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Review

Spatially Explicit River Basin Models for Cost-Benefit Analyses to Optimize Land Use

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Abstract: Recently, a wide range of models have been used in analyzing the costs and benefits of land utilization in river basins. Despite these advances, there is not enough information on how to select appropriate models to perform cost-benefit analyses. A literature search in the Web of Science (WOS) online database was implemented and resulted in the selection of 27 articles that utilized models to perform cost-benefit analyses of river basins. The models reviewed in these papers were categorized into five types: process-based, statistical, probabilistic, data-driven, and modeling frameworks or integrated models. Twenty-six models were reviewed based on their data and input variable needs and user convenience. A SWOT analysis was also performed to highlight the strengths, weaknesses, opportunities, and threats of these models. One of the main strengths is their ability to perform scenario-based analyses while the main drawback is the limited availability of data impeding the use of the models. We found that, to some extent, there is an increase in model applicability as the number of input variables increases but there are exceptions to this observation. Future studies should explicitly report on the necessary time needed for data collection, model development and/or training, and model application. This information is highly valuable to users and modelers when choosing which model to use in performing a particular cost-benefit analysis. These models can be developed and applied to assist sustainable development as well as the sustainable utilization of agricultural parcels within a river basin, which can eventually reduce the negative impacts of intensive agriculture and minimize habitat degradation on water resources.

Keywords: spatially explicit models; cost-benefit analyses; optimized land use; river basin models

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1. Introduction

Exponential population growth leads to land use changes (i.e., forest is converted into farmlands), which provides humans with water, food, fiber, and shelter [1]. Land use determines the utilization efficiency of local natural resources and the related economical, ecological, and social benefits [2]. Most often, land utilization is not sustainably planned and implemented [3–5]. Moreover, land uses are often related to and interact with each other, i.e., either synergistically or antagonistically, which may lead to critical trade-offs [1,6–8]. A methodological framework was therefore developed to measure land use efficiency, which includes models, conditions, classification, integrated methods, sequential evaluation procedures, and an indicator system [3].

A large portion of the land surface has been transformed either by altering natural landscapes for human beings or by human-dominated landscapes. Across the world, land use practices vary, but most often, their final consequences are similar: degradation of environmental conditions [1]. Over the past few decades, research has revealed that there are substantial changes in atmospheric composition and ecosystems throughout the earth [9–12]. Surface energy and water balance have been affecting regional climates, which are also attributed to land use changes [13]. Water balance have been altered due to the allocation of fresh water for irrigation, domestic, and industrial purposes [14,15]. Furthermore, the increasing application of fertilizer in agricultural land uses has contributed to nutrient input in lands and streams and has affected the water quality of freshwater and coastal ecosystems [11,16].

Recently, land use changes allowed the exploitation of an even-larger portion of the environment's goods and services, but at the same time, diminished the capacity of global ecosystems to maintain freshwater and forest resources, sustain food production, mediate infectious diseases and regulate climate and air quality. The result is clear: land use changes increase short-term goals but damage the long-term goals, such as ecosystem services on a regional or global scale [1].

For sustainable development, it is imperative to maintain an appropriate balance between the provision of human needs and the maintenance of healthy ecosystems [16]. Land uses are often related to and interact with each other, leading to critical trade-offs of ecosystem services. Ecosystems provide critical social and economic benefits but overexploiting them may lead to possible long-term degradation; this should also be recognized when assessing trade-offs between ecosystem services [13].

Assessing trade-offs between services is crucial for sustainable development. In this context, cost-benefit analyses (CBAs) are beneficial. CBA is defined as an efficient approach for economic evaluation by comparing the costs and benefits of various projects or policy decisions [17,18]. However, CBA is not only limited to financial analyses but is expanded to environmental and social indicators, some of which can be translated into monetary terms [19,20]. CBA is also used for weighing the environmental and social costs and benefits of different alternatives [19,21,22]. Other methods, such as the contingent valuation method, is also used to measure economic values of the environmental and ecosystem services. It uses a survey for the estimation of no-use values, i.e., asking people how much they are willing to pay or the compensation they are willing to accept for the environmental services [23]. However, this method has limitations, including that respondents may have biased and hypothetical answers rather than the intended, which may lead to wrong decisions [24]. In this regard, the CBA is advantageous because in most cases it provides quantitative outcomes and therefore is a valuable tool in spatial planning to resourcefully and efficiently use natural resources. For this reason, CBA is emerging and has received growing attention in research and policy making [25]. CBA potentially allows the attainment of optimal economic, ecological, and social policies [26]. Particularly, some spatially explicit models can perform cost-benefit analyses and aid in analyzing land use options, which support policy formulations. Figures 1 and 2 describe how spatially explicit models can be applied in cost-benefit analyses.

For the past two decades, the application of spatially explicit models in environmental studies has grown massively. Major progress is due to the increase in spatial resolution, improvements in computer technology, and increased availability of data [27]. Spatially explicit models have been applied in CBA, wherein the output of the model is used to perform CBA (Figure 1). Furthermore, these models can be used to assess multiple scenarios and identify scenarios that provide the optimal ecosystem services (Figure 2).

Despite these advances, there is not enough information on how to select appropriate models to analyze the cost and benefits of land utilization. Therefore, we reviewed the potential application of different models that are available and gathered information on the time needed for data collection, adopting or developing a model, and applying the model. This information is of paramount importance for selecting a model that is applied in cost-benefit analyses.

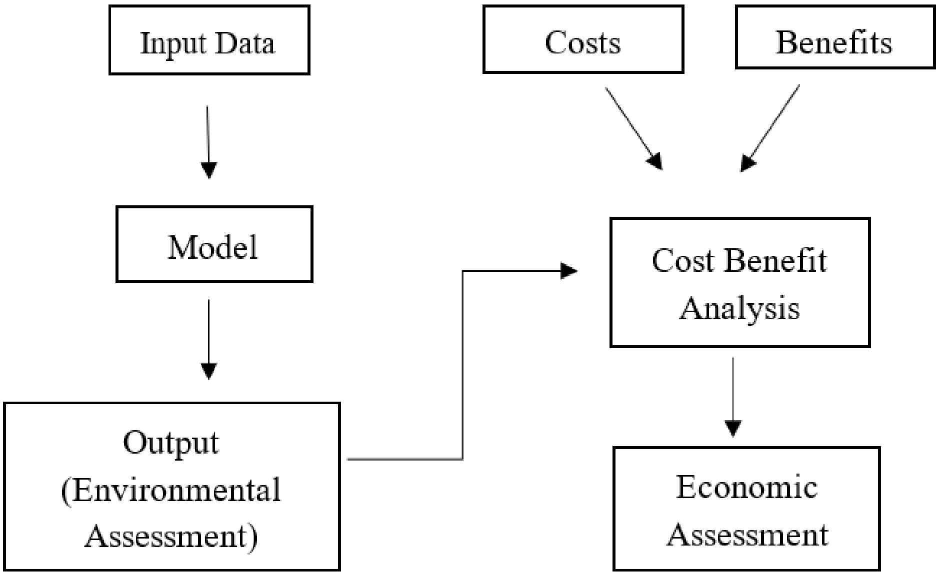


Figure 1. Flow chart describing the stepwise procedure for cost-benefit analysis using the model for environmental assessment. Data (e.g., geographic information system (GIS), field) are used in an environmental assessment model, the model output is used for the cost-benefit analyses, and then an economic assessment is performed.

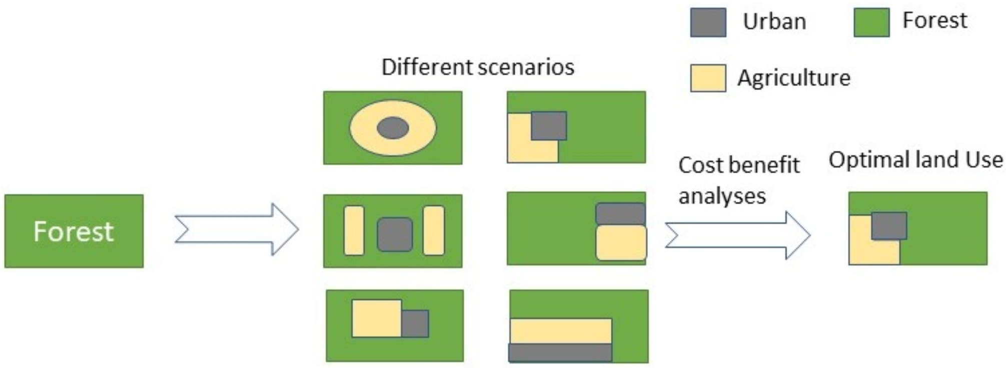


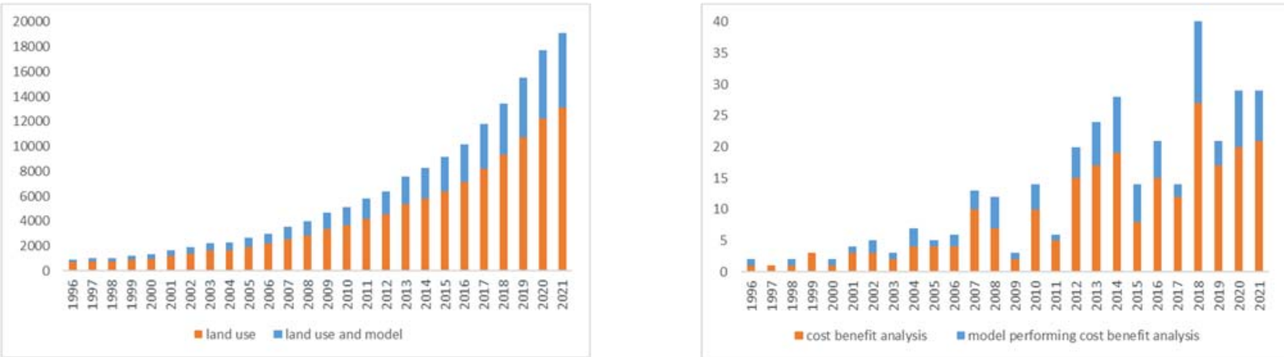
Figure 2. Ways that spatially explicit models can be used for cost-benefit analysis on certain land. Supposing that people will settle on forested land, an area for urban and agriculture would be needed. With the help of spatially explicit models, one can assess the multiple scenarios and quantify the respective ecosystem services, including agriculture and water provisioning, as well as mental well-being and health services, for instance. By simulating the different scenarios and analyzing the costs and benefits, one can determine the optimal land use based on predefined criteria.

In this study, we reviewed scientific literature that applied spatially explicit river basin models that perform cost-benefit analyses to optimize land use. We aimed to determine the models' data needs and whether the model is user-convenient. In particular, we investigated their strengths, weaknesses, opportunities, and threats and also the steps used in the modeling. This study provides insights into the different spatially explicit models that can be used for cost-benefit analysis and for assessing spatial configurations that potentially provide optimal ecosystem services.

2. Literature Search

The advanced search of the Web of Science (WOS) online database was used to gather articles for reviewing spatially explicit models. We used the search codes TS = ("Land use*" AND "Cost benefit analysis*" AND "model*") and TS = ("land use*" AND "models*" AND "cost benefits*") for publication years 1996–2021, with the document type "articles" and language "English". The start year we selected is 1996 instead of 1955 because there was no paper published before 1996 in the WOS when this search code was used. We reviewed the articles with spatially explicit models that were used for river basins. A total of one hundred and twenty eight (128) articles came out from the search codes mentioned above. Thirty-three (33) articles are the same in both of the search codes, sixteen (16) are related to transport, and twelve (12) are related to urban development. Only twenty-seven (27) articles fit our review scope using the criteria of river basin models and were used for cost-benefit analysis, i.e., the models that are or can be used for the cost-benefit analysis for river basins, with particular focus on changing land use, management practices, climate, flooding, and risk.

Since the use of computers has become a norm, there has been a growth of activities in the field of environmental modeling and environmental decision-support tools, which are increasingly applied [14]. Figure 3a reveals an increasing interest in using models to assess and analyze the impacts of land use and land use change in the past two decades. There is also not only a growing interest in cost-benefit analyses but also in the models that perform cost-benefit analyses in the past two decades (Figure 3b).



(**a**) (**b**)

Figure 3. The number of papers published on the web of knowledge from 1996 to 2021: (**a**) the search code TS = ("land use") and TS = ("land use*" AND "model*"); document type = articles; language = English; (**b**) the search code TS = ("land use*" AND "cost benefit analysis*") and TS = ("Land use*" AND "Cost benefit analysis*" AND "model*"); document type = articles; language = English.

3. Results and Discussion

3.1. Analysis of Selected Land-Use-Based Models

The computer age has revolutionized environmental modeling leading to the surged utilization of mathematical models as a decision-support tool [28]. The reviewed models were classified into five groups: process-based models, statistical models, probabilistic models, data-driven models, and integrated models or modeling frameworks. Among the reviewed articles, 8, 3, 1, 1 and 13 authors used process-based models, statistical models, probabilistic models, data-driven models and integrated models or modeling frameworks, respectively.

The different types of models make use of different mathematical methods. The process-based model is a mathematical formulation that explicitly integrates different approaches: the hydrologic state variables and fluxes that are theoretically observable and can be used in the laws of conservation of mass and energy and momentum at temporal scales characterizing the underlying physical processes [29]. The statistical model is described as a relationship of input and output variables between mathematical functions. These models have a stochastic and deterministic component [30]. The probabilistic model predicts future events on the theory of probability or randomness. These models integrate variables and probability distributions into the model or phenomenon. Recent progress in computational intelligence, specifically in machine learning, have greatly expanded the capabilities of empirical modeling. This new approach is called data-driven modeling (DDM) [31]. DDM is based on analyzing data about a system, especially without a clear knowledge of the physical behavior of the system, to find relationships between system state variables (input, internal, and output variables) [31,32]. Lastly, integrated models connect ecology with society and economy into one model or modeling framework. Integrated models consist of two or more different models or model types in which the output of one model is used as an input in the other. This type of model is widely used for policy making [28]. Integrated models are also called "meta discipline", which integrate practices across multiple scientific fields and knowledge to develop an understanding of the environmental, social, and economic consequences of management decisions.

3.1.1. Input Variables and Data Needed

The observations of some environmental variables can significantly alter over time and space [33]. Consequently, it is essential to select suitable input variables before developing the models [34–36]. Moreover, the model outcome depends on the assumptions made during the pre-processing steps of the modeling process [37].

Based on the reviewed models, process-based models generally require numerous input variables and may depend on different types of data (Figure 4 and Table 1). The number of input variables used for process-based models range from 10 to 52. For instance, SWAT that simulates nutrient dynamics in a river basin requires 52 input variables. On the other hand, input variables of statistical models range between 10 and 22. The simple statistical bivariate analysis model uses a minimum of 10 and the multiple regression model (olive trees) uses a maximum of 22 variables. The statistical model is described as a relationship of input and output variables between mathematical functions [30]. It is observed that probabilistic and data-driven models required a lesser amount of input data than process-based models. On the other hand, integrated models sometimes model both the ecological and economic aspects, which are valuable in policy making. Multicriteria decision analysis requires a maximum of 49 input variables while the DPSIR framework (The Climate Change Project), deterministic finite time horizon dynamic optimization model, and deterministic optimization approach with Monte Carlo methods require a minimum of 5 input variables.

3.1.2. User Convenience

User convenience is an important aspect of a model as it is the users who provide their perception of whether a model is convenient and easy to use. In Table 1, user convenience of each reviewed model is based on the combination of literature findings and a trade-off between the data needed and the number of possible applications. In general, easy-to-use models are preferred by users. Models are convenient if they can be applied to answer a wide range of research questions (e.g., for exploration and real-time control applications as well as for education purposes). Simple models (i.e., models with a lower number of input variables and data) are also generally convenient as their model output is straightforward to interpret. However, models with a higher level of completeness, integrating various processes, are of paramount importance for large-scale and time-specific environmental design studies [64]. User convenience is, therefore, a trade-off between model simplicity and the number of possible applications (Figure 5).

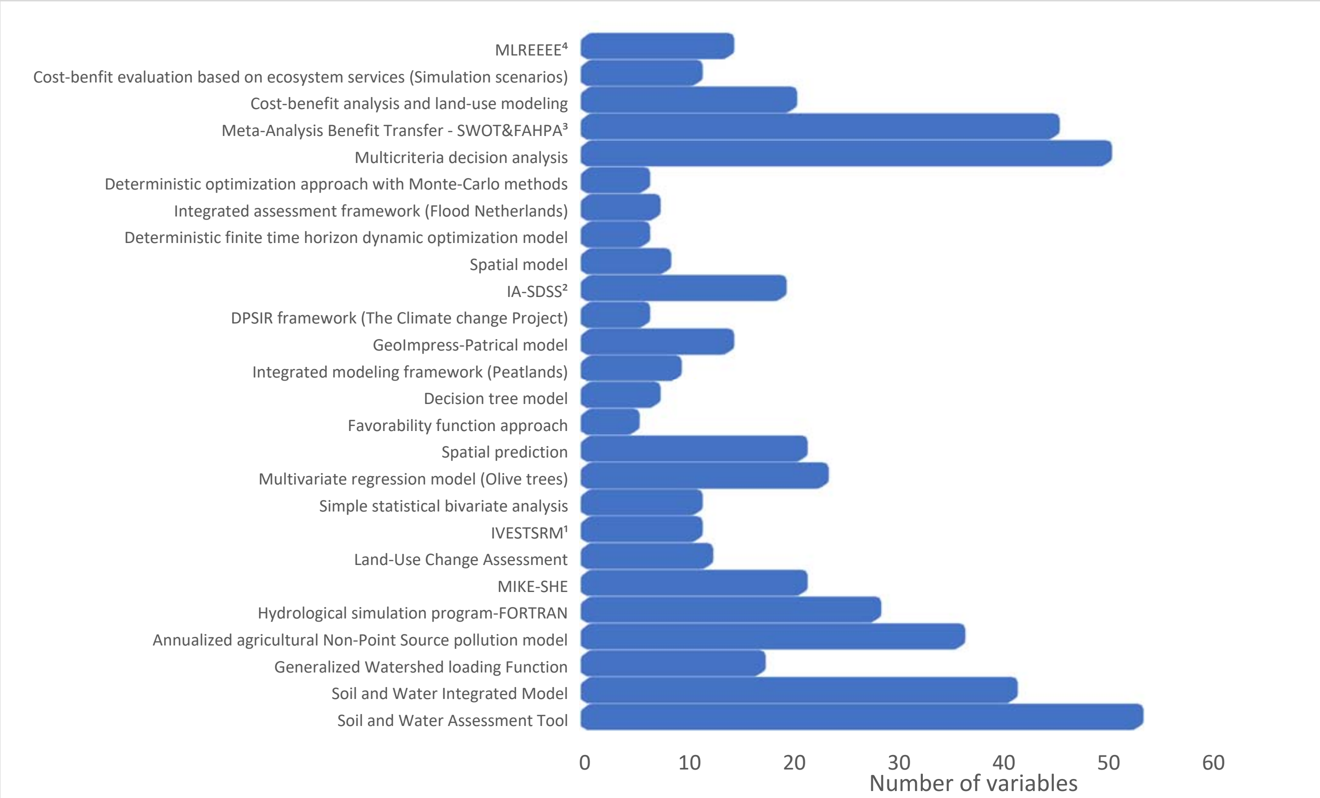


Figure 4. The number of variables required for the reviewed models. On the y-axis are the reviewed models and on x-axis is the number of variables needed. [1] Integrated valuation of ecosystem services and trade-offs sediment retention model, [2] integrated assessment framework and spatial decision support system (IA-SDSS), [3] meta-analysis benefit transfer—Strengths Weaknesses Opportunities Threats and fuzzy analytic hierarchical process analysis, [4] multinomial logistic regression and environmental and economic effect estimations.

Table 1. List of reviewed spatially explicit models that can be used for cost-benefit analyses for a river basin. The reviewed models are classified into five categories: process-based models, statistical models, probabilistic models, machine-learning models, and integrated models or modeling frameworks. L: Low, M: Medium, H: High.

	Models	**Data Needed**	**User Convenience**	**References**
		Process-Based Models		
1	Soil and Water Assessment Tool	52	L	Tuo, et al. [38], Sun, et al. [39], Strehmel, et al. [40], Liu, et al. [41], Rocha, et al. [42], Mtibaa, et al. [43]
2	Soil and Water Integrated Model	40	L	Tuo, Chiogna and Disse [38]
3	Generalized Watershed loading Function	16	L	Tuo, Chiogna and Disse [38]
4	Annualized agricultural Non-Point Source pollution model	35	L	Tuo, Chiogna and Disse [38]
5	Hydrological simulation program-FORTRAN	27	L	Tuo, Chiogna and Disse [38]
6	MIKE-SHE	20	L	Thorsen, et al. [44]
7	Land Use Change Assessment	11	M	Liu, et al. [45]
8	Integrated Valuation of Ecosystem Services and Trade-offs Sediment Retention model	10	L	Udayakumara and Gunawardena [46]

Table 1. *Cont.*

	Models	Data Needed	User Convenience	References
Statistical models				
9	Simple statistical bivariate analysis	10	H	Conforti, et al. [47]
10	Multivariate regression model (Olive trees)	22	H	Noori and Panda [48]
11	Spatial prediction	20	H	Qiu, et al. [49]
Probabilistic models				
12	Favorability function approach	4	L	Chung and Fabbri [50]
Data-driven models				
13	Decision tree model	6	H	Crossman, et al. [51]
Integrated models/modeling frameworks				
14	Integrated modeling framework (peatlands)	8	L	Van Hardeveld, et al. [52]
15	GeoImpress-Patrical model	13	L	Ferrer, et al. [53]
16	DPSIR framework (The Climate change Project)	5	M	Pouget, et al. [54]
17	Integrated assessment framework and spatial decision support system (IA-SDSS)	18	L	Wang, et al. [55]
18	Spatial model	7	M	Zarei, et al. [56]
19	Deterministic finite time horizon dynamic optimization model	5	L	Cerdá and Martín-Barroso [57]
20	Integrated assessment framework (flood Netherlands)	6	M	Brouwer and Van Ek [26]
21	Deterministic optimization approach with Monte Carlo methods	5	L	Monge, et al. [58]
22	Multicriteria decision analysis	49	L	Mwambo, et al. [59]
23	Meta-Analysis Benefit Transfer—Strengths Weaknesses Opportunities Threats and Fuzzy Analytic Hierarchical process analysis	44	L	Jahanifar, et al. [60]
24	Cost-benefit analysis and land use modeling	19	L	Pan, et al. [61]
25	Cost-benefit evaluation based on ecosystem services (Simulation scenarios)	10	M	Li, et al. [62]
26	Multinomial logistic regression and environmental and economic effect estimations	13	H	Bertoni, et al. [63]

Process-based models incorporate detailed environmental processes but are mostly data and input-variable intensive. However, some process-based models, such as SWAT, can be applied to long-term or time-specific simulations, such as assessing the impact of climate change and land use change on streamflow [65]. The risk of groundwater contamination and the outcome of alleviation measures can be predicted by a process-based deterministic model (coupled Mike SHE/DAISY system) [44]. Although these models are data and/or input-variable intensive, they can be applied to numerous research questions.

On the other hand, data-driven models and statistical models are relatively easy to implement as they are flexible with the number of input variables; therefore, their application depends on the input variables that are fed in the model. For instance, the decision tree model was developed to reconfigure agricultural land use to accomplish saving in water use and improve ecosystem services [51]. A statistical model (e.g., simple statistical bivariate analysis) was used to provide future land planning by drafting a landslide susceptibility map [47]. These models require a relatively low number of input variables, which can be only used in time-independent applications.

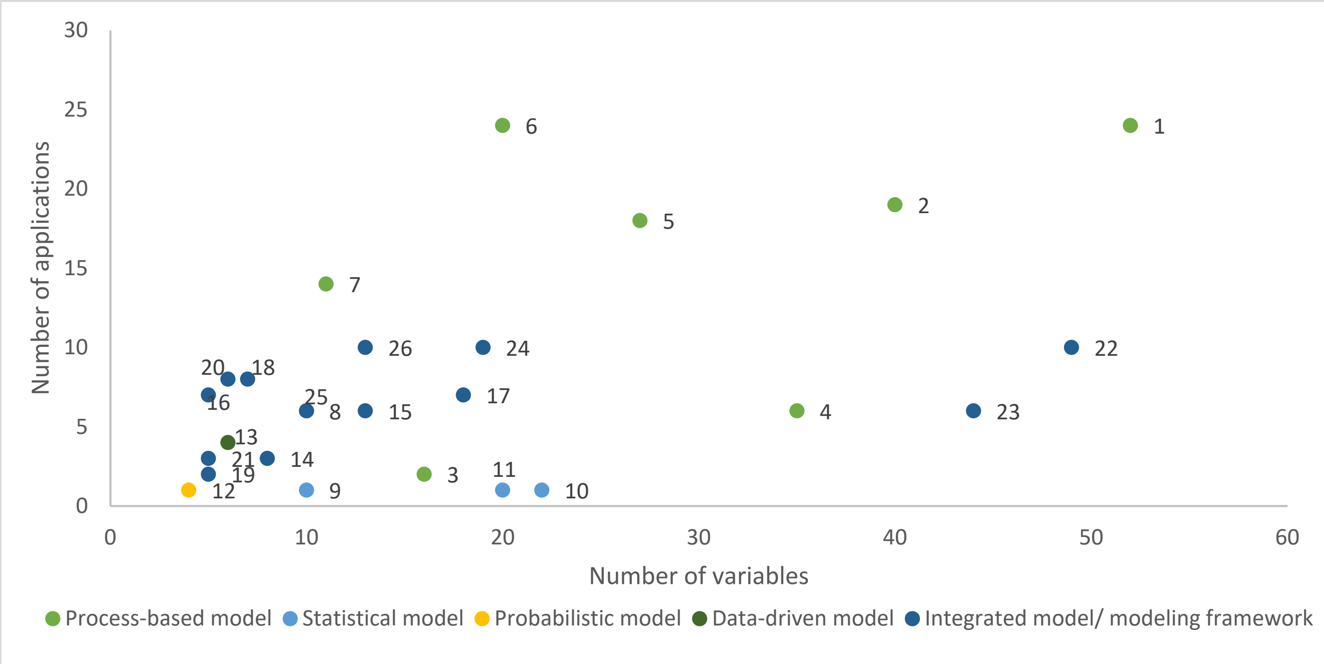


Figure 5. The number of potential model applications with the number of input variables of the reviewed models. The potential applications of each model are presented in Tables S1–S4.

Integrated models are a combination of different model types and therefore the number of input variables and applications as well as the number of research questions they can answer depends on the type of models that are combined. For instance, an integrated assessment network, which integrates environmental, economical, and social impact assessments, is applied to support decision making in the context of flood control policy in the Netherlands [26]. An integrated modeling framework, which assesses water levels, soil subsidence, and societal impacts, is applied for assessing strategies of water management in Dutch peatlands [52]. The spatial model, integrating spatial models and analysis, is adopted for determining methods that are advantageous to land use change [56].

3.2. Steps in Modeling

3.2.1. Data Collection

Before starting the modeling process, the modeler should have defined the aims and objectives of modeling a particular system [66–68]. The first step of modeling is data collection (Figure 6). Data collection may take a considerable length of time depending on the amount and duration of data that needs to be gathered. In the project timeline, the data management plan is often overlooked but it can increase efficiency and save time if performed correctly [69]. Nowadays, data can be collected in different ways as technology is advancing. For instance, ecological data can be collected by satellites, sensors, and sampling campaigns [69]. For spatially explicit models, one may need to collect various data and data types. It may also necessitate integrating them. For example, to estimate water and nutrient balances through the SWAT model, various data are integrated, such as the digital elevation model (DEM), soil and land use data, weather data, water quantity and quality data, crop management practices and fertilizer application. The latter two can be collected through a survey. Process-based models required much more data as compared to other models. However, to accomplish a high level of understanding of ecological systems and processes (e.g., population studies, hydrology, and meteorology), integration of data is critical [69,70]. Data integration can be time-consuming and is generally done manually [71,72]. Aside from data integration, cleaning the data as well as pre-processing the data into correct formats can also take time. Data visualization also allows the inspection of errors in the data. This process can be part of data cleaning.

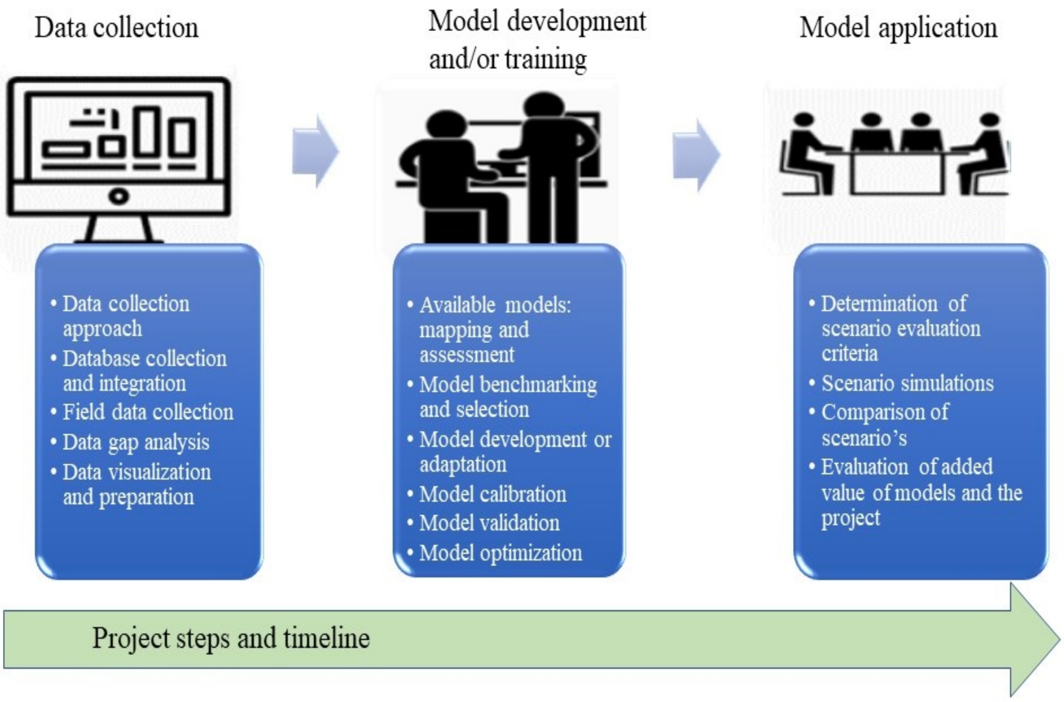


Figure 6. The different steps in the modeling process are data collection, model development and/or training, and model application.

One of the main problems in data collection is the data gap. To compensate for the lack of time-series data and historical data, the models make use of simple and practical functions (i.e., triangular and empirical), implementing various programming languages and software packages [69,73]. Several scripted analysis environments are also used to pre-process and clean the data such as R and MATLAB [69] and many approaches are emerging [74–76]. These processes transform linkage between the source and derived data, which greatly aid the scientific studies, particularly those that require a numerous variety of data.

3.2.2. Model Development and/or Training

The second step of the modeling process is model development and training for most data-driven models, such as statistical and machine learning models (Figure 6). Model calibration is commonly performed for process-based models. Once the model is constructed or selected, the model is calibrated or trained and validated. In process-based models, model calibration is a process of comparing model output (prediction) to model input data (parameters) with observed data in the set of assumed conditions [77], while model validation is a process of evaluating whether the model can produce sufficiently precise simulations [78]. Due to the advancement in computational technology, researchers are adopting more intense procedures for calibration and optimization [69]. For instance, hydrological calibration is substantial in many process-based models, which reduces uncertainty in model simulation [79]. Hydrological calibration involves (1) the use of weather and hydrological data, including dry, wet, and average years [80]; (2) subsequently, the use of multiple evaluation techniques to determine its accuracy [81]; (3) and lastly, the calibration of all other components that are to be evaluated [77]. Some models, such as machine learning models, are also optimized or tuned by adjusting the model parameters to enhance model efficiency or increase predictive accuracy [82–84]. The length of time needed for model development may vary from model to model. However, this information is not well-documented in most papers. Therefore, it is difficult to assess the total time needed to develop the model. For increasing model efficiency, both simulation and optimization are performed [85].

3.2.3. Model Application

Model application is the third step in the modeling process (Figure 6). Models can be used in scenario analysis, which is the method of predicting the occurrence of an object or situation, assuming the future trend will continue [86]. As a first step, the selection of relevant scenarios is implemented. Stakeholders can be involved in selecting different scenarios [87]. In strategic planning, scenario analysis is getting popular in both public and private sectors [88,89]. Simulations are performed after selecting the scenarios. Scenario simulation is a process of achieving stakeholders' required results by implementing scenarios in the model. When designing an effective simulation scenario, the modelers and stakeholders require careful planning. Simulation models can be optionally combined with an optimization model to help solve complex land use allocation problems by considering multiple, often competing demands on landscapes [90]. An optimization model is a decision-support tool used to find the best possible solutions to the problem and the purpose of optimization models is to reduce or remove uncertainty aspects using specific techniques [91]. These applications of the model may require a huge length of time but are highly dependent on the type of model. Unfortunately, the time needed to perform these model applications is not well-documented.

3.3. SWOT Analysis

To further discover the potential of spatially explicit models for river basins, we performed a Strengths Weaknesses Opportunities Threats (SWOT) analysis. This strategic assessment allows recognition of the strengths, weaknesses, opportunities, and threats associated with the use of spatially explicit models for river basins (Table 2). SWOT analysis gives insight into current capabilities and future possibilities of spatially explicit models applied for cost-benefit analyses of river basins.

Table 2. SWOT analysis of spatially explicit models for cost-benefit analyses of river basins.

Strengths Expert knowledge and empirical data can be used Analyses of various (spatially explicit) scenarios Applicable to various scales Provides time and spatial-specific output Some models includes both economic and environmental costs and benefits	**Weaknesses** Lack of model validation Presence of errors in data Limited data availability Models are too complex and some are too simple Some models are unable to incorporate other factors affecting the spatial variables such as land use Assumptions (e.g., spatial generalization) are used for the estimation of economic impacts
Opportunities Spatial explicit models becoming more reliable Spatial data availability and quality are increasing Modeling is advancing The growing interest in river basin modeling	**Threats** Data collection is expensive Limited data availability Over or under prediction Results (e.g., land use changes) of some scenarios are unfeasible environmentally or/and economically

3.3.1. Strengths

One of the main strengths of the models is the potential to use both empirical data and expert knowledge. In case of limited data availability, the incorporation of expert knowledge in the model is an important advantage [92]. For instance, using expert knowledge could add additional relationships to models in which data are limited [93].

Scenario-based analysis can be performed by using models to explore water quality by management and operation strategies [47,52,53,94]. For example, the GeoImpres (stationary) model was used to predict groundwater quality by applying different scenarios of fertilizer application [53]. Another scenario-based study uses simple statistical bivariate analysis for planning the land by drafting a landslide susceptibility map [47]. The analyses of scenarios allow users to predict potential outcomes and risks of management strategies.

River basin models can be implemented on various scales and provide adaptation and management strategies [52–54,56]. For instance, the DPSIR framework (The Climate Change Project) is used to define strategies for adaptation in the long-term planning of water resources [54]. In another study, the integrated modeling framework (peatlands) provides long-term management strategies to assess the impact of peatlands on water management [52].

The other main strength of spatially explicit models is that they provide time- and spatial-specific outputs [49–52,54]. For instance, the spatial prediction model, spatial model, and SWAT model deliver time- and spatial-specific outputs. These are particularly relevant when the research questions require time- and spatial-specific outputs.

3.3.2. Weaknesses

An important weakness of the river basin models is the lack of model validation and the presence of errors in the input data [44,47]. Mistakes in the input data can cause problems in the calibration and validation of models [95]. Thus, the Monte Carlo simulation technique is used for predicting the uncertainties in data [44]. Errors in data can also lead to an incorrect model outcome.

In numerous situations, models are difficult or even impossible to be implemented due to the limited availability of data [38]. The comparatively low amount of data is used to develop some models [38,96]. Due to the low amount of input data, model performance may result in either poor output or output covering a narrow range of environmental conditions. Furthermore, some models are not transferable to other regions due to the restricted data that were used to train the model, such as the simple statistical bivariate analysis model [47]. This model needs validation before it can be applied in other regions.

In this study, the reviewed models ranged from too simple to very complex. For instance, process-based models are very complex as compared to statistical models. Simple models are limited to their applications and scope depending on what input variables and data are used. Most of them cannot be used in time-specific outputs due to the lack of training data. On the other hand, a complex model requires extensive training of modelers and an enormous amount of data (not only the number of cases and observations but also the number of input variables), which are needed to calibrate and validate the model and perform uncertainty and sensitivity analysis.

3.3.3. Opportunities

Due to the increasing interest in river basin modeling, the number of these models is increasing. As observed from the search in the web of knowledge app over the past two decades, the number of research articles that used models for predicting future scenarios and aiding future policies and management strategies had increased. One of the important opportunities is the increase in data quality and availability, which improved the capacity of model predictions. The development of environmental monitoring technologies could result in datasets with a large number of variables of high-quality data that helps deal with data scarcity and variability [97,98]. Environmental monitoring networks have been established by many European countries, such as the reporting of their river water quality [94]. Data collection using remote sensing methods can also be considered another opportunity. There has been substantial progress made in modeling low quantity or quality data. Furthermore, the accuracy of the models' prediction can be analyzed by splitting the data into training and validation [99]. This process allows the determination of how well a model predicts an outcome by using performance metrics. Moreover, to support the decision making related to ecological issues in a river basin, a combination of ecological models can be used [100,101].

3.3.4. Threats

There are some threats to using modeling techniques for river basins regardless of the strengths and opportunities. Particularly, the modeling process is threatened if the optimum order of scientific method is not followed, i.e., research question—the selection of modeling technique—data collection—model development—model validation—interpretation of the model output [64]. The costs of collecting data may constrain the use of these models. This may result in limited data being available for modeling and may pose a threat to utilizing these models in cost-benefit analyses. Moreover, the model's output can over- or under-predict outcomes, such as the case of the simple statistical bivariate analysis model, which overpredicts landslide events in the most susceptible areas [47]. It is also a threat if the model output is applied to formulate management strategies but the model output is inaccurate or deviates from reality. It is therefore of paramount importance to evaluate the models before any application.

3.4. River Basin Models in the Context of Sustainable River Basin Management

Models can be developed and applied to assist sustainable development as well as the sustainable utilization of agricultural parcels within a river basin, which can eventually reduce the negative impacts of intensive agriculture [63]. Land use changes have been occurring in the past until the present, and these models can be useful to assess whether these changes are sustainable. These models provide valuable insights into the effect of land use changes; nevertheless, there is still room for improving them. In an integrated analysis incorporating the different sustainable development goal indicators, models have limitations, particularly not being able to integrate all processes, which, among other reasons, is the technological challenge for computation power. With fast technological evolution, the models will gradually become more holistic and will eventually be able to address the numerous sustainability questions at the river basin scale.

4. Conclusions

Our review confirms that there is a systematic increase in the use of models for cost-benefit analyses of river basins but there is a lack of information on the efforts and time needed to gather data, develop and adopt the model, and apply the model in real-world scenarios. Based on what we investigated, it seems that, to some extent, model applicability increases with more input variables but the high number of input variables does not always guarantee a high number of model applications. The information that is needed by a modeler to determine which river basin model to use are the availability of the data, how much the model is user-convenient, which CBA (i.e., environmental and/or economical) is needed in the study, and how much time is available. Based on these aspects, the modeler can decide which model is suitable for his/her study. Furthermore, future studies should explicitly report on the necessary time needed for data collection, model development, and/or training and model application (Figure 5). This information will aid model developers and users to evaluate the optimal model they can utilize for a particular cost-benefit analysis and should be available in a standardized format for future modeling research studies.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su14148953/s1, Table S1: Current and potential applications of the reviewed process-based models, Table S2: Current and potential applications of the reviewed statistical models, Table S3: Current and potential applications of the probabilistic and data-driven models, Table S4: Current and potential applications of the reviewed integrated models or modeling frameworks.

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