Remote Sensing for Typhoon Flood Economic Loss Estimation: Current State and Digital Twin Prospects

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Abstract:

Typhoon-induced flood events result in enormous property losses and lives, thereby jeopardizing the prospects of sustainable societal growth. Scientific, objective, and accurate information regarding the spatial pattern of their direct economic impacts is of great importance to flood emergency response planning, disaster-related insurance settlements, and reconstruction after such events. Systematic reviews on the direct economic estimation of typhoon flood events do not currently exist. This paper describes basic framework for estimating typhoon flood economic losses, explains data utilized in remote sensing on such economic losses, summarizes remote sensing simulation technologies on direct economic losses due to typhoon flood, and includes the most recent advances and demands for building digital twin watersheds to recommend core research technologies focusing on direct economic losses of Typhoon flood: (1) High-precision remote sensing recognition of principal factors leading to Typhoon flood and subsequent damage; (2) Property value and loss reconstruction and measurement with digital twin techniques; (3) Intelligent assessment and precision service technologies for direct economic loss estimation of typhoon flood.

1. Introduction

Flood disasters are one of the most pervasive and destructive natural disasters in the world, causing huge economic losses and loss of life every year(Tang et al., 2025). Floods are increasingly frequent and intense because of climate change and urbanization, causing progressively more devastating impacts(Wang et al., 2025). It is crucial to estimate direct economic loss from typhoon-triggered flooding accurately for efficient emergency response, insurance payout, reconstruction, and policy making(Kawasaki and Shimomura, 2024).

Conventional techniques of economic loss estimation due to typhoon floods are usually based on statistical analysis and field surveys after the events. However, these techniques possess some notable limitations: they are time-consuming and labor-intensive, thus hindering prompt emergency response; results may be affected by subjective bias and inconsistency; there may be weak spatial coverage, particularly in areas that are difficult to access; and the accuracy of results depends on the representativeness of samples and data quality(Merz et al., 2010). These limitations significantly undermine the application of traditional techniques for large-scale and rapid assessments of typhoon flood disasters(Wang et al., 2025).

Satellite remote sensing has become an essential tool for gathering large-scale information on typhoon flood disasters and estimating economic losses. Despite advancements in this field, there is still a lack of comprehensive reviews on remote sensing-based assessments of typhoon flood losses, along with limited comparative analyses of the effectiveness of various methodologies. Additionally, emerging technologies like digital twins highlight the need for a consolidation of current research and the identification of future directions(Li, 2024).

This study reviews the fundamental principles of estimating economic losses from typhoon floods, with a focus on the application of satellite remote sensing in disaster hazard analysis, exposure valuation, and estimation model development. We compare the advantages and limitations of different methods, and considering the development of digital twin watersheds, we propose future research directions. This work aims to provide technical guidance for enhancing emergency response, disaster mitigation, and integrated risk governance.

2. The fundamental and framework of Typhoon Flood Economic Loss Assessment

Estimating direct economic losses from typhoon floods involves assessing the immediate impacts on socio-economic systems, integrating insights from disaster science, sociology, economics, and geography. However, accurately assessing these losses is challenging due to the complex variability of typhoons and the diversity of affected assets, with no universally accepted method available.

Since the 1970s, researchers have proposed various approaches to loss estimation, including empirical equations, damage curves, regression models, and neural networks. A "three-factor" framework has emerged, which relies on damage rates that incorporate hazard indicators, exposure data, and vulnerability parameters (Figure 1).

Hazard indicators refer to meteorological conditions, inundation depth, duration, and extent of flooding. Exposure relates to the distribution and value of assets, including property types, development levels, construction costs, and agricultural patterns. Vulnerability indicates the likelihood of damage, which is influenced by structural resilience and adaptive capacity.

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Recent advancements in remote sensing technology and high-resolution satellite data have greatly enhanced the ability to identify hazards, simulate exposure, and assess vulnerability. This progress has strengthened the scientific basis for estimating flood-related economic losses.

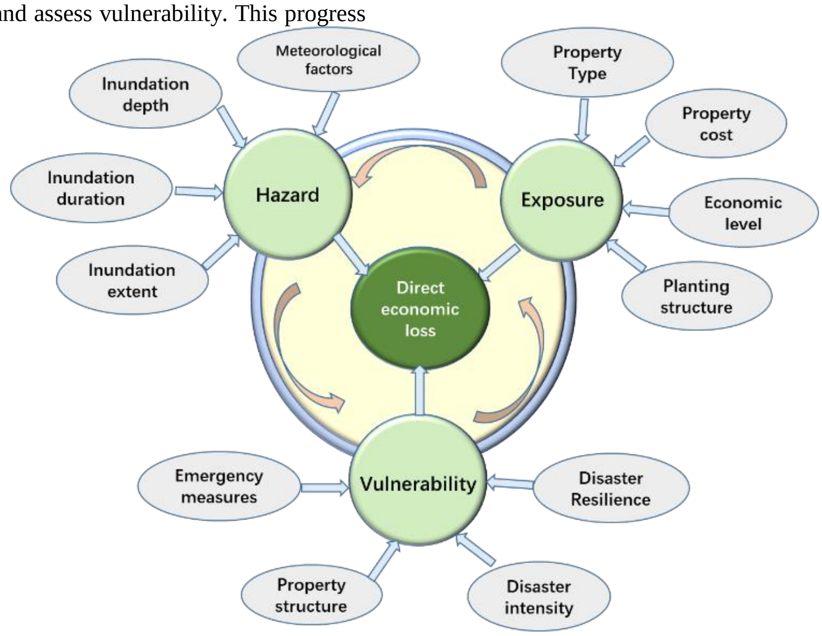

Figure 1. Basic framework for estimating typhoon flood economic losses

3. Hazard information extraction based on remote sensing

Extracting standardized hazard indicators is crucial for accurate loss estimation. Despite significant research efforts (Carisi et al., 2018; LI et al., 2014), no universal indicators for typhoon flood risks currently exist. Most studies concentrate on factors such as inundation depth, extent, and duration(Li et al., 2020; Wang et al., 2019). Although flow velocity is vital for assessing structural damage, it is often excluded due to a lack of field data.

Recent advances in machine learning methods have begun to integrate meteorological variables and complex interrelated factors. Remote sensing technologies have unique capabilities for extracting hazard information (Table 1), but varying spatial resolutions create challenges for multi-scale integration.

Satellite remote sensing is particularly effective in capturing the features of typhoon floods (Huang et al., 2018; Tang et al., 2015; Wan et al., 2019). The use of satellite constellations along with multi-source integration allows for multi-temporal flood mapping through both optical and radar imagery (Bioresita et al., 2019; Huang et al., 2014; Shen et al., 2019). When combined with elevation models, these technologies support the estimation of inundation depths (Kang et al., 2006; LI et al., 2014). However, remote sensing typically offers only static snapshots instead of continuous spatiotemporal representations(DeVries et al., 2020). While multi-source fusion enhances the feature of flood hazards, it also increases processing costs.

No	Feature	Description	Advantages	Limitations	References
1	Inundation extent	This method utilizes optical or radar remote sensing data to extract flood inundation areas by distinguishing water spectral and backscattering signatures from other surface features.	Provides rapid, accurate mapping of large-scale flooding with high temporal resolution.	Affected by occlusion and cloud cover.	(Grimaldi et al., 2016)
2	Inundation depth	This approach combines remote sensing imagery with hydrological models and high-resolution elevation data to estimate flood depth. Methods include multi-temporal image comparison and shadow-based analysis.	Provides spatially detailed flood depth distribution, supporting refined economic loss assessment.	Requires accurate elevation data and hydrological models	(Kang et al., 2006; Yi et al., 2005)
3	Inundation duration	This method analyzes flood duration using high-frequency satellite imagery compared with reference imagery.	Time-series imagery enables reconstruction of dynamic flood duration.	Limited by satellite revisit gaps	(Ding et al., 2013; Huang et al., 2018)
4	Other features (e.g., Rainfall intensity)	This approach uses meteorological satellite data to extract hazard features and overlays them spatially with inundation data to analyze spatiotemporal correlations between meteorological conditions and flood disasters.	High-resolution meteorological data enables spatiotemporal analysis of disaster mechanisms.	The resolution mismatch between meteorological hazard and flood hazard.	(Wan et al., 2019)

Table 1. Comparison of remote sensing extraction methods for hazard information

3. Exposure information extraction based on remote sensing

Typhoon floods can lead to significant property damage, resulting in direct economic losses. The spatial resolution of property value data plays a crucial role in the reliability of loss estimation (Kienberger, 2012; Li et al., 2003). Early studies relied on spatial interpolation of administrative data from statistical yearbooks. While this approach captured variations between different administrative units, it overlooked the heterogeneity of property values within those units, leading to considerable estimation errors (He et al., 2012; Sorichetta et al., 2015; Wang et al., 2011; Wu et al., 2018). Furthermore, flood boundaries rarely align with administrative boundaries, making accurate loss assessments challenging without detailed distributions of property values. Although integrating land use data, socio-economic data and nighttime light data has improved spatial resolution, the use of coarse land use classifications still limits accuracy(Leng et al., 2019; Ren et al., 2015; Zhao et al., 2017). The advantages and limitations of property value estimation based on different data are summarized in Table 2.

No	Data	Description	Advantages	Limitations	References
1	Statistical yearbook data	Extracts asset data from statistical yearbooks and government reports.	Provides highly authoritative data with comprehensive industry and land use classifications.	Has limited temporal and spatial resolution, reflecting only aggregated administrative values.	(Sorichetta et al., 2015)
2	Land use data	Uses remote sensing to map land use and calculate spatial asset distribution.	Offers high spatial resolution enabling dynamic updates based on pre- and post-disaster land use changes.	Shows regional variation in valuation coefficients and depends on classification accuracy.	(Zhao et al., 2017)
3	Remote sensing data	Employs nighttime lights or building data to estimate asset values.	Captures economic features, aligns with statistical units, and enables analysis of economic changes.	Suffers from brightness interference by various factors, low spatial resolution, and high valuation uncertainty.	(Elvidge et al., 1997; Jiang et al., 2018)
4	Multi-source data integration	Integrates remote sensing data, macroeconomic statistics, and POI data. Through data fusion, produces high-resolution maps of asset valuation.	Delivers high precision and timeliness, supporting multi-scale analysis across complex scenarios.	Involves high data complexity and acquisition costs, with modeling prone to overfitting and uncertainty.	(Yu et al., 2019)

Table 2. Comparison of statistical methods of property value based on different data

4. Research progress on the estimation method of direct economic losses caused by typhoon floods

Methods for estimating damage rates can be categorized into statistical and comprehensive approaches (Kourgialas and Karatzas, 2013; Rosser et al., 2017). Statistical models utilize inundation parameters as independent variables to create loss rate functions, resulting in depth-loss curves tailored to specific land uses(de MOEL and Aerts, 2011). In contrast, comprehensive methods take multiple factors into account, employing techniques such as fuzzy logic, Analytic Hierarchy Process (AHP), and grey relational analysis to assign weights(Zhu et al., 2007). However, the presence of strong autocorrelations among flood variables complicates the accurate assignment of these weights(Hoque et al., 2017). Grid-based techniques are used to address spatial variability, with Geographic Information System (GIS) frameworks determining suitable grid sizes for visualizing spatial risks(Zhu and Zhang, 2022).

Machine learning provides promising solutions through pattern recognition and spatial adaptability for complex multi-factor estimations (Wang et al., 2020). For instance, random forests incorporate features such as rainfall, runoff, and elevation (Wang et al., 2015), while support vector machines leverage multi-source remote sensing indicators (Mojaddadi et al., 2017). Additionally, deep neural networks can extract high-level features and generalize complex patterns, achieving an accuracy of 92.05% in flood prediction (Bui et al., 2020). A comparison of the strengths and weaknesses of these models is provided in Table 3.

No	Method	Description	Advantages	Limitations	References
1	Flood damage model based on depth-damage function	This approach uses water depth as a single variable to construct damage functions evaluating inundation impact on loss estimates.	The model is simple and mechanistic, with adjustable parameters that provide good generalizability and theoretical foundation.	The model shows weak adaptability to spatial heterogeneity and limited representation of real-world conditions.	(de MOEL and Aerts, 2011)
2	Multi-factor damage rate function	Extends single-factor models by incorporating duration, creating two-dimensional damage functions.	The approach captures multiple flood features, improves damage estimation precision, and is suitable for dynamic flood processes.	This approach involves high data acquisition costs, increased model complexity, and difficulties in determining factor weighting.	(Hoque et al., 2017; Zhu et al., 2007)
3	Grid-based flood loss	Employs grid-based modeling with spatial cells as calculation	The model introduces gridded modeling to	The method relies on high-resolution spatial data, making	(Zhu and Zhang, 2022)

No	Method	Description	Advantages	Limitations	References
	estimation model	units, mapping inundation extent to individual grids.	enhance spatial heterogeneity analysis of flood losses.	data acquisition costly for small and medium-scale watersheds.	
4	Machine learning	Uses supervised learning with historical disaster data to establish hazard-damage relationships.	This methodology extracts intrinsic patterns, improves model generalization, and supports model updates.	The model is highly dependent on training data, resulting in limited transferability across different regions.	(Mojaddadi et al., 2017; Wang et al., 2020)
5	Deep learning	This approach utilizes annotated training samples to develop predictive models that capture complex nonlinear relationships between hazard variables and corresponding damage rates.	The method captures complex patterns and processes large datasets efficiently.	The approach requires large volumes of labeled data and involves high computational costs.	(Bui et al., 2020)

Table 3. Comparison of economic loss estimation models of typhoon flood disasters

5. Future research directions

Digital twin technology has been applied extensively in the areas of urban and watershed management in recent years, and digital twin technology offers a new technical vision for typhoon-induced flood loss estimation(Chu et al., 2024). Digital twin systems, through creating a digital representation of the physical world, can realize real-time interaction between virtual models and physical entities and thus can facilitate dynamic simulation of disaster and loss estimation. In the aspect of direct economic loss estimation of typhoon flood, remote sensing and digital twin technology is advancing in the following directions:

(1) Remote sensing and digital twin technology for typhoon flood hazard identification and property damage. Through the integration of multi-source data—e.g., optical imagery, SAR, and hyperspectral data—intelligent classification models can be established to detect different categories of assets like residential homes, commercial buildings, industrial complexes, transportation infrastructure, and agricultural land(Guojin et al., 2018). Computerized change detection from pre- and post-disaster high-resolution images combined with deep learning methods enables automatic damage assessment of buildings, permitting fine-grained classification from undamaged to heavily damaged conditions. Quantitative remote sensing inversion models of inundation range, inundation depth, and inundation duration are also set up to retrieve key disaster intensity hazards for direct economic loss estimation. Spatiotemporal damage patterns of properties during typhoon occurrences are modeled, and quantitative correlations between damage intensity and hazards of disasters are quantitatively modeled to enable scientifically informed loss estimates.

(2) Digital twin-guided reconstruction of asset value and loss estimation. A remote sensing, GIS, and economic statistical data-based digital twin asset model is built to virtually replicate the value of physical assets (Ye et al., 2022). Model frameworks are described to demonstrate how typhoon flood intensity is transformed into economic losses by considering the types of assets, damage levels, repair costs, and depreciation rates. By integrating real-time remote sensing information with the digital twin system, economic losses can be directly computed and cumulatively estimated dynamically in flood inundation processes. Besides, an uncertainty quantification framework is also introduced to provide confidence intervals for loss estimation to improve damage estimation robustness.

(3) Typhoon flood intelligent loss assessment and precision service systems. By integrating large language models (LLMs), intelligent loss estimation techniques are built across various spatial scales, forming a multi-level estimation framework that covers from high-resolution asset-level estimates up to macroeconomic loss amounts(Wang et al., 2025). Companion digital twin platforms are tuned for insurance claims, disaster relief, and post-disaster reconstruction purposes and provide tailored outputs like loss reports, risk visualizations, and decision-making. A validation and calibration process is established, employing field investigations, insurance claim data, and government statistics to cross-validate the assessment outcomes and thereby increasing the accuracy and reliability of typhoon flood damage estimation.

6. Conclusion

This study addresses the existing gap in comprehensive reviews of direct economic loss assessment for typhoon floods. The research synthesizes current literature and establishes a foundational framework encompassing hazard factors, exposure elements, and vulnerabilities. Remote sensing methods for extracting hazard data and exposed assets are reviewed. Current modeling approaches for typhoon flood economic loss estimation are summarized, and key technical challenges for future research are identified. The objective is to advance intelligent, rapid, and accurate direct economic loss estimation methodologies and to support emergency response, disaster mitigation, and climate adaptation planning.

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