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EDITORIAL

Advances in spatial econometrics and geostatistics: methods, theory, and applications

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Statistical analysis of spatial and spatio-temporal data draws on several methodological traditions that historically have developed in parallel. Geostatistics offers continuous-space modelling frameworks grounded in structural assumptions on covariance functions and variograms. Spatial econometrics, in contrast, is tailored to discrete areal data, exploiting adjacency and spatial weight matrices within autoregressive formulations. A third major stream is the study of marked and unmarked spatial point processes, in which the point locations themselves are the key random objects, and dependence emerges through local interaction, inhibition, or clustering among points.

Although these traditions differ in formulation and terminology, they share a common goal: to capture spatial structure, spatial dependence, and spatial heterogeneity in a principled manner. Yet, they have often progressed with surprisingly limited interaction, driven by distinct communities, software cultures, and application areas, while bringing the different traditions together and broadening horizons will provide a host of opportunities for method development. Geostatistics offers a rich set of covariance constructions, such as non-stationary, anisotropic, or multi-resolution covariance functions, that can inform more flexible representations of spatial dependence than are currently considered in areal and panel-data settings, where weight matrices alone are often too rigid to capture spatial heterogeneity. Spatial econometrics, in turn, provides modelling strategies for high-dimensional panels that explicitly represent spatial feedback and spillovers, well-developed treatments of endogeneity, and marginal-effect decompositions directly applicable to modern geostatistical sensor networks with repeated measurements over time. Point process methodology provides methods for modelling local interactions, clustering, and inhibition, which can be applied to settings where spatial dependence is not purely covariance-driven, e.g. in latent-field models with local structure, agent-based systems, or settings with sparse spatial events embedded in continuous fields. This Special Issue on *Advances in Spatial Econometrics and Geostatistics* deliberately seeks

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to bring these perspectives closer together. It collects contributions that span theoretical work, methodological innovation, and empirical applications, reflecting both the methodological and applied sections of *AStA Advances in Statistical Analysis*.

The first two contributions examine spatial spillovers in socio-economic and public-health contexts. In their study on renewable-energy expansion and employment, Billé and Rogna (2024) use a dynamic spatial panel-data model covering 59 countries over nearly two decades. By carefully considering multiple spatial weight matrices, incorporating spatial error dependence and dynamic feedback, and calculating short- and long-run marginal effects, they demonstrate that renewable-energy production exerts a positive and statistically meaningful employment impact, with spillover magnitudes that vary by region and weighting specification. Mare et al. (2024) analyse COVID-19 vaccination uptake across Romanian municipalities. Their combination of spatial clustering diagnostics with a Spatial Durbin Error Model reveals pronounced spatial heterogeneity shaped by poverty, labour-market conditions, cultural attitudes, infection rates, and the urban–peri-urban structure. Although examining entirely different domains, both papers highlight the importance of spatial diffusion mechanisms in shaping social and behavioural outcomes.

This issue also discusses advances in spatial panel methodology. Doğan et al. (2024) propose an integrated modified harmonic-mean estimator to approximate marginal likelihoods in spatial panel models with fixed effects. By integrating out high-dimensional fixed effects analytically, their approach stabilises model comparison for both nested and non-nested alternatives, demonstrating robust performance in simulations and in an application to US house-price dynamics. Complementing this focus, Otto et al. (2025) study the estimation of a dynamic spatio-temporal ARCH model designed to capture volatility clustering that propagates both temporally and across a spatial network. By comparing two variants of quasi-maximum likelihood estimators with a generalised methods-of-moments estimator, they map out the theoretical conditions under which these estimators perform well and provide Monte Carlo evidence on their finite-sample behaviour. Their contribution is particularly relevant as volatility modelling increasingly extends to spatial domains such as financial networks, environmental monitoring, or sensor-driven systems. Together, these papers illustrate how spatial panel analysis continues to evolve, balancing statistical rigour with computational feasibility in increasingly high-dimensional settings.

A separate strand of contributions focuses on spatial clustering and latent-structure modelling, an area in which ideas from machine learning and multivariate analysis merge naturally with spatial statistics. Cerqueti et al. (2025) introduce a fuzzy group fixed-effects approach that incorporates spatial regularisation, enabling regionally coherent cluster assignments in panel regression models. Their iterative algorithm, which alternates between estimating cluster-specific fixed effects and spatially informed clustering of residuals, reveals interpretable regional groupings in applications to US cigarette consumption and Italian non-life insurance demand, uncovering meaningful East–West and North–South structures. A related but distinct contribution is provided by D'Urso et al. (2025), who extend fuzzy C-modes clustering for categorical spatial data by adding spatial regularisation and a noise cluster. Their approach is particularly robust in the presence of local irregularities and outliers, as shown in both simulations and analyses of sustainable urban mobility indicators across Italian provincial capitals. These papers illustrate the growing importance of uncertainty-aware, spatially coherent clustering methods for high-dimensional, heterogeneous spatial data.

A different perspective on latent spatial structure is offered by Muehlmann et al. (2025), who extend spatial blind source separation (SBSS) through anisotropic local covariance matrices. Whereas classical SBSS relies on isotropic local covariance functions, their approach allows directional effects to influence the decomposition, thereby improving the separation of latent spatial fields in settings with anisotropy. Their simulations and precipitation case study make a strong case for incorporating anisotropy directly into latent-field models, thereby bridging geostatistical structural modelling and multivariate source separation.

The breadth of these contributions also highlights several emerging directions for the future of spatial and spatio-temporal statistics. Spatial regression models will increasingly need to move beyond the mean and incorporate dependence in higher-order moments, such as variances, tail behaviour, or asymmetries. As data become more complex, high-dimensional, and object-valued—ranging from functional curves, shapes, matrices/tensors to images, text, and compositional observations—classical spatial models become insufficient. These data types often exhibit spatial or spatio-temporal structure that neither traditional covariance-based geostatistical models nor simple autoregressive specifications can capture, calling for new statistical modelling approaches that balance interpretability and scalability.

The increasing availability of data on fixed and dynamically evolving networks further blurs the boundaries between spatial and network models. Many modern systems—from financial markets and transportation to social interactions and mobility—combine spatial proximity with relational connections, requiring models that unify spatial, temporal, and network-based dependence. At the same time, machine learning, deep learning, and AI-based techniques offer unprecedented flexibility for modelling nonlinear interactions, yet require integration with interpretable spatial structures and careful statistical grounding. Hybrid models that combine neural representations with spatial constraints or covariances are a promising path forward, but ensuring their identifiability, stability, and uncertainty quantification poses substantial theoretical challenges.

The methodological developments anticipated in the coming years will therefore require a tight interplay between theory, methodology, computation, and application-domain knowledge. High-dimensional spatio-temporal models must be supported by rigorous statistical analysis, not only to ensure reliability and robustness, but also to enable principled model validation, cross-validation strategies tailored to spatial dependence, and meaningful uncertainty quantification. The contributions in this Special Issue emphasise that progress in spatial statistics increasingly depends on bridging geostatistics, spatial econometrics, and modern data science. By fostering exchange between these communities, this collection aims to encourage the development of new methods that draw upon the strengths of each, and to support advances in statistical modelling for the increasingly complex spatial and spatio-temporal data encountered across scientific disciplines.

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