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Review

# A Systematic Review on Case Studies of Remote-Sensing-Based Flood Crop Loss Assessment

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**Abstract:** This article reviews case studies which have used remote sensing data for different aspects of flood crop loss assessment. The review systematically finds a total of 62 empirical case studies from the past three decades. The number of case studies has recently been increased because of increased availability of remote sensing data. In the past, flood crop loss assessment was very generalized and time-intensive because of the dependency on the survey-based data collection. Remote sensing data availability makes rapid flood loss assessment possible. This study groups flood crop loss assessment approaches into three broad categories: flood-intensity-based approach, crop-condition-based approach, and a hybrid approach of the two. Flood crop damage assessment is more precise when both flood information and crop condition are incorporated in damage assessment models. This review discusses the strengths and weaknesses of different loss assessment approaches. Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat are the dominant sources of optical remote sensing data for flood crop loss assessment. Remote-sensing-based vegetation indices (VIs) have significantly been utilized for crop damage assessments in recent years. Many case studies also relied on microwave remote sensing data, because of the inability of optical remote sensing to see through clouds. Recent free-of-charge availability of synthetic-aperture radar (SAR) data from Sentinel-1 will advance flood crop damage assessment. Data for the validation of loss assessment models are scarce. Recent advancements of data archiving and distribution through web technologies will be helpful for loss assessment and validation.

**Keywords:** flood; crop; loss assessment; remote sensing; damage assessment

## 1. Introduction

Flooding is one of the most significant natural hazards that are responsible for considerable damage to crops globally [1]. Every year, crop production is hampered because of flooding [2]. Recent climate change impacts may aggravate crop production loss from frequent flooding [3–6]. It was estimated that a total of 93,319 ha and 1.6 million tons of crops were damaged or destroyed by floods in the world between 2003 and 2013, which account for 57% of crop damage by all natural disasters [1]. Flood risks are high because crop fields are typically located in floodplains that support fertile soils [7]. Furthermore, flood protection standards for croplands are weak compared to urban areas [8]. Therefore, crop fields are highly vulnerable to flooding. Flood damage and loss assessment have become more important because of recent paradigm shifts in flood management from traditional physical-based management approach to advanced risk management [9–11]. Crop loss assessment is one of the most important tasks in overall flood damage assessment in the agriculture sector. Accurate crop loss assessment after flood events is crucial for determining grain price, agricultural policy, grain trading, and insurance appraisal.

Since traditional loss assessment typically is time-consuming and costly, rapid assessments and early recovery assessments are more commonly used to support immediate policy and decision processes. The quickly assessed information on flood-affected cropland acreage with crop type and the degree of damage can be helpful for disaster risk reduction. Rapid assessments mainly report inundated acreage of different crop types and damage associated with different flood depth levels (Figure 1) [12–14]. The early recovery assessment provides subjective damage conditions (e.g., low impact, moderate impact, high impact) or percentage loss using information on crop types, crop conditions, crop seasonality, and vegetation indices (VIs) [15,16]. Thus, the utilization of remote sensing data becomes very common in these two early damage assessment models for flood crop loss.

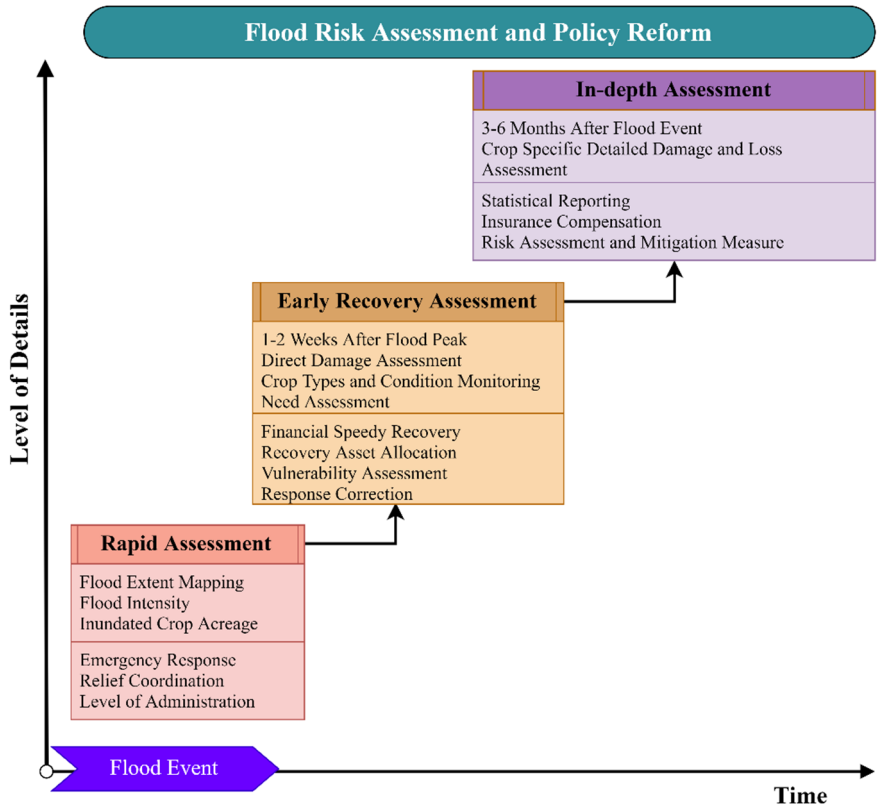


**Figure 1.** Types of flood assessment in various phases (adapted from Di et al. [17] and WMO [18]).

Remote sensing can play a vital role in every phase of the flood crop damage assessment process. Flood crop loss assessment primarily relies on flood information (e.g., extent, depth, duration) and crop conditions through VIs, which can be obtained from the analysis of remote sensing data [17,19–21]. Conventionally, crop loss or damage assessments are made by collecting and synthesizing crop acreage and production data acquired through field surveys. The conventional system is time-consuming, labor-intensive, cost-ineffective, and incomplete over vast croplands [15–17]. Moreover, it is quite difficult to conduct a field surveys and farmer interviews at any time of the season, meaning that remote sensing may be the only feasible option for crop loss estimation. Thus, detailed flood crop loss assessment based on the crop condition was not a usual practice in the last century. Remote sensing provides cost-effective and efficient solutions for crop mapping [19], crop condition monitoring [21], and flood mapping [22] by providing multitemporal images. Accordingly, flood crop loss assessments have been conducted more frequently in recent times because of the advancement of remote sensing technologies.

The use of remote sensing for flood crop loss assessment has increased rapidly in recent decades. Many studies have already been conducted by researchers, policymakers, and organizations to understand crop damage related to flood events utilizing remote sensing data. However, a systematic,

comprehensive assessment of these studies is helpful for determining the best practices for remote sensing data utilization in flood crop loss assessment. There exist few scholarly attempts to review the literature related to overall flood damage assessment. Brémond et al. [8] reviewed and analyzed existing methods of flood damage assessment in agriculture areas. Although their study mainly focused on flood hazard parameters and farm components, very little attention was paid to crop damage. Similarly, Gerl et al. [10] summarized models of flood loss assessment based on hazard intensity and loss functions. The economic assessment of flood damage was studied by Merz et al. [11], who included damage to all kinds of elements at flood risk. Smith [23] did a specialized review of flood loss estimation using stage–damage function for urban areas. Lea et al. [24] provided an extensive literature review and recommendation of flood damage assessment in general. However, there is possibly no comprehensive review of remote sensing data utilization in flood crop loss assessment in the existing literature. This study provides a systematic analysis of the literature on crop damage assessment using remote sensing and aids the discovery of knowledge gaps for future research.

The goal of this study is to review the utilization of remote sensing data in flood crop damage or loss assessment by exploring case studies. Specifically, this study has three specific objectives: (1) provide an overview of methods, remote sensing data utilization, and validation used in existing research; (2) evaluate the spatiotemporal scales of the selected case studies; (3) identify the challenges and opportunities of remote sensing data utilization in flood crop loss assessment.

## 2. Materials and Methods

### *2.1. Document Search*

This study performed a comprehensive literature search in March 2019 through scholarly electronic databases, focusing on remote sensing applications in the assessment of flood crop loss. The study covered the most popular electronic databases, including Web of Science, Science Direct, Google Scholar, Scopus, IEEE Xplore, Mendeley, and Springer Link. The preselected keywords aligned with the objective of the study were 'flood', 'flooding', 'crop', 'agriculture', 'remote sensing', 'loss', 'damage', 'impact', 'assessment', and 'estimation'. The selected keywords were searched in these scholarly databases. The following search terms with multiple combinations were used to identify documents published between 1983 and 2019 to capture all empirical studies:

["crop" OR "agriculture"]
AND
["loss" OR "damage" OR "impact"]
AND
["assessment" OR "estimation"]
OR
["flood" OR "flooding"]
OR
["remote sensing"].

Although searches using multiple languages were advantageous, this study searched documents only written in English because of two reasons. Firstly, it was very difficult to search literature in all languages, hence the scope was shortened only to English language; secondly, most of the literature of social science and natural science is written in English [25,26]. The "OR" operator was used between "crop" and "agriculture" because these two terms were used in literature interchangeably. Similarly, three terms "loss", "damage", and "impact" were often used to express similar meaning. Hence, the "OR" operator was used to get all studies related to loss, damage, and impact assessment. Moreover, it was observed that both "assessment" and "estimation" were used in studies on flood impact analysis. The "OR" operator was used before ['flood' OR "flooding"] to get an overview of crop loss assessment due to natural hazards other than the flood. Similarly, the "OR" operator was used before "remote sensing" to capture the loss assessment approach without the utilization of remote sensing data. Thus, the utilization of "OR" operator before the terms "flood" and "remote sensing" included several

studies in identification stage that may not have utilized remote sensing data or may have assessed crop damage from sources other than flood. Although these studies were helpful to understand an overall crop damage assessment process without the utilization of remote sensing data, such case studies were excluded in screening process. The time frame between 1983 and 2019 was chosen because the utilization of remote sensing in flood and crop study become popular after launching Landsat 4 satellite mission in 1982. The synonyms of keywords which were often utilized in academic research were chosen to capture most of the study in this field. A total of 173 related documents were found through this rigorous searching process (Figure 2).

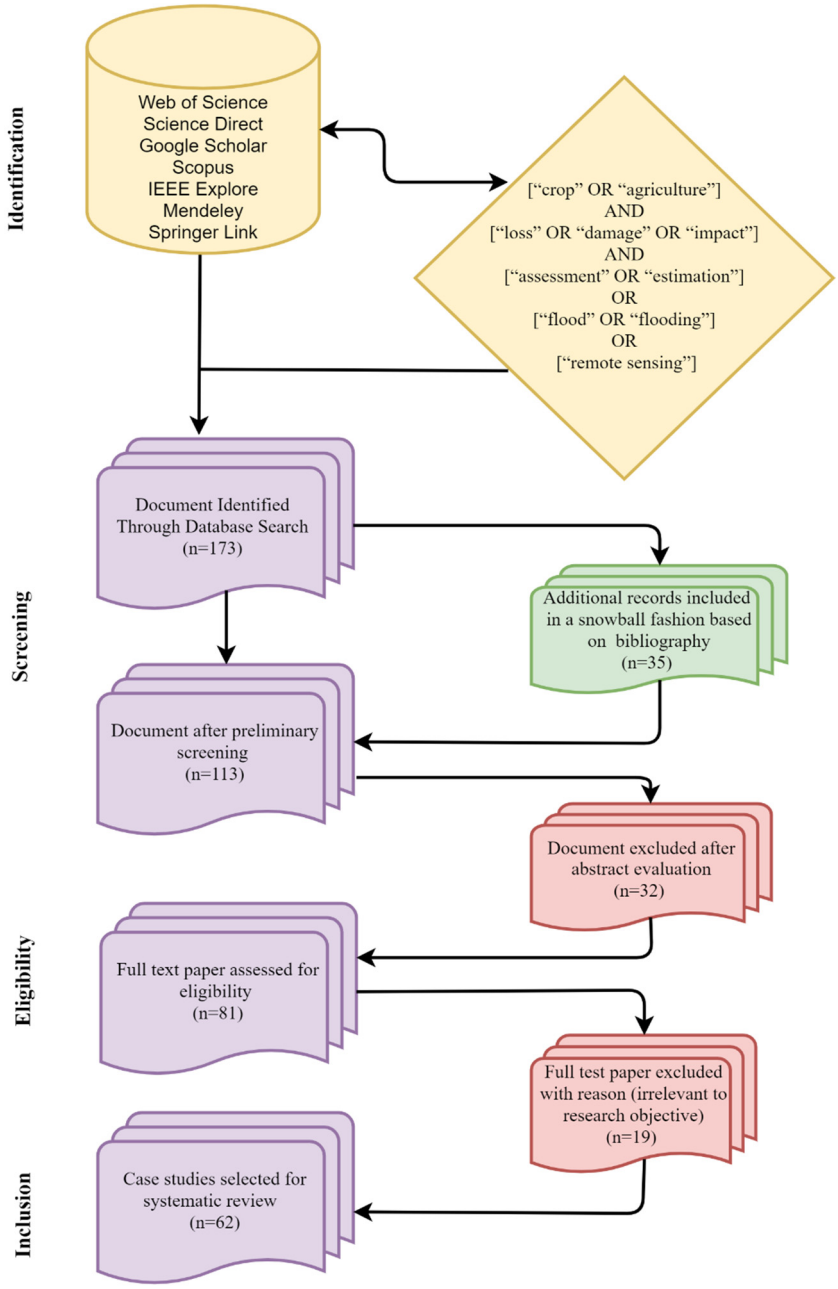


**Figure 2.** Flow chart for document search, screening, and categorization.

## 2.2. Document Screening and Categorization Process

The documents were downloaded and screened for a total of 173 identified documents from selected scholarly sources. Only 78 documents remained after removing 95 documents in preliminary

screening stage. An additional 35 relevant documents were found using snowball sampling from the bibliography of the identified documents, which were added to the collection of 78 documents. Snowball sampling is a method of survey used here to locate unidentified articles by the references from initially identified documents. Thus, a total of 113 (78 + 35) documents were selected for abstract evaluation. A total of 32 documents were removed after a careful evaluation of 113 abstracts. Then, only 81 documents were selected for eligibility checking, from which 19 documents were excluded. This study excluded review articles, articles with no use of remote sensing data, and articles primarily focused on non-flood crop damage. In addition, some articles were removed because of their primary focus on broader aspects of disaster management including monitoring, warning, and mitigation. Finally, a total of 62 empirical studies were selected for detailed analysis.

Documents were primarily categorized based on the flood-information-based loss assessment, crop-condition-based assessment, and hybrid utilization of both flood information and crop condition. Case studies were also grouped based on assessment types (e.g., rapid, in-depth). A catalog of selected studies was developed in Microsoft Excel based on metainformation including title, authors, year of publication, study location, journal name, methods, remote sensing data types, the scale of the studies, and validation process. Subgroups of case studies were also made based on the type of remote sensing data utilization such as the use of optical vs. microwave remote sensing and the spatial resolution of remote sensing (fine to coarse). Case studies were also categorized based on the methods and techniques utilized in damage assessment process such as flood-intensity-based approach, flood stage damage based approach, vegetation-index-based approach, and software-oriented approach. Moreover, case studies were also categorized based on the scale of studies (e.g., local, regional, and national) as well as damage reporting types.

### 2.3. Data Analysis and Interpretation

Both qualitative and quantitative approaches were used to analyze the selected case studies to summarize methods, approaches, data utilization, validation, assessment type, reporting type, and major challenges. The spatial–temporal distribution of case studies was mapped. Citation map and keywords cloud from the literature were plotted based on the database derived from the Web of Science. A network visualization was produced using the occurrence of keywords in selected documents. A citation network map was also developed using the links and number of citations. In both cases, Lin-Log/Modularity was chosen as the normalization method [27]. Clusters were formed based on the relatedness, where relatedness was determined by co-citation and co-occurrence in same document for citation map and keywords network, respectively [28].

## 3. Results

### 3.1. Remote Sensing Data Utilization

A large variety of remote sensing data from different sensors and platforms were utilized in different stages of crop loss assessment. A digital elevation model (DEM) was one of the mandatory elements for hydraulic flood modeling. DEMs were derived from multiple remote sensing sources and from the topographic survey. Since flood modeling for agriculture was usually conducted over vast areas, the utilization of a survey-based DEM was not viable. Although LiDAR DEM was the most reliable option for accurate flood modeling, LiDAR DEMs were scarce in most parts of the world because of high-cost involvement. Thus, most of the case studies utilized the Shuttle Radar Topography Mission (SRTM) DEM and the ASTER global DEM. ASTER DEM is available at 30 m spatial resolution on a global scale. Similarly, SRTM DEM is also available free of charge at 30 and 90 m spatial resolution. Apart from the utilization of DEMs in flood hydraulic modeling, DEMs were also used to determine flood depth using flood extent maps derived from remote sensing data [29,30].

Rainfall data were also a key parameter in flood modeling. Satellite-based remote sensing measurements such as the Tropical Rainfall Measuring Mission (TRMM) play a vital role in flood

modeling and mapping. Li et al. [31] utilized precipitation data to assess the impact of flooding on wheat yield. Satellite-based rainfall measurement is an option in addition to ground-based rainfall measurement for flood modeling. Many studies utilized optical remote sensing data, including Landsat and MODIS, for flood inundation mapping [15,32–34]. It was hard to find cloud-free images for flood mapping during the rainy season. Thus, the utilization of SAR data, especially Sentinel-1, can be advantageous for flood mapping during cloudy conditions. Only three case studies used images from uncommon remote sensing sources such as AWiFS-optical and HJ-CCD images for flood crop loss assessment [35–37].

Land cover maps were another important input parameter of flood modeling, which also served to determine the surface roughness (Manning's coefficient). Many studies used generalized land cover maps, including only top-level land cover types derived from remote sensing data [38]. The details of these land cover maps were varied from a generalized agriculture land cover class to crop-specific land cover types depending on the purpose of the study. Both optical and microwave data were utilized in land cover mapping and crop condition monitoring. Many studies utilized historical land cover and crop maps, which may not be appropriate for the flood loss estimation due to crop rotation and land-use change.

Optical remote sensing was widely utilized for land cover mapping, crop type identification, and crop condition monitoring [15,39–42]. Remote sensing data were utilized for in-season crop mapping to support accurate crop-specific loss estimation [43]. Although most of the studies utilized medium (e.g., Landsat) to coarse resolution optical imageries (e.g., MODIS, AVHRR), only a few studies used fine-resolution images (e.g., IKONOS, SPOT, WorldView, GeoEye, and RapidEye). MODIS and Landsat images were most frequently used in flood crop loss assessment because of their spatiotemporal scale and free-of-charge availability. The fine temporal resolution (1–2 days) of MODIS data is very suitable for crop growth stage monitoring. There is a high chance of getting cloud-free MODIS images compared to Landsat and Sentinel-2 because of the frequent revisit capability. Landsat was also the choice of many case studies because of the finer spatial resolution compared to MODIS data. The utilization of Sentinel-2 optical data will get wider attraction for crop mapping, crop condition monitoring, and flood mapping because of fine spatial resolution (10 m) and reasonable revisit capability (~5 days). However, the utilization of fine-resolution images for vast agricultural areas may not be suitable in terms of computational cost for the processing of many scenes.

Liu et al. [44] mapped waterlogging damage on winter wheat at field level using fine-resolution optical images from multiple sources including SPOT, WorldView, GeoEye, and Pleiades-1A. They derived seven VIs, leaf area index, and biomass from these fine-resolution images to monitor crop conditions over the whole growing season. They utilized only one image per month, which is very sparse in the context of crop phenology monitoring. They monitored impact of waterlogging only on a few fields because of the huge cost of fine-resolution images. Capellades et al. [45] utilized RapidEye images to calculate soil-adjusted vegetation index (SAVI) for crop loss assessment at the county level. Similarly, Silleos et al. [46] extracted normalized difference vegetation index (NDVI) from SPOT images for regression-based crop yield assessment.

Fine spatial resolution images (e.g., SPOT, IKONOS2) are also used for land cover mapping and crop field identification to support flood-intensity-based crop loss assessment [47–49]. Van der Sande et al. [49] mapped land cover through object-based image classification (segmentation approach) using IKONOS 2 images for assisting flood damage assessment. Case studies that utilized fine-resolution images were mostly conducted at local scale because it is not cost-effective for crop damage assessment for vast areas. All fine spatial resolution images utilized in case studies are from optical domains which have similar band properties. Thus, there is no mentionable technical difference in the utilization of images from these sensors and platforms. The choice of images sources mostly depends on the accessibility and availability to these fine spatial resolution images.

Many remote-sensing-derived products (e.g., land cover, VIs) available in data portals were frequently utilized in flood crop loss assessment. Shrestha et al. [13] used the Global Land 30 land cover

products to support stage–damage-based loss assessment. CORINE land cover map is used to improve the flood damage assessment models in Italy [12]. Most of the studies in the US utilized cropland data layer (CDL) for crop-specific loss assessment [16,21,50–52]. CDL comprises crop-specific national land cover data for the US derived through supervised image classification of Landsat data [43,53]. The advantage of CDL over other land cover products is the availability of detailed information on crop types. However, CDL is only available for the US croplands. Remote-sensing-based in-season mapping of crop types can support crop-specific damage assessment where crop types information is not available.

MODIS NDVI products (e.g., daily, weekly composite) were frequently used in crop condition monitoring during flood events. Ahmed et al. [15] used MODIS 16-day composite NDVI to assess pre- and post-flood crop conditions. The advantage of composite products is the consideration of best pixels in 16 days to avoid cloud contamination. Shrestha et al. [16] created a crop phenology curve using daily MODIS NDVI products for regression-based crop loss assessment. MODIS-derived biweekly enhanced vegetation index (EVI) composite was also used for flood impact assessment and crop phenology detection [2,54]. Similarly, other derived products such as MODIS leaf area index (LAI) were also be utilized in crop condition profile monitoring. MODIS-derived flood products such as the National Aeronautics and Space Administration (NASA)/MODIS near real-time (NRT) flood products were directly used in the crop loss assessment models [17,55]. Flood frequency and duration were also be calculated from MODIS-derived daily flood maps [56]. The use of these derived products leveraged some parts of the computational load on other systems, which makes the loss assessment model easy and simple. However, production errors of these derived products can directly impact on the accuracy of loss assessment models. The accuracies of these derived products are unknown in most of the cases; thus, the users of these products are unable to report precise accuracy of crop damage assessment.

Many case studies utilized microwave remote sensing, especially SAR, for flood delineation and crop mapping to overcome optical sensors' inability to see through clouds [30,37,47,54,57]. Rice crop areas were detected through thresholding of COSMO-SkyMed sigma naught for the assessment of crop loss by flooding of Typhoon Haiyan [54]. Similarly, Haldar et al. [37] delineated a flood inundation map by thresholding RADARSAT and RISAT backscatters. Waisurasingha et al. [30] and del Carmen Silva-Aguila et al. [47] mapped flood depth by combining the inundated area derived from the RADARSAT C band and DEM. Similar to optical remote sensing, supervised classification of pre- and post-flood SAR data were used to assess the degree of crop damage [32,57]. Hossain et al. [32] utilized data fusion of optical and RADARSAT time series for the identification of damaged crops. These supervised classification models were trained using signatures collected through field surveying. RADARSAT is the dominant SAR data source used in flood crop loss assessment because of the accessibility of RADARSAT data archives. Although no use of Sentinel-1 data was reported in these selected case studies, there is a high possibility of the use of Sentinel-1 in the near future because of the free-of-charge availability. Sentinel-1 provides C-band SAR data with multiple polarization, which is suitable for both flood mapping and crop condition monitoring [58].

### *3.2. Remote-Sensing-Based Flood Crop Loss Assessment Approaches*

#### 3.2.1. Flood-Intensity-Based Crop Loss Assessment

There was a wide variety of approaches for the utilization of flood information. Flood crop damage is often reported as inundation acreage, which is very generalized approach without considering crop conditions. The use of a stage–damage curve in damage assessment was varied based on flood parameters including depth, duration, flow velocity, and seasonality. Although many studies used a generalized curve for all crops, some case studies utilized crop-specific stage–damage function. Table 1 summarizes case studies on flood-intensity-based crop loss.

The spatial location of floods (flood extent) was the obvious factor because it was the most basic parameter for flood-intensity-based loss assessment in selected case studies. Flood extents answer a

very basic question as to where floods have occurred. Moreover, flood extent map is easy to derive from remote sensing image analysis or from hydraulic modeling compared to other flood variables. An assessment based on flood extent is only able to report flood loss as inundated cropland acreages. Thus, neither the degree of damage nor crop-specific damage estimation is possible to be obtained. Moreover, there is high possibility to get overestimated damage information because inundated areas may not have complete damage. Li et al. [59] presented a unique rainfall intensity–loss curve at the regional level based on the historic major floods in China without using flood extent information. A unique approach of crop yield loss assessment was implemented by Li et al. [59], where loss was estimated by comparing different yield models based on soil–water balance and saturation condition.

More than half of the flood-intensity-based case studies utilized flood depth information for loss assessment. The utilization of flood depth information can be categorized broadly in three types: depth–damage curve, categorical depth classes, and thresholding. The depth–damage curve was used as a continuous function for crop loss assessment, where x-axis and y-axis represent flood depth and corresponding loss, respectively. Many studies used three to four depth classes and associated potential damage in crop loss assessment [47,60–62]. Waisurasingha et al. [30] and Pacetti et al. [63] used 80 and 100 cm flood-depth threshold to determine crop damage. The depth–damage curve allows a continuous loss assessment at any flood depth, whereas loss assessment using depth categories or thresholds generalizes loss within the range of depth categories. The utilization of flood depth information along with inundation extents is helpful for precise damage estimation. Forte et al. [29] utilized a generalized depth–damage curve for the agricultural sector for damage estimation. Similarly, del Carmen Silva-Aguila et al. [47] utilized four damage classes that correspond to four flood depth classes. The main drawback of these studies is the utilization of a generalized curve or class for all crop types. These kinds of general assumptions may lead to huge over- or underestimation of crop damage. Different crop types have different tolerance levels to flood depth. Therefore, it is important to consider separate depth–damage curves for different crop types. Dutta et al. [61] and Kwak et al. [64] made precise estimation on crop damage by utilizing crop-specific depth–damage curves. A general curve or threshold of flood depth can be utilized if single crop type is the focus of damage assessment. The depth–damage relations were developed mostly based on the empirical evidence from the recent past events in the study area. Therefore, information on depth–damage relationship is often scarce in many areas. Only one-fourth of the case studies in Table 1 included flood duration information in loss assessment models. Categorical flood duration expressed in the range of days was used in most case studies of this kind. The ranges of duration classes were varied from a single day to several days (a few weeks) depending on the crop types and seasonality [61,62,65,66]. Only a few studies utilized flow velocity in crop loss assessment (Table 1). Citeau [67] mentioned that maximum tolerable inundation duration for cropland varies between three days in spring/summer to one month in autumn/winter. Crops can be completely damaged beyond the tolerable duration. Dutta et al. [61] utilized duration–damage relationship for rice damage assessment, where flood duration over a week was associated with above 80% crop loss at 1 m flood depth. Crop damage at a given flood duration can also be varied over two factors: flood depth and crop seasonality. Win et al. [68] utilized different depth–duration–damage curves for the three stages of rice-growing season. Dutta et al. [61] developed damage–duration relationships using empirical evidence, whereas Win et al. [68] relied on farmer interviews to develop such relationships. Depth–duration relationship based on farmer interviews may be error-prone since farmers relied mostly on their guesses of damage in past events. Flow velocity can only be obtained from hydraulic flood modeling. Although the high flow velocity can cause direct damage to the crop, it is very difficult to assess the impact of flow velocity over a large agriculture area. Moreover, flow velocity had less impact on agriculture loss [65]. Thus, flow velocity is rarely utilized in crop damage assessment.

**Table 1.** Comparison of case studies on flood crop loss assessment regarding the considered flood intensity variables.

| Reference, Location | Flood Extent | Flood Depth [1)] | Flood Duration [1)] | Flow Velocity | Seasonality | Crop-Specific [1)] |
|---|---|---|---|---|---|---|
| Imhoff et al. [72], Bangladesh | Yes | No | No | No | No | No |
| Consuegra et al. [69], Switzerland | Yes | No | Yes—days (three classes) | no | Yes—a period of 15 days | No |
| del Carmen Silva-Aguila et al. [47], Mexico | Yes | Yes—four classes | No | No | No | No |
| Dutta and Herath [48], Japan | Yes | Yes—four classes | Yes—hourly | No | No | Yes—eight classes |
| Dutta et al. [61], Japan | Yes | Yes—three classes | Yes—days | No | Yes—monthly | Yes—eight classes |
| van der Sande et al. [49], the Netherlands | Yes | Yes—damage curve | No | No | No | Yes—wheat |
| Forte et al. [29], Italy | Yes | Yes—damage curve | No | No | No | No |
| Waisurasingha et al. [30], Thailand | Yes | Yes—80 cm threshold | No | No | No | No |
| Förster et al. [65], Germany | Yes | No | Yes—four classes | No | Yes—monthly | Yes—multi crop |
| Pistrika [73], Greece | Yes | Yes—damage curve | No | No | No | No |
| Qi and Altinakar [74], USA | Yes | Yes—two classes | No | Yes | Yes—monthly | Yes—multi crop |
| Yue Ma et al. [34], Pakistan | Yes | No | No | No | No | No |
| Tapia-Silva et al. [41], Germany | Yes | No | Yes | No | Yes—monthly | Yes—multi crop |
| Li et al. [59], China | No | No | No | No | No | No |
| Haq et al. [75], Pakistan | Yes | No | No | No | No | No |
| Chau et al. [76], Vietnam | Yes | No | No | No | No | No |
| Chau et al. [71], Vietnam | Yes | Yes—four classes | No | No | Yes—monthly | No |
| Memon et al. [77], Pakistan | | No | No | No | No | No |
| Kwak et al. [64], Cambodia | Yes | Yes—two classes | Yes—two classes | No | No | Yes—rice |
| Samantaray et al. [62], India | Yes | Yes—three classes | Yes—five classes | No | No | Yes—rice |
| Chau et al. [60], Vietnam | Yes | Yes—four classes | No | No | No | Yes—rice |
| Vozinaki et al. [70], Greece | Yes | Yes—three classes | No | Yes—three classes | Yes | Yes—multi crop |
| Amadio et al. [12], Italy | Yes | Yes—damage curve | No | No | Yes—four stages | Yes—multi crop |
| Mao et al. [14], France | Yes | Yes—damage curve | Yes | Yes—threshold | Yes | Yes—multi crop |
| Nguyen et al. [78], Vietnam | Yes | Yes—four classes | No | No | No | Yes—rice |
| Pacetti et al. [63], Bangladesh and Pakistan | Yes | Yes—100 cm threshold | No | No | No | No |
| Win et al. [68], Myanmar | Yes | Yes—damage curve | Yes—three classes | No | No | No |
| Shrestha et al. [13], Philippines and Pakistan | Yes | Yes—damage curve | Yes—five classes | No | Yes—four stages | Yes—rice |
| Shokoohi et al. [79], Iran | Yes | Yes—damage curve | No | Yes | Yes—four stages | No |

[1)] Classes indicates the number of categorial classes which are utilized in case studies for the corresponding flood intensity (e.g., three classes, four classes).

Seasonality can be considered as the third most frequent parameter after extent and flood depth (Table 1). It is important to know at which stage of growing season floods have occurred because crops' vulnerability to flooding varies with phenology stages [8,69,70]. Win et al. [68] found that rice is more vulnerable in the seedling and vegetative stage compared to the reproductive stage through farmer interviews. Some studies also divided crop-growing season into three/four stages for flood impact assessment on crops [12,13]. The month of flood occurrence was also utilized as the function in flood loss estimation [41,71]. Machine learning approaches can also be utilized for crop damage assessment using flood duration and crop growth stage information. The idea is that a machine can learn from damage from past events corresponding to duration and growing stage. However, a strong historical

database is required to train machine learning models properly. Historical data on crop damage and flood intensity information may not be available in most of the cases.

Figure 3 illustrates conceptual examples of stage–damage relationship for flood crop loss assessment. The shape of stage–damage curve widely varies with crop types and geographic locations. Figure 3a represents the idea to have both flood depth and duration in continuous stage–damage function. The shape of the curve may vary with the crop-growing seasons such as vegetative stage, reproductive stage, maturity stage, and ripening stage [66]. A piecewise curve can also be utilized as a stage–damage function where loss percentage varies with the ranges of flood depth (Figure 3b). The utilization of a pricewise curve is very similar to the threshold-based application of flood parameters. There were a variety of shapes, including exponential, quadratic, and spline, which were also utilized as a stage–damage function for crop loss assessment. Most of the stage–damage curve used a certain water depth threshold as the ceiling, any water depth above that threshold indicates total crop loss (Figure 3a–c). Figure 3d represents a tabular loss assessment approach where each of the flood intensities is categorized into a finite number of classes. The level of crop damage can be assessed based on the level of two or three flood intensity parameters. The stage–damage curve should be crop type and geographic location specific to get a better result in crop loss assessment.

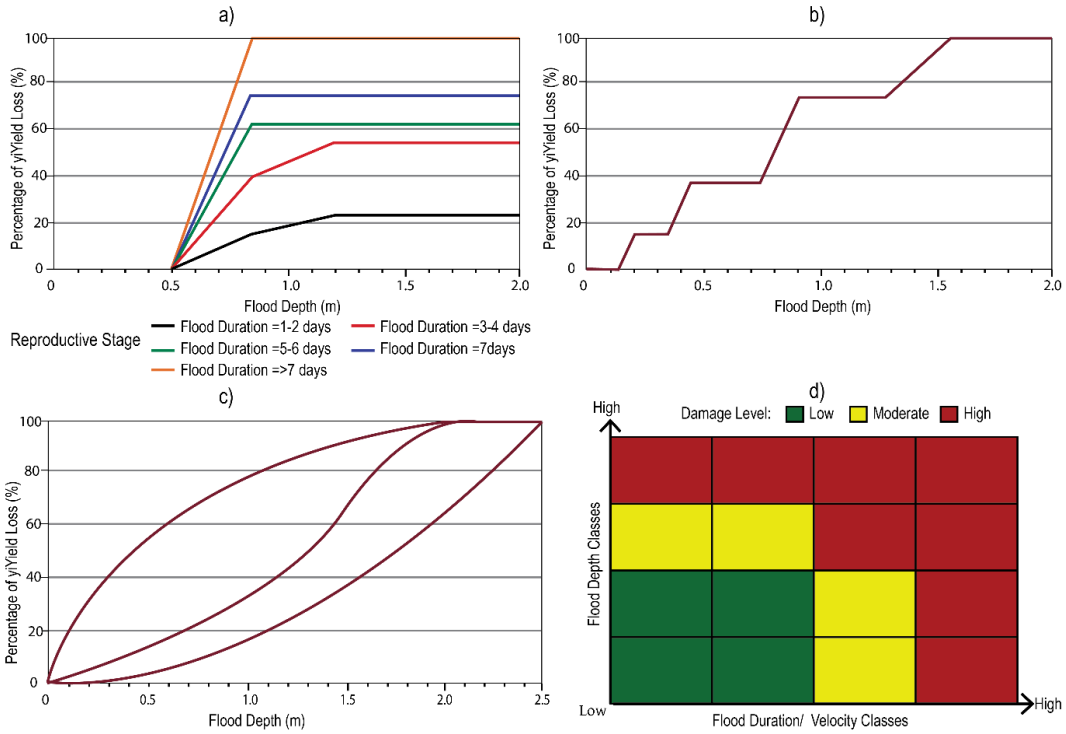


**Figure 3.** Schematic stage–damage function for flood crop loss assessment. (**a**) Conceptual example of depth–duration–damage curve adapted from Shrestha et al. [66] and Kwak et al. [64]; (**b**) example of depth–damage curve showing a linear piecewise curve adapted from Amadio et al. [12] and Mao et al. [14]; (**c**) example of some other depth–damage curves (exponential, quadratic, and S-shape) adapted from Dutta et al. [61], Van der Sande et al. [49], Forte et al. [29], Nguyen et al. [78], and Win et al. [68]; (**d**) conceptual example of tabular format of stage–damage function of loss assessment [62,65,70].

### 3.2.2. Crop-Condition-Based Crop Loss Assessment

Crop-condition-based flood crop loss assessment mainly assessed the impact of the flood on vegetation growth. These assessments were mostly based on VIs. Different types of approaches were utilized, including the comparison between pre- and post-flood conditions, regression analysis between VIs and crop yield, VIs thresholding, and clustering damaged areas based on remote sensing image

bands. Table 2 shows indices which were utilized for flood crop loss assessment in the selected case studies. A very simple approach is to monitor NDVI change in inundated cropland, which assumes that NDVI usually declines in the flood-affected crops. Shrestha et al. [51] compared the MODIS NDVI time series with historical median NDVI between 2000 and 2014 to show the impact of the flood on crops. The comparison between the NDVI of the affected field with normal NDVI requires historical data on NDVI. Okamoto et al. [80] used a feature space between the infrared band and red band to monitor rice phenology in North Korea. Flood damage was assessed by comparing the spectral growth track (SGT) of the flooded year with the usual crop growth track. The idea behind this approach was that rice may take a longer time to move between stages on the SGT because of the impact of flooding. Although SGT can be simply derived from the band ratio, crop damage estimation using SGT requires empirical knowledge on crop phenology stages. The SGT approach requires detailed records on crop plantation and phenological stage information which may make the damage assessment process complicated. Although these simple approaches can indicate crop damage, it is often not possible to quantify the degree of damage.

Regression between crop yield and VIs were often utilized for flood crop loss assessment, where VIs (one or multiple) were used as an independent variable to predict crop yield/loss. Silleos et al. [46] developed a linear regression model using NDVI and loss percentage collected from field surveying. Similarly, Shrestha et al. [16] used a linear regression model between the NDVI change ratio of pure corn pixels and yield change ratio for corn loss assessment in the US. Pure corn pixels were extracted from crop fraction layers derived from CDL at the spatial resolution of MODIS [81,82]. The utilization of pure pixel in regression was helpful for precise damage assessment without the influence of mixed pixels. Liu et al. [44] used multivariate regression using multidate VIs (e.g., NDVI, EVI, ratio vegetation index (RVI), optimized soil-adjusted vegetation index (OSAVI), modified triangular vegetation index (MTVI2), two-band enhanced vegetation index (EVI2), and green normalized difference vegetation index (GNDVI)), LAI, and above-ground biomass to assess the damage on winter wheat. They explored five regression models, namely linear, power, quadratic, exponential, and logarithmic models, where the power model having EVI as an independent variable outperformed than other models. These regression-based approaches often require historical data on yield and independent variables to establish regressing equations. Therefore, regression models cannot be utilized in these areas where historical data are scarce. Moreover, regression models based on the crop condition profiles of whole season are not useful for in-season rapid damage estimation. The advantage of regression models is that they are capable of providing quantitative loss assessment. The damage can be expressed as yield reduction compared to usual yield.

Gilbert et al. [83] compared LAI and yield from flood-affected fields with non-flooded fields to calculate the yield loss. Chejarla et al. [39] calculated crop production loss by comparing crop biomass before and after the flood event. The utilization of LAI or crop biomass differs from the utilization of VIs, since VIs are the indication of crop heath via greenness whereas biomass and LAI are indicators of physical properties of plants. However, case studies utilized similar damage assessment approaches including pre- and post-event comparison and the deviation from the normal conditions. Another approach for crop loss assessment is the simple thresholding of VIs. Islam and Sado [84] as well as Capellades et al. [45] utilized NDVI and SAVI thresholds, respectively, to estimate crop loss. Capellades et al. [45] categorized the difference between SAVI and mean SAVI within an image tile into the seven classes of crop loss. The main drawback in this case study is the comparison with mean SAVI of affected tiles, which is directly affected by flood-impacted pixels.

VIs used in flood crop loss assessment can be broadly categorized into two groups: Vis that are directly derived from remote sensing bands (e.g., NDVI, EVI, SAVI) and Vis that are derived from other VIs. The first group of VIs can be denoted as first-order VIs (e.g., NDVI). Similarly, the second group can be denoted as second-order VIs (e.g., vegetation condition index (VCI), mean VCI (MVCI)). Most of the second-order VIs are developed based on NDVI. Some second-order VIs are often affected by outliers because of the utilization of using maximum, minimum, and mean historical NDVI. A

historical NDVI database is required to calculate some VIs, such as VCI, median VCI (mVCI), and the ratio of current NDVI to the previous year (RVCI). It is very convenient to calculate historical NDVI for any parts of the world because of the long archives of optical images from MODIS and Landsat. Cloud contamination is another important issue which needs to be carefully examined while using historical NDVI for the calculation of VIs. In fact, cloud-contaminated pixels need to be carefully excluded from daily NDVI to calculate accurate VIs.

**Table 2.** Indices used in crop-condition-based flood loss assessment.

| Index | Definition [2)] | Source | Case Studies |
|---|---|---|---|
| Normalized difference vegetation index (NDVI) | $\frac{\rho_{NIR}-\rho_{RED}}{\rho_{NIR}+\rho_{RED}}$ | Rouse Jr et al. [85] | Liu et al. [44], Ahmed et al. [15], Shrestha et al. [16], Silleos et al. [46], Shrestha et al. [51], Pantaleoni et al. [86], Islam and Sado [84] |
| Enhanced vegetation index (EVI) | $\frac{2.5(\rho_{NIR}-\rho_{RED})}{(1+\rho_{NIR}-2.4\rho_{RED})}$ | Huete et al. [87] | Liu et al. [44], Kotera et al. [88], Son et al. [89] |
| Two-band enhanced vegetation index (EVI2) | $\frac{2.5(\rho_{NIR}-\rho_{RED})}{(1+\rho_{NIR}+2.4\rho_{RED})}$ | Jiang et al. [90] | Liu et al. [44] |
| Leaf area index (LAI) | – | – | Liu et al. [44], Gilbert et al. [83], Capellades et al. [45] |
| Land surface water index (LSWI) | $\frac{\rho_{NIR}-\rho_{SWIR}}{\rho_{NIR}+\rho_{SWIR}}$ | Chandrasekar et al. [91] | Kotera et al. [88], Son et al. [89] |
| Soil-adjusted vegetation index (SAVI) | $\frac{(1+L)(\rho_{NIR}-\rho_{RED})}{(\rho_{NIR}+\rho_{RED}+L)}$ | Huete [92] | Capellades et al. [45] |
| Optimized soil-adjusted vegetation index (OSAVI) | $\frac{(1+L)(\rho_{NIR}-\rho_{RED})}{(\rho_{NIR}-\rho_{RED}+L)}$ | Rondeaux et al. [93] | Liu et al. [44] |
| Ratio vegetation index (RVI) | $\frac{\rho_{NIR}}{\rho_{RED}}$ | Tucker [94] | Liu et al. [44] |
| Modified triangular vegetation index (MTVI2) | $\frac{1.5[1.2(\rho_{NIR}-\rho_{RED})-2.5(\rho_{RED}-\rho_{GREEN})]}{\sqrt{(2\rho_{NIR}+1)^2-(6\rho_{NIR}-6\sqrt{\rho_{RED}})-0.5}}$ | Haboudane et al. [95] | Liu et al. [44], Capelladeset al. [45] |
| Green normalized difference vegetation index (GNDVI) | $\frac{\rho_{NIR}-\rho_{GREEN}}{\rho_{NIR}+\rho_{GREEN}}$ | Buschmann and Nagel [96] | Liu et al. [44] |
| Vegetation condition index (VCI) | $\frac{NDVI_{(x,y)}-NDVI_{min}}{NDVI_{max}+NDVI_{min}}\times 250$ | Kogan [97] | Yu et al. [21], Zhang et al. [52], Di et al. [17] |
| The ratio of current NDVI to the previous year (RVCI) | $\frac{NDVI_{(x,y)}-NDVI_{p(x,y)}}{NDVI_{p(x,y)}}\times 100$ | Zhang et al. [52] | Yu et al. [21], Zhang et al. [52], Di et al. [17] |
| Mean/median vegetation condition index (MVCI/mVCI) | $\frac{NDVI_{(x,y)}-NDVI_{m(x,y)}}{NDVI_{m(x,y)}}\times 100$ | Yang et al. [98] | Yu et al. [21], Zhang et al. [52], Di et al. [17] |
| The difference between EVI and LSWI (DVEL) | $DVEL = (EVI - LSWI)$ | Xiao et al. [99] | Kotera et al. [88], Son et al. [89] |
| Disaster vegetation damage index (DVDI) | $DVDI = mVCI_a - mVCI_b$ | Di et al. [100] | Di et al. [101] |

[2)] $\rho_{GREEN}$, $\rho_{RED}$, $\rho_{NIR}$, and $\rho_{SWIR}$ denote remote sensing visible green, visible red, near-infrared, and short-wave infrared bands. L is an adjusting parameter; *p* (*x*,*y*) indicates the previous year and *m* (*x*,*y*) indicates mean or median value; *a* and *b* indicate after and before the disaster event, respectively. $mVCI_a$ and $mVCI_b$ are the vegetation conditions immediately after and before a disaster, respectively.

Although these vegetation condition indices were originally developed for the monitoring of crop response to drought, many recent studies utilized them in the context of other disasters like floods. Yu et al. [21] and Zhang [52] utilized various VIs to assess flood crop loss in the US. Yu et al. [21] concluded that all VIs are able to detect flood impacts on crops. However, VCI shows a higher damage estimation than ratio to median vegetation condition index (RMVCI) or MVCI. Flood impact in the middle to late growing season can be better explained by VIs compared to the early season. The difference between EVI and land surface water index (LSWI) (DVEL) was used for flood-affected rice field detection [88,89]. A decision tree based on EVI, LSWI, and DVEL is used to determine rice damage categories: no loss, partial loss, and complete loss [88]. Disaster vegetation damage index (DVDI) was developed by Di et al. [100] based on the difference between median VCI (mVCI) before and after a disaster event. The positive DVDI indicates no damage, whereas negative values indicate the degree of damage. mVCI is calculated using historical median NDVI instead of utilizing mean NDVI because the mean value can be affected by outliers. Di et al. [101] successfully utilized DVDI to assess the degree of crop damage of the 2011 Missouri River flood event. The ranges of negative DVDI may need to be adjusted to express it on a subjective scale for different geographic context as well as for different crop types. The length of window for mVCI selection before and after flood events need be carefully chosen because DVDI is sensitive to the selection of windows. The choice of window also depends on the objective of the assessment, whether the target is to capture instant effect of events or to capture the condition of recovered crop.

Another interesting approach is the utilization of machine learning techniques (e.g., supervised, unsupervised) on remote sensing time-series images for crop damage assessment. The idea here is to capture the change in crop condition profiles because of flooding. Machine learning or data mining algorithms can detect such change from the time series (e.g., image or NDVI) of pre- and post-event multidate data. The degree of damage is directly related to the degree of deviation from normal crop condition profiles. Figure 4 shows a conceptual diagram of the degree of crop damage based on time-series image bands or NDVI. An unsupervised clustering approach can be used to assess the degree of damage based on the multidate image stack. Chowdhury and Hassan [102] utilized RADARSAT time-series data to assess the degree of damage in rice fields using ISODATA clustering. A similar concept was used by Pantaleoni [86] for the damage assessment of corn and soybean in Indiana using Landsat time series. Ahmed et al. [15] utilized ISODATA clustering approach on MODIS NDVI time series instead of remotely sensed image bands for crop damage assessment in Bangladesh. They utilized NDVI time series with the basic assumption that crop NDVI may decline in flood-affected pixels. Although these studies used clustering approaches, the basic assumption is similar to the loss assessment based on the change in VIs. Lee and Lee [57] used the maximum likelihood supervised classification technique for the rice damage assessment using pre- and post-flood RADARSAT data. It is observed that SAR backscatter value is usually decreased from the flood-affected crop field. They collected ground truth on damage categories (e.g., damaged, recovered, and no damage) through field surveying to train the supervised classification model. Supervised learning algorithms require training data to train classification models. Training sample collection on crop damage is not only time- and cost-inefficient but also prone to subjective labeling. Thus, the unsupervised approach may be advantageous for rapid assessment. Case studies which utilized machine learning approaches reported the degree of damage on a subjective scale. Quantitative loss can be estimated by incorporating historical yield loss information associated with the degree of damage. Machine-learning-based assessments are advantageous because these approaches can support rapid damage assessment without relying on historical data.

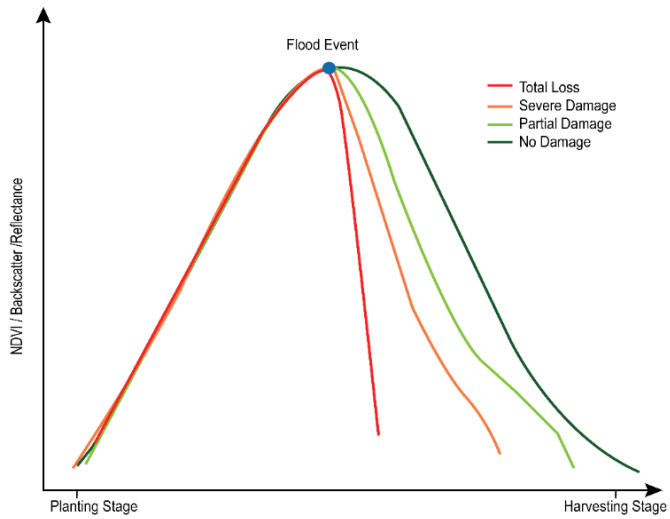


**Figure 4.** Conceptual diagram for flood crop loss assessment using crop condition profile adapted from Pantaleoni et al. [86], Ahmed et al. [15], Chowdhury and Hasan [102], and Shrestha et al. [16].

### 3.2.3. Combined Utilization of Flood Information and Crop Condition Profile

The combined approach takes both flood information and crop condition into account for crop damage assessment. Many studies integrated flood extent with crop condition profile for loss assessment [2,32,54]. Although some of the case studies utilized flood intensity for damage assessment, crops were identified through remote sensing image processing to support crop-specific loss assessment [41,66,103]. These types of case studies primarily fall into the first category: flood-intensity-based damage assessment. The only difference here is the incorporation of crop types rather than having a generalized estimation for all crops. Since crop condition is not considered in the damage estimation process, these case studies do not purely fall into the combined approach category. For instance, Dao and Liou [33] calculated flood-affected rice areas using flood extents derived from the rule-based classification of remote sensing images and rice areas extracted from MODIS VIs. Hossain [32] utilized a combined approach by incorporating inundation extents derived from MODIS and Advanced Very High Resolution Radiometer (AVHRR) images and crop damage profile through the supervised classification of multitemporal SAR data (RADARSAT 1). The supervised classification model was trained by the damage signature collected from field surveys. Chen et al. [2] utilized flood intensity information derived from the 2D hydraulic model to assess crop damage by flood disturbance detection. They calculated flood disturbance by taking the ratio of peak EVI to normal year mean peak EVI calculated from historical time-series data. Many VI-based case studies relied on historical VIs for the comparison. However, these case studies often ignored crop production factors including weather, climatic condition, and technological advancement, which may have significant impact on historical VIs. Thus, changes in these production factors need to be taken care of while using long-term historical data in damage assessment.

Chen et al. [35] developed a power function between flow velocity and crop yield loss for three different crops in mountain areas in China. They concluded that flow velocity is the most influential factor compared to depth and duration for crop yield loss during an extreme flood event in mountain areas. Yield loss was derived by a linear regression model using NDVI and EVI as the independent variables. They also concluded that EVI is more effective for crop growth monitoring compared to NDVI because of the saturation tendency of NDVI in dense canopy conditions. Thus, they utilized only EVI in their later study in 2019. Chen et al. [2] utilized a linear model to identify the long-term trend in EVI to improve the damage assessment model. Finally, yield loss was estimated through the linear regression between peak EVI and crop yield. Boschetti et al. [54] detected flood-affected cropland using a multitemporal rule-based algorithm, then MODIS-based EVI was utilized to monitor crop phenology

status before and after flood events. This approach is similar to the SGT approach by Okamoto et al. [80] to monitor the growth track of the major phenological stages of crops. These approaches can provide a simple indication of crop damage but are unable to provide damage estimation. Halder et al. [37] utilized a supervised classification approach to map flood-affected rice areas. They used the ISODATA clustering approach on MODIS NDVI time series to assess the degree of damage. Although Ahmed et al. [15] later followed a similar approach for crop damage assessment in Bangladesh as Halder et al. [37] applied in India, flood extents were not incorporated in their study. The water turbidity index is also used for flood crop loss assessment, especially for rice fields. Gu et al. [36] used perpendicular vegetation index, a function perpendicular to turbidity index plotting, in a two-dimensional space of NIR and red bands of HJ-CCD images. Then, a regression model was used between turbidity and yield for crop damage assessment [36,42]. Both Yamagata and Akiyama [42] as well as Gu et al. [36] found that there is a significant correlation between water turbidity and rice yield loss. Although water turbidity index can easily be calculated from remote sensing bands, only two studies utilized this approach for rice damage assessment.

The recent development of combined unitization of flood information and crop condition for crop damage assessment is aided by available remote sensing data as well as by advanced processing techniques. Combined damage assessment is advantageous for precise damage assessment because of the consideration of both flood information and crop condition profiles. Crops may not be damaged from an inundated condition for a short period of time. Thus, damage assessment relying on only flood intensity may have overestimation because the degree of crop damage is unknown. Similarly, crops may be damaged because of factors other than the flood. Therefore, flood intensities, crop condition profiles, and crop type information are crucial for precise damage assessment.

#### 3.2.4. Model-Based Crop Loss Assessment

Numerous models for flood loss assessment are available, including Hazards US (HAZUS), Impact Analysis for Planning (IMPLAN), ECON2, Hydrologic Engineering Center (HEC)-2, Methods for Evaluation Direct and Indirect Losses (MEDIS), Flood Loss Estimation Model (FLEMO), and loss assessment model of Joint Research Center (JRC) [104,105]. Many input parameters for these models can be derived from remote sensing data. For instance, the HAZUS model requires a digital elevation model (DEM) to generate flood extent and depth. Flood extents are also, in many cases, extracted from satellite images [104].

HAZUS is one of the most popular flood crop damage assessment models [106]. Although the HAZUS model is primarily developed for the US, many studies around the world used the HAZUS model for crop loss assessment using local input parameters. Similar to HAZUS, the MEDIS model has widely been used in European countries, especially in Germany [107]. MEDIS model considers four influencing factors—seasonality of the flood event, crop type, region, and inundation duration—to calculate crop loss as a percental deduction of the perennial average yield in monetary value [107]. Both HAZUS and MEDIS models are equipped with an extensive national database (USA and Germany, respectively) embedded in the software. Forete et al. [29] utilized Landsat images, airborne images, and digital terrain model (DTM) for land cover mapping, flood extent delineation, and flood depth calculation, respectively. These land cover maps and flood information were used as inputs for HAZUS model for crop loss assessment in Italy. Similarly, Tapia-Silva et al. [41] and Förster et al. [65] utilized the MEDIS model to estimate flood crop loss of the Elbe River flood in 2002. These models apply the concept of the risk function to hazards, vulnerability, and elements at risk. Flood intensities (extent, depth, and duration) serve as hazard parameters. Crop-specific vulnerability is expressed as the depth–duration–damage curve. Then, loss is usually assessed in monetary terms using damage factor and price of crops. None of these models consider vegetation-index-based crop condition profiles, which is the main drawback of the model-driven loss assessment.

Crow [104] assessed HAZUS crop loss modeling methodology through a case study for flooding in 2011 in Iowa. He concluded that the HAZUS model continuously overestimated the loss compared

to the estimation by the National Agricultural Statistics Service (NASS) of the US Department of Agriculture (USDA) and the Iowa Farm Bureau Federation (IFBF). The possible reason could be non-consideration of crop condition profiles and crop type information in model-based assessment. An agricultural plot being inundated does not necessarily mean significant loss of crop, unless crop conditions are examined. In addition, the assessment is too generic without consideration of crop types; for instance, soybean may take higher damage compared to corn from a short-lived flood event. Crow [104] also mentioned that the most critical factor in HAZUS model is the delineation of inundated areas, which are often overestimates of the actual flooded areas. The utilization of flood inundation extents derived from remote sensing observation may improve the accuracy of damage estimation using HAZUS model. Förster et al. [65] reported a realistic estimation of crop loss because of the utilization of multiple factors, including flood paraments, crop types, and seasonality, in contrast to the overestimation in the case study of Crow [104] in Iowa. Thus, incorporating crop-type information with flood intensity can provide better results.

These models can be used for all types of crop loss assessment from rapid to in-depth assessment. However, rapid assessment may be difficult for these areas for which no ancillary data are embedded in models. These models are built for a specific geographic region and may not be appropriate for other regions unless significant changes are made to make them suitable for study areas. For instance, depth–duration–damage curves will vary from place to place since crop types and flood tolerance are not the same in different regions. Moreover, these models often rely on many ancillary data which may not be available in other contexts than the contexts that the models are built upon.

### *3.3. Flood Crop Damage Reporting Indicators*

A wide range of damage reporting indicators were utilized by case studies. Damage assessments can primarily be categorized into qualitative assessment and quantitative assessment. Combined and crop-condition-based approaches often produced a damage assessment on a subjective scale. A subjective scale representing the degree of damage is often utilized in qualitative crop loss assessment. The number of classes and representations may vary in subjective loss assessment. A very abstract assessment is the mapping of affected and nonaffected croplands [30]. A simple three-class damage type can consist of damaged, partial damage (recovered), and no damage [32,57,88]. Many case studies also divided crop damage into four to six damage classes using a subjective scale such as no loss, slight damage, moderate damage, severe damage, and total loss [45,80,84,102]. The rapid processing is the main advantage of the qualitative loss assessment models. Index-based loss assessment approaches such as DVDI and DVEL are only limited to subjective assessment because these assessment models do not incorporate any yield information. Similarly, loss assessment through the supervised and unsupervised classification of remote sensing time-series data can only be reported on a subjective scale. Although qualitative assessments do not contain any information on the exact amount of crop loss either in yield estimation or in monetary terms, the degree of damage can be linked to percentage loss.

Crop loss can be expressed in many quantitative scales, including amount of yield loss, yield loss in percentage, and loss in monetary value. The simplest damage reporting of quantitative assessment is the inundated cropland acreages, which is also very frequent in flood-intensity-based case studies [33,51,62,72,89]. Crop-specific inundated acreage can also be reported by combining crop types with inundation maps [40,50,70,74]. Shan et al. [50] reported damage as the percentage of inundated cropland with respect to total cropland at the county level, which is similar to the reporting as inundated cropland acreages. This simple approach does not inform the degree of damage or probable yield loss. Many studies assumed flooded cropland would result in damages; however, crops can survive after flood events. For instance, van der Sande et al. [49] and Vozinaki et al. [70] used the yield value of per square kilometer inundated cropland to report flood loss in monetary terms, which is highly prone to overestimation. Crop loss reporting in percentage loss and in loss ratio were also frequently used in many studies [35,44,46,64]. Percentage loss can also be converted to categorical loss classes using different percentage ranges [64]. Chen et al. [2] compared flood disturbance and

associated yield with the normal year to provide percentage loss. They considered ±10% change in yield as no damage, which is a very rational consideration in order to accommodate uncertainty in change detection. The difference between predicted yield and historical yield can also be reported directly as crop loss [31]. In both cases, percentage loss and actual loss can be converted to monetary value by incorporating yield price [13,61,71,103].

Most of the regression-based loss assessments reported the percentage loss by incorporating historical yield and crop condition (VIs). Li et al. [31] and Shrestha et al. [16] used the regression equation to estimate crop yield using VIs to report yield loss in percentage by comparing with historical yield. Model-based and flood-intensity-based loss assessment approaches (e.g., HAZUS and MEDIS) reported crop loss in gross monetary value. These models often utilized a very rough valuation of crop price and yield rate, which may lead to inaccurate loss estimation. Loss assessments in yield and in monetary terms provide more detailed insight compared to simple reporting of inundated acreage. However, historic yield data and grain price are needed to be readily available, and these may not be available in many countries. Moreover, crop-specific price and yield data are very scarce at a local level. Although there are many ways to report flood crop loss, the choice of damage reporting completely depends on the purpose of the study and the audience.

### *3.4. Approaches for the Validation of Loss Assessment*

One of the most challenging parts of flood crop loss assessment is the validation of assessment results. Although validation may not be possible during a flood event in most of the cases, loss assessment models developed for the future assessment should be validated. Since a wide range of approaches were used for crop loss assessment, there are many validation techniques that evolved over time. Some case studies validated their inundated cropland acreages with affected crop acreage reported in census data [2,33,102]. Chen et al. [2] and Kotera [88] compared their flood-affected areas with gross affected areas at the province level. Son et al. [89] as well as Chowdhury and Hasan [102] validated their flood-affected rice area using ground reference collected from field surveys. Although field-survey-based validation is difficult, this approach is the most reliable for validation. Flooded inundation extents derived from optical remote sensing are often validated by flood maps derived from microwave remote sensing [32,49,62,88]. This kind of validation can be called the spatial agreement between two estimations instead of accuracy assessment. The error from both estimations can propagate to the loss assessment results. Dutta et al. [61] validated flood extents with the model-driven flood of the 100-year return period. Some studies validated their estimated flood depth and crop loss function using point data from field surveys [30,78]. Since crop-specific flood loss estimation relies on crop cover mapping from remote sensing images, the accuracy of crop mapping is crucial for the precise crop-specific loss assessment. Del Carmen Silva-Aguila et al. [47] and Boschetti et al. [54] validated their crop maps using ground truth collected through GPS survey. The value of the coefficient of determination ($R^2$) was used to validate regression-based damage assessment results [33,35,89]. Capellades et al. [45] validated their crop mapping using US CDL data as a reference. Although accuracy assessment through another derived product (e.g., CDL) or aggregated census data cannot be considered as strong validation, it is some sort of agreement assessment between two datasets.

Like the validation of crop mapping and flood mapping, crop loss estimation in yield and in monetary terms were also validated through census data as well as ground truth. Some case studies utilized flood-affected crop acreage and associated crop loss at different administrative levels for validation [15,66,103]. Tapia-Silva et al. [41] validated both crop loss acreages and loss in monetary values with official loss. They reported a huge difference (> 300%) between the two estimations. Similarly, Kwak et al. [64] found their crop loss estimation to be 80% consistent with the assessment of the Ministry of Agriculture of Cambodia. Vozinaki et al. [70] ran their model multiple times to measure the consistency of their loss assessment model. Li et al. [31] calibrated their soil–water balance model for crop yield forecast using the past year yield estimation. Then, the model was used to

estimate the yield loss in a flooded year. Likewise, Liu et al. [44] and Shrestha et al. [16] validated their VI-based yield forecast regression model with actual yield using $R^2$ and root-mean-square error (RMSE). These regression-based models reported high accuracy of crop loss assessment. These qualitative loss assessments reported above 90% overall accuracy through cross-validation. The qualitative crop damage assessment can also be validated with the damage assessment report from field investigation [37,57]. The ground truths for the qualitative loss assessment must be in qualitative format with the same number of classes. The success of the accuracy assessment of qualitative assessment depends on the subjective consideration of damage classes and field investigation. Moreover, expert knowledge is required for the validation of qualitative loss assessment results. About one-half of the selected case studies did not validate their crop loss assessment, perhaps because of the unavailability of validation data. Model validation is always challenging because of the scarcity of real damage and loss observations and lack of cost information [70]. Most of the studies validated aggregated crop loss from multiple administrative levels because data from affected fields are very scarce. Field-survey-based validation was not viable in most of the cases because of the high cost of data acquisition. Moreover, survey-based ground truth collection is a lengthy process which may not be able to support quick assessment.

### *3.5. Web Service Systems for Flood Crop Loss Assessment*

Cyberinfrastructure can be developed for flood crop loss assessment using remote sensing data. Users of the web service can interact with it to estimate crop loss. Moreover, users can download crop condition profiles as well as flood inundation information to estimate crop loss using their own models. Di et al. [17] developed an earth observation (EO)-based flood crop loss assessment web service system called Remote-Sensing-Based Flood Crop Loss Assessment (RF-CLASS) for the entire US cropland. This system was developed to support flood-related crop statistics and insurance decision-making. RF-CLASS system offers various flood intensity information, including flood extent, frequency, and duration, derived from remote sensing earth observation data. Similarly, various VIs and crop condition profiles such as VCI, MVCI, and DVDI are also available from the system. Crop loss assessment models and tools are also deployed for the user to estimate flood crop loss assessment. Shan et al. [50] described a state-level system called Indiana Flood Map and Damage Estimate Online with Google Earth. This system offers a web service to evaluate the flood extents and estimated crop damages along with other geospatial layers provided by Google Earth. New cyber systems will be developed for flood crop loss estimation in the near future with the support of advanced web technologies and available remote sensing earth observation data.

### *3.6. Spatiotemporal Distribution of Case Study Research*

The selected case studies covered 21 countries from three continents: North America, Europe, and Asia. Figure 5 shows the spatial distribution of the selected case studies. Almost two-thirds (64%) of the studies were from Asia (40 studies). An equal number of studies (11 each) were from Europe and North America. Case studies from Asia are mostly located in the South and Southeast Asian countries. Although countries in the Amazon Basin are flood-prone, no study on remote-sensing-based flood crop loss assessment is found from this region. One possible reason could be that most of the publications from the Amazon region are in other languages than English. Similarly, many countries in East Africa and parts of Australia are highly vulnerable to floods, but no case studies were identified from these areas.

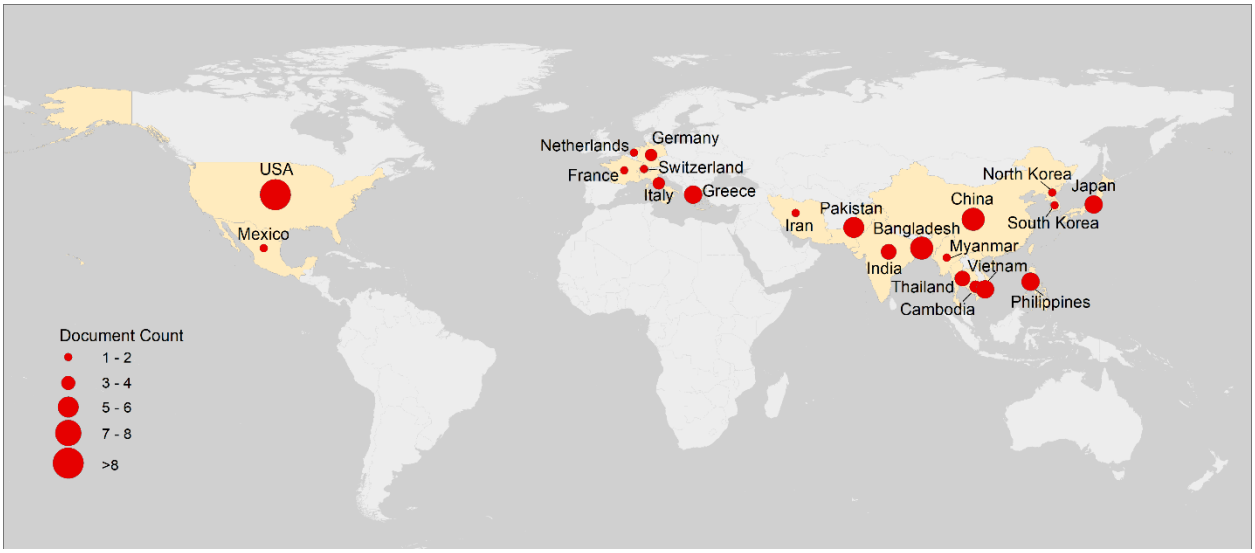


**Figure 5.** Spatial distribution of case studies.

The majority of studies were from the United States of America (USA) (17.19%), followed by Bangladesh (9.38%), China (9.38%), Pakistan (7.81%), Greece (6.25%), Philippines (6.25%), and Japan (6.25%). Studies from Asia were mostly dominated by rice [15,33,54,88,89]. Most of the studies in Europe were focused on loss assessment of multiple crop types [12,41,46,49]. Similar to Europe, case studies from the USA were also focused on multiple crops, especially corn and soybean [21,50,51,86]. The majority of the case studies were conducted at regional scales such as the areas of a river basin, large watershed, state/province level, and district levels. Only a few studies were focused on local scales, such as on the county scale or even on the scale of a chunk of few croplands. Local-scaled studies often utilized fine spatial resolution images to get a detailed assessment at a parcel level. Case studies are also conducted at the national level in some countries like Bangladesh, Pakistan, and Cambodia [32,63,64].

Selected case studies were categorized based on information utilization in flood crop loss assessment. Many studies relied only either on flood intensity information [49,64,74] or crop condition profiles [16,46,102]. Some studies also utilized both flood intensity and crop condition profiles for damage assessment [17,31,54]. The selected case studies were published between 1987 and 2019. Figure 6 shows the temporal pattern of selected case studies based on three different approaches. Only six (10%) studies were published before 2000, which indicates that the utilization of remote sensing data in flood crop loss assessment became popular mostly after 2000. The number of studies in this domain was significantly increased after 2010 (Figure 6).

A total of 24 studies were found between 2011 and 2015, which was more than double that of the previous five-year period (2006–2010). Two-thirds of the total selected studies were from the last nine years. A large number of case studies also utilized crop condition profiles in loss assessment. A hybrid approach of flood loss assessment combining crop conditions and flood information was seen to become popular after 2010. The availability of freely accessible data, advanced processing techniques, and computer systems played a vital role in the acceleration of remote sensing data utilization in flood crop loss assessment [22].

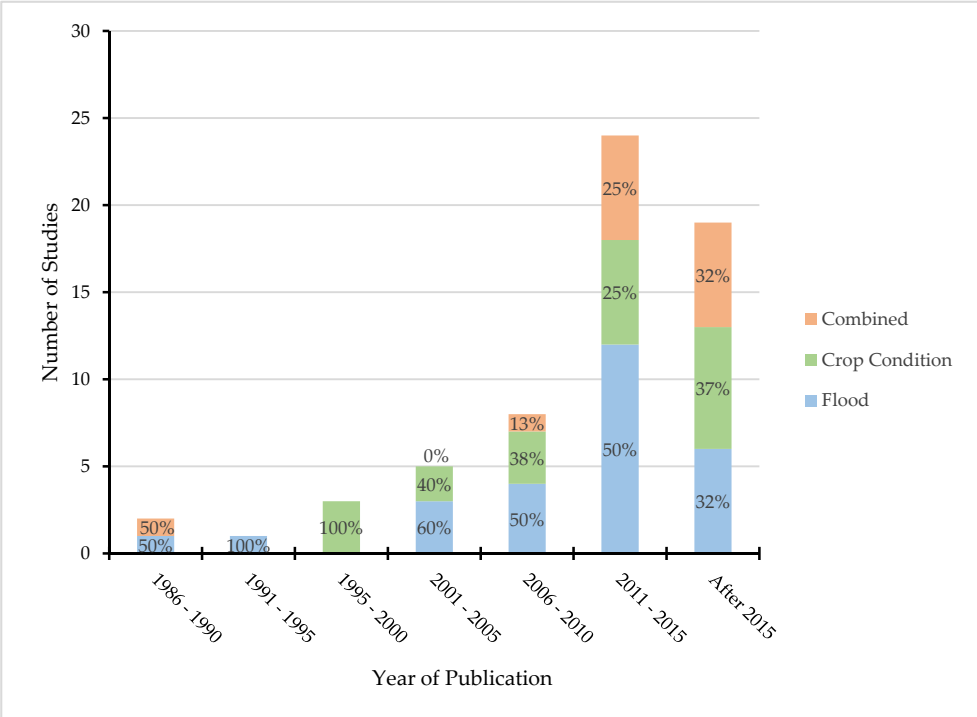


**Figure 6.** Temporal distribution of case studies categorized by flood crop loss assessment approach.

### 3.7. *Summary of Literature Sources, Keywords, and Citations*

Out of 62 selected case studies, 45 articles were published in peer-review journals, 13 studies were published as conference proceedings, and only four were book chapters. These peer-reviewed journal articles were published in 26 reputed journals in remote sensing, agriculture, natural hazard, and hydrology domains. The highest number of publications, about one-fifth of journal articles, were published in *Natural Hazards*. A significant number of articles were also published in *the International Journal of Remote Sensing*, *Remote Sensing*, *Journal of Hydrology*, and *Journal of Integrative Agriculture*.

Figure 7 illustrates the co-occurrence of keywords in documents and a citation network map. The relative size of the circles is determined by the frequency, and the links show the strength between two instances. Different colors indicate clustering among items. The high-frequency keywords were "remote sensing", "damage", "agriculture", "MODIS", "flooding", "flood", "risk", "growth", "management", "GIS", "vegetation indices", "yield", and "model" (Figure 7a). Two keywords, "MODIS" and "remote sensing", appeared in ten documents. "Agriculture" and "damage" appeared in nine documents, followed by "risk". The link between two keywords indicates the occurrence of two words. The highest number of links (64) was associated with "MODIS", followed by "agriculture" (63), "damage" (61), and "remote sensing" (56). Figure 7a shows five prominent clusters represented by five colors: red, green, blue, yellow, and purple. Keywords in same cluster are strongly associated with each other. For instance, keywords in the green cluster are mostly associated with remote sensing data, products, crop condition, and land cover types. Similarly, the red cluster represents keywords which are mostly related to damage estimation, crop production, flood characteristics, yield estimation, and crop management. Another large cluster represented by blue color is mostly associated with agriculture, crop types, crop tolerance, and crop phenology. Keywords in the purple cluster represent mostly physical crop properties including biomass, LAI, growth, soil, and yield. The most cited paper, by Dutta et al. [61], used stage damage function for the damage assessment of inundated crops. Similar to the keywords network map, publications in same cluster (represented in colors) cited each other. Most of the highly cited articles [61,65,72,75,76] used flood information only for crop loss assessment. Case studies [84,86] on crop-condition-based loss assessment were also highly cited. Although case studies based on combined approaches are yet to be highly cited compared to the other

two approaches, some studies such as the work of Tapia-Silva et al. [41] show recent progress of the combined approach. Damage assessments were mostly limited to the utilization of flood intensity because of the limited availability of remote sensing data and techniques for the assessment of crop condition profiles. It is expected that crop-specific damage assessment using crop condition profiles will gain popularity in the future. The network relationship of some recent studies [2,15,41,86] indicates the recent advancement of the utilization of crop condition profile in crop damage assessment.

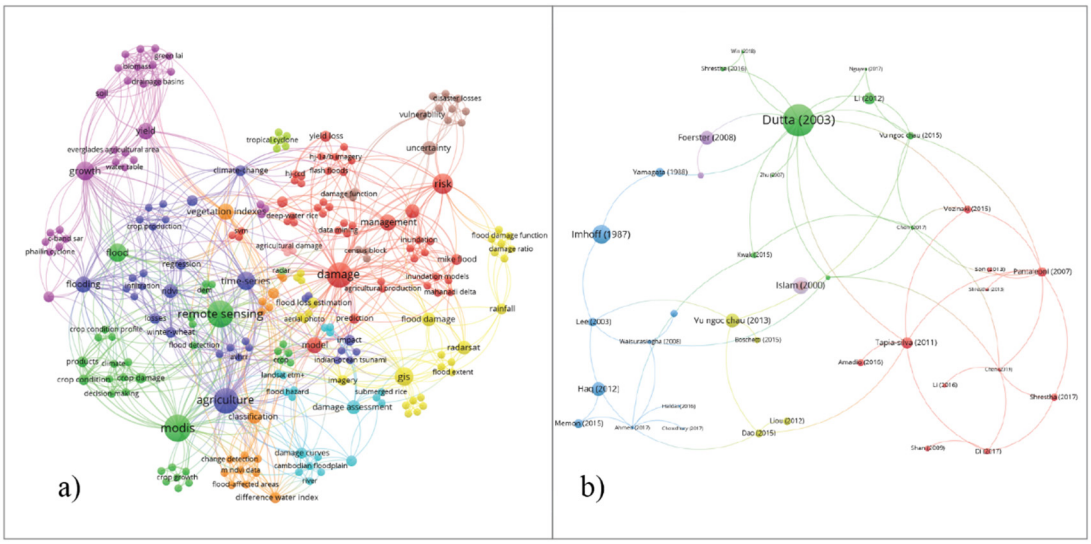


**Figure 7.** Co-occurrence of key words and citation network map of the selected case studies. (**a**) A cloud of keywords from the selected literature. (**b**) A Citation map of the selected literature based on the citation relationship derived from the Web of Science. The size of nodes indicates the count of citations.

## 4. Discussion

The utilization of remote sensing data in flood crop loss assessment has increased rapidly in the last two decades. Although crop loss assessment is aided by remote sensing data and derived products, many challenges were seen and addressed by empirical case studies. The most challenging part of the crop loss assessment is the scarcity of suitable data. Remote sensing earth observation is one of the vital sources for required data in flood crop loss assessment. Loss assessment models based on flood intensities utilized flood parameters derived from hydraulic models. The accuracy of flood intensity modeling largely depends on the accuracy of the DEM. A fine spatial resolution DEM is always desirable for precise flood modeling. However, fine spatial resolution DEMs are unavailable for most of the flood-prone areas. Although none of the studies utilized digital surface model (DSM) for flood modeling, the utilization of DSM can improve the result of flood modeling. The reason for the absence of DSM in flood modeling may be the unavailability for vast areas. Determination of flood depth through spot survey requires many points for accurate mapping, which is very time-consuming, labor-intensive, and costly. Many case studies relied on stage–damage functions for crop loss assessment. Although flood parameters can be derived from flood modeling, the high data requirement often hinders the application of these models [62,65]. Stage–damage functions are usually developed based on the empirical assessment of past floods and associated costs. It is also difficult to develop crop-specific stage damage functions for the different seasons because of the scarcity of data on past events [11,66]. Synthetic stage–damage curves can also be developed using expert knowledge in case of unavailability of historical data [11,108].

Cloud contamination in optical images is one of the most reported drawbacks in flood mapping and crop condition monitoring [21,57]. Flood mapping is very challenging, especially in tropical areas where cloud concentration is high during the rainy season. The utilization of fine-resolution optical images for crop classification and land cover maps can improve the performance of crop loss

assessment models. However, fine-resolution images are not available free of charge for most of the cases. The utilization of fine-resolution images for vast agricultural areas is not time- and cost-effective. Since the footprints of fine spatial resolution images are usually small, many images are required for the spatiotemporal monitoring of agricultural areas.

Remote-sensing-based flood mapping is very challenging under vegetation canopy cover. Thus, flood mapping in croplands may not be accurate when using remote sensing data since crop canopies hide the presence of water from optical sensors. Although microwave remote sensing can penetrate vegetation cover, double bounce effect can significantly reduce the accuracy of flood mapping [22,109]. The usual assumption is that SAR antenna receives low backscatter from inundated areas. However, crop fields which are not fully submerged by floodwater return strong backscatter to the SAR system because of the double bounce effect [109–111]. Long et al. [110] considered both increase and decrease in backscatters from the change between pre- and post-event SAR images to overcome the double bounce effect. They developed a histogram thresholding approach to map flooded pixels from the change in backscatter. Many studies improved flood mapping under canopies using data fusion of SAR, optical, LiDAR, and ancillary data [112,113]. The utilization of longer wavelength (L-band) SAR data is another option to overcome the double bounce problem for flood mapping in vegetated areas. Thus, the future free-of-charge availability of L-band SAR data will surely improve flood mapping in croplands [114,115].

Many case studies reported only inundated cropland without considering crop types and seasonality. Since different crop types have a different degree of exposure to flooding, inundated cropland information alone cannot provide precise damage information. Similarly, the degree of crop damage largely depends on the seasonality of crops, which was also ignored in most of the case studies. The consideration of different seasons and planting dates for different crops in different regions is crucial for the precise loss assessment [21].

Many studies utilized land cover maps and crop type maps derived from remote sensing data. The uncertainty of crop types identification has a direct impact on the accuracy of loss assessment [41]. The determination of threshold for VIs, SAR backscatter, and SAR sigma naught is very challenging for crop identification and flood delineation. These threshold values need to be carefully selected using expert knowledge [64]. Moreover, these thresholds may vary across many factors such as geographic location, crop types, and seasonality. Crop field boundaries derived from remote sensing data and products can also be helpful for field-level crop mapping and damage assessment [116]. Often yield data are available at field level instead of pixel level. Thus, regression-based damage assessment can benefit from crop field boundary information.

Long-term time series of yield data that are required to train regression models and machine learning models for loss assessment may not be available for many cases [31,51]. Although the regression model can be developed using yield reports collected through farmer surveys and associated VIs, field data collection is always time- and cost-intensive. Shrestha et al. [16] assessed the impact of flooding on crops using the areas under NDVI curves of the whole growing season. Thus, this model is not useful for in-season quick loss assessment until the growing season ends. Chen et al. [2] reported that EVI saturation is a problem for EVI-based damage assessment. They also reported that EVI can effectively detect the flood disturbance before crop greenness reaches the pick value and is less effective for the flood events after the crop's mature stage.

Some qualitative assessment models are also based upon the damage-level information collected by field survey. Signatures of these damage locations can be used for the training of supervised classification and regression-based damage assessment models. There are challenges associated with field-level damage data collection. Firstly, these survey activities are time-consuming, labor-intensive, and costly. Secondly, identification of this sampled field is often difficult for crop reporters or surveyors. Finally, damage type may be misinformed, since most of the surveyors may not have expert knowledge of damage categories. Thus, there are various challenges for remote-sensing-based crop loss assessment which needs to be addressed for the precise and timely flood crop damage assessment.

Apart from the challenges, there are many opportunities which are brought by remote sensing data and technology. LiDAR-derived DEMs are available for many watersheds in developed countries and can be utilized for precise flood modeling. The launching of many new satellite remote sensing systems in the last decade opens new opportunities for suitable remote sensing data. For instance, Sentinel-1 and Sentinel-2 satellite remote sensing missions by the European Space Agency (ESA) provide data in both optical and microwave domains free of charge. The optical data of Sentinel-2 provide finer temporal (~5 days) and spatial resolution (10 m) compared to Landsat. Thus, the accuracy of crop identification and land cover mapping will be increased using Sentinel 2 data compared to other coarse-resolution remote sensing options like MODIS. The weekly crop condition profile can be extracted from Sentinel-2 data, which can be helpful for frequent crop condition monitoring along with MODIS-derived products.

The inability of optical remote sensing data to penetrate through clouds hinders its application in flood mapping and crop condition mapping. Therefore, the demand for microwave remote sensing data has been very high for flood mapping. The unavailability of SAR data free of charge has limited its widespread use in the past. However, Sentinel-1 has provided SAR C-band data with multiple polarization free of charge since 2014, which is a remarkable milestone for the remote sensing community. Flood and water studies will benefit from the Sentinel-1 data [117]. Similarly, crop loss assessment models based on the soil–water balance can benefit from the recent launch of NASA's Soil Moisture Active Passive (SMAP) mission. Rapid flood progress monitoring in cropland using soil saturation can be mapped using SMAP data [58,118].

Many remote-sensing-derived products such as NDVI, MVCI, and EVI are readily available because of the development of computer systems, data cataloging, and dissemination systems. The advanced web application makes dissemination of these data easy, available, and convenient [119,120]. The historical data on crop condition (e.g., VIs) are also available from these large archive systems, which can be utilized to develop crop loss assessment models. Moreover, the time series of crop maps like CDL in the US can support the crop-specific loss assessment. The archives for crop yield data in many countries can also be useful to train the yield and loss assessment models. Like data sources, many methods and techniques have also been developed for flood modeling and crop loss modeling.

## 5. Conclusions

A wide range of approaches have been utilized for flood crop damage assessment. This study broadly categorizes these approaches into three groups: flood-intensity-based approach, crop-condition-based approach, and a hybrid approach of these two called the combined approach. Flood extent was the most widely used parameter in intensity-based loss assessment, followed by depth, duration, and flow velocity. A large number of studies only utilized flood extent as a proxy, reporting crop damage as inundated acreages, which is a very rough estimation. Thus, this kind of simple approach cannot provide the magnitude of crop damage. Stage–damage curves of flood intensity versus crop loss were also used in many case studies. The recent development and wide choice of remote sensing data enable the opportunities for crop-specific damage assessment using crop condition profiles. Many recent studies relied on crop condition profiles derived from remote sensing data and VI (e.g., NDVI, EVI, and LAI) products for crop damage estimation. Many studies utilized regression models for loss assessment, which required a historical database to establish a regression equation. Some recent studies also utilized machine learning and data mining approaches on remote sensing time-series for damage assessment, which is advantageous because these models did not rely on historical data of past years. Flood crop damage is more precise when both flood information and crop condition are incorporated in damage assessment models. The consideration of crop phenological stages is also very important for precise damage assessment. Thus, future studies may focus on machine-learning-based approaches for crop damage assessment using multiple variables, including flood intensities, crop conditions, and phenological stages. For instance, machine learning models can

be trained by the damage levels associated with different flood durations and phenological stages of past flood events for damage prediction.

A wide range of damage types is reported in both quantitative and qualitative scale. The quantitative damage assessment types are the estimation of inundated acreages, yield loss, percentage loss, and loss in monetary terms. The qualitative damage assessment is usually expressed in the degree of damage, i.e., low, moderate, or high damage. Loss assessment in monetary terms often depends on very generalized assumptions of crop yield price, which may lead to inaccurate estimation because of the inconsistency of price. Moreover, the results of damage assessments depend on many assumptions, which makes the loss assessment model highly sensitive to the accuracy of input parameters. The error in input parameters and inappropriate assumptions have a direct impact on the accuracy of loss assessment. Therefore, the uncertainty of models should be reported through the sensitivity test. A major limitation of damage modeling is that model validation is scarcely performed because of the unavailability of data for validation in most of the cases.

Although there are many challenges in flood crop loss assessment, some will be overcome in the future through use of advanced technology and greater availability of remote sensing data. The recent development of satellite remote sensing options such as Sentinel-1 and -2 and Visible Infrared Imaging Radiometer Suite (VIIRS) will be helpful for the accurate mapping of floods as well as the assessment of crop condition profiles. Substantial improvement in remote sensing data availability is expected in the coming years following the launch of more advanced satellite remote sensing systems. These systems will provide remote sensing data at a much finer scale within the required dates and timeframes, which will also facilitate accurate crop damage assessment at local scale. Data archives will be enriched through more remote sensing images, crop price, crop yield, and vegetation indices at different administrative levels. Data dissemination through cyberinfrastructure will also be improved with the help of the advanced web and computer systems. Thus, rich historical data archives will also be available through the web platforms for the development and validation of damage assessment models. Overall, loss assessment and validation procedures are likely to become easier with the advent of new technologies, methods, data, processing software, and cyber systems.

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