced models tend to perform well when the data exhibit stable periodicity. However, when there is significant drift of data distribution, simpler models, such as Multi-Layer Perceptrons, may demonstrate better adaptability.[2] The two pipelines shown on the left in Figure 1 illustrate the multiple choices and trade-offs researchers must face during the process of designing small models. Even for researchers with dual expertise, managing these intricate stages remains a considerable challenge.

Significant fragmentation exists within the scientific communities that use intelligent spatial-temporal analysis technologies. Different groups often rely on distinct tools and methodologies, hindering broader innovation. For instance, fields such as meteorology, geosciences, and ecology, despite their shared reliance on spatial-temporal data analysis, tend to develop independently and adopt unique algorithmic approaches. This lack of integration not only limits interdisciplinary collaboration and knowledge exchange but also constrains the broader application and refinement of analytical techniques. Additionally, the imbalance of data resources across disciplines hampers model design and evaluation, particularly in data-scarce areas.

TRANSFORMATIVE POTENTIAL OF LARGE MODELS IN SPATIAL-TEMPORAL DATA ANALYSIS

While there is a growing demand for spatial-temporal analysis technology in scientific research, significant challenges have impeded its development. Fortunately, the rapid advancements in spatial-temporal large models present promising opportunities to overcome these barriers. Examples include Amazon's Chronos time series forecasting model, IBM and NASA's geospatial foundation model, and Huawei's Pangu weather model.[3] Given their generality, scalability, and potential emergent capabilities, spatial-temporal large models are positioned to become super hubs in interdisciplinary research (Figure 1, right).

The limitations of generality and scalability in traditional spatial-temporal data analysis for knowledge abstraction and task modeling need to be addressed. Traditional neural networks are typically designed for specific problems, which limits their generality and scalability. In contrast, spatial-temporal large models eliminate the multiple choices and trade-offs associated with the design of classic spatial-temporal models. With their extensive capacity and capability, supported by a well-developed research ecosystem, they are well equipped to handle diverse tasks. Through pre-training on large-scale datasets[4], spatial-temporal large models achieve universal knowledge representation and multi-tasking capabilities, embodying a general approach to knowledge abstraction and task modeling.

Intelligent emergent capabilities need to be leveraged, and comprehensive costs need to be reduced significantly in scientific research. The computational "guess and verify" model of neural networks aligns closely with the scientific "hypothesis and verification" method. By pre-training on large-scale data, spatial-temporal large models are poised to evolve into versatile "guess machines" that detect subtle data variations and uncover patterns often elusive with traditional methods. Furthermore, spatial-temporal large models can be fine tuned for various tasks and datasets, streamlining model adjustment and deployment processes. This adaptability has the potential to drastically shorten the transition from concept validation to practical application.

Spatial-temporal large models are poised to significantly advance interdisciplinary collaboration by breaking through existing barriers within research communities. As versatile analytical tools, these models reduce dependence on specialized tools and methodologies, fostering greater standardization. For example, data from fields such as energy, meteorology, and transportation can be converted into more uniform formats, such as multivariate time series data or gridded sequence data. This integration not only enhances the model's generalization capabilities by incorporating diverse data modalities but also helps address the issue of imbalanced data resources. Furthermore, spatial-temporal large models provide a common platform that aids researchers from diverse fields in accelerating consensus formation and technological iteration, thereby enhancing collaborative research and knowledge sharing.

CHALLENGES AND FUTURE DIRECTIONS OF SPATIAL-TEMPORAL LARGE MODELS

Although spatial-temporal large models offer broad applications across interdisciplinary fields, their development still faces significant challenges.

Key obstacles in practical applications include issues such as inference speed, memory usage, and data privacy. To enhance inference performance, further optimization of technologies such as Deep Speed and Faster Transformer is essential. Additionally, adopting solutions such as homomorphic encryption and federated learning can help balance computational efficiency with ethical standards in data privacy.

The universality of large models also requires further enhancement to achieve end-to-end integration across all tasks. While current spatial-temporal large models have achieved a level of unity, fragmentation persists when handling different types of data. For instance, non-Euclidean spatial-temporal data (such as multivariate time series prediction) is suitable for time series analysis large models, while Euclidean spatial-temporal data (typically gridded sequence data) fits geographical spatial models. Future research should focus on establishing a unified paradigm to integrate various types of spatial-temporal data.

Moreover, while spatial-temporal large models provide researchers with ready-to-use analytical tools, domain-specific knowledge remains crucial, particularly in scenarios requiring complex features or high interpretability. Enhancing the scalability of large models and effectively incorporating domain-specific knowledge to improve prediction accuracy and interpretability is a critical direction for future work. This approach not only increases the practicality of these models but also unlocks greater potential in fields such as meteorology and urban science.[5]

CONCLUSION

Intelligent spatial-temporal data analysis has significantly expanded the scope and depth of scientific research, playing a vital role in disciplines such as geoscience, biology, and public health. As a highly promising technology, spatial-temporal large models are actively being developed by hundreds of research teams worldwide, driving continuous innovation and rapid iteration. Given their advantages in generality and scalability, emergent capabilities, comprehensive cost reduction, and fostering of interdisciplinary integration and innovation, these models are poised to become super hubs connecting multidisciplinary knowledge, intelligent algorithms, and research communities. We anticipate that this technology will mature rapidly and achieve broader applications across diverse fields.

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DECLARATION OF INTERESTS

The authors declare no competing interests.