FastNSA: A High-Performance QGIS Plugin for Network Spatial Analytics

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Abstract

Network-constrained spatial analytics is widely used in transportation planning, urban analytics, and public safety applications. However, existing tools often focus on a limited subset of network analytics tasks, require substantial programming effort or face scalability challenges on large datasets. We present FastNSA, a high-performance QGIS plugin for end-to-end network spatial analytics. FastNSA integrates network preprocessing, analytical computation, and result visualization within a unified workflow, enabling users to perform network K-function analysis, network kernel density visualization, and spatiotemporal network K-function analysis directly in QGIS. By leveraging efficient underlying algorithms and data structures, FastNSA supports scalable analysis on large road networks and spatial event datasets. This demonstration showcases the system architecture, supported analytics, and interactive workflow of FastNSA through representative real-world use cases.

CCS Concepts

• **Information systems → Geographic information systems**.

Keywords

network spatial analytics, GIS, fast plugin

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1 Introduction

Network spatial analytics has become an indispensable tool in transportation planning [13], urban computing [12], and crime analysis [14]. A wide range of network-constrained methods have been proposed for hotspot detection, density estimation, clustering analysis, and point pattern analysis. These methods help domain experts identify spatial patterns and better understand geographical phenomena on road networks. However, the rapid growth of spatial data collection has produced datasets with millions of events and large road networks, creating significant challenges for scalable network spatial analytics.

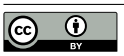
Although several software packages and systems have been developed for network spatial analytics, they still face several practical limitations. First, existing systems typically support only a limited set of analytics tasks. For example, PyNKDV [10] focuses exclusively on network kernel density visualization, requiring users to switch to additional tools for other analyses. Second, systems such as spNetwork [6] are primarily accessed through programming libraries, creating a barrier for GIS practitioners without strong programming backgrounds. Third, scalability remains a major challenge. Although SANET [4] and spNetwork [6] provide representative network analytics functions, their computational efficiency is limited when processing large road networks and millions of spatial events. As summarized in Table 1, no existing system simultaneously provides a graphical interface, multiple analytics modules, and scalable support for large-scale datasets.

Table 1: Comparison of existing network spatial analytics systems.

System	GUI	Multiple Analytics	Scalability
SANET	Yes	Yes	Low
spNetwork	No	Yes	Low
PyNKDV	No	No	High
FastNSA	Yes	Yes	High

To address these limitations, we present FastNSA [1], a high-performance QGIS plugin that provides an end-to-end workflow for scalable network spatial analytics. FastNSA integrates multiple analytics modules, including network K-function analysis [8], network kernel density visualization (NKDV) [7], and spatiotemporal network K-function analysis [9], within a unified GIS environment. By combining specialized computational methods with an intuitive graphical interface, FastNSA enables users to prepare network-aware data, configure analyses, and visualize task-specific results directly within QGIS. This combination of broad functionality, scalable computation, and ease of use lowers the barrier to advanced network spatial analytics on large datasets.

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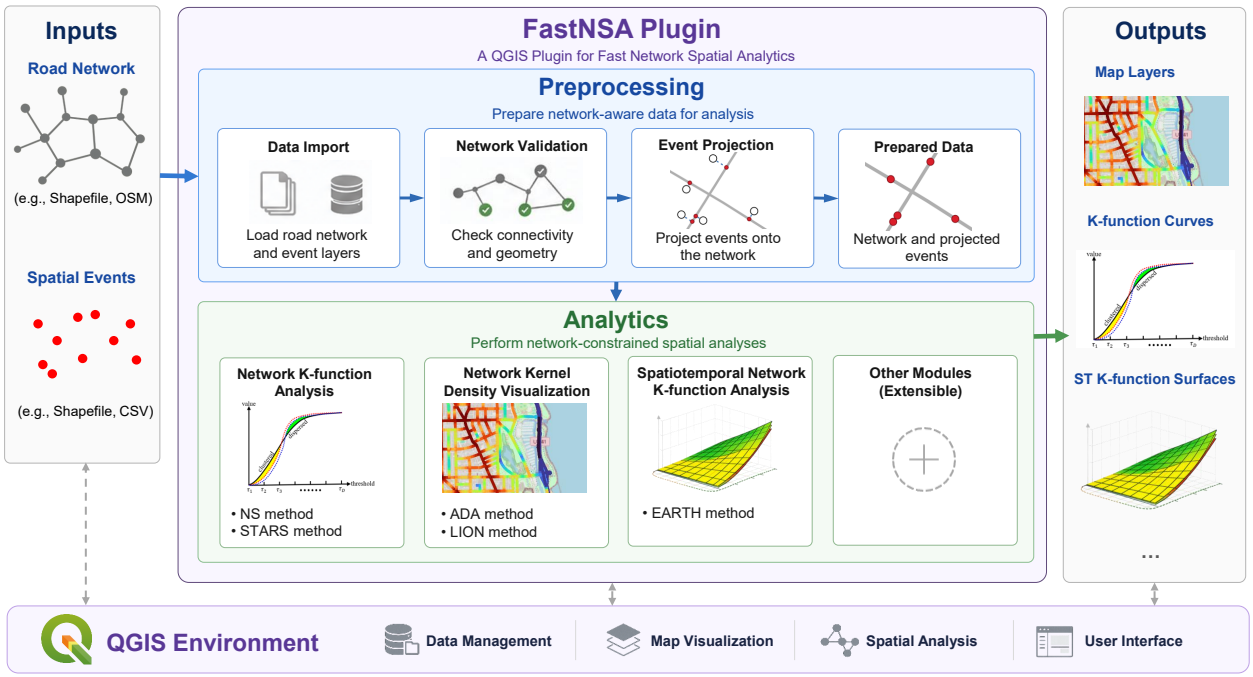


Figure 1: Architecture and workflow of FastNSA.

In summary, FastNSA contributes (1) a unified QGIS-based platform supporting multiple network spatial analytics tasks, (2) scalable computational methods for large-scale network analysis, and (3) an interactive interface for end-to-end analysis and result exploration.

The remainder of this paper is organized as follows. Section 2 presents the architecture and workflow of FastNSA, while Section 3 describes the demonstration plan.

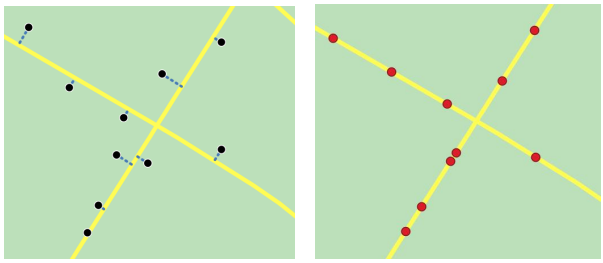
2 System Overview

2.1 Architecture Overview

Figure 1 illustrates the overall architecture and workflow of FastNSA. Starting from a user-provided road network and a set of spatial events, FastNSA first performs a series of data preparation procedures, including network validation and event projection, to generate network-aware input data for subsequent analyses. The prepared data are then processed by the built-in analytics modules, which currently support network K-function analysis, network kernel density visualization (NKDV), and spatiotemporal network K-function analysis, while allowing additional methods to be incorporated through an extensible design. The analysis results are returned to the QGIS platform as task-specific outputs, including network-aware map layers, K-function curves, spatiotemporal K-function surfaces, and statistical summaries for interactive visualization and interpretation. By integrating efficient data preparation and network spatial analytics within a unified QGIS plugin, FastNSA enables end-to-end network-constrained spatial analysis from raw inputs to visualized results.

2.2 Data Preparation

The first step of FastNSA is to prepare user-provided road networks and event datasets for subsequent analyses. As illustrated in Figure 2, spatial events are projected onto the underlying road network to produce a reusable network-aware representation. Since point-to-network projection is required by many network-constrained analyses, FastNSA performs this operation only once and reuses the projected events throughout the workflow. To efficiently process large-scale datasets, FastNSA incorporates our previously proposed point-to-line nearest neighbor search (PLNNS) algorithm [16].



(a) Raw spatial events (b) Projected network events.

Figure 2: Point-to-network projection in the preprocessing stage.

2.3 Supported Analytics

FastNSA supports multiple network spatial analytics modules through a unified QGIS interface. As summarized in Table 2, the current release includes network K-function analysis, network kernel density visualization, and spatiotemporal network K-function analysis.

Table 2: Network spatial analytics supported by FastNSA.

Analysis	Methods
Network K-function analysis	NS [8] / STARS [15]
Network kernel density visualization	ADA [7] / LION [11]
Spatiotemporal network K-function analysis	EARTH [9]

Network K-function analysis. Network K-function analysis characterizes second-order spatial point patterns on road networks by measuring the spatial interaction between events across multiple network-distance scales. As illustrated in Figure 3, FastNSA automatically computes the observed K-function and compares it with the complete spatial randomness reference, allowing users to identify clustering or dispersion patterns. FastNSA supports both the exact Neighbor Sharing (NS) method [8] and STARS [15], a scalable sampling- and threshold-sharing-based solution for large-scale analyses with controllable approximation error.

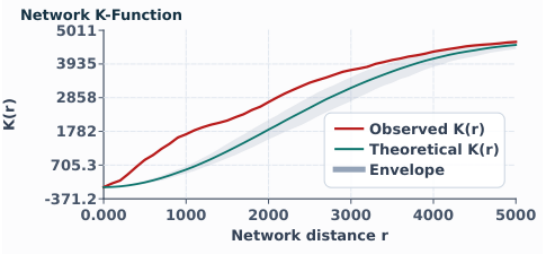


Figure 3: Network K-function analysis of a road network and spatial events in FastNSA.

Network kernel density visualization. Network kernel density visualization (NKDV) estimates the spatial intensity of events along road networks, enabling users to identify hotspot and coldspot regions. Figure 4 shows an example density map generated by FastNSA, where event intensity is visualized directly on the underlying road network. FastNSA automatically selects between ADA [7] and LION [11] according to the relative sizes of the event set and visualization domain, providing efficient density visualization under different data scales and output resolutions.

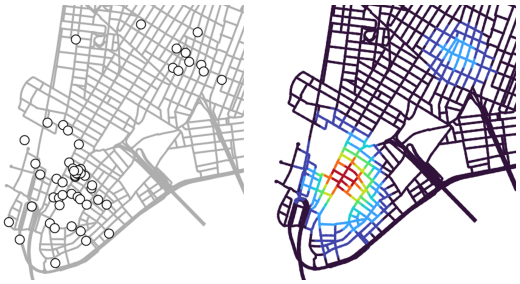


Figure 4: Network kernel density visualization of a road network and spatial events in FastNSA.

Spatiotemporal network K-function analysis. FastNSA also supports spatiotemporal network K-function analysis for exploring event interactions over road-network space and time. Powered by our EARTH method [9], it efficiently analyzes large spatiotemporal datasets and visualizes the resulting K-function surfaces with statistical significance envelopes for identifying clustering and dispersion patterns (Figure 5).

Unified Analytics Interface. Overall, FastNSA integrates these analyses into a unified QGIS interface, providing a consistent workflow for configuring parameters, executing analyses, and exploring task-specific results. Although different analytics tasks are powered by specialized computational methods, users interact with them through the same interface, making FastNSA both easy to use and readily extensible for future network spatial analytics.

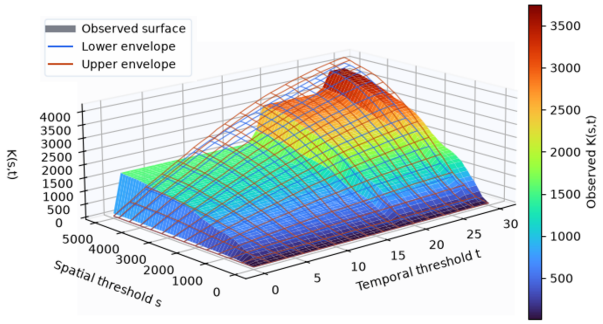


Figure 5: Spatiotemporal K-function analysis of a road network and spatiotemporal events in FastNSA.

2.4 User Interface

Figure 6 illustrates the unified user interface of FastNSA. To simplify network spatial analytics within QGIS, FastNSA organizes the complete workflow into a series of task-oriented panels. Users first specify the road network and event datasets in the *Data Setup* panel (Figure 6(a)). The *Data Preprocess* panel (Figure 6(b)) prepares reusable network-aware inputs, including point-to-network projection, for subsequent analyses. Users then select a network spatial analytics task and configure task-specific parameters through the *Analysis Setup* panel (Figure 6(c)). The generated results can be configured in the *Output Setup* panel (Figure 6(d)) before the analysis is executed via a single click (Figure 6(e)).

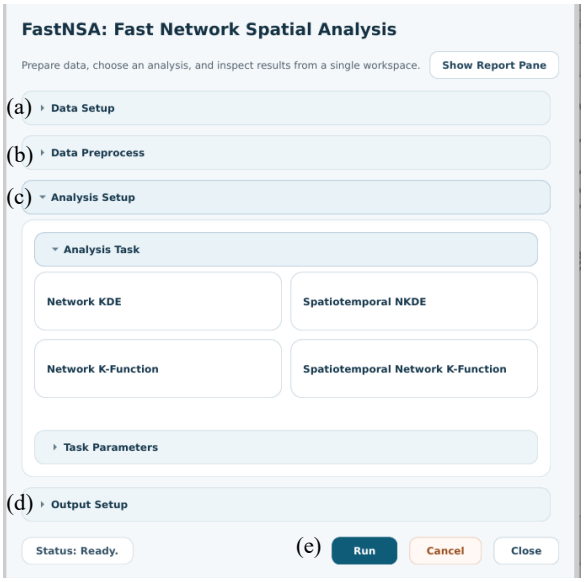
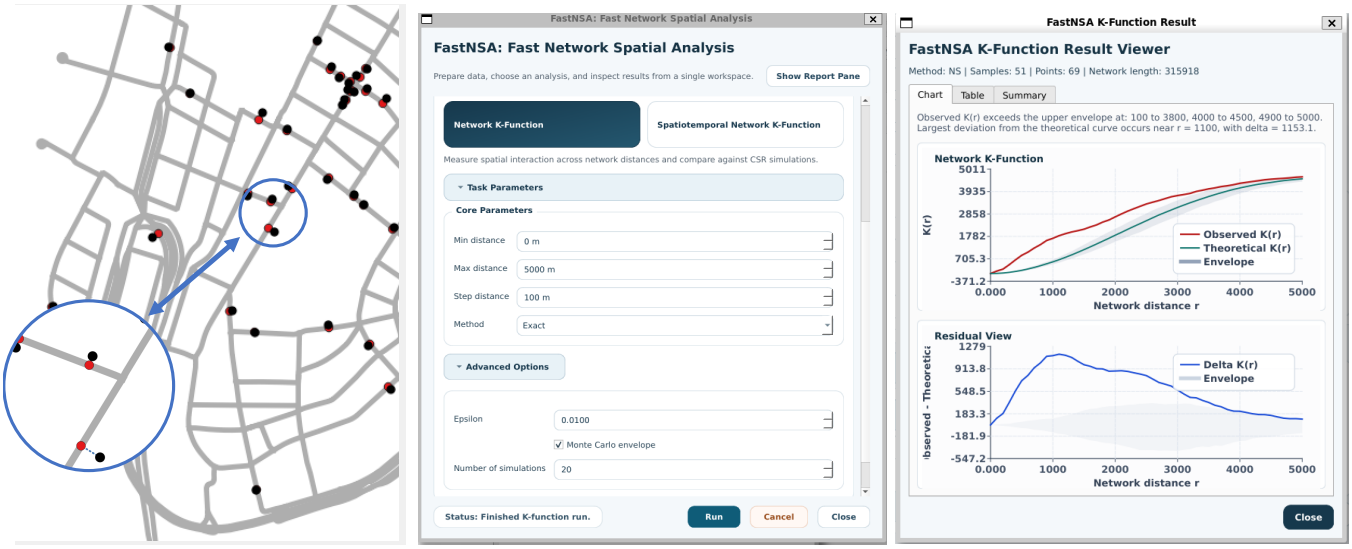


Figure 6: User interface of FastNSA.

3 Demonstration Plan

We demonstrate FastNSA through the end-to-end workflow illustrated in Figure 7. Participants prepare network-aware data, configure a supported analytics task, and inspect the generated results within QGIS. The demonstration highlights FastNSA's efficient integration of rapid preprocessing and high-performance network spatial analytics. To demonstrate its efficiency and versatility, we



(a) Point Projection (b) Analysis Configuration (c) Analytical Result

Figure 7: Demonstration workflow of FastNSA. (a) Spatial events are projected onto the road network. (b) Users configure and execute a network spatial analytics task. (c) FastNSA visualizes analytical results directly within QGIS.

use three large-scale real-world datasets: Seattle crime events [5], Maryland traffic violations [2], and San Francisco 911 calls [3].

Data Preparation. As shown in Figure 7(a), participants first load a road network and a spatial event dataset into QGIS. FastNSA validates the selected network and projects events onto their corresponding network locations, producing reusable network-aware inputs for subsequent analyses. Participants can inspect the projected events together with the original network layer before proceeding to analysis.

Analysis Configuration. Figure 7(b) presents the unified analysis interface of FastNSA. Participants select one of the supported network spatial analytics modules, configure task-specific parameters, and execute the analysis through a consistent graphical interface. Depending on the selected task, users can adjust analysis parameters, statistical settings, and computational options without writing scripts or switching to external software. This unified workflow simplifies the execution of diverse network spatial analytics within a single QGIS plugin.

Representative Results. Figure 7(c) presents representative outputs generated by FastNSA. Depending on the selected analysis, the plugin automatically produces network K-function curves, network density maps, or spatiotemporal analytical surfaces within the QGIS environment. These outputs are directly integrated as native QGIS layers or statistical visualizations, allowing users to interpret network spatial patterns without exporting data to external software.

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