Nitrogen Cycling

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Review

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# Watershed non-point source nitrogen apportionment: from qualitative to intelligence frameworks

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## Abstract

Excessive nitrogen (N) loading threatens the security and functioning of global aquatic ecosystems, necessitating the identification of watershed N sources for pollution control. Despite advances in watershed N source apportionment, the current methods remain fragmented and scale-dependent, often failing to capture heterogeneity and the underlying mechanisms, which limits their uptake in watershed management. Here, we synthesize the strengths and limitations of representative watershed N source apportionment methods and, for the first time, categorize them into four types: (1) qualitative methods based on chemical or microbial tracers; (2) quantitative methods using statistical models and isotope Bayesian approaches; (3) spatiotemporally refined approaches with process-based models and numerical analysis; and (4) intelligent technologies integrating remote sensing, unmanned aerial vehicles, and sensors. Studies indicate that watershed N source apportionment has shifted from traditional qualitative to quantitative frameworks. However, challenges remain in improving the spatiotemporal resolution, elucidating complex mechanisms, and integrating artificial intelligence (AI) technologies. We advocate integrating space–air–ground monitoring, multiscale tracing methods, and intelligent decision-support systems that integrate real-time data acquisition, AI-driven analysis, and scenario simulation, to advance the spatiotemporal resolution and understanding of the underlying mechanisms for watershed N source apportionment. By establishing an integrated framework for watershed N source apportionment, this review provides a scientific foundation for linking source identification to targeted mitigation strategies and watershed nutrient management.

**Keywords:** Non-point source pollution, Nitrogen source apportionment, Stable isotopes, Spatiotemporally refinement, Intelligent technologies

## Highlights

- Watershed N source apportionment methods are categorized into four types.
- Strengths and limitations of existing apportionment methods are synthesized.
- A roadmap toward intelligent N source apportionment is proposed.

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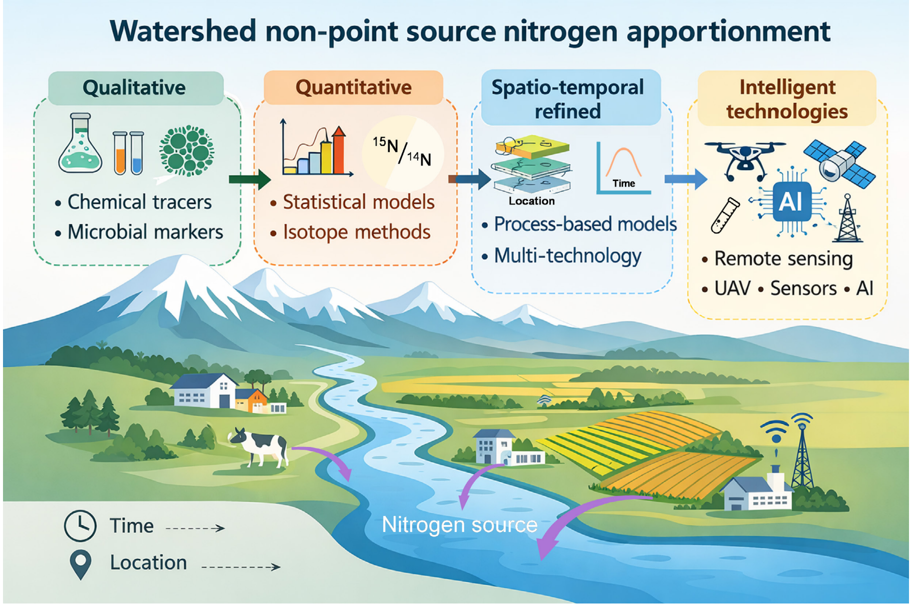
## Graphical abstract




# Introduction

Nitrogen (N) is a fundamental element of living organisms and plays a critical role in sustaining Earth's ecosystems. In natural environments, N cycles among soils, water bodies, the atmosphere, and biota in the forms of ammonium, nitrate, and organic N, thereby sustaining the balance of the global N cycle[1,2]. Since the Industrial Revolution, however, the extensive application of synthetic N fertilizers to support growing food demands has profoundly altered this cycle[1]. Currently, over 100 Tg of fertilizer N are produced and applied annually worldwide, far exceeding inputs from natural biological N fixation[3]. Although these inputs have greatly enhanced global food production, large amounts of N not taken up by crops are released into the environment, leading to a series of ecological and environmental problems, including acidification, loss of biodiversity, and water eutrophication[4−6].

Agricultural non-point source (NPS) pollution is the major contributor to rising N loads in aquatic ecosystems worldwide[7−9], from the Gulf of Mexico to Taihu Lake and the Baltic Sea[10−12]. NPS is defined as dissolved or particulate N transported into water bodies via runoff and subsurface flow from multiple sources, including fertilizer application, livestock waste, rural domestic sewage, and atmospheric deposition. These N sources are characterized by dispersion, strong spatiotemporal variability, diverse hydrological pathways, and delayed hydrological responses[12]. Moreover, mixing and biogeochemical transformation during N transport pathways further complicate the identification and quantification of N sources[13−15]. Given these challenges, developing a reliable framework for watershed N source apportionment is crucial for understanding the mechanisms, identifying critical source areas, and informing effective NPS control strategies.

Although N exists in watersheds in various forms, including ammonium ($NH_4^+$), nitrate ($NO_3^-$), and dissolved organic N (DON), research specifically identifying the sources of $NH_4^+$ and DON remains limited. For instance, recent approaches include using $^{15}N$–$NH_4^+$ to trace $NH_4^+$ in marine, estuarine, and freshwater systems, and applying excitation–emission matrix and fluorescence spectroscopy to characterize the sources of DON in Poyang Lake[16]. Nitrate, however, is the primary form of N loss from NPS pollution, because synthetic fertilizers and livestock manure are rapidly converted to $NO_3^-$ through nitrification[17]. In addition, $NH_4^+$ tends to adsorb onto soil colloids and is resistant to migration, whereas the mineralization of DON requires a certain turnover time[17]. Therefore, this study concentrates on the source apportionment of $NO_3^-$ within the watershed to support the management of NPS pollution control.

Advances have been achieved in N source apportionment (referring primarily to $NO_3^-$; the same applies below) methods in recent years, supported by technologies spanning isotopic techniques, molecular biological tracers, process-based models, and remote sensing[18−20]. Traditional watershed N source apportionment methods have shifted from qualitative to quantitative, spatiotemporally explicit, and intelligent frameworks, enabling the characterization of complex N dynamics in heterogeneous landscapes[21,22]. However, no single method provides universal applicability. The various N source apportionment approaches differ in terms of their analytical precision, spatiotemporal applicability, and data requirements. Consequently, each method is optimally suited to specific environmental susceptibilities and management targets[23−25]. These differences highlight the need for a more comprehensive understanding of the methodological foundations and characteristics of different approaches. To address these challenges, we synthesize the core principles, representative techniques, strengths, limitations, and recent advances of watershed N source apportionment, and, for the first time, classify these approaches into four major categories: (1) qualitative approaches, (2) quantitative approaches, (3) spatiotemporally refined approaches, and (4) intelligent technologies (Fig. 1 and Table 1). Finally, we identify critical gaps and priority research essential for developing precision and multiscale source apportionment systems that can effectively guide targeted watershed N management.

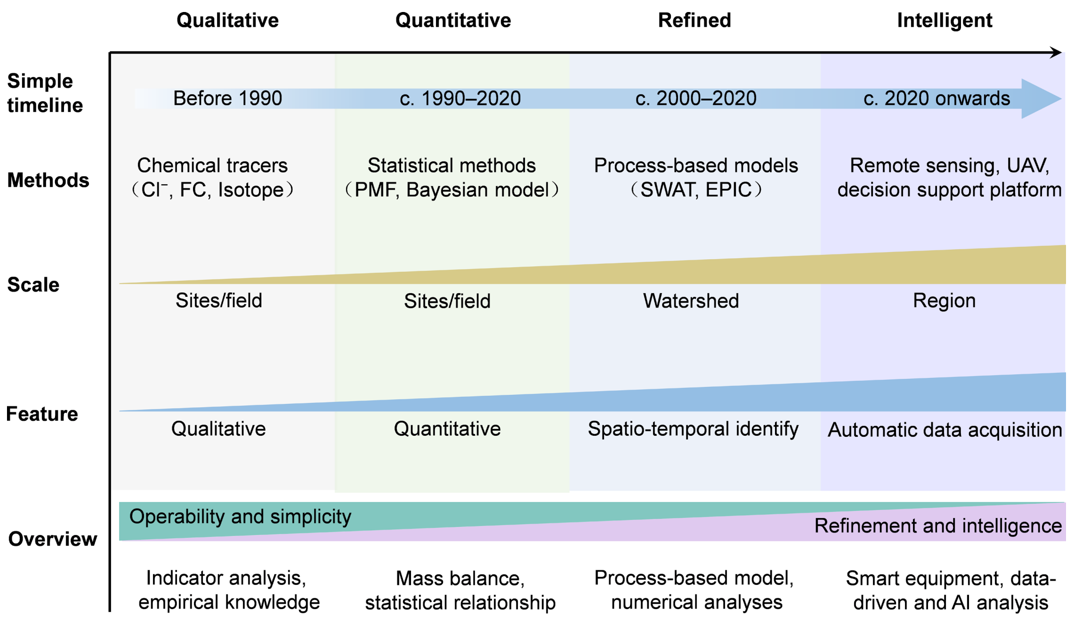



**Fig. 1** Classification and overview of methods for watershed nitrogen source apportionment. These methods are classified into four categories according to their objectives: qualitative approaches, quantitative approaches, spatiotemporally refined approaches, and intelligent technologies. Their corresponding methodological principles, applicability, and characteristics are described. FC, fecal coliform; PMF, positive matrix factorization; SWAT, soil and water assessment tool; EPIC, environmental policy integrated climate; UAV, unmanned aerial vehicle.

**Table 1** A comprehensive comparison of representative techniques of different methods

| | Qualitative | Quantitative | Spatiotemporally refined | Intelligent technologies |
|---|---|---|---|---|
| Representative techniques | $Cl^-$ and $NO_3^-/Cl^-$ ratio | Bayesian isotope models | Process-based model | Remote sensing |
| N species involved | $NH_4^+$, $NO_3^-$ | $NO_3^-$ | Total nitrogen (TN), $NO_3^-$ | TN |
| Uncertainty range | High (environmental variability; e.g., rainfall dilution, temperature, pH decay) | Moderate to high (overlapping isotopic signatures and fractionation (e.g., when the source error increases from 2‰ to 4‰, the standard error of apportionment results increases by 50% for the single isotope, dual-end-member model) | Moderate (extensive parameter estimation, simplification of complex physical mechanisms, and data scarcity in unmonitored regions) | Low to moderate (remote sensing resolution, sensor calibration, cloud cover, algorithmic biases, and insufficient mechanistic representation in complex conditions) |
| Applicable scale | Sites, field | Sites, sub-basin | Sub-basin, watershed | Regional, large-scale basins |
| Applicable N source types | Sewage, livestock, runoff, groundwater | Atmospheric deposition, fertilizer, soil nitrogen, manure/sewage | Cropland, rural life, urban area, atmospheric deposition | Landscape-scale agricultural NPS, dynamic pathway tracking, hydrological components separation |
| Typical data requirements | Chemical ion concentrations | Isotopic ratios | Meteorological data, land-use maps, soil properties, fertilizer intensity, water quality data | Satellite imagery, unmanned aerial vehicle-based high-resolution images, real-time in situ sensor networks, big data |
| Advantages | Rapid qualitative identification, operability, and simplicity | Quantifies fractional contributions and uncertainty ranges | Provides explicit spatial (pathways) and temporal patterns; enables scenario assessment and policy evaluation | High spatiotemporal resolution over large scales, automated data collection in real time |
| Limitations | Cannot quantify fractional contributions | Lacks spatiotemporal tracking, high uncertainty | Requires extensive model parameters/data; complex to calibrate | High infrastructure/deployment costs, inadequate mechanistic representation, challenges in integrating disparate departmental databases |
| Application examples | Differentiating sewage (high $Cl^-$) vs fertilizer runoff (low $Cl^-$)[26,27] | Quantifies rainfall, sewage, fertilizer, and soil N in Taihu (China), Naugatuck River (USA), and Flanders (Belgium)[28–30] | Widespread application of the SWAT model globally[31] | DPeRS predicting agricultural pollution dynamically; Sentinel-2 mapping river water quality transport pathways[32,33] |

# Qualitative methods for N source apportionment

## Chemical element tracers

Inorganic ions such as $Cl^-$, $Ca^{2+}$, and $B^{3+}$ have been widely used as rapid indicators for watershed N source apportionment since the 1990s[34–36] (Fig. 2). $Cl^-$ is particularly useful because of its conservative behavior in natural systems, where measured concentrations reliably indicate pollution sources' characteristics. Domestic sewage and livestock manure typically contain high $Cl^-$ concentrations, whereas fertilizer-derived $Cl^-$ concentrations are relatively low[27]. Moreover, the $NO_3^-/Cl^-$ ratio can be further used to distinguish sewage inputs (higher ratios) from livestock waste (lower ratios), as sewage treatment typically

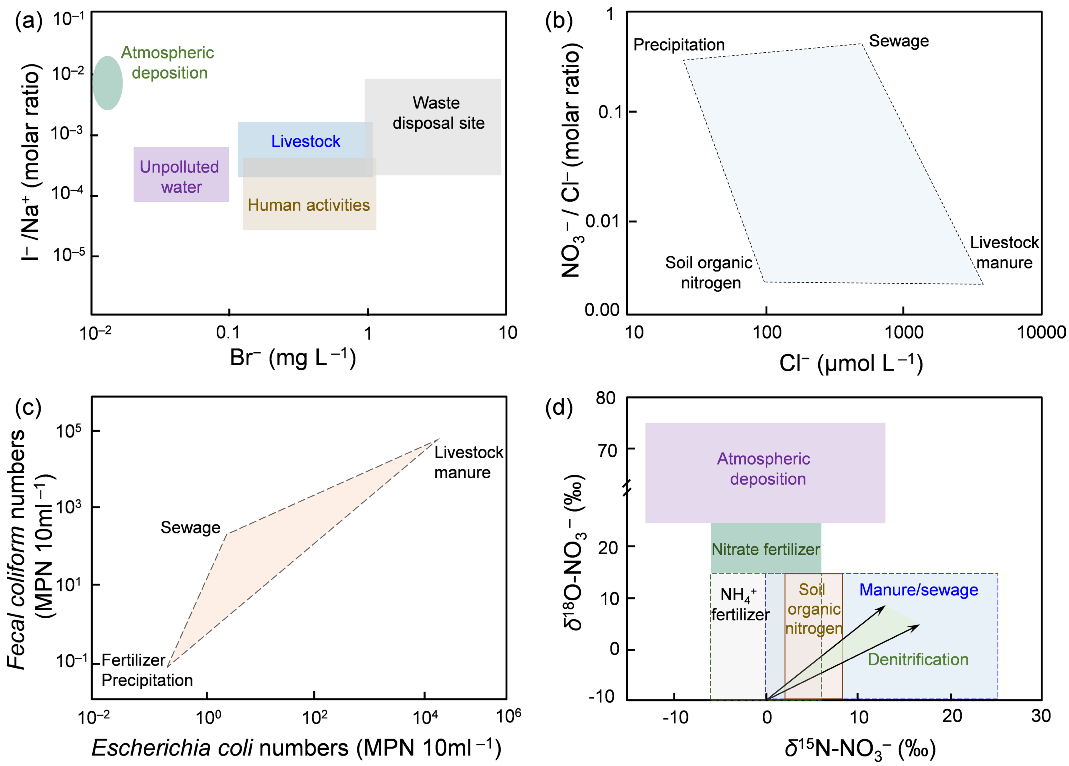



**Fig. 2** Representative qualitative methods for watershed nitrogen source apportionment. Different shades and positions represent the concentration and distribution characteristics of tracers from different sources.

reduces $Cl^-$ concentrations[26]. Other ionic tracers (e.g., $Br^-$, $I^-$, $Na^+$, $Ca^{2+}$, $B^{3+}$, $Sr^{2+}$) and isotopic ratios ($\delta^{11}B$ and $^{87}Sr/^{86}Sr$) can also serve as supplementary indicators for source identification[37–39]. For example, leachate from waste disposal shows elevated $Br^-$ due to organic waste degradation[40,41], whereas groundwater $\delta^{11}B$ and $^{87}Sr/^{86}Sr$ vary among agricultural runoff, livestock effluent, and domestic wastewater[42–44]. These indicators provide rapid qualitative identification of pollution sources; however, their reliability is often limited by environmental variability, as ion concentrations are affected by dilution, chemical reactions, and hydrological fluctuations. For example, heavy rainfall may rapidly leach fertilizer-derived $NO_3^-$ while leaving $Cl^-$ relatively stable, resulting in concentrations similar to those of sewage inputs, and denitrification further reduces $NO_3^-$ and disrupts its relationship with $Cl^-$[45]. Such processes limit the reliability of these chemical tracers in complex or mixed-source watersheds.

## Microbial indicators

Microbial markers are characterized by stronger specificity for identifying pollution sources than chemical element tracers[46,47]. Animal feces and treated domestic wastewater contain much higher concentrations of *Escherichia coli* (EC) and fecal coliforms (FCs) than those in rainfall or fertilizers[48,49] (Fig. 2c). Microbial markers stay effective despite the loss of diagnostic validity of $NO_3^-/Cl^-$ ratios caused by rainfall dilution or denitrification. For example, livestock-affected waters may exhibit $NO_3^-/Cl^-$ ratios similar to sewage during summer rainfall events, yet EC measurements still indicate the contribution of animal waste[50]. Within complex N source landscapes, this source specificity compensates for the shortcomings of traditional source apportionment methods based on chemical element tracers. However, microbial survival and DNA integrity are highly sensitive to environmental factors. Temperature and pH strongly influence detection rates, and FC persists for several weeks at 4 °C but has a half-life of only 2–3 d in warm summer waters (> 25 °C)[51,52]. These sensitivities underscore the necessity of accounting for ambient environmental factors during sampling when interpreting microbial marker data.

## Use of $\delta^{15}N$ and $\delta^{18}O$ isotopes in nitrate for qualitative identification

Unlike easily degradable microbial markers, $\delta^{15}N$ and $\delta^{18}O$ isotopes in $NO_3^-$ are relatively stable in aquatic systems and are less affected by environmental factors[53,54]. As N is transported in watersheds, the element undergoes biogeochemical processes such as mineralization, nitrification, denitrification, and ammonia volatilization, leading to isotope fractionation effects. These effects result in distinct $\delta^{15}N$ and $\delta^{18}O$ signatures across varying sources, which are extensively applied to identify N pollution sources[55,56] (Fig. 2d). For example, $NO_3^-$ from feces and sewage typically shows elevated $\delta^{15}N$ (+10‰ to +15‰) caused by preferential consumption of light isotopes during organic matter decomposition and denitrification[57], whereas soil $\delta^{15}N$–$NO_3^-$ (+3‰ to +8‰) is close to that of atmospheric $NO_3^-$ (–3‰ to +7‰)[58]. Atmospheric deposition generally exhibits higher $\delta^{18}O$–$NO_3^-$ (+25‰ to +75‰), whereas fertilizer-derived $NO_3^-$ has lower $\delta^{18}O$ (+15‰ to +25‰)[59]. Establishing a source-specific $\delta^{15}N$–$NO_3^-$ and $\delta^{18}O$–$NO_3^-$ database would enable the qualitative identification of $NO_3^-$ sources. Nevertheless, $\delta$-values from different sources may overlap, such as $\delta^{15}N$–$NO_3^-$ from mineralized soil and fertilizer N, and in-stream N cycling may further reshape isotopic signatures[26,30,60]. Therefore, combining chemical indicators, microbial markers, and isotopic techniques alongside watershed hydrology and environmental conditions would enhance the reliability of watershed N pollution source identification.

# Quantitative methods for N source apportionment

## Multivariate statistical and export coefficient methods

Multivariate statistical methods have been applied to quantify contributions from different non-point pollution sources, such as absolute principal component–multiple linear regression (APCS-MLR) and positive matrix factorization (PMF) models[61,62]. These methods typically establish a mass balance between pollutant concentrations in samples and potential sources via mathematical solutions to estimate the sources' contributions. For example, PMF was used to identify feces and sewage as the dominant $NO_3^-$ sources in Poyang Lake groundwater, contributing over 50% of the N load[63]. The key advantage of these methods is that they do not require prior knowledge of the sources' characteristics (e.g., the specific categories of local pollution sources); however, source identification relies heavily on the researcher's judgment and can be influenced by data quality and the lack of a description of the processes. Similarly, the export coefficient method, based on pollutant runoff and retention ratios, can also quantify watersheds' non-point source contributions[64–66]. This approach is simple and easy to implement with few data requirements, but it fails to account for pollutants' transport and transformation, leading to substantial uncertainty in source apportionment.

## Stable nitrate isotopes for quantitative source apportionment

Isotopic signal can be used not only to qualitatively identify the sources of N pollutants but also to quantitatively apportion them when combined with an end-member mass balance framework. Unlike multivariate statistical models that operate without prior information on pollutant sources, isotope-based approaches with $\delta^{15}$N–$NO_3^-$ and $\delta^{18}$O–$NO_3^-$ are considered to be more robust because the isotopic signatures of potential sources are known in advance[28,29,67]. The general workflow involves collecting isotope signatures from representative sources such as fertilizers, soils, livestock manure, domestic sewage, and atmospheric deposition, followed by establishing a mathematical relationship between these end-members and the isotopic composition measured in polluted water bodies. SIAR and MixSIAR models with a Bayesian framework are widely used to estimate source contributions as follows:

$$X_{ij} = \sum_{k=1}^{k} p_k\left(S_{jk} + C_{jk}\right) + \varepsilon_{ij}$$

$$S_{jk} \sim N\left(\mu_{jk}, \omega_{jk}^2\right)$$

$$C_{jk} \sim N\left(\gamma_{jk}, \tau_{jk}^2\right)$$

$$\varepsilon_{ij} \sim N\left(0, \sigma_j^2\right)$$

where, $X_{ij}$ represents the value of isotope $j$ in sample $i$ ($i$=1, 2, 3,…, N; $j$=1, 2, 3,…, J), $S_{jk}$ is the value of isotope $j$ in source $k$ ($k$=1, 2, 3,…, K), $\mu_{jk}$ is the mean value, $\omega_{jk}^2$ is the variance of the normal distribution, and $C_{jk}$ is the fractionation factor for isotope $j$ in source $k$ with a mean $\gamma_{jk}$ and the variance $\tau_{jk}^2$, and $p_k$ is the contribution of source $k$ estimated by the model. The residual term $\varepsilon_{ij}$ represents unexplained variability with a mean of zero and variance of $\sigma_j^2$.

The Bayesian isotope model offers the advantage of quantifying the uncertainty range of source contributions and the isotopic fractionation associated with in-stream denitrification. Denitrification is widespread in river systems and shifts $\delta^{15}$N by approximately −40‰ to −5‰ and $\delta^{18}$O by approximately −16‰ to −4‰; neglecting this process increases the uncertainty in nitrate source apportionment[56,68,69]. Within Bayesian frameworks, the fractionation coefficient can be estimated using the Rayleigh formulation, which assumes a linear relationship between the residual nitrate and the isotopic value:

$$\delta_{Rt} = \delta_{R0} + \varepsilon \ln(f)$$

where, $\delta_{Rt}$ represents the isotopic value at time $t$, $\delta_{R0}$ is the initial isotopic value in nitrate, $f$ is the proportion of residual nitrate in the water body, and $\varepsilon$ is the fractionation coefficient.

Although isotopic Bayesian models are widely applied for quantitative nitrate source apportionment, several limitations remain in practice. First, overlaps in isotopic signatures among different sources compromise source discrimination, particularly between livestock manure and domestic wastewater[55]. Source signatures also vary across regions and seasons. For example, a survey of 28 vegetable planting greenhouses in Zhejiang Province showed that soils to which organic fertilizer had been applied had significantly higher $\delta^{15}$N values (mean = 7.97‰) than those with chemical fertilizers (mean = 5.13‰)[70]. In addition, the selection of source categories, specification of the models' parameters, and the definition of prior information also influence the accuracy and uncertainty of Bayesian models' results[57,71].

# Spatiotemporally refined N source apportionment

## Process-based models

Although statistical methods quantify the total contribution of N loads, these approaches provide limited information on the spatial (e.g., location and transport pathways) and temporal (from hours to months and decades) origins of pollution within the watershed (Fig. 3). Process-based hydrological models simulate the generation, transport, and transformation of N from source to sink, thereby providing explicit spatial and temporal patterns of pollutant loss[72]. These models integrate climate variability, land-use configuration, and fertilizer intensity to provide scenario assessments and policy evaluations for watershed N source apportionment, such as the soil and water assessment tool (SWAT), AGNPS, HSPF, and WPLT[73–76]. For instance, SWAT combined with multivariate statistics successfully identified critical source areas in the Choctawhatchee watershed, where 28% of the land area accounted for 47% of total N export[77]. HSPF was applied to quantify the spatiotemporal distribution of N loading across subbasins in the Rappahannock watershed[78]. Using historical human activity and meteorological data, long-term and daily nitrate exports (1980–2010) at hydrologic response units were simulated with SWAT in an intensive agricultural catchment of Southwestern France[79]. Despite these advantages, process-based models require extensive model parameters, which are often limited in data-scarce regions[25,80].

To reduce the complexity and data requirements of fully process-based models, semiempirical and process models that integrate empirical relationships and mechanistic processes have been developed to identify watershed N sources. Representative models such as SPARROW, IMAGE-GNM, NutriShed, and DPSs balance data requirements and detailed descriptions of the processes, thereby maintaining accuracy at large-scale estimates[72,81–83]. For instance, the NutriShed model simulates pollutant transport and removal along flow paths and identifies N source contributions at a grid-level resolution[82]. With the NutriShed model at a 30 m × 30 m resolution, 71% of the N runoff from croplands was estimated to be removed in a typical rice watershed in southern China[82]. Overall, semiempirical and process models provide a practical compromise between

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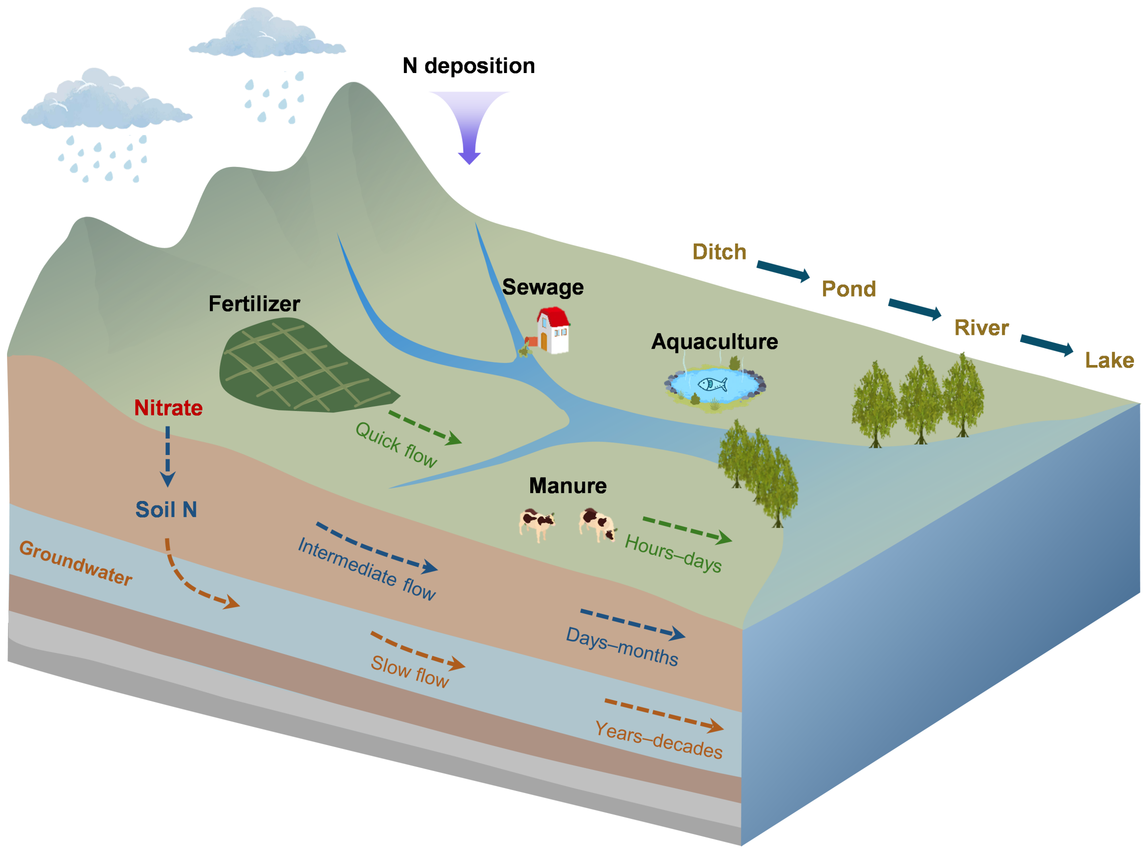


**Fig. 3** Processes and spatiotemporal characteristics of nitrogen transport in watersheds. Watersheds' non-point sources of nitrogen typically include fertilizer, livestock waste, rural domestic sewage, atmospheric deposition, and aquaculture. These pollutants are transported into water bodies through the surface, vadose zone, and groundwater as quick, intermediate, and slow flow, with travel times spanning from days to months and decades.

mechanistic detail and data availability, with acceptable accuracy and broad applicability (Table 2).

### Numerical analysis methods

In addition to non-point source pollution models, approaches that rely on hydrological analyses and numerical simulations also provide refined spatiotemporal source apportionment. For example, by combining hydrological partitioning with end-member mixing analysis, the contributions of surface flow, subsurface flow, and baseflow to total N and nitrate under different land-use types were distinguished in the Qinhuai River Basin[84]. On the basis of $\delta^{15}N–NO_3^-$ and $\delta^{18}O–NO_3^-$ with N transformation modeling, the rates of nitrate transport, nitrification, and denitrification in surface–subsurface systems were identified in the Cane Run karst watershed in Kentucky[85,86]. Furthermore, by incorporating the connectivity index of surface–vadose zone–groundwater and the SIAR model, researchers identified the N source types, spatial location, and transport pathways[87]. Moreover, these isotopic data and numerical simulation approaches can further be combined with process-based models to quantify the dynamics of N sources, transformations, land-use contributions, and the drivers of watershed N transport[88,89].

## Intelligent technology for N source apportionment

With the rapid development of intelligent equipment for watershed management, N source apportionment is shifting from low-frequency, field sampling toward data-rich, mechanism-informed, and intelligent online systems (Fig. 4). To distinguish it from spatiotemporally refined N source apportionment, we define intelligent methods as necessarily including equipment such as satellite-based remote sensing, unmanned aerial vehicles (UAVs), and *in situ* sensor networks to automatically collect high-frequency, real-time, long-term, or large-scale data. These devices not only facilitate the collection of such data but also integrate environmental data with numerical algorithms to support N source apportionment and watershed management.

### Intelligent technologies for large-scale N source apportionment

Intelligent technologies provide a unique advantage for N source apportionment at large spatial scales by enabling spatially extensive observations across heterogeneous watersheds. Traditional field-site monitoring is often insufficient to represent complex landscape configurations and hydrological connectivity for watersheds, leading to large uncertainties in source attribution at regional or basin scales. In contrast, satellite-based remote sensing and UAV-based imaging offer large-scale spatially explicit information that bridges water quality patterns with upstream landscape characteristics and management practices. For example, the DPeRS model integrates remote-sensing imagery and meteorological data to dynamically predict the contribution of agricultural activities to water pollution in large-scale watersheds[32]. Additionally, machine learning algorithms such as Random Forest have been coupled with UAV imagery to accurately delineate subsurface agricultural drainage networks, providing critical data for pathway-specific source attribution[90,91]. These technologies

**Table 2** Comparison of representative fully process-based and semiempirical and process models for watershed N source apportionment

| Typical model | Fully process-based models | | Semiempirical and process models | |
|---|---|---|---|---|
| | SWAT | HSPF | NutriShed | SPARROW |
| Spatial scale | Hydrologic response unit (HRU), sub-basin | HRU, sub-basin, catchment segment | Grid-cell resolution (e.g., 30 m × 30 m) | Regional, basin, continental scale |
| Temporal scale | Daily, monthly, annual | Subhourly to daily | Rainfall event, annual | Steady-state long-term annual or seasonal mean |
| Typical input data requirements | Topography (DEM), land-use, soil properties, daily weather data, agricultural management practices | High-frequency meteorological data, land use, detailed channel cross-section geometries | Spatially explicit pollutant source inputs, DEM for flow routing, retention coefficients | Spatially distributed nutrient sources, land-to-water delivery efficiency, digital stream network topology |
| Advantages | Comprehensively simulates biogeochemical processes; high accuracy | Captures highly detailed in-stream hydrologic and water quality dynamics (e.g., storm events); adjustable HRU | Balancing data requirements and accuracy; grid-spatially explicit source and retention identification | Simple to implement; easily targets large-scale or continental sources |
| Limitations | High data/parameter demand; complex calibration process; fails to simulate flood events | High data/parameter demand; high uncertainty associated with the empirical formulas and parameters | Simplifies complex biogeochemical processes; sacrifices some accuracy compared with full process models | Fails to capture short-term dynamic variations; relies heavily on high-quality monitoring networks for calibration |

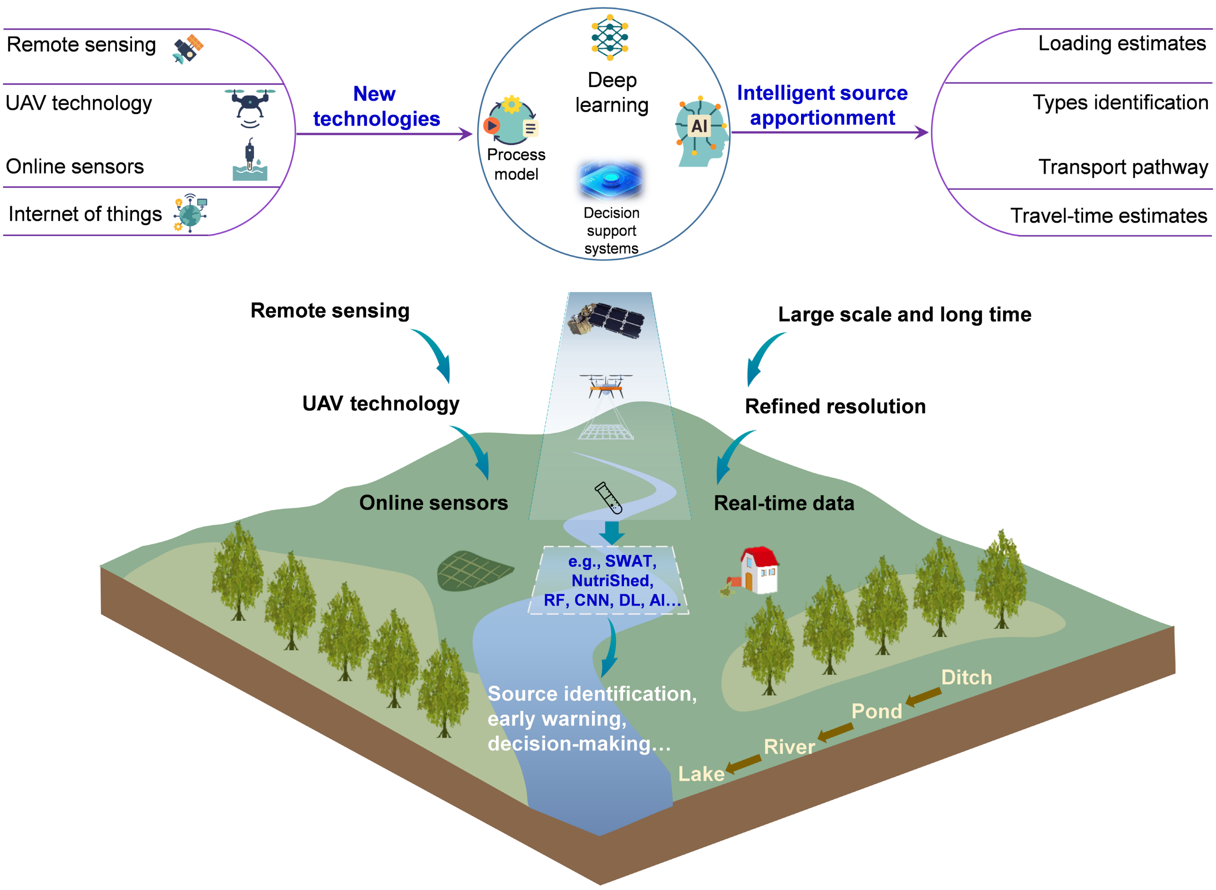


**Fig. 4** Intelligent technology and prospects of watershed nitrogen source apportionment. The intelligent source apportionment system acquires data via remote sensing, UAV, and sensor technologies, integrating process-based models with AI-driven data processing to characterize the dynamics of pollutant transport. This system has the advantages of large-scale monitoring and high-resolution spatiotemporal analysis, as well as providing targeted decision-making support for watershed management.

offer advantages in large-scale monitoring that can not be achieved by field-site monitoring.

## Intelligent technologies for refined resolution N source apportionment

Compared with manual monitoring, another key advantage of intelligent monitoring technologies is their capacity to generate high-frequency and long-term observations. Such data are critical for elucidating N transformation and transport processes, as conventional weekly or monthly sampling fails to capture rapid concentration dynamics and often misses hydrologically driven key events. In contrast, automated data acquisition at an hourly or subhourly resolution provides a more detailed interpretation of pollutants' transport processes. Through the use of high-frequency sampling and

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isotope techniques, the distinct contributions of surface, subsurface, and groundwater to river water's quality during spring and summer were identified[92]. The relative contribution of different hydrological components to riverine N loading during storm events was distinguished, based on high-frequency sampling of isotopic data[93]. Sentinel-2 images were used to map the detailed spatial patterns of water quality along seven major rivers in Zhejiang Province from downstream to upstream, allowing the identification of long-term transport pathways[33]. Moreover, the application of high-frequency monitoring technologies to elucidate the processes of water quality pollution during extreme precipitation events is crucial for mitigating the challenges of climate change.

## Integrated platforms for intelligent N source apportionment

With the accumulation of multisource datasets and the development of source apportionment methods, intelligent source apportionment is increasingly implemented through integrated operational platforms. These systems typically include modules for data acquisition, analysis and processing, visualization of the results, and decision support. International projects such as the SmartWaters system in Europe and the NGWOS, BASINS, and WMOST platforms in the United States demonstrate the potential of such integrated systems to provide timely evaluations of pollution sources, forecast high-risk regions, and support cost-effective watershed management strategies[94]. Though SmartWaters excels in high-frequency sensor data integration for European catchments, BASINS primarily focuses on providing comprehensive geographic information system (GIS)-based frameworks for long-term regulatory assessment across diverse North American landscapes. However, a common limitation across these systems is the inadequate mechanistic representation in highly complex watershed conditions. In China, rapid progress has been made in constructing national monitoring networks and digital river basin simulation systems such as the Yangtze and Yellow River Simulators. Nevertheless, important challenges remain regarding (1) insufficient integration across departmental data systems and the construction of standard databases; (2) inadequate mechanistic representation under complex watershed and hydrological conditions; and (3) weak connections among system modules for field monitoring, source identification, early warning, and decision-making.

# Prospects of future N source apportionment

To address these limitations of current source apportionment technologies, several key research focuses are expected to be advanced in future studies (Table 3). First, heterogeneous datasets from remote sensing, UAV, and *in situ* sensors vary in their spatiotemporal resolution and accuracy, limiting the feasibility of their combined application. Developing integrated space–air–ground monitoring platforms, together with standardized databases and automated preprocessing workflows, is expected to provide a robust foundation for model inputs. Second, more refined representations of pollutant transport, especially under complex watershed conditions and extreme events, are needed to improve models' generality and spatiotemporal accuracy. The understanding of N's source–flow–sink transport would benefit from the development of a unified framework that couples statistical models, process-based models, and isotope tracing. Finally, decision support systems should be further integrated with artificial intelligence technologies and large language models to enhance their accessibility and operational utility. For example, by integrating UAVs and deep learning, GeoAI can monitor compost heaps' volume and footprint to assess non-point source pollution[90]. By integrating scenario simulation and cost–benefit analyses, such systems can support adaptive watershed management while providing interactive, user-friendly interfaces that lower application barriers and facilitate the implementation of intelligent watershed management.

# Ethical statements

Not applicable.

# Author contributions

The authors confirm their contributions to the paper as follows: Xing Yan: study framework design, draft manuscript preparation and

**Table 3** A short list of priority research questions and actionable steps for advancing future watershed N source apportionment

| Strategic direction | Priority research questions | Actionable steps | Expected outcomes |
|---|---|---|---|
| 1. Space–air–ground data collection and integration | 1. How can we ensure the data quality of automated monitoring networks?<br>2. How can we harmonize multiscale spatial and temporal data from satellites, UAVs, and sensors? | 1. Implement algorithms such as text recognition to identify anomalous data, followed by manual inspection.<br>2. Establish standardized database protocols to unify multisource data formats and databases. | A reliable, high-resolution, and continuous data foundation for regional and watershed model inputs. |
| 2. Model mechanisms and coupling for source apportionment | 1. How can we improve models' performance for extreme events to face climate change?<br>2. How can we improve simulations under complex watershed conditions?<br>3. How can we balance models' accuracy with high data/parameter demand? | 1. Integrate high-frequency sensor data into nonlinear processes to capture nitrogen transport during peak storm runoff.<br>2. Integrate multitracers and pathway modeling to identify hydrological and biogeochemical processes across mountainous, plain, and karst terrains.<br>3. Construct hybrid semiempirical modules to simplify parameters while preserving the core mechanisms | A robust and easy-to-use framework achieving high precision for extreme events and complex catchments. |
| 3. Construction of smart decision support systems | 1. How can we build systems integrating massive datasets with source apportionment models?<br>2. How can source apportionment guide watershed management, such as source control and wetland restoration?<br>3. How can we operationalize these platforms for practical watershed management? | 1. Accelerate development of a platform that integrates source tracking, mechanistic explanation, and decision support.<br>2. Leverage artificial intelligence for user-friendly interfaces to lower the entry barrier.<br>3. Incorporate cost–benefit analysis to maximize investment returns.<br>4. Cultivate collaboration among government, scientists, the public, and farmers for implementation. | An operational and economically viable platform enabling rapid source apportionment and watershed management decision support. |

revision; Wei Hu: manuscript review; Yongqiu Xia: study framework design and manuscript review. All authors reviewed the results and approved the final version of the manuscript.

# Data availability

The datasets used or analyzed during the current study are available from the corresponding author upon reasonable request.

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# Declarations

## Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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