forests

MDPI

Article

Remote Sensing-Based Estimation on Hydrological Response to Land Use and Cover Change

Ying Ding, Huihui Feng * and Bin Zou

School of Geosciences and Info-Physics, Central South University, Changsha 410083, China
* Correspondence: hhfeng@csu.edu.cn

Abstract: Hydrological processes are an important driving force of environmental pollutant variation that has aroused global concern. Land use and cover change (LUCC) strongly affects hydrological processes. Remote sensing technology has played an increasingly important role in studying the relationship between LUCC and hydrological processes. This study summarizes the progress of hydrological responses to LUCC. Overall, remote sensing can provide spatially continuous data of land cover and hydrological variables. With the aid of the retrieved data sets, the effects of LUCC on hydrological processes can be evaluated via correlation analysis, multiple regression method, experimental watershed approach and trajectory-based approaches. However, due to the high complexity of geographical systems, it is difficult to quantitatively separate the actual components of the influence of LUCC. The heterogeneous surface properties also lead to various results at different spatial and temporal scales. Future research should meet the challenges in data estimation, research methodology and analysis process.

Keywords: land use and cover change; runoff; evapotranspiration; soil moisture; remote sensing

check for updates

Citation: Ding, Y.; Feng, H.; Zou, B. Remote Sensing-Based Estimation on Hydrological Response to Land Use and Cover Change. *Forests* **2022**, *13*, 1749. https://doi.org/10.3390/f13111749

Academic Editor: Olga Viedma

Received: 7 August 2022
Accepted: 21 October 2022
Published: 24 October 2022

1. Introduction

Environmental pollution has caused worldwide concern due to its negative effects on human health, climate change and sustainable development [1–5]. Moreover, hydrological processes are an important driving force of pollutant variation and the basis for the eco-environmental evolution [6,7]. The major hydrological variables include precipitation (P), soil moisture (SM), evapotranspiration (ET) and runoff (R), with research occurring across local, regional and global scales [8–15]. Several ways can be adopted to estimate the variables, including in-situ measurement, hydrological modeling and remote sensing [16]. In-situ measurement is a traditional method for directly measuring the hydrological variables within a small area [17–19]. For hydrological studies, it is important to monitor the variables at a large scale [18,20,21]. The models simulate the variables based on the physical connection of the variables at various spatial scales [22]. However, the theory assumption, simplified model structure and error in input data could generate significant uncertainty [23–25]. As well as the in-situ measurement and hydrological models, remote sensing allows for the real-time collection of observations with high efficiency over a wide range of areas and thus plays an increasingly important role in research on the hydrological processes at large spatial scale [26–30].

Hydrological processes are characterized by several spatiotemporal changes, including inter-annual and intra-annual periodic changes as well as progressive trends in long time series [31–34]. The characteristics of changes, which are the result of the combined effects of the natural environment and human activities, are highly complex. Land use and cover change (LUCC) is one of the most direct and significant influencing factors of human activity (i.e., re- or de-forestation). It modifies the characteristics of the regional land surface, soil structure and physical properties and thereby affects the spatiotemporal distribution of hydrological factors (especially SM, ET and R). Quantitative analysis of the manner and magnitude of influence of LUCC on various hydrological factors has become a major focus of research on hydrological processes [35–38].However, LUCC affects hydrological process under a complex interaction with natural factors [21,39,40]. The interaction leaves great uncertainty for understanding the physical mechanism of the hydrological process. Therefore, a full summary on the response of hydrology on LUCC should be presented to guide further investigation.

This paper summarizes advances in remote sensing for estimating the responses of hydrological processes to LUCC. Precipitation is absent in this study. On the one hand, precipitation is characterized by substantial natural variability [41]. On the other hand, LUCC indirectly affects precipitation mainly through influencing factors such as atmospheric moisture and temperature [41,42], which may lead to strong uncertainty in contribution estimation. Directions for future development are proposed in view of the existing problems. This study could provide an overview for understanding the physical mechanism of the hydrological process, and supporting the methodology for future research.

2. Remote Sensing-Based Estimation of Hydrological Response to LUCC

LUCC and its hydrological response have always been a focus of research on hydrological processes. However, the hydrological processes are characterized by significant complexity. Firstly, hydrological processes are determined by several environmental factors, such as vegetation, climate and topography [43,44]. Moreover, variation in hydrological processes in turn affect meteorological conditions and vegetation. For example, changes in soil moisture exert a strong influence on vegetation, which may feed back on soil moisture by directly affecting evapotranspiration and indirectly regulating precipitation [45]. These make it difficult to quantitatively determine the manner and magnitude of influence of LUCC on various hydrological factors.

2.1. General Methodology

The monitoring approach is favorable for directly analyzing the relationship between LUCC and hydrological factors. Many researchers have studied the characteristics of hydrological response to LUCC using different analysis methods based on remote sensing, including correlation analysis [46,47], multiple regression method [48–51], experimental watershed approach [37,52] and trajectory-based approach [39,53,54].

Correlation analysis evaluates the dependence between LUCC and hydrological factors using correlation coefficient. For example, Wang et al. [46] investigated the relationship between LUCC and SM in the Yongding River Basin using three sets of remote sensing imagery data from 1997, 2000 and 2005. The largest decreases in SM, which ranged from 60% to 100%, were found in areas converted from woodland to grassland. Correlation analysis was conducted to assess the association between the change of surface runoff and land use driving factors by Das and Esraz-Ul-Zannat [47]. The results revealed that rise in runoff depth was positively correlated ($p < 0.01$) to the growth of urban impervious areas and negatively correlated to the changes in vegetation in Khulna City. Correlation analysis describes the degree of change in LUCC and hydrological factors; however, they do not reveal the degree of influence that was exerted by climate change and LUCC. In addition, correlation analysis may not be able to accurately infer the causality of factors.

Multiple regression model estimates the hydrological response to LUCC by establishing the statistical relationship between factors affecting hydrological processes and hydrological factors. For instance, Ekness and Randhir [48] established a regression model of annual runoff with vegetative activity, evaporation, precipitation, temperature and soil moisture as independent variables. Regression results showed that for each day's increase in the photosynthetic activity, there was a decrease in runoff by 0.1% in the continental United States. Zheng et al. [49] revealed that LUCC explained ~40% of runoff variations (1948~2019) in Liuxihe River using multiple linear regression analysis. It was revealed by Xu et al. [51] that human-induced LUCC was the main driving factor causing a runoff decrease in the Haihe River Basin. Based on the partial least squares regression (PLSR) method, Shawul et al. [50] showed that lateral flow was strongly correlated with pasture, whereas surface runoff was significantly attributed to the change in urban and cropland in the Upper Awash Basin. This method can estimate hydrological response, but it has the disadvantages of poor spatio-temporal transferability and a lack of physical basis. The accuracy of analysis results may be affected by the study period, time scale and spatial resolution of data.

The experimental watershed approach selects two or more areas with similar environmental factors and analyzes the variability in SM under different land covers, which provides a practical method for evaluating the influence of LUCC. Venkatesh et al. [52] selected small watersheds with three LCTs and compared the SM changes at different depths in the Ghats mountain region of West India. Wang et al. [37] selected five comparative watersheds with similar slopes and aspects to analyze SM changes in vegetation restoration sites on the Loess Plateau. However, this approach is generally only applicable to small areas. At the large scale (regional or global), it is more difficult to select areas with similar environmental factors, which restricts the applications of experimental watershed approach. To reveal the effects of LUCC on hydrological process, Feng and Liu [39] proposed a novel trajectory-based approach based on the basic idea of watershed experiment method for detecting impact of forest change on soil moisture. Specifically, soil moisture in permanent forest trajectory represents a synthetic result of natural influences and serves as a reference for isolating soil moisture alternation due to LUCC. Through this way, the effects of LUCC on hydrology can be identified at a large scale. However, this method does not consider the interaction between the influencing factors and the scale effect.

2.2. Hydrological Response

Preliminary achievements have been made on the response characteristics in temporal and spatial and with extreme hydrological events. Hydrological processes are subject to the combined effects of environmental factors and human activities. Specifically, LUCC affects the hydrologic cycle through direct and indirect ways. Direct human activities, including reservoir construction and water withdrawal for irrigation directly reduce flow discharge through water consumption [55]. In addition, LUCC impacts soil properties and infiltration [56]. The indirect effects of LUCC are mainly reflected in the changes of vegetation cover and regional meteorological conditions. Deforestation or afforestation significantly alters evapotranspiration and thus influences runoff [57]. Moreover, temperatures, which significantly affect hydrological processes, are known to increase with urbanization due to heat capacity and albedo shift, as well as greenhouse gas emissions [58].

2.2.1. Impact of Historical LUCC

At the inter-annual scale, there are relatively small variations in environmental factors such as climate; however, LUCC is associated with large variations and thus has strong effects on hydrological factors. Numerous quantitative studies have investigated the influence of LUCC on hydrological factors, but with varying results under different natural condition. LUCC resulted in significant reduction in SM in Europe [59] and mid-latitudes of East Asia [60,61], and increase in Eastern South America [62,63] and North Africa [59]. For example, Holsten et al. [64] investigated SM changes in the Brandenburg Nature Reserve in Germany and predicted a 4%~15% reduction in SM by the mid-21st century due to the influence of climate change. LUCC has intense impacts on ET change at the local scale. Specifically, the reduction effects of LUCC on ET primarily occurred in deforestation areas of tropical rainforests where rainforest had been replaced by farmland [65,66]. LUCC increased ET in the regions experiencing farmland replaced by forest (e.g., eastern America [67,68], southern Europe [69], and North China [70]). LUCC increased runoff at global scale from 1901 to 1999 due to deforestation [71]. Teuling et al. [69] found that LUCC (mainly large-scale reforestation and afforestation) had negative effect on streamflow in Europe from 1960 to 2010, while precipitation variation had opposite effect, resulting in small net streamflow changes. These studies indicated that influence of LUCC on hydrological factors is highly spatially heterogeneous.

At the intra-annual scale, environmental factors have more significant changes than LUCC. The influence of LUCC on SM under different climatic conditions has become a focus of current research. Sehler et al. [72] explored the relationship between precipitation and soil moisture at global scale, which showed that precipitation and soil moisture have the strongest correlations in LCT with limited vegetation, whereas forests and densely vegetated regions have weaker correlations between precipitation and soil moisture. Wang et al. [73] comprehensively evaluated the influence of seasonal variations in vegetation and temperature on SM in a permafrost region on the Tibetan Plateau over the period from 2004 to 2006. Yang et al. [74] performed a comparative analysis of the regional SM response to land cover and tree planting under different precipitation events on the Loess Plateau from April 2009 to August 2010. He et al. [75] investigated the responsiveness of subtropical grassland and meadow SM to varying precipitation intensities in a semi-arid area of the Qilian Mountains on the monthly scale from 2003 to 2008; the SM of the two LCTs followed similar trends with varying precipitation intensities. The existing studies have mostly focused on the response of SM to LUCC under specific climatic conditions; however, the influence of other factors has been ignored, which makes it difficult to reflect the combined effects of climatic conditions on SM. This may lead to the overlapping of other factors with land cover, which will make it difficult to distinguish the influence of LUCC. Although Mahmood et al. [76] analyzed the correlation of SM with temperature and precipitation, their research was performed at the comparative analysis level. There is a lack of quantitative conclusions about the response of SM to LUCC under integrated climate change. Few studies have provided systematic analyses of the influence of LUCC under multiple climate scenarios [77].

2.2.2. Future LUCC Response

In addition to exploring the impact of historical LUCC, the researchers also conducted simulations of hydrological responses to future LUCC. Previous studies assessed the future hydrological response by simulating the changes of hydrological factors under different future land use scenarios. Kundu et al. [78] projected the LUCC impact on ET for the Narmada River Basin in Central India, which shows that ET is decreasing due to the removal of forest and vegetation cover from 1990 to 2050. Talib and Randhir [79] revealed that climate change and LUCC will increase total runoff by about 4% by 2035, 6% by 2065 and 7% by 2100 in the SuAsCo River watershed, USA. Li et al. [80] investigated the impact of future urbanization on water balances across the United States; results show that urbanization increases in imperviousness, decreases in green areas, decreases soil infiltration capacity and reduces ET, and thus elevates stormflow. Tian et al. [81] predicted future climate and LUCC, then simulated future runoff with different climate and LUCC scenarios, finding that LUCC only accounting for 2%–16% to future runoff. Urbanization could lead to increase in stream flow and groundwater recharge in the Don catchment, UK. Increasing the woodland area had the most significant impact, reducing stream flow by 17% and groundwater recharge by 22% [82]. Thiha et al. [83] revealed that simulated annual mean river flow will increase by 3.1% for 2030 and 3.43% for 2050 compared to 2011 in Myanmar, because land-use changes, mainly deforestation, may result in increasing the catchment yield and decreasing the catchment storage capacity.

2.2.3. Extreme Hydrological Events

Extreme hydrological events are rare hydrological events in a particular region and time period (within one year) and mainly include extreme precipitation, extreme floods and extreme droughts [84,85]. Extreme hydrological events represent abnormalities in the hydrological cycle and lead to significant changes in the response of the hydrological factors to LUCC. Anderson et al. [86] used the Landsat near-infrared band to retrieve ET and then applied it for drought and flood monitoring. Based on the distribution patterns of SM using MODIS satellite data, Zhang et al. [87] analyzed the relationship between agricultural droughts and the growth of rice in Jiangxi Province in 2003. Moreover, the influence of LUCC on hydrological processes varies with the intensity of the hydrological events. Sriwongsitanon and Taesombat [36] investigated the influence of land cover on the runoff coefficient using geographic correlation analysis and other methods with Landsat TM data, daily precipitation data and daily runoff data. They found that the runoff coefficient was relatively high in basin areas with high forest cover during large floods; however, it was relatively low during small flood events. The main reason is that forests have strong evaporation and infiltration capacities during small flood events, which result in large precipitation losses; in contrast, forests have high water holding capacities during large floods, which increases the SM to saturation more easily and thereby reduces the infiltration of precipitation. These studies elucidated the changes in the hydrological factors during hydrological events. However, the same types of extreme hydrological events may have different origins and can have different influences on hydrological processes [88,89]. For example, droughts can be divided into different types based on their origin and influence, including meteorological droughts, hydrological droughts, agricultural droughts and socio-economic droughts [90]. On the other hand, these different types of droughts are related. For instance, hydrological droughts are the result of long-term meteorological droughts, while agricultural droughts are the main reflection of meteorological droughts. This phenomenon leads to a particular relationship of the response of hydrological processes to LUCC. This interrelation with differences and connections results in tremendous complexity in studies of hydrological processes during extreme hydrological events, which needs to be examined by additional studies [91].

Overall, LUCC modifies the characteristics of the regional land surface, soil structure and physical properties and thereby affects the spatiotemporal distribution of hydrological factors. However, the physical mechanism of the hydrological response to LUCC is quite complex. In the meantime, LUCC has significant interaction with various environmental factors, which makes it difficult to quantitatively analyze the hydrological response to LUCC.

3. Challenges and Future Directions

Remote sensing provides an effective tool for analyzing hydrological responses to LUCC. Compared with in-situ measurement, satellite remote sensing has the advantage of providing spatially continuous data of the major hydrological variables with high efficiency. Furthermore, remote sensing technology is less limited by ground conditions, therefore, it can provide observation under harsh environmental conditions. However, many challenges still need to be solved to further improve remote sensing applications in large-scale hydrological studies.

3.1. Data Estimation

Accuracy has always been a core issue for remote sensing-based data acquisition of land cover and hydrological factors. For example, the accuracy of supervised classification using Landsat ETM+ data is approximately 60%–70% [92]. AMSR-E data provide the SM products that are most applicable at the regional or global scale; the RMSE is approximately 6% [93–96]. The relative error of regional ET estimates that are based on characteristic relationships is approximately 15%–30% [97]. Due to recent applications of new approaches, such as neural machine learning and deep learning [98–100], the results of land cover classification and hydrological factors estimation have improved greatly. However, these new approaches involve many parameters, and there is a need to study intelligent classification methods for improved classification accuracy and efficiency. The algorithms for the remote sensing retrieval of hydrological factors need to be improved to obtain high-precision hydrological factors. The relationship between hydrological variables and electromagnetic signals is implicit, so complex nonlinearity and physical mechanism should be considered to improve the retrieval algorithm in the future. For example, researchers from the University of Amsterdam retrieved global SM products using the Land Parameter Retrieval Model (LPRM) with AMSR-E low-frequency microwave brightness temperature data, which obtained better accuracy than the standard AMSR-E data products [87,101].

The spatiotemporal resolution and coverage are another critical factor that affects hydrological factor analysis. Although passive microwave remote sensing can provide high-precision SM products, their microwave transmitting capacity is relatively weak, which generally results in low spatial resolution [102]. Assimilation of multi-source data is an important strategy to improve the spatiotemporal resolution and coverage of remote sensing-based data [103]. The assimilation approach integrates the advantages of different approaches and datasets, which could improve the reliability of data sources. Yin et al. [104] fused eight currently available ET datasets by using process-based ET models and machine learning methods. Results showed that integrated ET estimates were more accurate than original ET products. Moreover, unmanned aircraft vehicle (UAV) presents a flexible platform to deploy sensors to efficiently and non-destructively measure hydrological factors at fine scales. Houtz et al. [105] mounted L-band radiometer on UAVs to provide tools for monitoring areas with both high temporal resolution and high spatial resolution (~6 m). For application scenarios such as precision agriculture, satellite measurements can provide basic information in a large range, while UAVs provide detailed data at high spatial resolution. Previous studies mostly integrated single platform data (such as satellite, numerical model simulation, etc.). Future studies can further develop the integration of multi-platform data such as satellite, model simulation, ground monitoring, and UAV to achieve spatio-temporally seamless fine monitoring.

3.2. Research Methodology

The terrestrial land is characterized by higher spatial variability than the slope and small watershed scales, which leads to major issues in the quantitative analysis of the impact of LUCC on hydrological processes using conventional methods. For example, the experimental watershed approach is conducive to comparative analyses of the manner and degree of influence of land cover under similar environmental conditions. However, it is impossible to find two areas with exactly identical geographical and meteorological conditions at the basin scale. Conditions can change in the same basin over two standard periods [106]. Therefore, practical research should combine and improve conventional methods to adapt them to basin-scale spatial variability. For example, hydrological models can predict the impacts of changes in forest vegetation on hydrological parameters as well as the hydrological characteristics of a basin that lacks observed hydrological and meteorological data. These models are highly versatile and are immune from interference. However, they can only reflect the influence of LUCC under ideal conditions; the complexities of real cases need to be considered in the simulations. Future studies must analyze the components of the impact of LUCC on hydrological processes at different time scales using a combination of observation and simulation data by the integrated use of geostatistics, GIS spatial analysis (e.g., spatio-temporal statistical modeling, spatio-temporal clustering, etc.) and hydrological models. Specifically, remote sensing big data is helpful to construct data-driven GIS models considering spatial heterogeneity to simulate the variations of hydrological factors and subsequently separate LUCC effect. However, the generalization and universality of such models are poor. The hydrological model based on physical knowledge can provide a prior knowledge constraint to coupling with GIS model, which will effectively reduce simulation uncertainty and improve model interpretability [107,108]. For example, the revised Penman-Monteith (PM) formula was coupled into the loss function of the deep learning (DL) model, and subsequently, a hybrid DL model for simulation of evapotranspiration was formulated in the study of Chen et al. [109]. Another way to build a hybrid model is to encode the physical equations into a certain layer of the model structure [110]. Subsequent research may further integrate the energy balance and water balance for further improvement in the representation.

3.3. Analysis Process

The response of hydrological processes to LUCC has significant spatiotemporal variability. In general, infiltration is higher than SM loss by evaporation and interception in humid areas with abundant rainfall, which contributes to an increase in the SM content of forests. However, limited precipitation cannot compensate for the SM loss that is caused by interception and evaporation in dry areas, which lead to lower SM contents of forests compared with other LCTs [111]. Current analysis methods based on remote sensing mainly focus on the statistical relationship between LUCC and hydrological factors, ignoring the physical process and mechanism. Moreover, hydrological processes have different time scales with both intra-annual periodic variations [112] and long time-series trends [113–115]. Furthermore, the manner and degree of influence of LUCC vary at different time scales. Research has shown that climate change often has a more significant influence on hydrological and water resources over longer time scales, whereas LUCC is one of the major drivers of short-term hydrological changes [116–118]. Therefore, it is necessary to comparatively analyze temporal variations of hydrological factors in different areas and combine climate, topography and other factors to investigate the response of hydrological factors to LUCC under different regional conditions from the perspective of the water balance. In addition, further investigation of the scale effect and full-process simulation is required.

4. Conclusions

This paper summarizes the advances in remote sensing-based research on hydrological responses to LUCC, as well as how remote sensing approaches have been used to understand and quantify the response of hydrological processes to LUCC.

Remote sensing can provide spatially continuous data of land cover and hydrological factors. With the aid of the retrieved data sets, the effects of LUCC on hydrological processes can be evaluated via correlation analysis, multiple regression method, experimental watershed approach and trajectory-based approaches. However, due to the high complexity of geographical systems, it is difficult to quantitatively separate the actual components of the influence of LUCC. Existing research on process analysis has evaluated the influence of LUCC on hydrological factors in historical, future, and during extreme hydrological events; however, the spatiotemporal variability of surface properties leads to significantly different results.

Remote sensing has opened new opportunities for the study of hydrological response to LUCC due to the ability to offer large-scale spatially distributed observations. Although numerous studies have been carried out and published with the improvement of remote sensing technology and analysis method, remote sensing-based estimation of hydrological response to LUCC needs further investigation. First, it is necessary to improve the spatio-temporal coverage and accuracy of remote sensing-based retrieval. Improving inversion algorithms by considering complex physical mechanisms and assimilating multi-source data is a developing trend. Second, the previous hydrological response analysis methods did not fully consider the spatio-temporal heterogeneity of the impact of LUCC. The comprehensive utilization of geostatistics, GIS spatial analysis and hydrological model is a promising direction. In addition, LUCC affects the hydrological cycle in complex ways with scale effects, therefore, full-process simulation under different spatial-temporal scales and regional conditions will be required in the future. This research will not only provide theoretical support for understanding the inherent nature of the influence of LUCC on hydrological processes but will also provide necessary supporting evidence for water resource management. Overall, future research should quantitatively evaluate the manner and degree of the influence of LUCC on hydrological processes at different spatial and temporal scales by integrating the water balance and other principles and improving or introducing new methods. Relevant studies will provide effective analysis tools for understanding hydrological processes and scientific evidence for water resource management and planning.

Author Contributions: Conceptualization, H.F.; data curation, Y.D.; funding acquisition, H.F. and B.Z.; investigation, Y.D.; methodology, Y.D. and H.F.; supervision, H.F.; writing—original draft, Y.D. and H.F.; writing—review and editing, H.F., B.Z. and Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China, (Grant No. 42071378) and the Natural Science Foundation of Hunan Province (No. 2020JJ3045).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Luo, P.; Xu, C.; Kang, S.; Huo, A.; Lyu, J.; Zhou, M.; Nover, D. Heavy metals in water and surface sediments of the Fenghe River Basin, China: Assessment and source analysis. *Water Sci. Technol.* **2021**, *84*, 3072–3090. [CrossRef]
2. Xu, S.; Zou, B.; Xiong, Y.; Wan, N.; Feng, H.; Hu, C.; Lin, Y. High spatiotemporal resolution mapping of PM2.5 concentrations under a pollution scene assumption. *J. Clean. Prod.* **2021**, *326*, 129409. [CrossRef]
3. Shen, M.X.; Gu, X.Y.; Li, S.X.; Yu, Y.; Zou, B.; Chen, X. Exposure to black carbon is associated with symptoms of depression: A retrospective cohort study in college students. *Environ. Int.* **2021**, *157*, 106870. [CrossRef]
4. Wei, X.D.; Wang, N.; Luo, P.P.; Yang, J.; Zhang, J.; Lin, K.L. Spatiotemporal Assessment of Land Marketization and Its Driving Forces for Sustainable Urban-Rural Development in Shaanxi Province in China. *Sustainability* **2021**, *13*, 7755. [CrossRef]
5. Xie, D.; Duan, L.; Si, G.; Liu, W.; Zhang, T.; Mulder, J. Long-Term ^{15}N Balance After Single-Dose Input of ^{15}N-Labeled NH_4^+ and NO_3^- in a Subtropical Forest Under Reducing N Deposition. *Glob. Biogeochem. Cycles* **2021**, *35*, e2021GB006959. [CrossRef]
6. Luo, P.; Mu, Y.; Wang, S.; Zhu, W.; Mishra, B.K.; Huo, A.; Zhou, M.; Lyu, J.; Hu, M.; Duan, W.; et al. Exploring sustainable solutions for the water environment in Chinese and Southeast Asian cities. *Ambio* **2021**, *51*, 1199–1218. [CrossRef]
7. Zha, X.; Luo, P.; Zhu, W.; Wang, S.; Lyu, J.; Zhou, M.; Huo, A.; Wang, Z. A bibliometric analysis of the research on Sponge City: Current situation and future development direction. *Ecohydrology* **2021**, *14*, e2328. [CrossRef]
8. Chavez, S.P.; Silva, Y.; Barros, A.P. High-Elevation Monsoon Precipitation Processes in the Central Andes of Peru. *J. Geophys. Res. Atmos.* **2020**, *125*, e2020JD032947. [CrossRef]
9. Loaiciga, H.A.; Valdes, J.B.; Vogel, R.; Garvey, J.; Schwarz, H. Global warming and the hydrologic cycle. *J. Hydrol.* **1995**, *174*, 83–127.
10. Ohmura, A.; Wild, M. Is the hydrological cycle accelerating? *Science* **2002**, *298*, 1345–1346. [CrossRef]
11. Sheffield, J.; Wood, E.F. Characteristics of global and regional drought, 1950–2000: Analysis of soil moisture data from off-line simulation of the terrestrial hydrologic cycle. *J. Geophys. Res. Atmos.* **2007**, *112*, D17115. [CrossRef]
12. Barnett, T.P.; Pierce, D.W.; Hidalgo, H.G.; Bonfils, C.; Santer, B.D.; Das, T.; Bala, G.; Wood, A.W.; Nozawa, T.; Mirin, A.A.; et al. Human-induced changes in the hydrology of the western United States. *Science* **2008**, *319*, 1080–1083. [CrossRef]
13. Garcia-Ruiz, J.M.; Lana-Renault, N.; Begueria, S.; Lasanta, T.; Regues, D.; Nadal-Romero, E.; Serrano-Muela, P.; Lopez-Moreno, J.I.; Alvera, B.; Marti-Bono, C.; et al. From plot to regional scales: Interactions of slope and catchment hydrological and geomorphic processes in the Spanish Pyrenees. *Geomorphology* **2010**, *120*, 248–257. [CrossRef]
14. Wohl, E.; Barros, A.; Brunsell, N.; Chappell, N.A.; Coe, M.; Giambelluca, T.; Goldsmith, S.; Harmon, R.; Hendrickx, J.M.H.; Juvik, J.; et al. The hydrology of the humid tropics. *Nat. Clim. Change* **2012**, *2*, 655–662. [CrossRef]
15. Mu, D.; Luo, P.; Lyu, J.; Zhou, M.; Huo, A.; Duan, W.; Nover, D.; He, B.; Zhao, X. Impact of temporal rainfall patterns on flash floods in Hue City, Vietnam. *J. Flood Risk Manag.* **2021**, *14*, e12668. [CrossRef]
16. Rast, M.; Johannessen, J.; Mauser, W. Review of understanding of Earth's hydrological cycle: Observations, theory and modelling. *Surv. Geophys.* **2014**, *35*, 491–513. [CrossRef]
17. Chiew, F.; Kamaladasa, N.N.; Malano, H.M.; Mcmahon, T.A. Penman-Monteith, FAO-24 reference crop evapotranspiration and class-A pan data in Australia. *Agric. Water Manag.* **1995**, *28*, 9–21.
18. Walker, J.P.; Willgoose, G.R.; Kalma, J.D. In situ measurement of soil moisture: A comparison of techniques. *J. Hydrol.* **2004**, *293*, 85–99. [CrossRef]
19. Liu, C.; Allan, R.P. Observed and simulated precipitation responses in wet and dry regions 1850-2100. *Environ. Res. Lett.* **2013**, *8*, 034002. [CrossRef]
20. Brocca, L.; Tullo, T.; Melone, F.; Moramarco, T.; Morbidelli, R. Catchment scale soil moisture spatial-temporal variability. *J. Hydrol.* **2012**, *422*, 63–75. [CrossRef]
21. Feng, H.; Liu, Y. Combined effects of precipitation and air temperature on soil moisture in different land covers in a humid basin. *J. Hydrol.* **2015**, *531*, 1129–1140. [CrossRef]
22. Blöschl, G.; Sivapalan, M. Scale issues in hydrological modelling: A review. *Hydrol. Process* **1995**, *9*, 251–290.
23. Roessler, O.; Loeffler, J. Potentials and limitations of modelling spatio-temporal patterns of soil moisture in a high mountain catchment using WaSiM-ETH. *Hydrol. Process.* **2010**, *24*, 2182–2196. [CrossRef]

24. Teng, J.; Vaze, J.; Chiew, F.H.S.; Wang, B.; Perraud, J.-M. Estimating the Relative Uncertainties Sourced from GCMs and Hydrological Models in Modeling Climate Change Impact on Runoff. *J. Hydrometeorol.* **2012**, *13*, 122–139. [CrossRef]
25. Brigode, P.; Oudin, L.; Perrin, C. Hydrological model parameter instability: A source of additional uncertainty in estimating the hydrological impacts of climate change? *J. Hydrol.* **2013**, *476*, 410–425. [CrossRef]
26. McKim, H.L.; Pangburn, T.; Walsh, J.E.; LaPotin, P.J. Remote sensing of soil moisture. *Adv. Space Res.* **1987**, *7*, 139–145.
27. Brakenridge, G.R.; Nghiem, S.V.; Anderson, E.; Chien, S. Space-based measurement of river runoff. *Eos Trans. Am. Geophys. Union* **2005**, *86*, 185–188. [CrossRef]
28. McCabe, M.F.; Wood, E.F.; Wojcik, R.; Pan, M.; Sheffield, J.; Gao, H.; Su, H. Hydrological consistency using multi-sensor remote sensing data for water and energy cycle studies. *Remote Sens. Environ.* **2008**, *112*, 430–444. [CrossRef]
29. Ahmad, S.; Kalra, A.; Stephen, H. Estimating soil moisture using remote sensing data: A machine learning approach. *Adv. Water Resour.* **2010**, *33*, 69–80. [CrossRef]
30. Petropoulos, G.P.; Ireland, G.; Barrett, B. Surface soil moisture retrievals from remote sensing: Current status, products & future trends. *Phys. Chem. Earth* **2015**, *83–84*, 36–56. [CrossRef]
31. Entekhabi, D.; Rodriguez-Iturbe, I. Analytical framework for the characterization of the space-time variability of soil moisture. *Adv. Water Resour.* **1994**, *17*, 35–45. [CrossRef]
32. Grayson, R.B.; Bloschl, G.; Western, A.W.; McMahon, T.A. Advances in the use of observed spatial patterns of catchment hydrological response. *Adv. Water Resour.* **2002**, *25*, 1313–1334. [CrossRef]
33. Tao, F.; Yokozawa, M.; Hayashi, Y.; Lin, E. Changes in agricultural water demands and soil moisture in China over the last half-century and their effects on agricultural production. *Agric. For. Meteorol.* **2003**, *118*, 251–261. [CrossRef]
34. Chen, J.M.; Chen, X.Y.; Ju, W.M.; Geng, X.Y. Distributed hydrological model for mapping evapotranspiration using remote sensing inputs. *J. Hydrol.* **2005**, *305*, 15–39. [CrossRef]
35. Mao, D.; Cherkauer, K.A. Impacts of land-use change on hydrologic responses in the Great Lakes region. *J. Hydrol.* **2009**, *374*, 71–82. [CrossRef]
36. Sriwongsitanon, N.; Taesombat, W. Effects of land cover on runoff coefficient. *J. Hydrol.* **2011**, *410*, 226–238. [CrossRef]
37. Wang, S.; Fu, B.; Gao, G.; Liu, Y.; Zhou, J. Responses of soil moisture in different land cover types to rainfall events in a re-vegetation catchment area of the Loess Plateau, China. *Catena* **2013**, *101*, 122–128. [CrossRef]
38. Liu, Y.; Pan, Z.; Zhuang, Q.; Miralles, D.G.; Teuling, A.J.; Zhang, T.; An, P.; Dong, Z.; Zhang, J.; He, D.; et al. Agriculture intensifies soil moisture decline in Northern China. *Sci. Rep.* **2015**, *5*, 11261. [CrossRef]
39. Feng, H.; Liu, Y. Trajectory based detection of forest-change impacts on surface soil moisture at a basin scale [Poyang Lake Basin, China]. *J. Hydrol.* **2014**, *514*, 337–346. [CrossRef]
40. Renner, M.; Brust, K.; Schwaerzel, K.; Volk, M.; Bernhofer, C. Separating the effects of changes in land cover and climate: A hydro-meteorological analysis of the past 60 yr in Saxony, Germany. *Hydrol. Earth Syst. Sci.* **2014**, *18*, 389–405. [CrossRef]
41. Zhang, H.H.; Delworth, T.L. Robustness of anthropogenically forced decadal precipitation changes projected for the 21st century. *Nat. Commun.* **2018**, *9*, 1150. [CrossRef]
42. Perugini, L.; Caporaso, L.; Marconi, S.; Cescatti, A.; Quesada, B.; de Noblet-Ducoudre, N.; House, J.I.; Arneth, A. Biophysical effects on temperature and precipitation due to land cover change. *Environ. Res. Lett.* **2017**, *12*, 053002. [CrossRef]
43. Tang, M.; Li, W.; Gao, X.; Wu, P.; Li, H.; Ling, Q.; Zhang, C. Land use affects the response of soil moisture and soil temperature to environmental factors in the loess hilly region of China. *PeerJ* **2022**, *10*, e13736. [CrossRef]
44. Huang, X.; Shi, Z.H.; Zhu, H.D.; Zhang, H.Y.; Ai, L.; Yin, W. Soil moisture dynamics within soil profiles and associated environmental controls. *Catena* **2016**, *136*, 189–196. [CrossRef]
45. Zhang, W.M.; Wei, F.L.; Horion, S.; Fensholt, R.; Forkel, M.; Brandt, M. Global quantification of the bidirectional dependency between soil moisture and vegetation productivity. *Agric. For. Meteorol.* **2022**, *313*, 108735. [CrossRef]
46. Wang, H.; Li, X.; Long, H.; Xu, X.; Bao, Y. Monitoring the effects of land use and cover type changes on soil moisture using remote-sensing data: A case study in China's Yongding River basin. *Catena* **2010**, *82*, 135–145. [CrossRef]
47. Das, P.C.; Esraz-Ul-Zannat, M. Assessing the impacts of land use-land cover changes on direct surface runoff: A remote sensing approach in Khulna City. *Water Sci. Technol.* **2022**, *85*, 3122–3144. [CrossRef]
48. Ekness, P.; Randhir, T.O. Effect of climate and land cover changes on watershed runoff: A multivariate assessment for storm water management. *J. Geophys. Res. Biogeosci.* **2015**, *120*, 1785–1796. [CrossRef]
49. Zheng, J.H.; Wang, H.L.; Liu, B.J. Impact of the long-term precipitation and land use changes on runoff variations in a humid subtropical river basin of China. *J. Hydrol. Reg. Stud.* **2022**, *42*, 101136. [CrossRef]
50. Shawul, A.A.; Chakma, S.; Melesse, A.M. The response of water balance components to land cover change based on hydrologic modeling and partial least squares regression (PLSR) analysis in the Upper Awash Basin. *J. Hydrol. Reg. Stud.* **2019**, *26*, 100640. [CrossRef]
51. Xu, H.S.; Ren, Y.F.; Zheng, H.; Ouyang, Z.Y.; Jiang, B. Analysis of Runoff Trends and Drivers in the Haihe River Basin, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 1557. [CrossRef]
52. Venkatesh, B.; Lakshman, N.; Purandara, B.K.; Reddy, V.B. Analysis of observed soil moisture patterns under different land covers in Western Ghats, India. *J. Hydrol.* **2011**, *397*, 281–294. [CrossRef]
53. Diao, W.J.; Zhao, Y.; Zhai, J.Q.; He, F.; Wang, Q.M.; He, G.H. Impact of Land-cover Change Trajectories on Water Cycle Dynamics in the Jing-Jin-Ji Region, China, from 2000 to 2015. *J. Coast. Res.* **2019**, *96*, 76–83. [CrossRef]

54. Wang, L.H.; Xie, Z.H.; Jia, B.H.; Xie, J.B.; Wang, Y.; Liu, B.; Li, R.C.; Chen, S. Contributions of climate change and groundwater extraction to soil moisture trends. *Earth Syst. Dyn.* **2019**, *10*, 599–615. [CrossRef]
55. Bosmans, J.H.C.; van Beek, L.P.H.; Sutanudjaja, E.H.; Bierkens, M.F.P. Hydrological impacts of global land cover change and human water use. *Hydrol. Earth Syst. Sci.* **2017**, *21*, 5603–5626. [CrossRef]
56. Stephens, C.M.; Lall, U.; Johnson, F.M.; Marshall, L.A. Landscape changes and their hydrologic effects: Interactions and feedbacks across scales. *Earth-Sci. Rev.* **2021**, *212*, 103466. [CrossRef]
57. Li, Y.; Piao, S.L.; Li, L.Z.X.; Chen, A.P.; Wang, X.H.; Ciais, P.; Huang, L.; Lian, X.; Peng, S.S.; Zeng, Z.Z.; et al. Divergent hydrological response to large-scale afforestation and vegetation greening in China. *Sci. Adv.* **2018**, *4*, eaar4182. [CrossRef]
58. Ding, Y.; Feng, H.H.; Zou, B.; Nie, Y.F. Heterogeneous air pollution controls its correlation to urban heat island: A satellite perspective. *Adv. Space Res.* **2022**, *69*, 4252–4262. [CrossRef]
59. Qiao, L.; Zuo, Z.Y.; Xiao, D.; Bu, L.L. Detection, Attribution, and Future Response of Global Soil Moisture in Summer. *Front. Earth Sci.* **2021**, *9*, 745185. [CrossRef]
60. Chen, X.; Su, Y.; Liao, J.; Shang, J.; Dong, T.; Wang, C.; Liu, W.; Zhou, G.; Liu, L. Detecting significant decreasing trends of land surface soil moisture in eastern China during the past three decades (1979-2010). *J. Geophys. Res. Atmos.* **2016**, *121*, 5177–5192. [CrossRef]
61. Yu, B.W.; Liu, G.H.; Liu, Q.S. Effects of land use changes for ecological restoration on soil moisture on the Chinese Loess Plateau: A meta-analytical approach. *J. For. Res.* **2020**, *31*, 443–452. [CrossRef]
62. Warburton, M.L.; Schulze, R.E.; Jewitt, G.P.W. Hydrological impacts of land use change in three diverse South African catchments. *J. Hydrol.* **2012**, *414*, 118–135. [CrossRef]
63. Jiang, Y.T.; Fu, P.; Weng, Q.H. Assessing the Impacts of Urbanization-Associated Land Use/Cover Change on Land Surface Temperature and Surface Moisture: A Case Study in the Midwestern United States. *Remote Sens.* **2015**, *7*, 4880–4898. [CrossRef]
64. Holsten, A.; Vetter, T.; Vohland, K.; Krysanova, V. Impact of climate change on soil moisture dynamics in Brandenburg with a focus on nature conservation areas. *Ecol. Model.* **2009**, *220*, 2076–2087. [CrossRef]
65. Lathuilliere, M.J.; Johnson, M.S.; Donner, S.D. Water use by terrestrial ecosystems: Temporal variability in rainforest and agricultural contributions to evapotranspiration in Mato Grosso, Brazil. *Environ. Res. Lett.* **2012**, *7*, 024024. [CrossRef]
66. Liu, J.Y.; You, Y.Y.; Li, J.F.; Sitch, S.; Gu, X.H.; Nabel, J.; Lombardozzi, D.; Luo, M.; Feng, X.Y.; Arneth, A.; et al. Response of global land evapotranspiration to climate change, elevated CO2, and land use change. *Agric. For. Meteorol.* **2021**, *311*, 108663. [CrossRef]
67. Shi, X.Y.; Mao, J.F.; Thornton, P.E.; Huang, M.Y. Spatiotemporal patterns of evapotranspiration in response to multiple environmental factors simulated by the Community Land Model. *Environ. Res. Lett.* **2013**, *8*, 024012. [CrossRef]
68. Yang, Q.C.; Tian, H.Q.; Li, X.; Tao, B.; Ren, W.; Chen, G.S.; Lu, C.Q.; Yang, J.; Pan, S.F.; Banger, K.; et al. Spatiotemporal patterns of evapotranspiration along the North American east coast as influenced by multiple environmental changes. *Ecohydrology* **2015**, *8*, 714–725. [CrossRef]
69. Teuling, A.J.; de Badts, E.A.G.; Jansen, F.A.; Fuchs, R.; Buitink, J.; van Dijke, A.J.H.; Sterling, S.M. Climate change, reforestation/afforestation, and urbanization impacts on evapotranspiration and streamflow in Europe. *Hydrol. Earth Syst. Sci.* **2019**, *23*, 3631–3652. [CrossRef]
70. Shi, P.; Ma, X.X.; Hou, Y.B.; Li, Q.F.; Zhang, Z.C.; Qu, S.M.; Chen, C.; Cai, T.; Fang, X.Q. Effects of Land-Use and Climate Change on Hydrological Processes in the Upstream of Huai River, China. *Water Resour. Manag.* **2013**, *27*, 1263–1278. [CrossRef]
71. Piao, S.L.; Friedlingstein, P.; Ciais, P.; de Noblet-Ducoudre, N.; Labat, D.; Zaehle, S. Changes in climate and land use have a larger direct impact than rising CO_2 on global river runoff trends. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 15242–15247. [CrossRef]
72. Sehler, R.; Li, J.J.; Reager, J.T.; Ye, H.C. Investigating Relationship Between Soil Moisture and Precipitation Globally Using Remote Sensing Observations. *J. Contemp. Water Res. Educ.* **2019**, *168*, 106–118. [CrossRef]
73. Wang, G.; Li, Y.; Hu, H.; Wang, Y. Synergistic effect of vegetation and air temperature changes on soil water content in alpine frost meadow soil in the permafrost region of Qinghai-Tibet. *Hydrol. Process.* **2008**, *22*, 3310–3320. [CrossRef]
74. Yang, L.; Wei, W.; Chen, L.; Mo, B. Response of deep soil moisture to land use and afforestation in the semi-arid Loess Plateau, China. *J. Hydrol.* **2012**, *475*, 111–122. [CrossRef]
75. He, Z.; Zhao, W.; Liu, H.; Chang, X. The response of soil moisture to rainfall event size in subalpine grassland and meadows in a semi-arid mountain range: A case study in northwestern China's Qilian Mountains. *J. Hydrol.* **2012**, *420*, 183–190. [CrossRef]
76. Mahmood, R.; Littell, A.; Hubbard, K.G.; You, J. Observed data-based assessment of relationships among soil moisture at various depths, precipitation, and temperature. *Appl. Geogr.* **2012**, *34*, 255–264. [CrossRef]
77. Gómez-Plaza, A.; Martinez-Mena, M.; Albaladejo, J.; Castillo, V.M. Factors regulating spatial distribution of soil water content in small semiarid catchments. *J. Hydrol.* **2001**, *253*, 211–226. [CrossRef]
78. Kundu, S.; Mondal, A.; Khare, D.; Hain, C.; Lakshmi, V. Projecting Climate and Land Use Change Impacts on Actual Evapotranspiration for the Narmada River Basin in Central India in the Future. *Remote Sens.* **2018**, *10*, 578. [CrossRef]
79. Talib, A.; Randhir, T.O. Climate change and land use impacts on hydrologic processes of watershed systems. *J. Water Clim. Change* **2017**, *8*, 363–374. [CrossRef]
80. Li, C.; Sun, G.; Caldwell, P.V.; Cohen, E.; Fang, Y.; Zhang, Y.D.; Oudin, L.; Sanchez, G.M.; Meentemeyer, R.K. Impacts of Urbanization on Watershed Water Balances Across the Conterminous United States. *Water Resour. Res.* **2020**, *56*, e2019WR026574. [CrossRef]

81. Tian, J.; Guo, S.; Yin, J.; Pan, Z.; Xiong, F.; He, S. Quantifying both climate and land use/cover changes on runoff variation in Han River basin, China. *Front. Earth Sci.* **2022**. [CrossRef]
82. Afzal, M.; Ragab, R. How do climate and land use changes affect the water cycle? Modelling study including future drought events prediction using reliable drought indices. *Irrig. Drain.* **2020**, *69*, 806–825. [CrossRef]
83. Thiha, S.; Shamseldin, A.Y.; Melville, B.W. Assessment of the Myitnge River flow responses in Myanmar under changes in land use and climate. *Model. Earth Syst. Environ.* **2021**, *7*, 1393–1415. [CrossRef]
84. Calanca, P. Climate change and drought occurrence in the Alpine region: How severe are becoming the extremes? *Glob. Planet. Change* **2007**, *57*, 151–160. [CrossRef]
85. Alexander, L. Climate Science: Extreme heat rooted in dry soils. *Nat. Geosci.* **2011**, *4*, 12–13. [CrossRef]
86. Anderson, M.C.; Allen, R.G.; Morse, A.; Kustas, W.P. Use of Landsat thermal imagery in monitoring evapotranspiration and managing water resources. *Remote Sens. Environ.* **2012**, *122*, 50–65. [CrossRef]
87. Zhang, X.; Li, R.; Lei, S.; Fu, Q.; Wang, X. The Study of Dynamic Monitor of Rice Drought in Jiangxi Province with Remote Sensing. In Proceedings of the 3rd International Conference on Environmental Science and Information Application Technology (ESIAT), Xi'an, China, 20–21 August 2011; pp. 1847–1853.
88. Bonaccorso, B.; Bordi, I.; Cancelliere, A.; Rossi, G.; Sutera, A. Spatial variability of drought: An analysis of the SPI in Sicily. *Water Resour. Manag.* **2003**, *17*, 273–296. [CrossRef]
89. Bathurst, J.C.; Iroume, A.; Cisneros, F.; Fallas, J.; Iturraspe, R.; Gavino Novillo, M.; Urciuolo, A.; de Bievre, B.; Guerrero Borges, V.; Coello, C.; et al. Forest impact on floods due to extreme rainfall and snowmelt in four Latin American environments 1: Field data analysis. *J. Hydrol.* **2011**, *400*, 281–291. [CrossRef]
90. Mishra, A.K.; Singh, V.P. A review of drought concepts. *J. Hydrol.* **2010**, *391*, 204–216. [CrossRef]
91. Bagley, J.E.; Desai, A.R.; Harding, K.J.; Snyder, P.K.; Foley, J.A. Drought and deforestation: Has land cover change influenced recent precipitation extremes in the amazon? *J. Clim.* **2014**, *27*, 345–361. [CrossRef]
92. Hansen, M.C.; Loveland, T.R. A review of large area monitoring of land cover change using Landsat data. *Remote Sens. Environ.* **2012**, *122*, 66–74. [CrossRef]
93. Njoku, E.G.; Chan, S.K. Vegetation and surface roughness effects on AMSR-E land observations. *Remote Sens. Environ.* **2006**, *100*, 190–199. [CrossRef]
94. Njoku, E.G.; Jackson, T.J.; Lakshmi, V.; Chan, T.K.; Nghiem, S.V. Soil moisture retrieval from AMSR-E. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 215–229. [CrossRef]
95. Bindlish, R.; Jackson, T.J.; Gasiewski, A.J.; Klein, M.; Njoku, E.G. Soil moisture mapping and AMSR-E validation using the PSR in SMEX02. *Remote Sens. Environ.* **2006**, *103*, 127–139. [CrossRef]
96. Brocca, L.; Hasenauer, S.; Lacava, T.; Melone, F.; Moramarco, T.; Wagner, W.; Dorigo, W.; Matgen, P.; Martinez-Fernandez, J.; Llorens, P.; et al. Soil moisture estimation through ASCAT and AMSR-E sensors: An intercomparison and validation study across Europe. *Remote Sens. Environ.* **2011**, *115*, 3390–3408. [CrossRef]
97. Garcia, M.; Fernandez, N.; Villagarcia, L.; Domingo, F.; Puigdefabregas, J.; Sandholt, I. Accuracy of the Temperature-Vegetation Dryness Index using MODIS under water-limited vs. energy-limited evapotranspiration conditions. *Remote Sens. Environ.* **2014**, *149*, 100–117. [CrossRef]
98. Ben Abbes, A.; Jarray, N. Unsupervised self-training method based on deep learning for soil moisture estimation using synergy of sentinel-1 and sentinel-2 images. *Int. J. Image Data Fusion* **2022**, 2106317. [CrossRef]
99. Parikh, H.; Patel, S.; Patel, V. Classification of SAR and PolSAR images using deep learning: A review. *Int. J. Image Data Fusion* **2020**, *11*, 1–32. [CrossRef]
100. Shakya, A.; Biswas, M.; Pal, M. Fusion and classification of multi-temporal SAR and optical imagery using convolutional neural network. *Int. J. Image Data Fusion* **2022**, *13*, 113–135. [CrossRef]
101. Sahoo, A.K.; Houser, P.R.; Ferguson, C.; Wood, E.F.; Dirmeyer, P.A.; Kafatos, M. Evaluation of AMSR-E soil moisture results using the in-situ data over the Little River Experimental Watershed, Georgia. *Remote Sens. Environ.* **2008**, *112*, 3142–3152. [CrossRef]
102. Cheema, M.J.M.; Bastiaanssen, W.G.M.; Rutten, M.M. Validation of surface soil moisture from AMSR-E using auxiliary spatial data in the transboundary Indus Basin. *J. Hydrol.* **2011**, *405*, 137–149. [CrossRef]
103. Xiao, Z.Q.; Jiang, L.M.; Zhu, Z.L.; Wang, J.D.; Du, J.Y. Spatially and Temporally Complete Satellite Soil Moisture Data Based on a Data Assimilation Method. *Remote Sens.* **2016**, *8*, 49. [CrossRef]
104. Yin, L.C.; Tao, F.L.; Chen, Y.; Liu, F.S.; Hu, J. Improving terrestrial evapotranspiration estimation across China during 2000-2018 with machine learning methods. *J. Hydrol.* **2021**, *600*, 126538. [CrossRef]
105. Houtz, D.; Naderpour, R.; Schwank, M. A cost-effective portable l-band radiometer for drone and ground-based applications. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Electr Network, Hawaii, HI, USA, 26 September–2 October 2020; pp. 6531–6534.
106. Huang, L.; Shao, Q.; Liu, J. Forest restoration to achieve both ecological and economic progress, Poyang Lake basin, China. *Ecol. Eng.* **2012**, *44*, 53–60. [CrossRef]
107. Karniadakis, G.E.; Kevrekidis, I.G.; Lu, L.; Perdikaris, P.; Wang, S.F.; Yang, L. Physics-informed machine learning. *Nat. Rev. Phys.* **2021**, *3*, 422–440. [CrossRef]
108. Bajracharya, P.; Jain, S. Hydrologic similarity based on width function and hypsometry: An unsupervised learning approach. *Comput. Geosci.* **2022**, *163*, 105097. [CrossRef]

109. Chen, H.; Huang, J.J.; Dash, S.S.; Wei, Y.Z.; Li, H. A hybrid deep learning framework with physical process description for simulation of evapotranspiration. *J. Hydrol.* **2022**, *606*, 127422. [CrossRef]
110. Jiang, S.J.; Zheng, Y.; Solomatine, D. Improving AI System Awareness of Geoscience Knowledge: Symbiotic Integration of Physical Approaches and Deep Learning. *Geophys. Res. Lett.* **2020**, *47*, e2020GL088229. [CrossRef]
111. Gaur, N.; Mohanty, B.P. Evolution of physical controls for soil moisture in humid and subhumid watersheds. *Water Resour. Res.* **2013**, *49*, 1244–1258. [CrossRef]
112. Guo, J.; Guo, S.; Li, T. Daily runoff simulation in Poyang Lake Intervening Basin based on remote sensing data. In Proceedings of the 3rd International Conference on Environmental Science and Information Application Technology (ESIAT), Xi'an, China, 20–21 August 2011; pp. 2740–2747.
113. Hicks, B.J.; Beschta, R.L.; Harr, R.D. Long-term changes in streamflow following logging in western Oregon and associated fisheries implications. *JAWRA J. Am. Water Resour. Assoc.* **1991**, *27*, 217–226. [CrossRef]
114. Brocca, L.; Zucco, G.; Moramarco, T.; Morbidelli, R. Developing and testing a long-term soil moisture dataset at the catchment scale. *J. Hydrol.* **2013**, *490*, 144–151. [CrossRef]
115. Destouni, G.; Verrot, L. Screening long-term variability and change of soil moisture in a changing climate. *J. Hydrol.* **2014**, *516*, 131–139. [CrossRef]
116. Vörösmarty, C.J.; Green, P.; Salisbury, J.; Lammers, R.B. Global water resources: Vulnerability from climate change and population growth. *Science* **2000**, *289*, 284–288. [CrossRef]
117. Guo, H.; Hu, Q.; Jiang, T. Annual and seasonal streamflow responses to climate and land-cover changes in the Poyang Lake basin, China. *J. Hydrol.* **2008**, *355*, 106–122. [CrossRef]
118. Haddeland, I.; Heinke, J.; Biemans, H.; Eisner, S.; Floerke, M.; Hanasaki, N.; Konzmann, M.; Ludwig, F.; Masaki, Y.; Schewe, J.; et al. Global water resources affected by human interventions and climate change. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 3251–3256. [CrossRef]