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Review

Agricultural Non-Point Source Pollution: Comprehensive Analysis of Sources and Assessment Methods

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Abstract: Agricultural non-point source pollution (ANPSP) significantly affects worldwide water quality, soil integrity, and ecosystems. Primary factors are nutrient runoff, pesticide leaching, and inadequate livestock waste management. Nonetheless, a thorough assessment of ANPSP sources and efficient control techniques is still lacking. This research delineates the origins and present state of ANPSP, emphasizing its influence on agricultural practices, livestock, and rural waste management. It assesses current evaluation models, encompassing field- and watershed-scale methodologies, and investigates novel technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) that possess the potential to enhance pollution monitoring and predictive precision. The research examines strategies designed to alleviate ANPSP, such as sustainable agricultural practices, fertilizer reduction, and waste management technology, highlighting the necessity for integrated, real-time monitoring systems. This report presents a comprehensive analysis of current tactics, finds significant gaps, and offers recommendations for enhancing both research and policy initiatives to tackle ANPSP and foster sustainable farming practices.

Keywords: agricultural non-point source pollution; nutrient leaching and runoff; assessment techniques; sustainable agriculture; ecosystem stability

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1. Introduction

The emission of ANPSP pollutants has posed a substantial risk to the global water supply [1]. One of the most pressing issues is ANPSP, primarily caused by the leaching of nitrogen (N), phosphorus (P), and other heavy metals from agricultural landscapes [2,3]. Overutilizing fertilizers and manure contributes to water pollution, leading to eutrophication, harmful algal blooms, and the degradation of aquatic ecosystems [3,4]. For example, in the Taihu Basin, China, ANPSP accounts for 52% of P and 54% of total nitrogen loading [5]. Similarly, these statistics are 24% and 71% in Italy, respectively [6]. NPS pollution has increased in Europe, the US, and China due to rapid industrialization and agricultural activities. Furthermore, heavy metal contamination worsens these environmental issues [7]. In the United States, ANPSP remains the primary source of nutrients in lakes and streams, with significant impacts on the Mississippi River Basin and Great Lakes region. Notably agricultural farm runoff contributes 10% of the N and 30% of the P load in the Mississippi River [8]. In Europe, the Danube and Rhine rivers face substantial challenges from NPS pollution. NPS pollution activities contribute to approximately 55% of water pollution in the Danube [9]. Despite reductions, 80–85% of the original nitrogen load from the Rhine still impacts the North Sea and the Wadden Sea [10]. Nitrate pollution has become a prominent environmental concern globally, with distinct difficulties about agricultural runoff and water contamination in each location. A survey of over 93 locations in Asia indicated concerning results, with 20 regions, including segments of India, Palestine, and Saudi Arabia and territories in China and Pakistan, displaying average nitrate concentrations above the World Health Organization's (WHO) limit of 50 ppm. Despite 19 additional locations exhibiting average nitrate levels below WHO standards, over 25% of their water tests were over the 50 ppm threshold, signifying extensive localized contamination [11]. In Europe, the same increases were noted across 71 areas, with 9 regions indicating average nitrate concentrations above 50 ppm. Furthermore, 16 locations had average amounts within this threshold; however, over 25% of the samples surpassed the 50 ppm limit, highlighting the ongoing challenges of agricultural runoff and wastewater discharge despite general adherence to global regulations [12]. In Africa, 94 locations were examined, of which 30 had mean nitrate concentrations over 50 ppm, with certain places recording levels as elevated as 776 mg/L, mostly due to inadequate sanitation and agricultural methods. This illustrates the significant effects of agricultural non-point source pollution (ANPSP) and the pressing necessity for enhanced water quality management throughout the continent. A survey of 34 areas in the Americas indicated that just 1 region exhibited nitrate concentrations above 50 ppm. Nevertheless, four locations had averages below the 50 ppm threshold; however, over 25% of the samples were still over this level, underscoring regional pollution concerns, especially in some areas of Mexico. These findings underscore the necessity for more rigorous water management rules and the adoption of sustainable agriculture techniques worldwide. The data from several continents illustrate the global problem of controlling nitrate pollution and emphasize the necessity of effective water quality monitoring systems and thorough environmental laws to protect public health and ecosystems globally [13].

Agricultural runoff includes surplus water from irrigation and rainfall. This runoff often carries various pollutants, such as heavy metals, nitrates, ammonium, phosphorus compounds, and persistent organic pollutants [14,15]. Agricultural runoff has garnered considerable research attention in recent decades, as illustrated in Figure 1.

N and P are critical for aquatic plant development and are the primary limiting nutrients in eutrophication [16,17]. Anthropogenic eutrophication threatens aquatic ecosystems' health and security worldwide [18,19]. Environmental contamination, exacerbated by water's non-renewable nature, remains a major obstacle to maintaining clean water supplies [6,20]. The availability of freshwater resources enormously affects the nation's economic development [21,22]. In the 21st century, the fast-paced process of urbanization and the increase in population necessitate the availability of new water resources to sustain livelihoods [23].

The evaluation criteria should consider the primary sources of pollution, the routes through which they spread, and the processes through which they transform. Effective criteria for ANPSP assessment should rely on scientific principles, ensure comprehensive and impactful evaluations, and maintain independence, representativeness, wide applicability, and practicality. The indexes are highly responsive to variations in ANPSP resulting from ecological measures [24], water and fertilizer management [25], climate change [26], and labor-force quality [27]. These variables encompass precipitation, land use categories, topographical characteristics, fertilization methods, irrigation water amounts, soil types,

types of fertilization, ecological ditches, and labor quality. This study also estimated the pollution burden from ANPSP at various sizes. There are two well-known estimating methods: The first includes unit pollution load, regional pollution load balance, and a simulation model. The second is field monitoring, which provides accurate estimates of ANPSP pollutant loads [24].

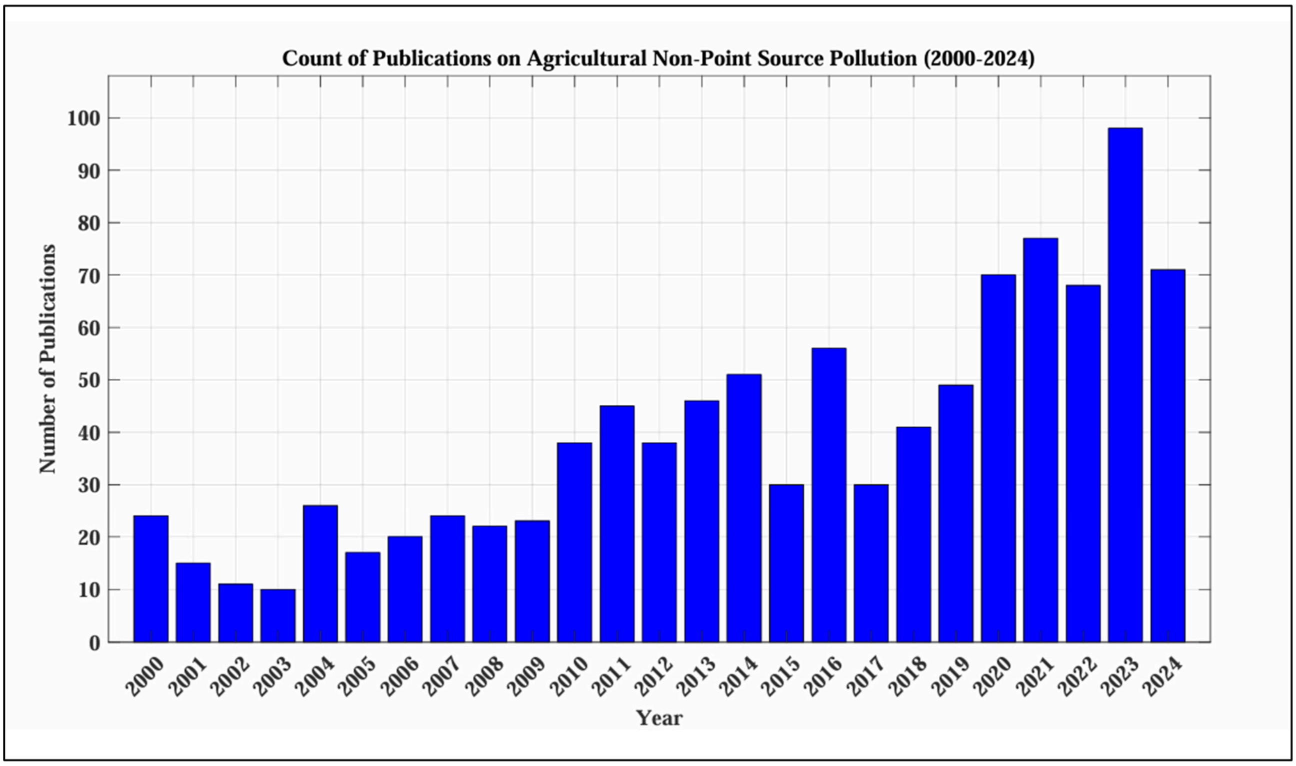

Figure 1. Number of publications on agricultural non-point source pollution from 2000 to 2024 (source: Crossref).

To mitigate the issues of ANPSP, it is crucial to understand the underlying resources, structures, transportation, and pathways involved. Implementing efficient management techniques such as optimizing conserving tillage, fertilizer application, and using cover crops can significantly decrease nutrient losses and safeguard water quality [28–31]. A key element of addressing ANPSP entails employing non-point source (NPS) pollution models. These models play a vital role in forecasting the movement of pollutants and devising efficient strategies for their control. Commonly employed models include the Hydrological Simulation Program-Fortran (HSPF) [32], the Soil and Water Assessment Tool (SWAT) [33], and the annualized agricultural non-point source (AnnAGNPS) model [34]. These models provide useful insights into the dynamics of pollutants in different agricultural environments [35].

Additionally, implementing these models necessitates considering several scales, ranging from the level of individual fields to the level of entire watersheds. Field-scale models such as the DeNitrification–DeComposition (DNDC) model specifically examine the vertical transfer of materials between the soil and atmosphere [36]. These models primarily investigate the transformation of water and pollutants in agricultural fields. Catchment-scale models investigate the interactions between slopes and channels [37] among several components, including surface water, groundwater, soil erosion, hydrologic processes, sediment transport, and nutrient dispersion.

Current developments in in situ monitoring technology provide immediate and accurate data to evaluate contaminants such as N and P. Automated sensors continuously monitor nitrate and phosphate concentrations. Researchers use flow gauges and soil probes to measure the risks of runoff and nutrient leaching. Remote monitoring stations collect and transmit data from various sensors located in real time, enabling prompt and thorough monitoring of agricultural runoff. Zhu et al. (2019) effectively utilized a portable optical nitrate sensor to detect nitrate pollution in drainage water [38]. Hanrahan et al. (2019) employed soil probes to evaluate the amount of N and P lost from Ohio agricultural fields. Their findings provide important information for managing the runoff of nutrients [25].

This review will provide a comprehensive analysis of agricultural non-point source pollution (ANPSP), emphasizing its origins, consequences, and the several models employed to evaluate and forecast its impacts (Figure 2). This will examine the advantages and drawbacks of field-scale and watershed-scale models, as well as emerging technologies such as AI, Machine Learning, and IoT that show potential for enhancing pollution assessment and management. This review seeks to improve the comprehension of ANPSP by assessing existing techniques, pinpointing limitations in present methodologies, increasing awareness of its environmental hazards, and providing a robust basis for formulating more localized and effective prevention and control measures. Ultimately, it aims to address the ANPSP difficulties encountered by various regions and advocate for sustainable agriculture techniques.

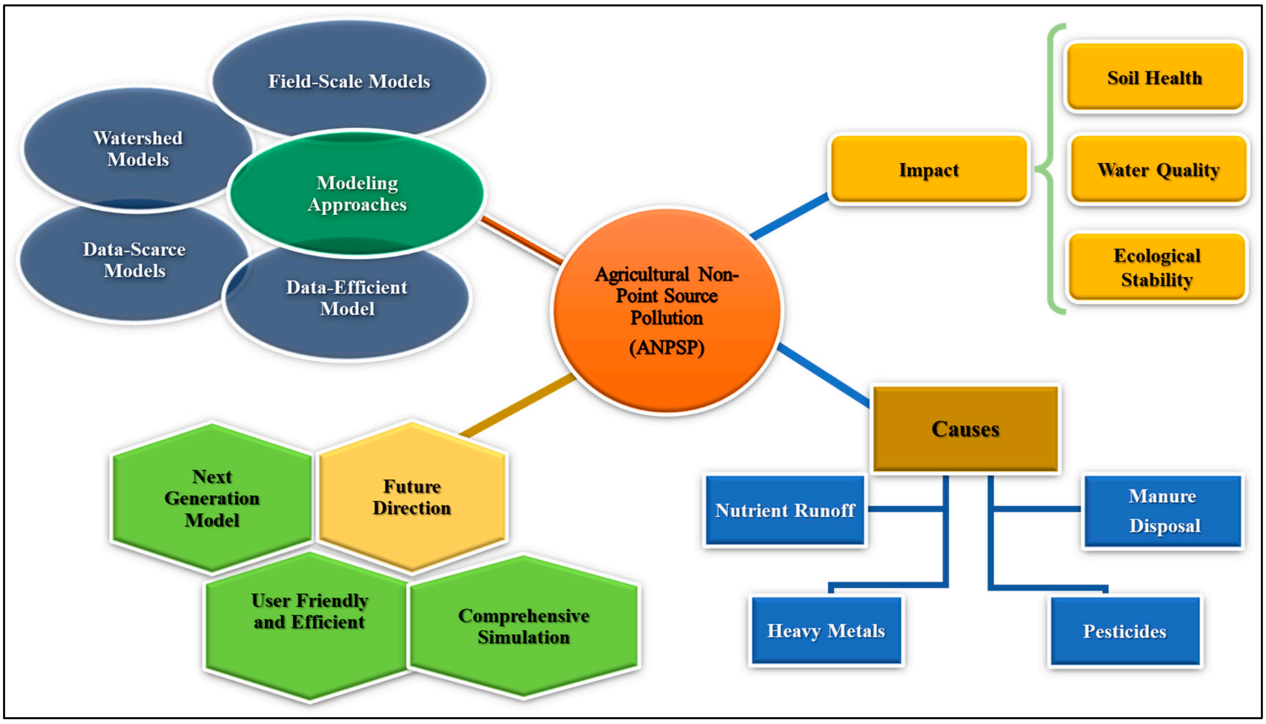

Figure 2. A precise view of the study showing various key aspects of ANPSP.

2. Agricultural Non-Point Source (ANPSP) Pollution

Over the last few decades, the environmental hazards caused by ANPSP have significantly increased, mainly due to its extensive scale and multiple origins. According to China's second pollution source survey conducted in 2019, ANPSP is responsible for 47% of N and 68% of P entering water bodies. The inefficient use of N and P in Chinese agriculture, coupled with the direct runoff of livestock and poultry waste into water bodies, has exacerbated water quality issues in the country [39]. Despite this, agricultural production remains crucial as China faces the challenge of feeding 1.4 billion people. China faces a major challenge in managing ANPSP effectively while producing enough food to support healthy freshwater ecosystems. Managing ANPSP effectively while ensuring enough food is produced to support healthy freshwater ecosystems is a major challenge for the development of agriculture in China [40]. Significant causes of ANPSP are captured in Figure 3.

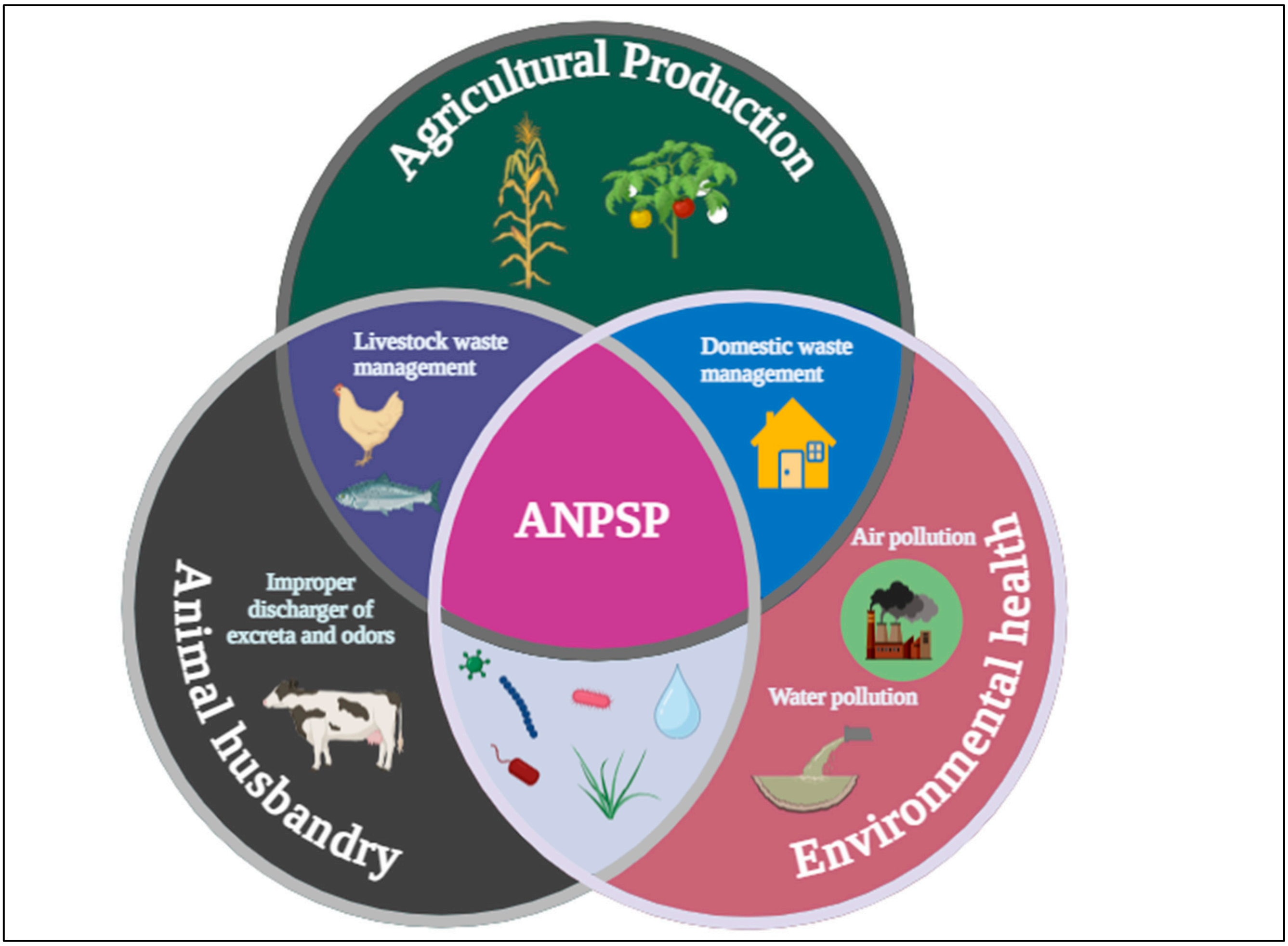

Figure 3. Key sources and causes of ANPSP, highlighting inefficient fertilizer use, livestock waste, and pesticide runoff.

2.1. Current Situations of ANPSP Caused by Agricultural Production

The substantial losses of N and P due to agricultural activities constitute a major source of ANPSP in China. According to recent survey data [41], for China's agriculture, the utilization efficiency of nitrogen (N) is 30–35%, phosphorus (P) is 10–20%, and potassium (K) is 35–50%, approximately. These rates are notably 15–20 percentage points lower than those observed in more industrialized nations. Notably, N losses in China can be as high as 45% [41]. Another study conducted by Zeng et al. on corn-rice planting systems in the Dong Jiang River Basin in South China from 2019 to 2020 found that the recovery rates of nitrogen in rice grains and corn straw were only 26.22% and 37.48%, respectively. Similarly, the recovery rates for phosphorus were just 12.35% and 19.51%, respectively [42]. Approximately 67.0% of all pesticides used in farming in China consist of highly toxic pesticides, including organophosphorus and aminoguanidine pesticides. The experimental findings indicated that the most extremely poisonous pesticides utilized in fruit trees, vegetables, and cereals were either directly introduced or deposited into the soil or surface water. This situation led to a pesticide use efficiency of just 30% of the overall pesticide consumption [43].

The depletion of N and P in agricultural output is a primary determinant of water quality. The eutrophication process in water bodies will result in alterations to the ecological composition of these rivers, the deterioration of ecological processes, and significant economic damages. Synergistically, using chemical fertilizers and pesticides in intensive agriculture will result in pesticide residues and their buildup in food, impacting public health. So, addressing the issue of ANPSP resulting from agricultural production leads to developing several national laws and innovative technologies to mitigate the negative impact of agricultural output on the environment.

ANPSP refers to the contamination that arises when pesticides, N, P, heavy metals, and other organic and inorganic pollutants like inorganic materials infiltrate the water bodies in the environment via rainfall, surface runoff, paddy field runoff, and subsurface leaching. This contamination arises from several agricultural practices, including farming, pesticide use, fertilization and irrigation, and poultry and cattle breeding [44]. The main embodied pollutants are water-soluble chemical compounds, including N, P, and COD, as well as water-insoluble macromolecular particles like crop straw and agricultural film [45]. ANPSP is mainly caused by the following: arbitrary disposal of agricultural plastic film, excessive pesticide and fertilizer application in the planting industry, haphazard dumping and cremation of crop straws, and incorrect livestock disposal excrement.

2.2. Pollutants from Chemical Fertilizers

Farmers often employ a substantial quantity of fertilizers, including nitrogen fertilizer, phosphate fertilizer, and potassium fertilizer, to achieve fast crop growth, boost yield, and maximize income. An assessed value of 86% of agricultural products are manufactured using chemical fertilizers [46]. The regions that are characterized by extensive fertilizer application, as well as elevated levels of nitrogen (N) and phosphorus (P) contamination, can easily be identified [47,48]. The predetermined rate at which crops use fertilizers can lead to the introduction of excessive fertilizers into adjacent water bodies through irrigation water or rainwater. This can significantly burden the water body, causing elevated levels of N and P, ultimately resulting in eutrophication and severe harm to the established environment.

The fertilizer application is 335.3 $kg \cdot hm^{-2}$ in China, whereas certain regions exceed 500 $kg \cdot hm^{-2}$ [49]. The utilization of inorganic fertilizers has varied considerably during the past two decades, affecting nutrient concentrations and agricultural output globally. The need for essential nutrients—nitrogen (N), phosphorus (P_2O_5), and potassium (K_2O)—has increased as worldwide agriculture intensifies to satisfy escalating food requirements. Figure 4 depicts these trends, emphasizing the rise in fertilizer usage and the environmental issues associated with nutrient runoff and non-point source pollution [50].

The data in Figure 4 indicate a consistent rise in nitrogen utilization, highlighting its essential function in intensive agricultural practices. Phosphorus and potassium exhibit upward trends, albeit at a more gradual pace, underscoring the importance of balanced nutrient application for sustainable crop production. Nitrogen consumption has shown a consistent increase over this period, rising from approximately 81 million tons in 2000 to around 108 million tons in 2022. This increase demonstrates the critical importance of nitrogen in enhancing agricultural productivity. Phosphorus and potassium have demonstrated growth, albeit at a more moderate rate, with phosphorus consumption increasing from approximately 32 million tons to 42 million tons and potassium from roughly 21 million tons to 35 million tons. The heightened dependence on nitrogen underscores its significance in intensive agriculture while simultaneously highlighting the necessity for balanced nutrient management to mitigate potential environmental consequences. The global trends highlight the importance of sustainable practices to maintain agricultural productivity without jeopardizing environmental health.

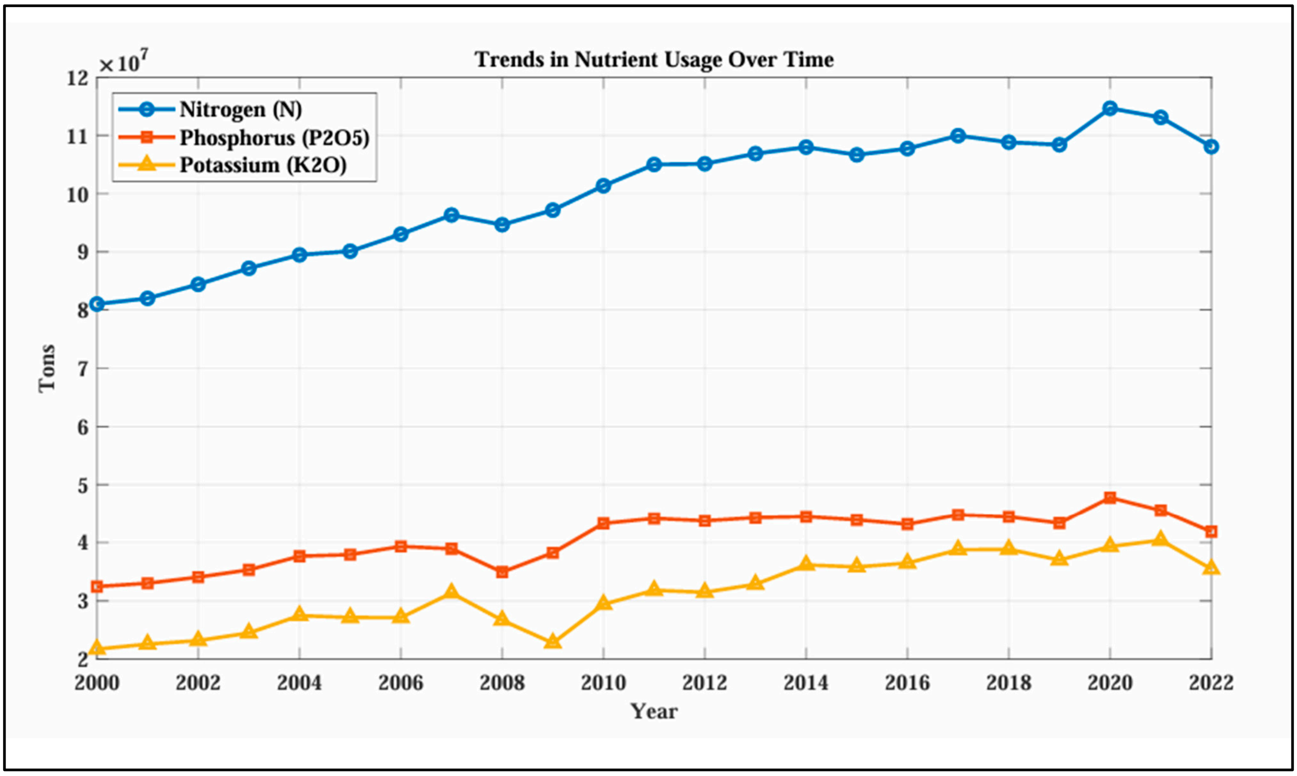

Figure 4. Global consumption of nitrogen (N), phosphorus (P_2O_5), and potassium (K_2O) fertilizers from 2000 to 2022.

Figure 5 illustrates the aggregate nitrogen (N) fertilizer consumption from 2000 to 2022 among the 10 leading nitrogen-utilizing nations. During this period, China emerged as the foremost user, with total nitrogen consumption approximating 27.5 million tons, indicative of the substantial agricultural requirements of its vast population. India ranks next, with approximately 15.6 million tons, highlighting comparable agricultural challenges. The United States occupies the third position, employing around 11.5 million tons of nitrogen over the past two decades.

Other nations, such as Brazil, Pakistan, and Indonesia, also play a notable role in world nitrogen consumption, albeit at reduced levels relative to the top three contributors. These variations underscore geographical variances in fertilizer usage, influenced by agricultural techniques, crop varieties, and population requirements. The aggregated usage data highlight the persistent dependence on nitrogen fertilizers, which, although enhancing crop yields, presents environmental issues such as nutrient runoff and water contamination. This concept emphasizes the significance of sustainable practices in fertilizer application to reconcile productivity with environmental health.

The patterns seen in Figures 4 and 5 underscore the dual challenge confronting global agriculture: fulfilling food production requirements while mitigating environmental hazards. Overapplication of fertilizers, particularly nitrogen, can result in nutrient runoff into aquatic systems, leading to non-point source pollution and adversely affecting biodiversity. Sustainable nutrient management techniques, including precision agriculture and tailored fertilizer delivery, provide a means to reconcile productivity with environmental conservation.

2.3. Pesticide-Derived Pollutants

In agriculture, pesticides are employed to manage weeds and insects. Approximately one-third of agricultural products are manufactured using pesticides [46]. After application to crops, pesticides can undergo degradation by microbes, light, or chemical reactions [51]. The deprivation process of insecticides can vary in duration, ranging from hours to days or even years, depending on the molecules' specific environmental circumstances and chemical properties [52,53]. Following the use of pesticides, the remaining chemical compounds in the environment, including soil, water bodies, and crops, dissolve due to landslides, rainwater erosion, and geological changes. Soil and water loss result in the transfer of remaining chemical pesticide components from the soil to surface runoff and underground runoff, ultimately leading to pollution in nearby water bodies [54]. Ultimately, the introduction of pesticides into water bodies poses a significant hazard to rivers, lakes, reservoirs, and aquatic ecosystems [51,55].

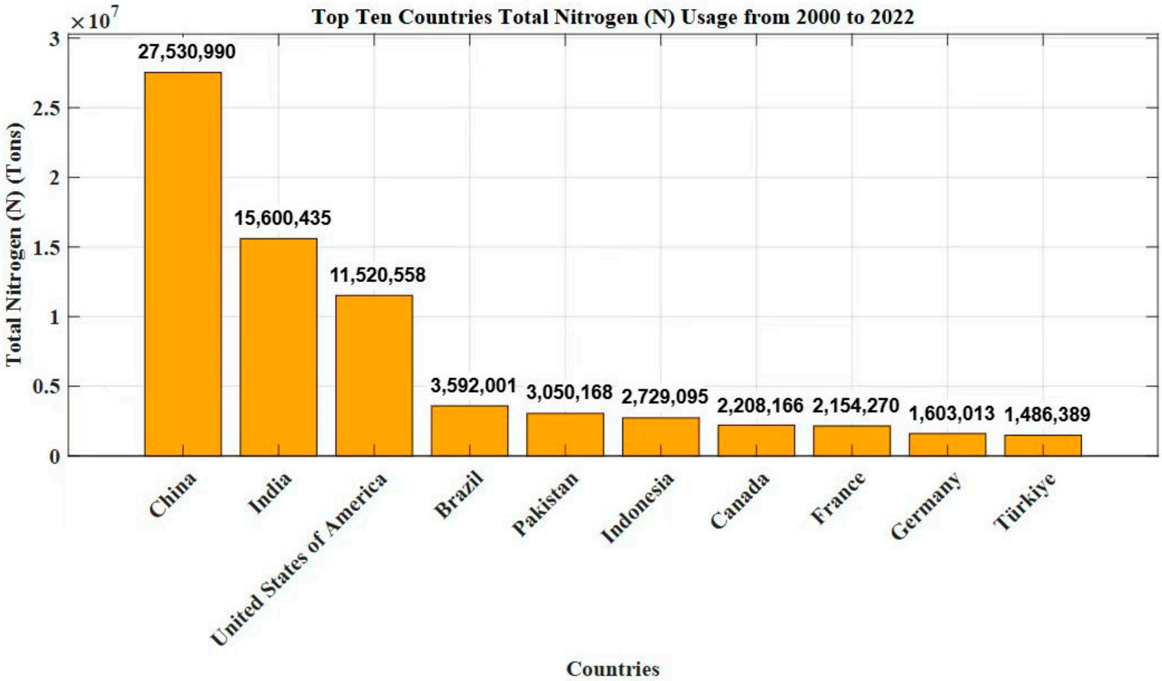

Figure 5. Cumulative nitrogen (N) fertilizer usage by the top ten countries from 2000 to 2022. China and India lead in nitrogen usage, followed by the United States, reflecting the high agricultural demand in these regions. The data highlight the critical role of nitrogen in global agriculture and the need for efficient nutrient management to reduce environmental impact.

The yearly global pesticide consumption amounts to over 2 million tons, with China accounting for around 16%, Japan for 14%, the Netherlands for 11%, the USA for 8%, Korea for 7%, the UK for 6%, France for 5%, Germany for 3%, Austria for 3%, Pakistan for 1%, India for 1%, and other areas accounting for the remaining 25%, as shown in Figure 6 [56]. The National Bureau of Statistics of China presented a statistical analysis of pesticide usage in China in 2021, which amounted to 1.31 million tons. This estimation represents a decrease of 27.62% compared to the peak of 1.81 million tons recorded in 2014. However, the utilization of pesticides per unit area in China remains significantly higher than the global average. The yearly mean pesticide consumption in the United States ranges from 400,000 to 450,000 tons. Surface water samples from 609 USA cities have shown the presence of approximately 150 distinct pesticides, with herbicides and insecticides being highly prevalent [57,58]. Highly intensive land use practices in Chile, Argentina, Costa Rica, and Brazil have led to a rise in pesticide application, causing pollution of soil and water sources [59]. Elevated levels of organophosphate pesticides in specific water bodies in developing nations such as India have surpassed acceptable environmental limits, leading to almost 300,000 cases of organophosphate pesticide poisoning worldwide [60]. Excessive and inappropriate pesticide use has not only resulted in soil and water contamination, presenting a substantial risk to aquatic organisms and the well-being of neighboring inhabitants, but has also impacted the overall economy. Moreover, extended exposure to surroundings contaminated with pesticides significantly increases the prevalence of illnesses and cancer in humans. A comparison of the countries is presented in Figure 7, regarding the expenditure on importing pesticides from 2012 to 2022.

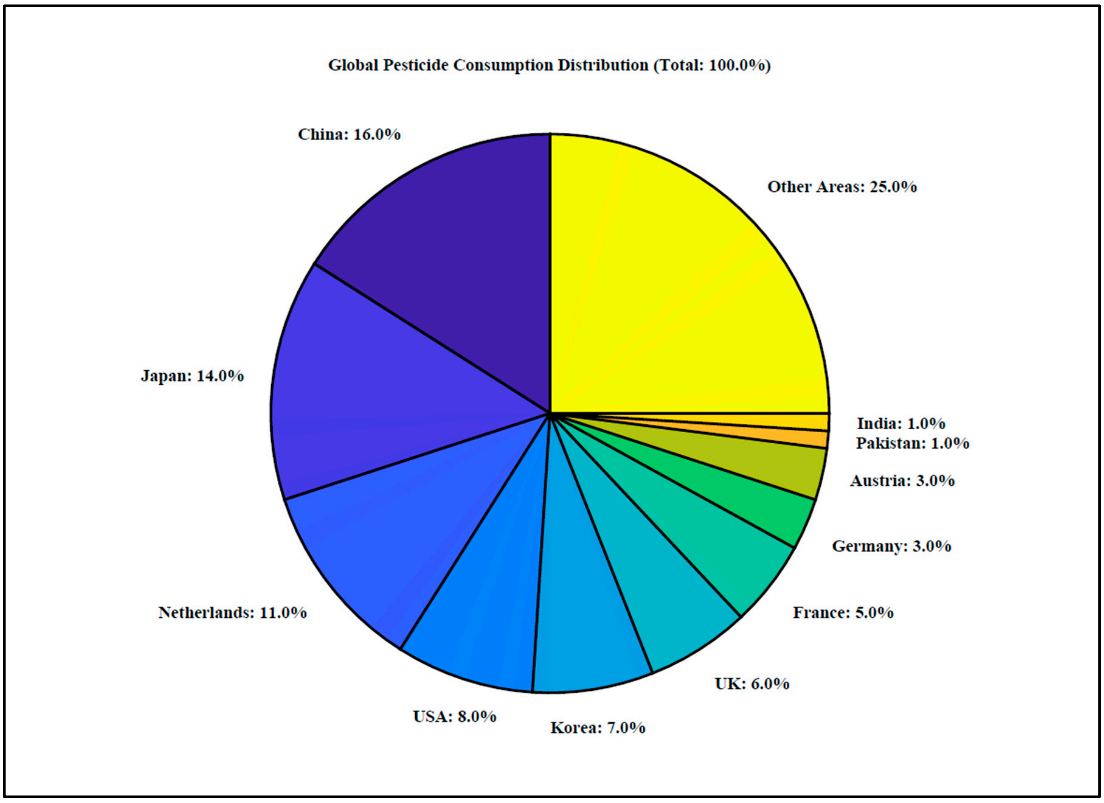

Figure 6. Global highest pesticide consumption.

2.4. Pollutants via Livestock and Poultry

With an enhancement in living conditions among inhabitants, the rural livestock and poultry breeding sector has experienced significant growth in recent years [61]. Most farms lack a dedicated fecal treatment system, particularly small-scale farmers who opt to raise livestock for breeding purposes. Animal waste is a major source of agricultural non-point source (ANPSP) pollution due to its high production rates and widespread contamination. However, the strategies currently in place to prevent pollution are largely inadequate [62]. The discharge of livestock and poultry waste is extensive and unpredictable, making it difficult to manage its impact on the environment. When nutrients like nitrogen and phosphorus enter water bodies, either directly or indirectly, they can significantly degrade water quality by promoting eutrophication [63]. Hence, raising livestock and poultry has emerged as a substantial concern in the context of ANPSP.

According to statistics from the "Ecological Environment Data" and the "China Statistical Yearbook 2022", China recorded annual sales of 104.86 million livestock and 15.57 million poultry. These activities have resulted in the release of approximately 600,000 tons of ammonia nitrogen (NH3-N), making up about 25% of the nation's total pollution emissions [49,64,65]. Eutrophication in coastal lagoons in America has been caused by pollution resulting from agricultural and livestock production [66]. In El Pescado Creek, Argentina, animal effluent contains high concentrations of organic debris, nutrients, and pharmaceutical chemicals [67]. Runoff can carry these pollutants into water bodies, exacerbating eutrophication. Elevated levels of N, P, and heavy metals in water bodies, mainly resulting from agricultural and livestock farming, pose significant environmental risks.

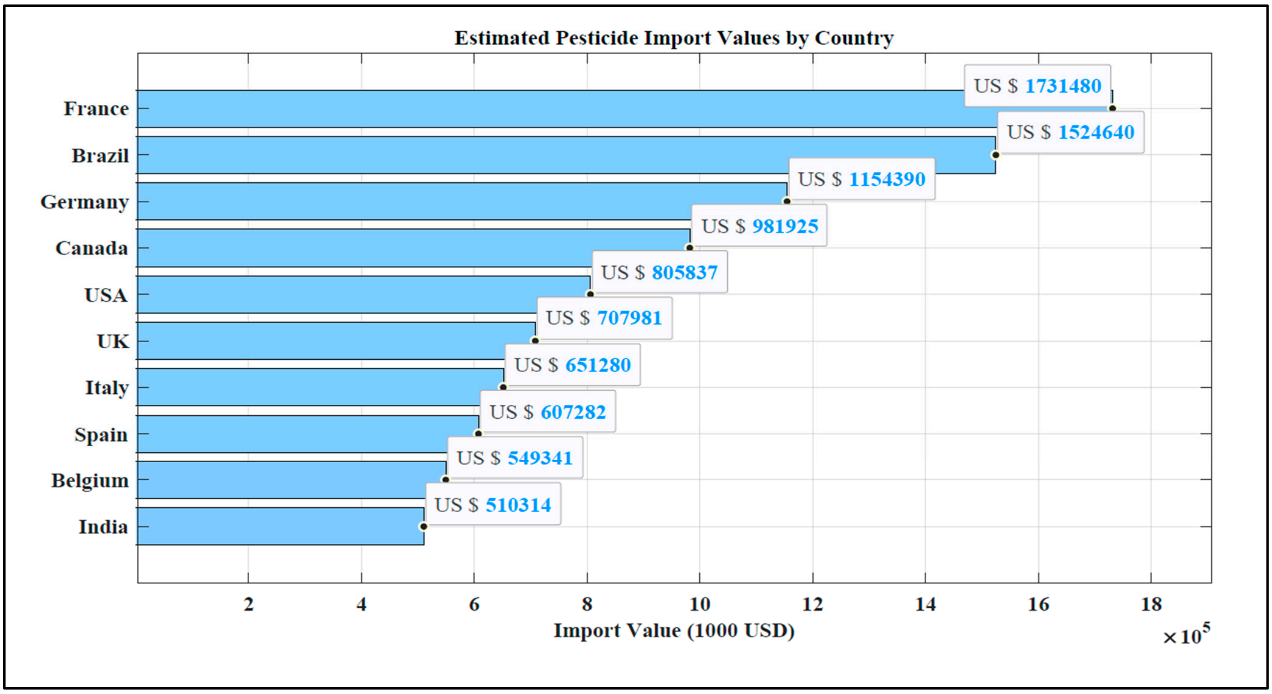

Figure 7. Comparison of expenditure for importing pesticides.

2.5. Pollutants from Crop Straw

Crop straw, a secondary product of agricultural operation, plays a crucial role in reclaiming farmland to enhance production [68]. Nevertheless, as high-efficiency coal and liquefied gas have become more widely used, the traditional burning method has been progressively substituted, accumulating numerous straw wastes in rural regions. Empirical evidence suggests that interring agricultural waste in the soil leads to elevated concentrations of methylmercury and cadmium in the soil and crops [69,70]. There has been significant growth in China's grain production since the 1980s, which has resulted in a corresponding increase in the amount of crop straw generated. In terms of production from 2010 to 2017, China's agricultural straw increased from 700 Mt to 780 Mt. Of this, 27% was incinerated, 38% was reintegrated into farmland, 17% was sold as fuel, and 14% was utilized as animal feed [71].

In 2019, a notice from the General Office of the State Council was issued about the Comprehensive Utilization of Agricultural Straw. This notice seeks to encourage the reuse of straw in fields or for other purposes, including substrates, feed, energy fuel, and raw materials for feed. Nevertheless, the percentage of agricultural straw incinerated in fields remains excessive, ranging from 10% to 50% in the majority of China and even exceeding this number in certain locations [72,73]. Improper management of crop straw, whether by direct burning, accumulating in fields, or discharging into rivers, results in a considerable loss of valuable resources and substantial environmental contamination. When waste straw is not properly disposed of and left in fields and rivers, it increases the stages of N and P in water systems, leading to eutrophication.

3. Assessing the Agricultural Non-Point Source Pollution (ANPSP)

The most commonly used NPS models were developed by foreign researchers, particularly in North America, in the 1960s [74]. NPS pollution involves the movement and transportation of pollutants across various environmental spheres influenced by natural conditions and human activity [75]. The terrestrial and aquatic transport methods are notably distinct due to differences in underlying surfaces, making both processes complex [76,77]. Pollutants typically migrate by runoff, accumulating in rivers or lakes. Through evaporation, infiltration, and vegetation interception, some contaminants reach groundwater or become deposited. Pollutants can attach to or detach from soil, sediment, and riverbanks, settle on the bottom, or be resuspended in the water. Exchanges between pollutants can occur in the water column, inclined by vegetative or aquatic species. In wetlands or lakes, the slow water flow facilitates NPS pollutants. The stratification leads to distinct pollutant migration and transportation compared to rivers.

Simulation processes often encompass hydrology, soil erosion, and material transport. Hydrological models cover various processes, including infiltration, evapotranspiration, surface runoff, and groundwater. The Green-Ampt, Philip, Horton, and Holtan algorithms are frequently used for infiltration [78]. The Soil Conservation Service (SCS) approach is widely utilized for simulating runoff in NPS models [79]. The Universal Soil Loss Equation (USLE) model is often used in NPS models to address soil erosion issues [80]. Pollutant transit is simulated by considering soil erosion, the runoff processes, chemical reactions, and morphological transformation. It is important to acknowledge that including every intricate process is often not feasible due to a simplified framework, unique conditions, and limited data availability.

3.1. ANPSP Assessment Model Developments

Groundwater Loading Effects on Agricultural Management Systems (GLEAMSs) and hydrological models, like the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMSs) developed by the USDA Agricultural Research Service (USDA-ARS), are used to create conceptual and NPS models [81], as well as ANPSP [82]. Not only is NPS pollutant load prediction important, but watershed management, pollution control, and improving water quality are becoming increasingly important. The development of NPS models was aided by the emergence of geographic information systems (GISs), and more intricate and interconnected models, like the Hydrological Simulation Program-Fortran (HSPF) model, were created [83]. Annualized agricultural NPS (AnnANPSP) [84] and the Soil and Water Assessment Tool (SWAT) are mechanical models used for managing large- and medium-scale watersheds on a daily basis [85], created by the USDA-ARS. The aforementioned NPS models primarily focus on the terrestrial transfer of pollutants, sometimes neglecting the conveyance process in rivers.

Multiple models have been developed to simulate and predict NPS and ANPSP. Table 1 compares the widely used models, including their applications, equations, strengths, and limitations.

Table 1. Overview and comparison of widely used models for assessing NPS pollution, including their applications, strengths, and limitations, to guide effective environmental management strategies.

Model	Pollutants	Scale	Descriptions	Mathematical Equations
SWAT [85]	Sediment, fertilizers, pesticides, heavy metals, and other substances.	Watershed	Semi-distributed models accurately simulate runoff and pollutant transport by considering topographical features, land management practices, climatic conditions, soil characteristics, hydrological parameters, and various other factors that can impact soil erosion, pollutant leaching, and groundwater quality.	$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - W_{seep} - E_a - Q_{gw})$ SW_t : $Final\ soil\ water\ content$ SW_0 : $Intail\ soil\ water\ content$ R_{day} : $Daily\ rainfall$ Q_{surf} : $Surface\ runoff$ W_{seep} : $Water\ seepage$ E_a : $Evapotranspiration$ Q_{gw} : $Ground\ water\ flow$

Table 1. *Cont.*

Model	Pollutants	Scale	Descriptions	Mathematical Equations
SPF [83]	Sediment, fertilizers, pesticides, salts, pathogens, and other substances.	Watershed	A distinct model capable of simulating water quality and the runoff for each sub-basin separately, as well as the movement and transformation of river contaminants based on the upstream and downstream connections of the basin.	Runoff Calculation: $Q_{runoff=P-I_a-S}$, $Q_{runoff}: Runoff$ $P: Precipitation$ $I_\alpha: Initial\ abstraction\ (water\ loss\ before\ runoff)$ $S: Storage\ in\ soil$ Water Quality: $C_{t=}C_{t-1} + \frac{(L_t - K \cdot C_{t-1}) \cdot \Delta t}{V}$ $C_t:\ Pollutant\ concentration\ at\ time\ t$ $C_{t-1}:\ Pollutant\ concentration\ at\ time\ t-1$ $L_t:\ Load\ of\ pollutant\ added\ during\ time\ step$ $K:\ Decay\ rate\ constant$ $V:\ Volume\ of\ water$ $\Delta t:\ Time\ step$
ANPSP [82]	Chemical oxygen demand (COD) and nutrition are among the topics discussed.	Watershed	The event-oriented distributed model is mostly utilized for estimating and predicting agricultural NPS contamination. It consumes less data than other distributed models.	$S_{out} = \sum(P_{load} \cdot F_{eff})$ $S_{out}: Output\ pollutant\ load$ $P_{load}: Pollutant\ load$ $F_{eff}: Efficiency\ factor$
AnnANPSP [86]	Chemical oxygen demand (COD) and nutrition are among the topics discussed.	Watershed	The continuous distributed model, derived from the ANPSP model, retains the benefits of the ANPSP model, except for simulating individual rainfall events.	$L_{out} = L_{in} \cdot (1 - e^{-k \cdot t})$ $L_{out}: Output\ load$ $L_{in}: Input\ load$ $k: Decay\ rate$ $t: Time$
GWLF [87]	Sediment and nutrients.	Catchment and watershed	The model described is a partially distributed and semi-empirical approach for estimating nutrient loads from various sources in a watershed, including groundwater, rural runoff, point sources, urban runoff, and saprophytic drainage systems. It can also be used in watersheds that lack monitoring data.	$P_{load} = (F_{source} \cdot C_{source} \cdot R_{source})$ $P_{load}: Pollutant\ load$ $F_{source}: Source\ factor$ $C_{source}: Source\ concentration$ R_{source}: Source runoff
DNDC [81,88, 89]	The carbon © and nitrogen (N) cycles.	Field	The plot model is designed to mimic the carbon and nitrogen cycles in terrestrial ecosystems. It exhibits excellent presentation, specifically in paddy field environments. It allows for the simulation and analysis of various farm management scenarios.	$N_{min} = f(T) \cdot f(WC) \cdot C_{org}$ $N_{min}:\ Mineralized\ nitrogen$ $f_t: Temperature\ function$ $f_{wc}: Water\ content\ function$ $C_{org}: Oranic\ carbon\ content$
CREAMS [81]	Pesticides, nutrients, and so on.	Field	This field model is designed to simulate the pollution of nitrogen, phosphorus, and sulfur (NPS) and assess the impact of various management techniques on pesticide levels in groundwater.	$P_{out} = \frac{P_{in} \cdot K_d \cdot Fr_w}{Z}$ $P_{out}: Output\ pollutant\ concentration$ $P_{in}: Input\ pollutant\ concentration$ $K_d: Distribution\ coefficient$ $Fr_w: Water\ fraction$ $Z: Soil\ depth$
GLEAMS [81]	Pesticides, nutrients, and so on.	Field	A field model employing a layering structure is used to assess the impact of agricultural management methods on soil erosion, fertilizer and pesticide leaching, and runoff.	$C_{out} = C_{in} \cdot \left(1 - e^{-k \cdot t}\right)$ $C_{out}: Output\ concentration$ $C_{in}: Input\ concentration$ $k: Decay\ rate$ $t: Time$
APEX [90,91]	Sediment, fertilizers, pesticides, and other substances.	Catchment/ watershed	This model can geographically divide a field or small watershed into spatial units with similar landscape positions, soil type, surface hydrological properties, and management methods. River channels link these units. Additionally, it can reproduce pollutants at subdivision outlets or watershed outlets.	$N_{load} = \sum(C \cdot P)$ $N_{load}: Nitrogen\ load$ $C: Concentration$ $P: Preceipitation$

Table 1. *Cont.*

Model	Pollutants	Scale	Descriptions	Mathematical Equations
SWMM [87,92]	Nutrients, pesticides, total suspended solids, substances derived from oil, fat, or grease, and so on.	Catchment/ watershed	An urban NPS model is generally utilized for simulating water quality, predicting scenarios, and assessing pollution management in the context of long-term continuous rainfall runoff or single rainfall event processes in metropolitan environments.	$\mathrm{Q_{runoff}} = \frac{\partial(\mathrm{P}-\mathrm{E_a})}{\partial \mathrm{t}} + \nabla\cdot(\mathrm{D}\cdot\nabla \mathrm{h})$ Q_{runoff} : *Runoff flow rate* P : *Precipitation* E_a : *Evapotranspiration* D : *Diffusion coefficient* h : *Water depth*
SPARROW [93]	Pesticides, nutrients, heavy metals, etc.	Watershed	The proposed numerical model analyzes watershed spatial features using empirical statistics and mechanisms. To quantify pollution transmission from source to river and upstream to downstream river network locations, it assesses land and water parameters separately. This method uses less data and works in regions with uneven monitoring locations.	Pollutant Load Estimation: $L_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + \epsilon_i$ L_i : *Pollutant load for watershed i* β_0 : *Intercept term* β_j : *Coefficient for the j − th explanatory variable* X_{ij} : *Explanatory variable j for watershed i* ϵ_i : *Error term* Transport Function: $T_{ij} = exp(-\alpha D_{ij})$ T_{ij} : *Transport fraction from watershed i to j* α : *Decay coefficient* D_{ij} : *Distance from watershed i to reach j*
PLOAD [94,95]	Pesticides, nutrients, heavy metals, etc.	Watershed	A geographic information system (GIS) model is utilized to compute NPS pollution loads originating from various sub-watersheds. The calculations are based on the amount of yearly or seasonal precipitation and the land use in each sub-watershed.	$L = C \cdot V$ *L*:*Load* *C*:*Concentration* *V*:*Volume*
Export Coeffi-cient [96,97]	Pesticides, nutrients, heavy metals, etc.	Watershed	A rite conventional statistical NPS model, which primarily calculates pollutant loads using export coefficients and does not account for subsurface conditions, is very applicable in data-limited settings.	Pollutant Load Calculation: $L = \sum_{i=1}^{n} (E_i \cdot A_i)$ L : *Total pollutant load* E_i : *Export coefficient for land use type i* A_i : *Area of land use type i* *Number of different land use types* Annual Load Estimation: $L_{annual} = P \cdot C_{export}$ L_{annual}: Annual pollutant load P : *Precipitation* C_{export} : *Export coefficient*
EFDC [98]	Dissolved oxygen (DO), chemical oxygen demand (COD), algae, nutrients, active metals, etc.	Water bodies such as rivers, lakes, reservoirs, estuaries, oceans, and wetlands	The Environmental Fluid Dynamics Code (EFDC) is a three-dimensional model used extensively to study the dispersion of contaminants in various bodies of water such as lakes, reservoirs, and rivers. This model is frequently employed to evaluate the environmental impact of NPS pollution and to simulate the occurrence of algal blooms.	Advection-Dispersion Equation: $\frac{\partial C_p}{\partial t} + u\frac{\partial C_p}{\partial x} + v\frac{\partial C_p}{\partial y} + w\frac{\partial C_p}{\partial \ddagger} = K_{\S}\frac{\partial^2 C_p}{\partial \S^2} + K_y\frac{\partial^2 C_p}{\partial y^2} + K_z\frac{\partial^2 C_p}{\partial z^2} - rC_p$ C_p : *Pollutant concentration* mgL^{-1} u, v, w : *Velocity components in x, y, and z directions* K_x, K_y, K_Z : *Dispersion coefficients in x, y, and z directions* r : *Reaction rate* Continuity Equation: $\frac{\partial h}{\partial t} + \frac{\partial(hu)}{\partial x} + \frac{\partial(hv)}{\partial y} + \frac{\partial(hw)}{\partial z} = 0$ h : *Water depth in meters* u, v, w : *Velocity components in x, y, and z directions*
OTIS [99]	Solutes carried by water, such as chloride, phosphate, nitrate, and dissolved metals.	Stream and river	An analytical framework that emphasizes river or stream-dissolved substance dynamics and movement. The model simulates longitudinal pollutant movement well but not vertical deposition. The model's main channel depicts advection and dispersion, and the storage zone contains the dead pool's porous portion and the riverbed for transitory storage.	$\frac{\partial C}{\partial t} = -v \cdot \frac{\partial C}{\partial x} + D \cdot \frac{\partial^2 C}{\partial x^2}$ C : *Concentration Pollutants in water* mgL^{-1} v : *Velocity* D : *Dispersion coefficient*

The Environmental Fluid Dynamics Code (EFDC) and One-Dimensional Transport with Inflow and Storage (OTIS) are both used to model the movement of non-point source pollutants in aquatic environments [98,99].

Table 2 details standard NPS models, their applications, equations, and pros and cons. SWAT and HSPF are renowned for accurately modeling watershed dynamics. ANPSP and AnnANPSP models, designed for agricultural settings, require less data. DNDC and CREAMS provide comprehensive information on nutrient cycling and field-scale processes.

Hydrologic process measurement approaches classify net primary productivity (NPS) models into two main categories: statistical models and mechanistic models. Statistical models, often referred to as "black box" models, establish functional relationships between variables through statistical analysis and typically require substantial amounts of data. This approach is suitable for regions where data are limited, as it tends to overlook the specific surface characteristics of the study area. Common statistical models used in NPS studies include the exported coefficient model, pollutant load model (PLOAD), and spatially referenced regressions on watersheds, such as the SPARROW model. In contrast, mechanistic models, also known as "white box" models, simulate the movement and behavior of pollutants by incorporating detailed hydrological, chemical, and biological processes. Examples of mechanistic models include HSPF, SWAT, ANPSP, GWLF, APEX, and DNDC. These models typically account for the migration of NPS pollutants through various hydrological pathways, while also considering the transfer of contaminants between water, soil, and atmosphere [100,101]. Due to the complexity of mechanistic models and the substantial data they require, "grey box" models have become increasingly popular. These models combine statistical methods with mechanistic frameworks to estimate parameters and simulate pollutant behavior more effectively when complete data are unavailable. The Universal Soil Loss Equation (USLE) serves as a practical example of a "grey box" model, frequently used to predict soil erosion within models like SWAT, ANPSP, and other NPS modeling tools [82,102,103].

Varying flora, geography, soil, and land use variables affect NPS contaminants differently. Using lumped, semi-distributed, or distributed techniques, NPS models discretize spatially [104]. These approaches differ in terms of input parameters and regional variability. The soil, vegetation, and land use are shown as constant in the lumped (no discretization) watershed model. The semi-distributed model assigns values to simulation units based on topography, soil type, and land use. The basic geographical unit, known as a Hydrologic Response Unit (HRU), might vary in terms of vegetation, soil, land use, and other factors [85]. In semi-distributed SWAT-style models, HRUs rarely interact. Distribution creates components of a watershed that are hydraulically linked. Elements have different parameters. Unpredictable "cells" are used by ANPSP and AnnANPSP with regular land and soil maintenance [82,86].

NPS models at the field, catchment, and watershed scales are informed by the principal pathways of NPS contamination at various geographical sizes. Field-scale models emphasize interactions between upstream and downstream areas, focusing on the transformation of pollutants and water movement, including vertical exchanges of materials between soil and the atmosphere in agricultural regions [105]. DNDC is widely used as a field-scale model, while catchment-scale models examine interactions between slopes and channels, even though ANPSP models typically do not consider pollutant transformations [106]. The most popular watershed models for simulating surface water and groundwater and their interactions with soil erosion, hydrologic processes, sediment transport, and nutrient dispersion are SWAT, HSPF, and AnnANPSP [86].

It must be noted that certain models of watersheds are multi-scale [107]. SWAT has been applied to an extensive area of 491,700 km^2 within the Upper Mississippi River Basin in Cairo, Illinois [108], as well as a smaller area of 5.5 km^2 at the University of Kentucky Animal Research Center [109]. Most of this review looks at the scale effect in relation to models of NPS contamination. We advise researchers to choose a model that is appropriate for their issues and topic.

3.2. Current Strategies for Limiting ANPSP

ANPSP-limiting approaches can be effectively summarized by the 3R principle, i.e., reduction at the source, interception, and repair [110]. This method has specific strengths and limitations, making it essential to select appropriate control techniques based on the type of pollution and the level of contamination in different regions. This study outlines strategies for controlling three primary sources of pollution: managing the use of fertilizers and pesticides (such as herbicides, insecticides, fungicides, and rodenticides), handling livestock waste effectively, and improving the treatment of agricultural residues. Adopting a comprehensive and diversified treatment strategy is crucial for reducing the risk of high N, P, and heavy metal levels in aquatic ecosystems [54]. Soil fertilization involves carefully using organic fertilizers to meet the specific nutrient needs of crops, enhance the soil's ability to supply nutrients, and maximize the fertilizer's efficiency [111,112]. Broad-spectrum fertilizer enhancers work well when combined with various types of fertilizers, including organic materials, manure, and traditional chemical fertilizers. These enhancers greatly improve fertilizers' effectiveness and help meet crops' diverse nutrient needs throughout their growth phases [113,114]. Applying organic fertilizers under optimal conditions promotes producing and releasing hormones, nutrients, and elements advantageous to crops, primarily because of the rich presence of beneficial microbes [115].

Direct effects on water quality can result from the runoff of fertilizers and various chemicals (herbicides, insecticides, and fungicides) used in agricultural production on unsuitable soils. Integrated pest management is a pest control technique that employs various complementary strategies to reduce pests, costs, and, consequently, the use of chemical pesticides. Herbicides, insecticides, fungicides, nematicides, and rodenticides are examples of agricultural pesticides. Irrigation in agriculture also has repercussions; for example, salt runoff causes salinization of surface waters, while fertilizer and pesticide runoff causes ecological degradation and bioaccumulation in edible fish species [116]. The subsequent analysis will focus on regulating pesticide use and soil remediation procedures. Pesticide reduction is commonly accomplished by implementing integrated pest management, which includes utilizing biological, chemical, and cultural control methods.

Botanical insecticidal methods focus on using natural plant-based products. These technologies are known for their reduced toxicity and improved safety for humans and the environment, in comparison to conventional chemically produced pesticides [117]. Biocontrol involves utilizing natural predators to manage pest populations. Each insect usually has one or more natural enemies that can efficiently suppress their excessive population [118,119].

Physical control techniques include various methods, such as light traps and sticky yellow boards, to eliminate pests from agricultural fields. The Clean Breeding Project focused on mitigating and regulating pollutants resulting from livestock and poultry breeding, emphasizing the treatment of wastewater and manure. This project encompasses four main areas: livestock and poultry manure applications, animal feed, fertilizer, fuel, and raw materials. Integrating off-the-shelf technologies into waste treatment ensures that pollutants from livestock and poultry operations are managed effectively. At present, prevailing technologies include aerobic composting and anaerobic digestion of organic waste [54]. Manure composting technology focuses on controlling the microbial breakdown of organic material under specific conditions. This process leads to mineralization, humification, and detoxification [120].

Biogas production from livestock manure is another feasible method for energy recovery. Biological gas digestion transforms organic waste from manure into renewable resources such as biogas, slurry, and biosolids, which can be reused widely in the ecological realm [41]. The primary approach to handling crop straw is through recycling and reuse, which includes five main techniques: converting straw into fuel [121], fermenting straw for fertilizer manufacturing [122–124], processing straw into feed for livestock and poultry [125], converting straw into industrial raw materials, and using it as a planting substrate [126]. In addition to effectively mitigating pollution caused by crop residues left in their natural state, these recycling systems significantly contribute to a sustainable agricultural resource cycle.

Soil remediation involves restoring the environmental properties of soils that various pollutants have damaged through different technological methods. The main objective in addressing heavy metal pollution in soils is either to decrease the concentration of these metals or to minimize their ability to be absorbed by living organisms. Chemical stabilization involves introducing substances such as lime, phosphates, or silicates into the soil, leading to reactions with heavy metals that produce less soluble or less bioavailable compounds. This process greatly reduces the mobility and bioavailability of heavy metals [127,128]. Phytoremediation uses selective plants known as hyperaccumulators, which can absorb and concentrate heavy metals from the soil. These plants are then harvested, and the heavy metals are effectively removed from the environment through proper disposal [129]. Microbial remediation leverages the metabolic activities of specific microbes to degrade, transform, or stabilize heavy metals present in the soil. This technique can be enhanced using either naturally occurring or genetically modified microbes, which have shown increased effectiveness in reducing heavy metal pollution in soils [130,131].

3.3. Assessment Modeling Results

The output of the major assessment models for ANPSP is presented. Most researchers have employed the Soil and Water Assessment Tool (SWAT) to investigate non-point source (NPS) nitrogen pollution in the Huang Shui Basin. This study revealed significant insights into the hydrological and nitrogen processes in the region (Figure 8). The model exhibited commendable performance, demonstrating R^2 values over 0.5, while the Ens values corroborated substantial accuracy. This study revealed that NPS's total nitrogen (TN) loads grew by 836.49 tons annually, primarily attributed to agricultural practices. In contrast, ammonium nitrogen (NH_4N) loads decreased by 576.72 tons annually, especially in the Huang Shui River segment. In several sub-basins, TN loads exhibited considerable variation, with certain regions demonstrating significant increases while others encountered decreases. Agricultural activities accounted for 4597% of total nitrogen loads, while livestock and rural habitation significantly contributed to ammonium nitrogen pollution. The SWAT model effectively simulated NPS contamination, providing essential insights to inform targeted pollution management measures for the basin.

In another study published in 2023 [132], the ANPSP model was calibrated and validated utilizing data from rainfall events in 2003 and 2004, attaining a correlation coefficient (R^2) of 0.94 for runoff and 0.93 for soil loss, with Nash–Sutcliffe efficiency (NSE) values of 0.73 and 0.79 for calibration and validation, respectively. Simulations of 15 precipitation events during the 2017 rainy season indicated a maximum runoff of 50.75 mm and a corresponding soil loss of 8.23 t ha^{-1} for a rainfall total of 81 mm. The data highlight the substantial influence of agricultural land use on erosion rates, especially during periods of heavy rainfall, as illustrated in the combined Figure 9 [132].

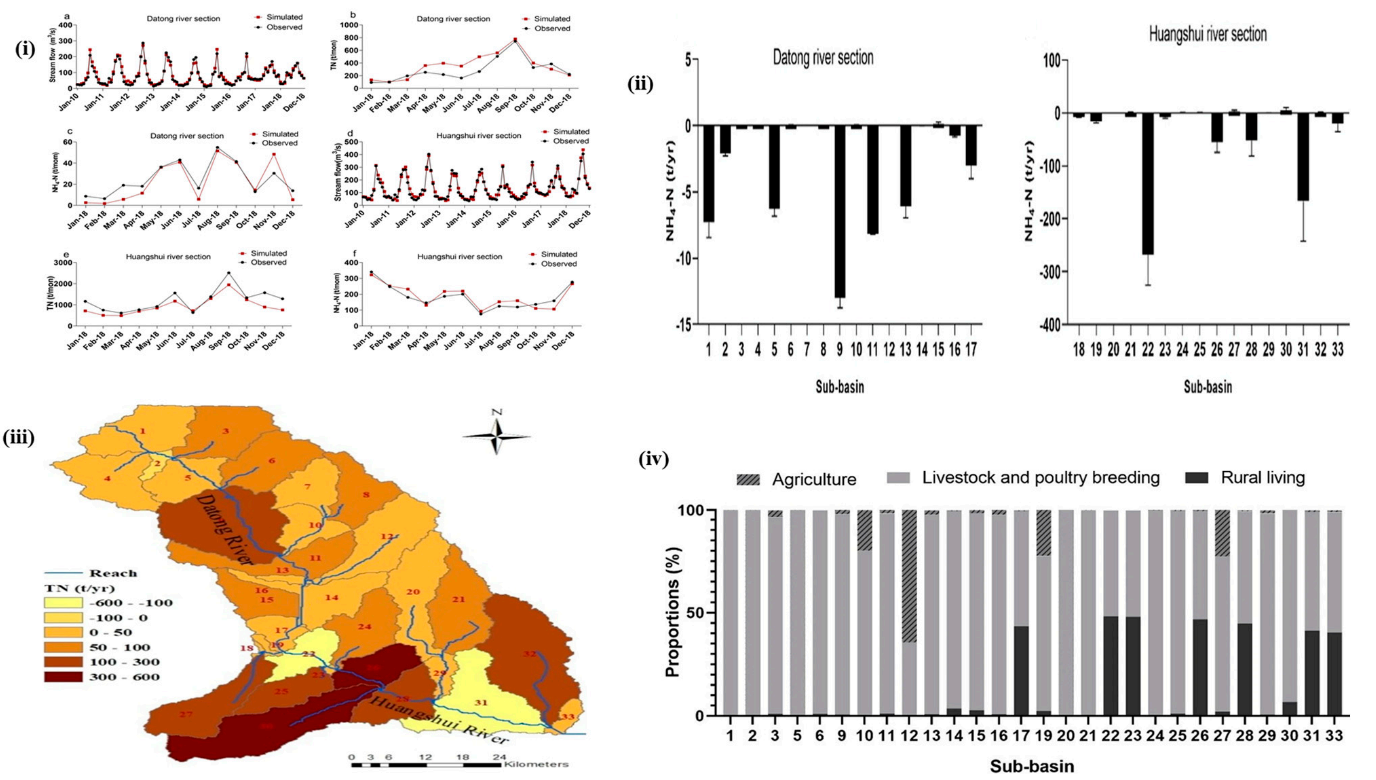

Figure 8. Hydrological and nitrogen dynamics in the Huang Shui Basin [129]. (**i**) Simulated and observed monthly streamflow, total nitrogen (TN), and ammonium nitrogen (NH_4-N) for the Datong (left) and Huang Shui (right) River sections, demonstrating model accuracy. (a) Streamflow (m^3/s) for the Datong River section: This panel compares the simulated (red squares) and observed (black circles) streamflow for the Datong River section over the year (January 2018–December 2018). It illustrates seasonal variability in streamflow, with clear peaks during certain months (e.g., high flow periods), providing insights into the river's hydrological behaviour. (b) Total Nitrogen (TN, μmol) for the Datong River section: This panel presents a comparison of simulated and observed total nitrogen (TN) concentrations in the Datong River section. A clear seasonal trend is seen, with variations in nitrogen levels that correlate with the changes in the river's hydrology. It provides a quantitative representation of nitrogen dynamics across the year. (c) Ammonium Nitrogen (NH_4-N, μmol) for the Datong River section: This panel compares simulated and observed ammonium nitrogen (NH_4-N) levels in the Datong River section. The data shows the variation in ammonium nitrogen concentrations throughout the year, indicating patterns that could reflect seasonal influences such as agricultural runoff or weather events. (d) Streamflow (m^3/s) for the Huang Shui River section: Similar to panel (a), this panel compares the simulated and observed streamflow, but for the Huang Shui River section. This panel displays the river's hydrological patterns over the same period, showing seasonal peaks and troughs in flow. (e) Total Nitrogen (TN, μmol) for the Huang Shui River section: This panel presents the comparison of simulated and observed total nitrogen (TN) levels in the Huang Shui River section. The data shows significant temporal fluctuations in TN, with clear seasonal differences and highlighting the river's nitrogen load across the different months. (f) Ammonium Nitrogen (NH_4-N, μmol) for the Huang Shui River section: This panel compares the simulated and observed ammonium nitrogen (NH_4-N) concentrations for the Huang Shui River section. Similar to panel (c), it reflects seasonal variation in ammonium nitrogen, with patterns possibly driven by both hydrological and anthropogenic influences. (**ii**) Ammonium nitrogen (NH_4N) load reductions across sub-basins in the Datong (**left**) and Huang Shui (**right**) River sections, with more substantial decreases observed in the Huang Shui River section. (**iii**) Spatial distribution of total nitrogen (TN) loads across sub-basins, with higher TN loads seen in agricultural areas such as sub-basins 26, 27, and 30. (**iv**) Source contributions to ammonium nitrogen (NH_4N) loads, with agriculture, livestock, and rural living as the key contributors, varying across sub-basins

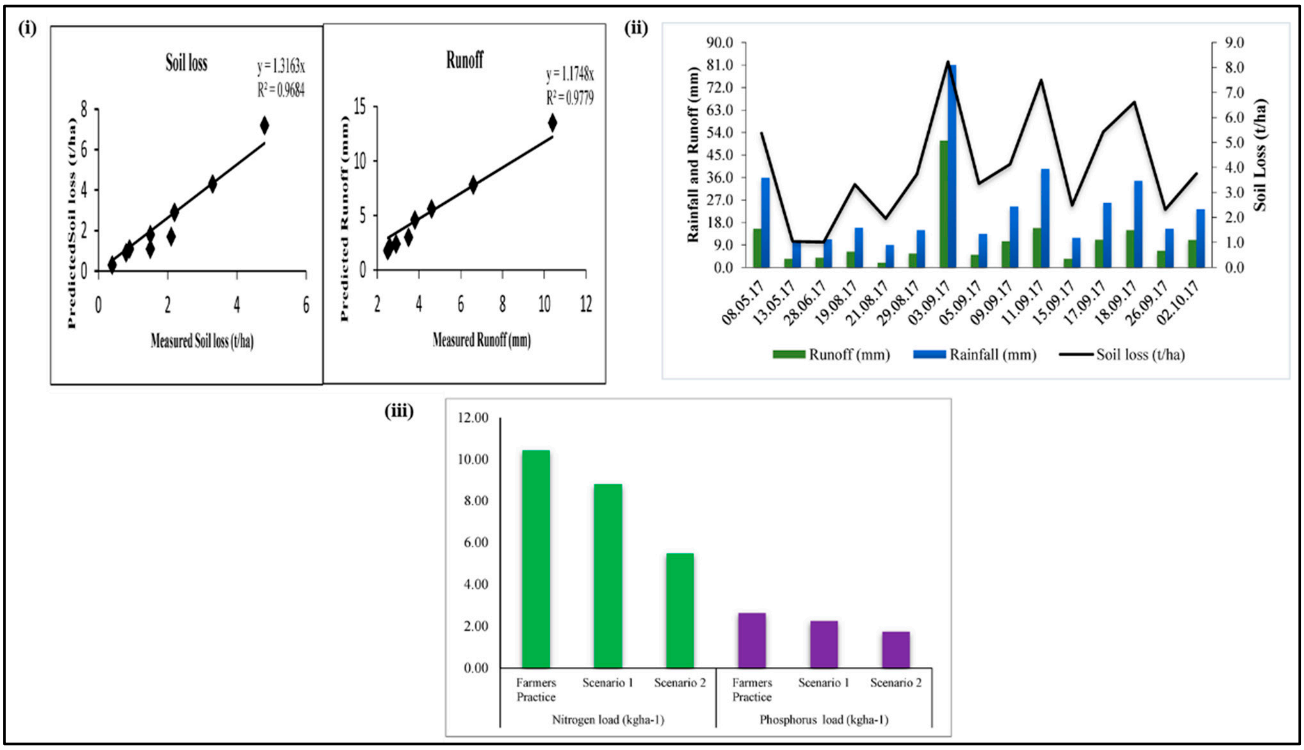

Figure 9. Calibration, validation, and simulation results from the ANPSP model show the correlation between measured and predicted runoff and soil loss, the impact of rainfall events on runoff and soil erosion, and nutrient load reductions under different fertilizer management scenarios. (**i**) The ANPSP model's calibration shows a high correlation between measured and predicted values for soil loss (R^2 = 0.9684) and runoff (R^2 = 0.9779). (**ii**) Simulated runoff and soil loss for 15 rainfall events in 2017, demonstrating the positive relationship between rainfall intensity and soil erosion. (**iii**) Nutrient load reduction under two scenarios: 25% and 50% fertilizer reduction compared to current farmers' practices, showing significant decreases in nitrogen and phosphorus runoff.

4. Mitigation Strategies for ANPSP Techniques

Dissolved pesticides, nutrients, and sediments in agricultural runoff cause various problems, including persistent organic translocation, nutrient loss, and soil erosion [133]. Reasonable tillage practices can significantly improve surface roughness and reduce surface runoff, thus reducing runoff emissions and pollution load at the source. As a food staple, rice (Oryza sativa) is the most important staple food crop for over half of the world's population, and it provides 21 per cent of global human per capita energy; globally, rice is cultivated in an area of 165.04 million hectares [134]. Rice requires a great deal of water, which leads to massive agricultural runoff [135]. The dissolved N, P, and sediments create a huge pollution load on the surrounding waters [136–138].

4.1. Cover Cropping

Cover crops protect and improve soil [139]. They can be ploughed into the soil as green manure or utilized as live or dead mulch [139,140]. The Soil Science Society of America (SSSA) describes CCs as "close-growing crops that provide soil protection, and soil improvement between periods of normal crop production, or between trees in orchards and vines in vineyards" [141]. Cover crops are usually legumes or non-legumes/grasses, but can be any plant. Much research has examined the effects of CCs on agricultural systems [142,143]. Benefits include better soil physical and chemical qualities, biological benefits, and lower production costs. Qi and Helmers (2010) and Villamil et al. (2006)

found that rye and hairy vetch-amended soils preserve moisture and improve the water table [144,145].

Depending on CC species and biomass production, cover crops reduce sediment and dissolved nutrient loss in water erosion [146]. Rye and oats reduced rill erosion by 54% and 89%, respectively, after 3 years [147]. Winter triticale, lentil, and pea residues reduced water erosion compared to controls [146]. P loss to runoff was significantly reduced in US plots using red clover and rye [148] and alfalfa [149] CCs inter-seeded into silage corn. CC reduces water erosion, improving water quality, soil fertility, crop productivity, and water pollution [147,150]. CCs "provide protective cover to the soil, absorbing raindrop energy, reducing soil aggregate detachment, increasing soil surface roughness, delaying runoff initiation, intercepting runoff, reducing runoff velocity, increasing the opportunity time for water infiltration, and promoting the formation of water-stable aggregates" [151–153].

4.2. Conservation Tillage

Conservation tillage strategies like reduced- and no-tillage decrease erosion despite disturbing the soil surface [154]. Furthermore, conservation tillage enhances soil structure and boosts the organic matter content, leading to increases in the ratio of water infiltration to runoff and a decrease in evaporation [155,156]. Both reduced-tillage and no-tillage are efficient forms of conservation tillage. As an illustration, Clausen et al. conducted a study on the impact of tillage on runoff in croplands located in Vermont, USA. Their findings revealed that using lower tillage practices resulted in a 64% reduction in runoff [157]. Liang et al. showed that no-tillage reduced rice-planting water shed runoff by 25.9% [158]. Reduced-tillage and no-tillage methods decrease the frequency and severity of soil disturbance caused by tillage practices while also mitigating the effects of rainfall through the use of crop residues to shield the soil surface. Land coverings and soil additions, such as biochar, have been employed in recent years to safeguard the soil by improving its structure and porosity [159,160]. Won et al. employed rice straw, polyacrylamide, and gypsum to remediate a Chinese cabbage field, leading to an 86.6% reduction in suspended particles and a 34.7% reduction in total nitrogen (TN) [161]. In a 33 mm of natural rainfall day, adding biochar and polyacrylamide to field soils reduced soil loss by 70.4% without influencing runoff. Lee et al. found that 4% wood biochar reduced field soil runoff by 16.8% and inorganic N by 41.8% [162]. Biochar is used in agricultural runoff management and soil remediation. The effects of biochar on soil structure and nitrogen fixation need more study [163,164].

4.3. Management of Fertilizer Usage

Fertilization management is a widely used approach for controlling sources [165]. N, P, and K fertilizers are extensively employed in agriculture. The effectiveness of N fertilizer varies depending on the crop. The mean N fertilizer efficiencies of maize, wheat, and rice are 37%, 18%, and 31%, respectively [166].

The calculated nitrogen use efficiency (NUE) is 36%. Surface runoff transports additional nitrogen (N) and phosphorus (P) to the receiving water. Hence, the application of fertilizer necessitates meticulous management. Effective fertilizer management involves the strategic distribution of fertilizer at greater depths to minimize the release of nitrogen into water bodies. Urea deep implantation resulted in a 50% reduction in nitrogen loss in paddy fields in Taihu Lake [167]. Using fertilizer band and hole placement reduces nitrogen loss by 63.6% and 77% and phosphorus loss by 42.8% and 53.8% [168,169]. Granulated organomineral fertilizers (OMFs) significantly decrease potassium (K) leaching by 70%, offering a favorable solution for sustainable agriculture by optimizing nutrient utilization [170]. This is because positioning the band can decrease the interaction with soil microorganisms and impede the speed of the nitrification process. Zeng et al. conducted a study to investigate the influence of fertilization depth on the loss of total nitrogen (TN) [171]. The authors discovered that applying fertilizer at a depth of 20 cm decreased 36.2% in TN (total nitrogen) and 31.4% in TP (total phosphorus) compared to applying fertilizer on the surface. Utilizing controlled-release fertilizer is an alternative method that allows for the gradual release of nitrogen (N) and phosphorus (P) to match the pace of crop growth. This approach enhances the efficiency of nutrient consumption [172]. Tan et al. investigated the impact of fertilization on N loss in a wheat–maize rotation system [173]. The study found that controlled-release N fertilizer effectively reduced inorganic N concentration in runoff. Using controlled-release P fertilizer can reduce P loss by 62% in paddy systems and 33% in maize systems [174]. Fertilizer timing and application rate optimization are crucial for reducing nitrogen loss [175]. The losses exhibit seasonal patterns, with increased nutrient loading in summer and autumn. Nitrate-N loss increased steadily with rainfall, but ammonia-N loss declined. A model-based study has been proposed for the long-term consequences of fertilization management based on these characteristics [176]

4.4. Irrigation Conservation

Field drainage and heavy rain can cause surface runoff. Surface runoff contributes to 86% of total N losses during the rice growing season, which coincides with the rainy season [177]. Due to conventional flooding irrigation (CFI), high flood water levels persist throughout fields. Water-saving irrigation (WSI) systems can dramatically lower floodwater levels, enhancing field buffering and reducing runoff and nutrient losses. WSI increases root growth and grain yield compared to CFI [178]. Alternate Wetting and Drying (AWD) irrigation is commonly used in rice cropping systems to reduce water inputs and improve water efficiency [179–181]. AWD irrigation reduced surface runoff by 30.2–36.7% compared to conventional techniques [182]. Nutrient concentrations do not decrease with reduced surface runoff when using AWD alone. The interaction time between water and soil will not diminish. It is recommended that irrigation management be integrated with tilling and fertilization procedures.

All source management methods can effectively reduce surface runoff and nutrient concentrations. However, they cannot prevent runoff from entering the receiving water. Source control measures have dramatically reduced N and P concentrations in agricultural runoff. However, safe discharge concentrations remain challenging to obtain. Long-term nutrient accumulation in receiving waterways increases eutrophication risk. Completely treating agricultural runoff requires extra process management and end-treatment technology.

5. Precision Agriculture (PA) for Sustainable Farming

Precision agriculture utilizes information and communication technology to manage spatial and temporal variability in fields. Management zones can be identified by analyzing field and crop attributes. Professor Pierre C. Robert, an early innovator in precision farming, described it as an information revolution facilitated by contemporary technologies. He stated that precision agriculture transcends the mere use of novel technologies to provide a more accurate and intricate farm management system [183]. Food production must substantially expand due to an anticipated world population of 9.7 billion by mid-century [184]. To mitigate field variability, many methods have been developed that employ ground-based sensing systems. These systems comprise mobile platforms and tractors outfitted with cameras, ultrasonic sensors, and light detection and ranging (LiDAR) sensors, sometimes referred to as laser sensors.

The extensive mechanization of agriculture in the twentieth century supplanted labor with machines, enhancing land productivity and realizing economies of scale. Precision farming has substantial potential for augmenting farmer earnings, improving both the extrinsic and intrinsic quality of agricultural goods and mitigating the detrimental environmental impacts of agriculture [185]. While not a panacea, precision farming can substantially enhance sustainable agricultural methods. The current Fourth Industrial Revolution is transforming agriculture, manifesting in the age of Agriculture 4.0. This next phase is characterized by data-driven management, innovative tool-based production, sustainability, professionalization, and reduced environmental impact [186]. The principal elements of Agriculture 4.0 encompass contemporary smart technologies, including robotics (such as drones), big data, Artificial Intelligence, computer vision, 5G, cloud computing, and the Internet of Things, as well as blockchain technologies and tools and approaches for precision agriculture that are presently effective [187].

Agriculture constitutes 85% of worldwide water management, highlighting the imperative for meticulous water management in orchards, especially in semi-arid locations, where water input represents a significant economic investment. Climate change exacerbates these issues for the fruit business by inducing extended droughts in specific regions. Small and marginal farmers constitute over 95% of the agricultural sector, with over 550 million of the world's 608 million farms classified as small (under 2 hectares) or medium-sized (under 50 hectares). Consequently, it is imperative to enhance the adoption rate of precision farming technologies (PFTs) among farmers to guarantee sustainable and healthier crop production [188].

Precision farming technologies can markedly enhance land production. Nonetheless, owing to the considerable investment necessary, larger farms with more acreage and enhanced access to revenue and finance are more inclined to implement PF. Larger farms are expected to be early adopters of precision farming, utilizing economies of scale to their benefit. In smaller fields, the substantial expense of positioning systems can be mitigated by employing a dead reckoning system, which involves determining the current position of a moving object based on a previously established location and integrating estimates of speed, direction, and elapsed time. This technology, suitable for small, uniformly shaped fields, employs in-field markers such as foam to guarantee consistent application, providing farmers with a reliable and efficient method of spatial field management [189]. Numerous obstacles impede the use of precise technologies by farmers, such as inadequate education, inexperience, disinterest, and a pervasive lack of commitment. A significant number of farmers lack awareness of the advantages of precision technologies and fail to dedicate time to obtaining the requisite information and knowledge. Furthermore, there is frequently a deficiency in cooperative attitude and a markedly low degree of trust among farmers.

Precision agriculture presently faces numerous obstacles, such as unsustainable resource utilization, extended monoculture practices, intensive livestock farming, environmental degradation, uneven digital adoption, food safety issues, an inefficient agri-food supply chain, as well as opposition to change. These issues hinder the achievement of efficiency, productivity, and sustainability in agricultural production, while intensifying unintended consequences on ecosystems. Moreover, precision agriculture techniques frequently exhibit disadvantages, such as elevated equipment expenses, rigorous terrain prerequisites, and vulnerability to environmental influences [190].

Precision farming (PF) significantly decreases greenhouse gas emissions by employing machine guidance and controlled traffic farming to prevent operational overlaps, leading to a 6% reduction in fuel usage. These advantages are particularly pronounced in extensive agricultural areas, providing other benefits such as reduced soil compaction, runoff, and erosion. PF also reduces effluents, encompassing nitrogen losses such as ammonia and nitrogen oxides [191]. To enhance production, competitiveness, resource utilization efficiency, and environmental sustainability, agricultural enterprises must implement precision farming. Regarded for its capacity to accomplish various objectives, precision farming is a vital instrument in contemporary agricultural operations.

6. AI and IoT Integration in Smart Farming

The integration of AI and IoT in smart farming incorporates Artificial Intelligence (AI) and the Internet of Things (IoT) into cyber-physical systems for holistic agricultural management. AI applications encompass several domains like soil management, crop health assessment, disease identification, and weed management. Prominent examples encompass Soil Risk Characterization Decision Support Systems (SRCDSSs) utilizing fuzzy logic, Management-Oriented Modeling (MOM), Artificial Neural Networks (ANNs), CALEX, PROLOG, computer vision systems, ANN-GIS, Invasive Weed Optimization (IWO), and Support Vector Machines (SVMs) [192]. A notable use of AI is mobile expert systems, allowing farmers to utilize smartphones for functions such as disease diagnosis, species identification, and soil health assessment via mobile applications. Moreover, AI enables real-time analysis of satellite imagery to assess agricultural development. These innovations establish a scientific foundation for precision agriculture, improving its efficacy in maximizing agricultural yields. The Internet of Things (IoT) comprises a network of interconnected devices and technologies that are essential for precision agriculture and smart farming. The IoT architecture in agriculture combines agricultural sensors with information and communication technology (ICT) and unmanned aerial vehicles (UAVs), enabling critical data collection for precision farming [193]. The increasing prevalence of IoT and mobile data are essential in the framework of the Fourth Industrial Revolution. Progress in communication technologies and wireless networks, including 5G, LoRaWAN, NB-IoT, Sigfox, ZigBee, and Wi-Fi, has substantially expanded the utilization of IoT across various sectors. These technologies provide real-time remote management, high-capacity phenotyping, and enhancements in coverage, bandwidth, connection density, and end-to-end latency. In agriculture, IoT technology, combined with cloud computing, facilitates smart farming applications such as livestock monitoring, intelligent greenhouses, aquaculture management, and meteorological surveillance. Prevalent IoT communication technologies encompass Wi-Fi, Zigbee, LoRa, Bluetooth, and 5G [194]. Communication for agricultural machinery necessitates characteristics such as minimal power usage, economic efficiency, and rapid response times. LoRa is distinguished by its long range, minimal application costs, ease of networking, and capacity to support several nodes concurrently. Artificial Intelligence is essential to the operation of Robotics and Autonomous Systems (RASs). Its interaction with IoT enables the perpetual creation of data streams. Data mining techniques are essential for transforming agricultural data into meaningful insights for decision-making [186]. AI examines varied environmental data and previous agricultural records housed in extensive data repositories, revealing concealed patterns essential for pest identification, disease detection, yield prediction, and fertilizer optimization inside agricultural decision support systems. These insights are crucial for enhancing the accuracy and efficacy of agricultural methods, facilitating informed decisions grounded in thorough data analysis. Agro-Bots are engineered for specific agricultural functions including harvesting, weeding, spraying, and transporting, utilizing innovative technology to enhance efficiency. These improvements guarantee precise chemical application, mitigating environmental effect by decreasing the usage of harsh chemicals and conserving water. In 2020, the global agricultural robot (Agro-Bot) market was valued at USD 4.9 billion and is projected to expand to USD 11.9 billion by 2026, indicating the rising implementation and development of robotic technologies in agriculture. The principal objective of Agro-Bots is to attain accurate, real-time targeting at the plant level, substantially reducing labor expenses, alleviating hazards linked to hazardous tasks, and supplying farmers with essential data for informed decision-making [195]. Nonetheless, the integration of Agro-Bots poses specific obstacles, especially in developed countries. The challenges encompass labor shortages and escalating production expenses. Agricultural fields present unpredictable conditions, including fluctuating light, weather, and terrain, while crops exhibit significant diversity in color, size, form, and sensitivity, frequently concealed by foliage.

7. Progress and Obstacles in Integrating Agro-Bots for Precision Agriculture

Agro-Bots have been effectively utilized in regulated environments such as simulated plantations, greenhouses, and various outdoor agricultural contexts. Recent improvements in robotics have facilitated automated fruit harvesting and intelligent machinery for weed eradication in agricultural settings [196]. These robots incorporate interdisciplinary technologies like machine vision, electronics, and mechanical engineering. Historically, robotics encountered difficulties in adjusting to dynamic settings and executing various activities necessary in warehouses and agricultural areas [197]. Currently, advanced image processing algorithms combined with cost-effective, high-performance sensors and technology enable adaptable task management for natural objects of diverse sizes and geometries, frequently seen as 'unknown' or partially recognized entities.

8. Methods for Safeguarding Plant and Fruit Health and Detection

Strategies for safeguarding plant and fruit health detection encounter various risks, with weeds presenting a considerable challenge by competing for essential resources like nutrients, light, and water, thus affecting growth and product quality if not swiftly recognized and eradicated [196]. Machine vision technology has been widely utilized to automate weed detection, particularly in situations with low color contrast between the plant and the weed [198]. Furthermore, insects constitute a significant hazard to plant health. Automated insect monitoring assists farmers in safeguarding their crops and fruits. Machine vision systems have demonstrated efficacy in illness detection and the identification of nutrient deficits.

9. Insect Detection

Pest management is a paramount concern for farmers because of their capacity to diminish crop yields and inflict damage. Consequently, farmers utilize diverse techniques to alleviate pest effects. In recent years, reliance on chemical pesticides has emerged due to their initial cost-effectiveness, accessibility, rapid efficacy, and inadequate awareness among farmers, despite the inherent risks to public health, animals, and the environment [199]. Consequently, investigating alternate pest management approaches to chemical pesticides is essential, given the considerable harm insects can cause to plants and fruits.

10. Identification of Diseases and Nutrient Deficiencies

Automated identification of harmful plant components is a vital and intricate field of research. Identifying illnesses and nutritional deficiencies is difficult due to the diversity of symptoms according to the individual disease, kind of deficiency, and fruit or plant species [200]. Infected plant sections display alterations in hue and texture, which may be additionally affected by differing light conditions.

11. Prospects, Challenges, and Future Trends in ANPSP

The future of ANPSP analysis offers advancements in standardized frameworks and the identification of contributions from various farming practices. Robust models for calculating NPS pollution loads, incorporating various agricultural activities and pollutant entry coefficients into water bodies, are essential. Integrating multiple methods for source tracing, such as diffusion and receptor models, can improve accuracy and reliability. Research on characteristic pollutants like pesticides and fertilizers should be enhanced to establish a fingerprint database for effective source tracing.

Managing ANPSP presents several challenges. The complex and unpredictable nature of ANPSP makes it difficult to identify and control pollution sources accurately. Variations in farming practices, weather, and soil types across different regions further complicate management efforts. Insufficient funding and limited access to modern technologies hinder effective management, particularly among small-scale farmers. Additionally, there is significant resistance to abandoning traditional farming practices due to lack of awareness, inadequate training, and insufficient financial incentives. Effective monitoring and enforcement of ANPSP provisions require substantial resources and the engagement of multiple stakeholders. Addressing these challenges is essential for the successful management of ANPSP.

To address these challenges, several innovative technologies, including AI, ML, and IoT, have been proposed to enhance ANPSP management. Integrating the Internet of Things (IoT), big data, and Artificial Intelligence (AI) technologies presents formidable prospects for improving the scientific rigor and accuracy of ANPSP analysis. The comparison in Table 2 demonstrates how different AI/ML models and IoT technologies can be utilized to improve ANPSP management by offering predictive analysis and continuous data via real-time monitoring.

These technologies offer predictive analysis and continuous data through real-time monitoring, enhancing ANPSP management. AI models like Support Vector Machines (SVMs) and Random Forest (RF) enable precise prediction of nutrient runoff and pollution levels, making them valuable for monitoring pollution events. On the other hand, IoT sensors, such as nitrate/phosphate sensors, provide real-time data on pollution levels in water bodies, enabling dynamic responses to pollution spikes.

By integrating these technologies, real-time monitoring systems can be developed to improve the accuracy of pollution predictions, while IoT provides continuous data for AI/ML models. Although AI/ML models offer robust predictive capabilities, the challenge lies in acquiring sufficient, clean data, a task that IoT sensors can address effectively. The key to future innovation will be combining these technologies to create adaptable, scalable models that can improve pollution management across various agricultural systems.

Table 2. Summary of AI/ML models and IoT technologies used for agricultural non-point source pollution (ANPSP) management.

Technology	Application	Strengths	Weaknesses
Support Vector Machines (SVMs) [201].	Predict nutrient runoff and classify pollution levels	High accuracy with small datasets	Struggles with large, noisy datasets
Artificial Neural Networks (ANNs) [202].	Pattern recognition for pollution dynamics	Handles complex patterns well	Requires large datasets and can overfit
Random Forest (RF) [86].	Pollutant load prediction using multiple variables	Can process large and varied datasets	Can be computationally expensive
Gradient Boosting Machines (GBMs) [203].	Optimize prediction models for nutrient runoff	High prediction accuracy with feature selection	Requires significant tuning and data preparation

Table 2. *Cont.*

Technology	Application	Strengths	Weaknesses
IoT Sensors (Nitrate/Phosphate Sensors) [204].	Continuous nutrient concentration monitoring in water bodies	Real-time continuous monitoring	Sensor accuracy can degrade over time
Drones and UAVs (Multispectral Imaging) [205].	Capture real-time data on crop health and soil conditions	Real-time, wide-area coverage for data collection	Expensive and requires data processing expertise
Remote Sensing Satellites [206].	Monitor land use and pollution sources remotely	Extensive area monitoring with spatial coverage	Limited by cloud cover and spatial resolution
Smart Irrigation Systems [207].	Optimize water usage to minimize runoff pollution	Water-efficient and reduces pollution risk	Initial high cost and technology integration challenges

12. Conclusions

Agricultural non-point source pollution (ANPSP) remains a major environmental concern, especially with rising agricultural intensification and industrialization. This review illustrates that ANPSP is influenced by a complex interaction of factors, such as the overuse of synthetic fertilizers, inadequate nutrient management, poor livestock waste disposal, and pesticide runoff. Pollutants, especially nitrogen (N), phosphorus (P), and assorted heavy metals, are conveyed through surface runoff and leaching, resulting in extensive environmental degradation, notably the eutrophication of aquatic systems, deterioration of soil quality, and decline in biodiversity. Notwithstanding heightened awareness, the effective mitigation of ANPSP has proven elusive, primarily due to the spatial and temporal intricacies of pollutant transport and transformation processes, the variability in agricultural practices across diverse regions, and the difficulties in data acquisition and model implementation.

Contemporary methodologies for evaluating ANPSP, including field-scale and watershed-scale models, have yielded significant insights into the transport and transformation of pollutants. Nevertheless, these models, albeit beneficial, exhibit distinct limits. Field-scale models provide significant accuracy in evaluating nitrogen cycling at reduced scales; however, their utility diminishes when applied to larger agricultural landscapes or watersheds due to limitations in data and computational resources. Conversely, watershed-scale models may forecast pollutant dynamics across extensive areas; nevertheless, they frequently necessitate substantial data and may lack accuracy in data-deficient locations, hence constraining their applicability in specific situations. Moreover, models grounded in conventional methodologies frequently neglect to sufficiently account for the diversity of landscapes, agricultural practices, and the evolving characteristics of environmental systems.

This review underscores the burgeoning potential of novel technologies in propelling the domain of ANPSP research forward. Real-time monitoring technologies, such as remote sensing and in situ sensors, have demonstrated efficacy in acquiring data on nutrient concentrations, pollutant dynamics, and environmental variables. These technologies provide a substantial enhancement in the frequency and precision of environmental data collecting, facilitating more accurate contamination evaluations. Nonetheless, despite these developments, real-time monitoring systems continue to be fragmented, exhibiting inadequate integration across platforms and geographies. The establishment of a cohesive, real-time monitoring system that consolidates data from diverse sensors and remote sensing platforms is a significant deficiency in contemporary research.

An essential finding from this review is the possible integration of Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) in the advancement of next-generation ANPSP models. Artificial Intelligence and Machine Learning technologies can augment the predictive capacities of current models by facilitating the efficient processing and analysis of extensive datasets, hence enhancing the precision of pollution forecasts. These systems can incorporate data from several sources in real time, facilitating adaptive learning and dynamic modifications in pollution management techniques. The use of IoT sensors facilitates ongoing surveillance of nutrient levels and contaminant loads, delivering immediate input for informed decision-making. Collectively, these technologies possess the capacity to transform ANPSP evaluation and oversight by delivering more precise, context-relevant, and prompt forecasts of pollution levels.

Notwithstanding the exciting potential of these technical developments, numerous difficulties persist. A critical challenge is the availability and quality of data necessary for the proper training of AI/ML models. In areas with insufficient data or weak monitoring systems, the precision of AI-driven forecasts may be undermined. Moreover, the incorporation of these new technologies into current agricultural systems poses logistical, financial, and technical challenges, particularly in low-resource environments where small-scale farmers may be deficient in the requisite infrastructure and training for implementation. Moreover, greater investigation is required regarding the longevity and accuracy of IoT sensors, which are frequently influenced by environmental variables such as temperature, humidity, and interference from external sources.

It is essential to prioritize the development of scalable, multi-scale models that integrate both field- and watershed-level processes. These models must be engineered to accommodate various environmental contexts and agricultural activities, facilitating more tailored and efficient pollution management measures. Moreover, ANPSP contamination is a complex, multifaceted issue that necessitates the participation of interdisciplinary teams, including environmental scientists, engineers, policymakers, and agricultural practitioners for effective control. This collaborative strategy will be essential for the effective implementation of novel technology and methodologies across various agricultural contexts.

The amalgamation of AI, ML, IoT, and real-time monitoring technologies would not only alleviate ANPSP but also promote sustainable agriculture practices by optimizing fertilizer application, enhancing water use efficiency, and minimizing overall environmental impacts. Nonetheless, accomplishing this necessitates continuous investment in research, technological advancement, and the education of farmers and policymakers. It is imperative to establish frameworks that promote the adoption of these technologies, especially in developing regions, via financial incentives, capacity-building initiatives, and joint endeavors among governments, the private sector, and international organizations.

In summary, although much progress has been achieved in comprehending and modeling ANPSP, the future of efficient pollution management depends on the incorporation of advanced technologies and the implementation of sustainable farming practices. Tackling the intricacies of ANPSP necessitates ongoing innovation, interdisciplinary collaboration, and a dedication to enhancing both the scientific and practical dimensions of pollution control. By integrating research, technology, and practical applications, we can facilitate the development of more effective, scalable, and sustainable solutions to alleviate the detrimental effects of agricultural non-point source pollution on global ecosystems and human health.

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