ORIGINAL PAPER

Mapping of food hazard induced by land subsidence in Semarang City, Indonesia, using hydraulic and spatial models

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Received: 16 February 2023 / Accepted: 28 December 2023 / Published online: 7 February 2024 © The Author(s), under exclusive licence to Springer Nature B.V. 2024

Abstract

Frequent foodings in Semarang City have generated increasing damages and losses in property and life quality. The cause of fooding is related to the coupled impacts of land subsidence, hydraulics hazards along with poor drainage and water retention systems. This paper studies the most recent fooding hazards caused by hydrological origins (i.e., river discharge, tidal) and land subsidence. In the study, riverine origin of fooding is simulated with the help of HEC-RAS 2D, while the tidal origin is simulated to high highest water level. However, due to the absence of the most recent topographic data, the role of land subsidence is measured by estimating the vertical changes of digital elevation model taken from Sentinel 1A. Flooding extent, in terms of depth and coverage, is verifed based on satellite imagery Sentinel-2 which is cloud-processed using Google Earth Engine (GEE) and feld survey. Fluvial food is simulated with several boundary condition scenarios using combinations of 5-, 25-, or 50-year return periods of food which is integrated with mean sea level (MSL) or high highest water level (HHWL) tides. Those boundary conditions are then incorporated into diferent terrains, namely LiDAR, DEMNAS, and TerraSAR DEM, to see how diferent digital elevation models (DEMs) can impact model sensitivity. By overlaying model outputs and land cover map, it can be concluded that settlements and water bodies are among the most potentially affected areas, covering up to 17 km^2 . This study is expected to help policymakers make a primary assessment of combined tidal and fluvial flood hazard through mitigation and adaptation measures.

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Keywords Hazard · Land subsidence · Digital elevation model · Fluvial food · Tidal food

1 Introduction

1.1 Background and rationale

Semarang City, the capital of Central Java Province, Indonesia, has been sufering from episodic fooding that generates increasing annual losses. It was reported that the economic loss of approximately 20 years under business as usual scenario (BAU) amounts to 79 trillion IDR (present value), which translates into about 2% of GRDP per year (Mahya et al. [2021\)](#page-34-0). Another report noted a severe food happened in early 1990, due to overfow of Garang river and other fowing rivers through the City of Semarang. It resulted in 47 deaths and losses counting to 8.5 billion IDR (at that time) (Dewi [2007\)](#page-33-0).

Flooding in Semarang is getting worse under the infuence of land subsidence (Yuwono et al. [2016;](#page-35-0) Abidin et al. [2012;](#page-32-0) Abidin et al. [2013\)](#page-32-1). The phenomenon of land subsidence in Semarang has been investigated through a combination of methods, including levelling surveys (Marfai and King [2007](#page-34-1); Murdohardono et al. [2007\)](#page-34-2), GPS surveys (Abidin et al. [2013;](#page-32-1) Andreas [2019](#page-32-2)), DInSAR (Yastika et al. [2019](#page-35-1); Chaussard et al. [2013](#page-33-1); Lubis et al. [2011;](#page-33-2) Kuehn et al. [2010\)](#page-33-3), microgravity (Supriyadi [2008\)](#page-35-2), and geometric-historic approaches (Abidin et al. [2015](#page-32-3)). In general, land subsidence in Semarang City has a spatial and temporal variation with typical rates of about 3–0 cm year⁻¹.

Research on land subsidence in Semarang is urgently required due to adaption and mitigation measures for fooding. Floods triggered by land subsidence resulted in signifcant catastrophic damage such as economic losses (Kurniawati et al. [2020;](#page-33-4) van de Haterd et al. [2021\)](#page-33-5), infrastructure damage (Putra et al. [2020\)](#page-34-3), land value change (Amar et al. [2020;](#page-32-4) Utami and Marzuki [2020](#page-35-3)), and environmental damage (Marfai [2014](#page-34-4)). The community's socio-economic activities are also impacted by the inundation depth and duration, causing increased population relocation, deteriorating public health, disruption of livelihood activities, and unpredictable income levels (Pratikno and Handayani [2014](#page-34-5)). One food with such impacts was food 2020, which was found on Terboyo arterial road and the North Semarang area (Fig. [1](#page-2-0)).

According to Merz ([2010\)](#page-34-6), food risk mapping is an essential element of food risk management and risk communication. It is used to determine food-prone locations and enhance food risk management and catastrophe readiness. Flood hazard assessments and maps often examine the anticipated extent and depth of fooding in a specifc place, depending on various scenarios (e.g., 100-year events, 50-year events, etc.). Flood hazard maps are intended to make the public, local governments, and other organizations more aware of the likelihood of fooding. Additionally, they advise those who live and work in food-prone locations to learn more about their region's food risk and take the necessary precautions (Uddin and Matin [2021](#page-35-4)).

1.2 Previous fooding studies

The mapping of food hazards has been conducted by The Disaster Management Capacity of the National Agency for Disaster Management (BNPB) using topographic index (BNPB [2016\)](#page-34-7). The calculations heavily depend on the resolution of the Digital Elevation

a. Arterial road Terboyo

c. Sinking house in Tambak Lorok

Fig. 1 Flood extent induced by land subsidence in North Semarang on 19 Dec 2020. **a** Arterial road Terboyo. **b** Inundation in Islamic Sultan Agung Hospital and c. The deteriorated environment in Tambak Lorok

Model (DEM) and slope. The generated food maps cannot yet diferentiate whether the foods are caused by river overfow or tidal fooding. Additionally, the recent changes in topographic surface dynamics, where the Semarang region is experiencing land subsidence, have not been considered in the modelling.

Tidal and fuvial foods are two distinct types of fooding events that occur due to diferent causes. Tidal foods, also known as coastal or storm surges, result from the rise and fall of ocean tides combined with strong winds and storms (McInnes et al. [2003](#page-34-8)). These foods typically afect coastal areas and are infuenced by factors such as lunar cycles and weather conditions. On the other hand, fuvial foods, often referred to as riverine foods, stem from the overfow of rivers and streams due to excessive rainfall or snowmelt. Fluvial foods are prevalent in inland regions and can be exacerbated by factors like topography and land use. Although tidal and fuvial foods difer in their sources and locations, both pose signifcant risks to human settlements and infrastructure. Tidal fooding has a signifcant contribution in causing inundation in Semarang (Marfai et al. [2008\)](#page-34-9). Tidal fooding caused by high tides and land subsidence seriously threatens urban areas in Indonesia. Floods will overfow or overtop barriers like dikes, resulting in the land behind the dikes being inundated and prone to fooding. The low-lying areas of various cities in Indonesia, such as Semarang, often experience tidal foods (Kobayashi [2003](#page-33-6)). Several studies suggested that tidal fooding in Semarang is due to the combined infuences of land subsidence and sea level rise. It was recorded that in May 2005, at least 14 sub-districts were inundated by tidal fooding with an inundation area of 2.6 ha (Ismanto et al. [2012\)](#page-33-7). However, historically the worst tidal food conditions occurred in 2013 which were triggered by high tides. As a result,

six districts in Semarang were submerged with inundation heights reaching 1 m (Irawan et al. [2021\)](#page-33-8). Handoyo et al. [\(2016](#page-33-9)) explained that the tidal fooding that occurred in the Semarang Utara district in 2014 covered 823.5 ha with Tanjung Mas as the most widely afected village. Figure [2](#page-3-0) shows the map of study area that experienced fooding.

Most of the fuvial foods that happened in Semarang were triggered by high-intensity rainfall and the physical condition of Semarang city which is dominated by the lower areas in the north. Accumulated fuvial foods did not immediately fow into the sea and the areas became inundated instead (Wismarini and Ningsih [2010\)](#page-35-5). These foods damaged hundreds of houses as well as several public facilities such as schools, mosques, and orphanages and killed six people (Waskitaningsih [2012](#page-35-6)).

DEM plays a crucial role in applying food modeling as it provides essential topographic information needed for accurately simulating food events. The DEM serves as a depiction terrain of the Earth's surface, enabling the generation of precise foodplain maps, identifcation of fow patterns, and computation of water depths for food simulations. DEM data are fundamental for hydraulic models like HEC-RAS, which rely on accurate elevation information to simulate river fow, identify fow paths, and predict food extents. Moore et al. (1991) (1991) , Xu et al. (2021) (2021) , Qin et al. (2018) (2018) , and Han et al. (2020) (2020) highlighted the importance of DEM resolution in food modelling. They emphasized that fner-resolution DEMs enable more accurate representation of foodplain topography, leading to improved food predictions, better estimation of inundation extents, and more reliable food hazard assessments.

In food modelling, it is essential to correct DEM using land subsidence rate to accurately assess potential food risk and inundation areas. DEM is used to depict the topography of the land, including the elevation of various points on the surface especially in areas that experience land subsidence. Land subsidence refers to the sinking or lowering

Fig. 2 Location map of the study area

of the Earth's surface, which can be caused by various factors such as groundwater extraction, natural geological processes, or human activities (Abidin et al. [2013\)](#page-32-1). Irawan et al. ([2021](#page-33-8)) used the major causes of inundation in coastal areas, i.e., extreme water levels and subsidence combined with sea level rise to obtain coastal fooding simulation. The DEM was used for boundary conditions using TerraSAR-X, which has a relative vertical accuracy of around 6 m and was corrected using the 2009 land subsidence rate. Zainuri et al. [\(2022\)](#page-35-8) conducted an assessment of tidal food inundation areas based on inundation height, rate of sea level rise, topographic height data, and land subsidence. DEM was obtained through a topographic survey, whereas land subsidence was processed using Sentinel-1 Synthetic Aperture Radar (SAR) image data with Single Band Algorithm (SBA) diferential interferometry. Some of the methods used for assessing food hazards include a spatial analysis mapping system with a GIS-raster system (Marfai and King [2008;](#page-34-12) Suhelmi et al. [2014](#page-35-9)) and physical modelling (Khattak et al. [2016\)](#page-33-11). Marfai and King ([2008\)](#page-34-12) studied a GIS-raster system using a spatial analysis with neighborhood operation for tidal inundation mapping. However, spatial analysis with the neighborhood method does not consider hydrological analysis, i.e., discharge, stream, and fow velocity. Considering the physical modelling techniques, food modelling is classifed as 1D and 2D. Both the longitudinal and transverse directions of the river channel are taken into account by 2D hydrodynamic models for urban foods (Tarekegn et al. [2010\)](#page-35-10). Two-dimensional hydraulic models are more commonly employed to solve unsteady fow problems that need more input data. Moreover, they can simulate the magnitude of the fooded area at diferent times (Horritt and Bates [2001](#page-33-12)). It has been discovered that integrating hydrological models with Geographic Information Systems (GIS) is benefcial in determining the geographical variability of food hazards (Qi and Altinakar [2011\)](#page-34-13).

Flood inundation analysis refers to the process of mapping and studying the scope and depth of fooding in a particular area. Two commonly utilized methods for analyzing food inundation are HEC-RAS (Hydrologic Engineering Centers River Analysis System) and spatial analysis techniques. In the case of fuvial fooding caused by land subsidence in east Semarang, specifcally in the Tenggang Watershed and Sringin Watershed, researchers utilized HEC-RAS to investigate this phenomenon (Pujiastuti et al. [2016;](#page-34-14) Aini and Filjanah [2020\)](#page-32-5). The fndings indicated that land subsidence contributed to a yearly increase of 1.39% in food inundation. Additionally, spatial analysis techniques were employed to determine the extent of fooding (Marfai et al. [2008\)](#page-34-9). The purpose of this study is to provide a case study on local spatial-scale food hazards induced by land subsidence. The approaches proposed as a whole employ GIS, remote sensing, and hydraulic modelling to examine them in an integrated manner. Estimating maximal food fows is crucial in calculating food hazards (Q5, Q25, Q50). This study investigates how to evaluate the food triggered by fuvial, tidal, and combined conditions. The study uses hydrology data from 6 rivers modelled with HEC-RAS 2D with 1m LiDAR high-resolution DEM with improving cross-section feld data. The suggested procedures seek to identify food intensity, depth inundation, the model area's sensitivity, and food hazard level. Information on the characteristics and extent of the damage can be useful to predict future impact typology because impact types and severity within the fooded area can vary depending on factors like food water depth, velocity, land cover type exposed, and others. Types of food impacts, their locations and the severity of the impacts can be determined by tracking the spatial distribution of these impacts. Having said that, hopefully it will provide government officials as well as related stakeholders with an important reference for development planning, disaster prevention, and disaster mitigation.

2 Study site

Semarang is the capital of Central Java province, located at $6^{\circ}58'$ S and $110^{\circ}25'$ E on the northern coast of Java (see Fig. [2\)](#page-3-0). It has a coverage area of about 37,370 ha, a coastline length of 13.6 km, and a population of 1.81 million people with a growth rate of 1.57% per year (Yuwono et al. [2019\)](#page-35-11). Semarang's northern area is dominated by diverse infrastructures such as airport and bus stations, as well as densely populated areas, ponds, and agricultural land. Meanwhile, the southern area is dominated by green areas, open spaces, and settlements (Setioko et al. [2013](#page-35-12)). The geological structure of Semarang City is formed by three lithological units: volcanic rocks of the Damar Formation located in the South-West, marine sediments in the North, and alluvial deposits, also in the North (Kuehn et al. [2010](#page-33-3)). The northern part of the city is a coastal plain while the southern part is higher ground. The elevation level of this city varies from about 0–453 m (Marfai and King [2007](#page-34-1)). There are several rivers indicated to experience fuvial fooding namely Bringin, Silandak, Siangker, Banjir Kanal Timur, Tenggang, and Babon River.

3 Methodology

The methodology adopted for the study is shown in Fig. [3](#page-5-0). The frst step is developing a terrain data set directly in HEC-RAS by using the ras mapper tool. All geometric and hydrological data are modelled and utilized, including historical food events for model

Fig. 3 Flowchart of research methodology

validation and designed food events. The LiDAR, DEMNAS, and TerraSAR terrainbased food models are frst tested using historical hydrological data in order to judge their sensitivity and to select which DEM produces the most reliable result. Prior to that, the DEM data are also corrected by extracting the levelling data to obtain new river depths. The food model is simulated with a combination of 40-m grid spacing for foodplain area and fner grid spacing concerning river dimension due to computation requirements. To enhance model reliability, the model with selected DEM is then calibrated and validated by adjusting Manning's roughness coefficient (*n*).

Essentially, the calibrated and validated food model will then be used as a basis for flood hazard simulations for various return period scenarios. There are three flood model scenarios for mapping food extent: fuvial food, tidal food, and combined food. Each model will display the results of the analysis of the inundation area and food depth. In the end, by overlaying model outputs (food intensity and land subsidence rate), the fnal result of this research is the mapping of food hazards induced by land subsidence.

3.1 Data preparation

3.1.1 Hydrological data

HEC-RAS 2D hydraulic mode is utilized for hydraulic modelling. The fexibility to convert fle formats in both directions between GIS and the model, as well as its availability for free, are factors in the decision to use this 2D model. Data processing with the HEC-RAS model begins with geometric data input using the HEC-RAS extension based on DEM and geometric data. Geometric data are represented by cross sections, fow paths, bank lines, and Manning's roughness coefficient. Furthermore, cross sections are very important input data because they improve terrain characterization.

In the case of hydraulic modelling, the model area is represented by 6 hydrograph designs fowing in food-prone areas of Semarang City. The selection of the hydrographs refers to national priority rivers that must be managed in Indonesia (BPDAS, [2015](#page-32-6)) consisting of Bringin, Silandak, Siangker, Banjir Kanal Timur, Tenggang, and Babon River. In the steady fow analysis, defning the values of upper and lower boundary conditions for the stations in the model area is a crucial step. As upper boundary conditions, the maximum food discharge can be categorized into three types: high (5-year-return period), medium (25-year-return period), and low occurrence (50-year-return period). Hydrograph design in 50-year return period is employed (Fig. [4](#page-7-0)).

The purpose of the post-processing is to process the water levels for specifc cross-sections and produce a surface model of the water levels in TIN format. The water depth is created by intersecting the TIN terrain model and the TIN water level model. Flow velocity rasters are also produced from the feld of cross-cutting velocities in specifc cross-section profles or their components, in addition to water depth rasters.

3.1.2 Landcover and DEM

Landcover for the study area is acquired from the GEE Landcover Classifcation System (LCCS) database with a supervised approach method which is based on the Sentinel2-m. Moreover, the 10 m Sentinel-2 latest satellite data is used for food hazard mapping and to identify potential land cover damage. The data utilize Sentinel-2 images in 2022. To choose the clearest image, a cloud flter has to be applied to the image before processing

Fig. 4 Hydrograph design of six rivers in 50-year return period

begins. To lessen the impact of the cloud, our study employs a straightforward smilecart method from the Earth Engine package. This program chooses the lowest range of cloud scores at each location from a set of several temporal pictures. From the acceptable pixels, it produces per-band percentile values. A total of 30 samples from each class are chosen randomly and under supervision. Landcover consists of four classes including waterbody, settlement, vegetation, and vacant lot. The GEE's classifer function is used to carry out the classifcation process. Data validation using a confusion matrix has been used in other studies. A confusion matrix is a built-in algorithm in GEE that validates and evaluates the classifcation accuracy of the images.

Various DEMs with diferent spatial resolutions are utilized in this study, including LIDAR DEM, DEMNAS, and TerraSAR. These DEMs have resolutions of 1-m, 8-m, and 9-m, respectively which covered Semarang City. According to Wedajo ([2017\)](#page-35-13), the LiDAR DEM is particularly well-suited for precise and detailed food modelling, especially in urban regions and areas with fat terrain. DEMNAS stands for the national DEM for Indonesia, which is a combination of multi-DEM from TerraSAR, IFSAR, ALOS PALSAR, and mass points (Atriyon and Djurdjani [2018](#page-32-7)). Besides, TerraSAR should be suitable for urban food detection because of its high resolution in strip map/spotlight modes (Mason et al. [2010](#page-34-15)). The DEM sensitivity analysis is conducted by comparing food extent in each DEM with the food events in Semarang City. All DEMs have data acquisitions in the year 2014 with vertical coordinate reference system using Earth Gravitational Model 2008 (EGM2008). Considering the highly dynamic changes in terrain due to the infuence of land subsidence, it is necessary to correct the DEM using the latest land subsidence rates.

3.2 Land subsidence

Land subsidence is a condition where vertical displacement occurs against a certain height reference (Abidin et al. [2010](#page-32-8)). Land subsidence data are derived from Sentinel 1 data from 2017–2020 with DinSAR method. DinSAR is a method of obtaining two paired SAR images that involves combining complex image information from either the same location or a slightly diferent location within the same area. This process involves the multiplication of multiple sets of conjugate images, which leads to the creation of a digital elevation model (DEM) or the detection of displacement in the Earth's surface (Prasetyo et al. [2013](#page-34-16)). The basic concept of the DinSAR method is to utilize coherence in phase measurements in obtaining distance diferences and changes in distance from two or more SAR images that have complex values from the same area (Prasetyo et al. [2018\)](#page-34-17). Rate of land subsidence is calculated using average diferences of vertical heights of two consecutive years during the period 2017–2020. See Eq. ([1](#page-8-0)).

$$
\left(\frac{D_{2018-2017} + \Delta_{2019-2018} + \Delta_{2020-2019}}{3}\right) = \vartheta/\mathrm{yr}
$$
 (1)

where Δ is vertical displacement in each year, and θ is land subsidence rate per year. Rate of land subsidence is important to update DEM. To generate DEM correction Eq. [2](#page-8-0) is used (Ward et al. [2011](#page-35-14)).

$$
DEM_{t(x)} = DEM_{t(0)} - (\vartheta * (t_x - t_0))
$$
 (2)

where $DEM_{t(x)}$ is the DEM at a certain time (*t*) (i.e., year *x*), $DEM_{t(0)}$ is the DEM in the baseline year (t_0) and θ is the spatially differentiated annual rate of subsidence in cm year−1. The use of this method allows for a simple reassessment of the future DEM as updated and improved estimates of spatial and temporal subsidence rates.

3.3 DEM sensitivity analysis selection

It is critical to evaluate the contribution of various conditioning elements to food modelling in order to assess a model's dependability. The choice of DEM is one of the most important aspects of food modeling. In that respect, before carrying out proper food model calibration and validation, the food model's sensitivity to various digital elevation models (DEMs), including the 9-m TerraSAR, 8-m DEMNAS, and 1-m LiDAR, is evaluated using the assumption of equal river Manning's roughness coefficient of 0.06 and floodplain's roughness coefficient, as shown in Table [1](#page-8-1). Furthermore, simulations are carried out using Q50 and HHWL as upstream and downstream boundary conditions respectively, based on

Land cover	Manning's n
Forest	0.1
Built-up area	0.013
Open spaces	0.027
Maritime wetlands	0.04
Mine	0.013
Arable land	0.03
Channel	Manning's n
Uniform firm soil bed: Bringin, Silandak, Siangker, Tenggang, and Babon	$0.025*$
Uniform firm soil bed with obstruction: Banjir Kanal Timur	$0.025 - 1.6$ **

Table 1 Manning's *n* (roughness coefficient) for different land covers and channel characteristics

*Manning's *n* value is uncalibrated due to flood event image data unavailability and scarcity

**Scenarios for validation of additional adjustment factors for channel's *n* values based on Arcement ([1989\)](#page-32-9) which was the modified version of (Aldridge, [1973\)](#page-32-10)

Indonesia's Minister of Public Works and Housing statement referring to the 50-year return period storm event in February 2021 [\(https://www.bbc.com/indonesia/indonesia-56007](https://www.bbc.com/indonesia/indonesia-56007558) [558](https://www.bbc.com/indonesia/indonesia-56007558), accessed August 2023). This model is then compared to food2020 and food2021 events from Semarang City's Regional Agency for Disaster Countermeasure (BPBD) data and feld survey. The terrain that produces the best ftting result will then be used in subsequent food modeling calibration and validation procedures.

We choose four confusion matrix measures to assess the four models' performance: accuracy (*A*), precision (*P*), recall (*R*), and *F*-score (*F*). These confusion matrices have been commonly adopted by a substantial portion of researchers, including references (Li et al*.,* [2019](#page-33-3); Razali et al. [2020](#page-34-18)), for the prediction of food risks. In summary, accuracy measures overall correctness, precision focuses on correct positive predictions, recall assesses the model's ability to fnd all positive instances, and the *F*-score reveals balances precision and recall. These indicators may serve as a gauge of how well the model captures the dangers associated with fooding.

$$
P = \frac{\text{TP}}{\text{TP} + \text{FP}}
$$
 (3)

$$
R = \frac{\text{TP}}{\text{TP} + \text{FN}}
$$
 (4)

$$
A = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{TP} + \text{TN} + \text{FN}}
$$
 (5)

$$
F = \frac{2 \times P \times R}{P + R} \tag{6}
$$

where TP (true positive) is the proportion of samples that is accurately classified as flooding foodplain; TN (true negative) is the proportion of samples that is accurately classifed as non-fooding foodplain; FP (false positive) is the proportion of samples that is incorrectly classifed as fooding foodplain; and FN (false negative) is the proportion of samples that is incorrectly classifed as non-fooding foodplain.

3.4 Flood modelling

A two-dimensional HEC-RAS model is used in modelling the food inundation extent. The model takes into account hydrodynamics, horizontal and vertical fows, and 2D fow visualization—things that a 1D model cannot solve (Dasallas et al. [2019\)](#page-33-13). A fnite-volume algorithm allows for the use of a computational mesh. With this approach, the wetting and drying of 2D elements are particularly resilient. A rapid surge of water can be handled in 2D Flow Areas visualized by grid cells, which can start of dry. The algorithm can also handle mixed fow regimes (fow crossing past critical depth, like a hydraulic leap), supercritical, and subcritical fow regimes (Brunner et al. [2015](#page-32-11)).

The stage-storage relationships of foodplains in the simulation grid cells are obtained from the terrain or DEM information, allowing for bigger computational cells without sacrifcing landscape details. As for the channel, the terrain is built based on cross-sections at multiple locations along the channel. Both the foodplain and the channel are linked using a lateral structure, in this case, levees to better depict the existing condition. All of those components are then calculated using 2D fow areas that serve as the basis for the hydraulic geometry.

While HEC-RAS is capable to accommodate both difusion wave and Saint Venant equation set, for tidal-infuenced food conditions, it is recommended to use a 2D Saint Venant equation rather than a 2D difusion wave equation set to better capture the propagation of waves into a river system (Brunner [2016\)](#page-32-12). Hence relevantly, the usage of Saint Venant equation is usually recommended in a case such as this study which utilizes a tide stage hydrograph as a downstream boundary condition. However, it is also important to note that the 2D difusion wave equation's running time is much faster and generally has better stability than the 2D Saint Venant (Martins et al. [2017](#page-34-19); Quiroga et al. [2016](#page-34-20)). Given that both techniques are initially tested, they produce results that are remarkably similar, particularly in the study area, the foodplain area. This is due to the insignifcant gap between the high highest water level (HHWL) tide and river food water, so the wave propagation efect as well as the backwater efect are almost inevident, producing nearly identical results. Thus, a 2D difusion wave is chosen over a 2D Saint Venant equation set. The 2D diffusion wave equations are as follows (Brunner et al. [2015](#page-32-11)):

$$
\frac{\partial H}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} + q = 0 \tag{7}
$$

$$
g\frac{\partial H}{\partial x} + c_{\rm f}u = 0\tag{8}
$$

$$
g\frac{\partial H}{\partial y} + c_f v = 0\tag{9}
$$

$$
c_f = \frac{g|V|}{M^2 R^{4/3}}
$$
 (10)

where *H* is the surface elevation (m); *h* is the water depth (m); *u* and *v* are the velocity components in the *x*- and *y*-directions respectively (ms⁻¹); *q* is a source/sink term; *g* is the gravitational acceleration (ms⁻²); c_f is the bottom friction coefficient (s⁻¹); *R* is the hydraulic radius (m); |*V*| is the magnitude of the velocity vector (ms−1); and *M* is the inverse of Manning's *n* (m(1/3) s⁻¹).

Following advice from the HEC-RAS River Analysis System 2D Modelling User's Manual, Manning's *n* is assigned following the type of land cover. Therefore, Manning's *n* value for each land cover is assigned based on Chow ([1959\)](#page-33-14) whereas for the channel and foodplains Manning's *n* value is derived from the United States Geological Survey's guide written by Arcement ([1989\)](#page-32-9) due to its further consideration on adjustment factors (Table [1](#page-8-1)).

3.5 Evaluation of food modelling performance

The comparison of observed food images using satellite and food simulation is commonly used to evaluate the performance of the food model with channel and foodplain's Manning's roughness coefficient (n) as the calibrated variable (Horrit et al. [2007](#page-33-15), Di Baldassarre et al. [2009,](#page-33-16) Liu et al. [2019](#page-33-17)). In this study, the progression of the channel's *n* value for the model's calibration is based on adjustment factors stated in Arcement ([1989\)](#page-32-9), which

$\frac{1}{2}$ 11000 because $\frac{1}{2}$ because on boundary conditions					
Boundary condition	Fluvial flood	Tidal flood	Combined		
Upstream: river Discharge Downstream: tidal	Q_5, Q_{25}, Q_{50} Mean sea level	Q_{initial} High highest water level	Q_5, Q_{25}, Q_{50} High highest water level		

Table 2 Flood scenarios based on boundary conditions

take into account the channel's degree of irregularity, obstruction, and vegetation. Importantly, this method is limitedly used only to evaluate the fuvial food at Banjir Kanal Timur (Table [1](#page-8-1)), especially based on the January 1st—January 2nd, 2022 food event (referring to the news*:* [https://radarkudus.jawapos.com/jateng/02/01/2022/pergantian-tahun-warga](https://radarkudus.jawapos.com/jateng/02/01/2022/pergantian-tahun-warga-semarang-ditemani-banjir/)[semarang-ditemani-banjir/](https://radarkudus.jawapos.com/jateng/02/01/2022/pergantian-tahun-warga-semarang-ditemani-banjir/)*).*

The Sentinel-2 satellite imagery process is utilized under GEE using the NDWI method to derive the observed food extent on the respective date and location. Using the same date's river discharge record as an upstream boundary condition, which is obtained from BBWS Pemali Juana, this food extent is then compared with the modelled food. Concerning the validation of model results in other rivers, such data are regrettably either scarce or unavailable for the model area, a problem commonly found in similar studies (Apel et al. [2009,](#page-32-13) Vojtek and Vojteková [2016](#page-35-15)). Therefore, as for the tidal food, 20th–29th of February 2020 Sentinel 2 satellite imagery is used to evaluate the performance of the food model (referring to the highest IOC tidal data in 2020), especially near the coastal area. The tidal boundary conditions used for food modelling refer to 2020 observation (Andnur [2022](#page-32-14)) (more explanation see **3.6**).

The flood model's performance is evaluated using a measure of fit F index (Horrit et al. [2007,](#page-33-15) Quiroga et al. [2016,](#page-34-20) Liu et al. [2019\)](#page-33-17) and C Index (Liu et al. [2019](#page-33-17)) with equations as follows:

$$
F = \left(\frac{A_{\rm om}}{A_{\rm o} + A_{\rm m} - A_{\rm om}}\right) \tag{11}
$$

$$
C = \frac{A_{\text{om}}}{A_{\text{o}}} \tag{12}
$$

*A*o refers to the observed fooded area, *A*m is the modelled fooded area, and *A*om refers to the ft between both the observed and the modelled fooded area. Both F and C range from 0 to 1 with a value closer to 1 meaning better performance. However, it is important to note that higher *F* needs to be prioritized rather than higher *C* concerning how *F* indicates a degree of how perfectly the model matches the observed event, while C just represents the percentage of correctly predicted food map extent area.

3.6 Flood scenarios

In this study, three food scenarios are simulated to better understand the pattern and occurrence of hazards derived from their sources, upstream (river discharge hydrograph) and/or downstream (in this case: tidal elevation) which are set through the HEC-RAS boundary condition. These scenarios are explained and shown in Table [2.](#page-11-0)

 Q_5 , Q_{25} , and Q_{50} refer to 5-year, 25-year, and 50-year return period discharge hydrographs respectively (Semarang drainage master plan, 2020) while $Q_{initial}$ is an average discharge value in the wet season derived from the automated water level recorder (AWLR) river discharge measurement closest to the study area obtained from BBWS Pemali Juana. Furthermore, the mean sea level (MSL) and high highest water level (HHWL), 185.2 and 277.7, respectively, are modifed from Andnur [\(2022](#page-32-14)). The boundary condition for HHWL is +0.925 referring to the diference between Andnur ([2022\)](#page-32-14)'s HHWL and MSL value.

3.7 Flood hazard categories

Flood hazard categorization in this study takes into account the factors of food intensity (FI), classifcation of food hazard, and a class of function area. Flood intensity is based on the raster of water depth (*d*) and flow velocity (*v*) for each flood scenario ($\ddot{\theta}$, $\ddot{\theta}$, $\ddot{\theta}$, $\ddot{\theta}$) using Eq. [\(13\)](#page-11-1) (Drbal et al. [2009](#page-33-18)):

$$
\text{FI} = \left\{ \begin{array}{l} 0 \to d = 0m \\ d \to d > 0m, v \le 1m/s \\ d.v \to v > 1m/s \end{array} \right\} \tag{13}
$$

Considering the National Agency for Disaster Countermeasure (BNPN) Indonesia Guidelines, the food hazard is based on the distance from the river and slope. There is no classifcation of food hazard maps due to land subsidence. Therefore, in this study, we will use a classifcation based on Flood Intensity and subsidence rate as an indicator to determine the risk of fooding. Since the fooding strength in the fooded area is greater, the food hazard will also be greater. Flood hazard categories are shown in Table [3.](#page-13-0)

4 Result and discussion

4.1 Land subsidence

To fnd out the current condition of land subsidence that occurs in Semarang, DinSAR is processed using sentinel 1A period 2017–2020. The outcome is illustrated in Fig. [5](#page-14-0). It can be perceived that the land subsidence value is spatially and temporally distributed. Several colorless areas are found and defned as low coherence. It usually is found in areas with dense vegetation, water surfaces, or relatively fat areas. Areas that have a high land subsidence rate between 8 and 14 cm/year are generally located in the eastern region of Semarang City. For validation purposes, the results of the DinSAR processing are compared with the GPS observation methods from GPS measurements in 2017 (Wirawan et al. [2019](#page-35-16)) and (Istiqomah et al. [2020](#page-33-19)). Table [4](#page-14-1) presents the results of the calculation of mean square error (RMSE). RMSE represents DinSAR processing overall ft to the GPS measurement, in addition to how closely the DinSAR data points match the values of the GPS measurements. From the table, it is evident that land subsidence from 2017 to 2018 has an RMSE value of 2.72 cm, and from 2018 to 2019 it has an RMSE value of 1.95 cm. DinSAR observations have a deviation of up to 2.7 cm compared to GNSS survey. One of the causes of the deviation is that backscatter may not be well received or interpreted accurately. This outcome can be attributed to several factors, including sensor frequency, incident angle, and terrain features such as slope, hardness,

Fig. 5 Land subsidence rate 2017–2020 derived from DinSAR

Table 4 Land subsidence comparison of DinSAR and GPS method

inhomogeneity in texture, and dielectric constant (Srivastava [2022\)](#page-35-17). RMSE represents the difference between the results of DInSAR and GPS, which is generally within a few centimeters (Luo et al. [2014](#page-33-20); Liu et al. [2015](#page-33-21); Yastika et al. [2019](#page-35-1)). Therefore, it can be stated the DinSAR results in this study are acceptable. The rate of land subsidence has been similar to previous studies. In certain locations, land subsidence rate reaches 14 cm year⁻¹. According to Abidin et al. [\(2010](#page-32-8)), monitoring land subsidence has been carried out through geodetic techniques such as levelling, InSAR, and microgravity data. The research revealed that subsidence reached a maximum rate of approximately 15 cm year−1 between 1979 and 2006. Yastika et al. ([2019](#page-35-1)) noted that specifc regions experienced even more severe subsidence, measuring 24–36 cm within a two-year period from 2015 to 2017.

4.2 DEM sensitivity analysis and selection

The Regional Agency for Disaster Countermeasure (BPBD) of Semarang City's data and feld survey are used to compare food2020 and food2021 occurrences to the 50-year return period food model employing all TerraSAR, DEMNAS, and LiDAR. Simulations of food inundation using TerraSAR (Fig. [6a](#page-16-0)) and DEMNAS (Fig. [6](#page-16-0)b) show that food is not found in the middle part of northern Semarang. However, it is quite clear that the spatial distribution of food depths reaching a fairly high depth ranging from 1.0—1.5 m is found in the northern area of the Mangkang, Randusari Tugurejo, and Tambakharjo. To the north of Genuk district, such as in Terboyo and Trimulyo, characteristics of the food depth in the inundation are almost similar based on both DEM models. However, for simulation using LiDAR DEM (Fig. [6](#page-16-0)c), significant flood extent with depths ranging up to 1.5 m is spatially distributed at Mangkang, Rangdugarut, Tugurejo, Tanjung Mas, and Terboyo dan Trimulyo with elevation of terrain lower than MSL (mean sea level).

Table [5](#page-17-0) shows that the simulated food extent areas for the DEMNAS and TerraSAR DEMs are not much diferent, while the model using LiDAR-based terrain produces almost double the extent. It is important to note that all the models produce maximum velocity ranging closely between 1.4 and 1.6 m s^{-1} which proves how all the terrain scenarios have an almost similar fat sloping despite the diferent elevations. Velocity sensitivity analysis shows that simulated food velocity is lower for the DEMNAS, while LiDAR and TerraSAR velocities do not show signifcant diferences. The modelled velocity depends on the maximum depth, where a higher depth corresponds to a higher velocity. However, the velocity does not afect the extent of the inundation. The extent of inundation is greatly infuenced by the accuracy of the digital elevation model (DEM) used. A more precise DEM will provide higher accuracy in determining the extent of inundation. Moreover, the extent of inundation as well as its accuracy is highly related to fow accumulation which is further explained in Appendix [1.](#page-29-0)

In this study, the assessment of DEM performance relies on confusion metrics such as model accuracy, precision, recall, and the *F*-score. These confusion matrices have been commonly adopted by a substantial portion of researchers, including references (Li et al. [2019;](#page-33-3) Razali et al. [2020](#page-34-18)), for the prediction of food risks. Overall, the results show that the accuracy of LiDAR DEM (88%) is better than other DEMs which are DEMNAS (23%), and TerraSAR (31%). DEM sensitivity analysis depicts that the DEMNAS 8.1-m and TerraSAR 9-m have terrain errors and cannot be used in representing the foodplain in Semarang City. However, the analysis of food extent using LiDAR 1-m shows a rather satisfying ratio of correctly predicted area. Therefore, LiDAR 1-m is selected to be used for food modelling in this research.

4.3 Evaluation of food model performances

One of the most important factors that imply food dynamics is the selection of channel's *n* values which are derived not only from bed material but also the channel's cross-section geometry, as well as obstruction and vegetation characteristics. For each selected channel Manning's *n* ranges from 0.020 to 0.08 is simulated to illustrate the correlation between the channel's roughness coefficient and model performances measured by F and C . As can be seen in Fig. [7,](#page-17-1) both models' ftness generally increases as channel's *n* progresses. Additionally, the model reaches its peak stagnant performances in Manning's *n* range of 0.05–0.06, 0.3 higher than its initial Manning's value which is portrayed as a fully clean unobstructed

a. Flood extent derivated from TerraSAR 9-m

b. Flood extent derivated from DEMNAS 8.1-m

c Flood extent derivated from LiDAR 1-m

Fig. 6 Flood model sensitivity analysis against various DEM **a** 9-m TerraSAR **b** 8.1-m DEMNAS and c. 1-m LiDAR

No.	DEM	Maximum depth(m)	Velocity $(msec^{-1})$	Flood extent (Km2)	Precision		Recall Accuracy	<i>F</i> Measure
$\mathbf{1}$	TerraSAR-X 2.38		1.56	22.4	0.11	0.64	0.31	0.19
2	DEMNAS	1.50	1.43	27.38	0.57	0.41	0.23	0.47
3	LiDAR	1.95	1.54	42.03	0.74	0.94	0.88	0.83

Table 5 Flood model sensitivity

Fig. 7 Model fitness of Banjir Kanal Timur's flood model with different manning's *n* values

frm soil bed stream. This is probably caused by the fact that Banjir Kanal Timur's crosssectional area (by validation period), despite its homogeneous topography and typical normalized cross-section, is occupied by a decent part of sediment which impacts the variation of the channel cross-section and intensifes the efect of obstruction. Table [5](#page-17-0) summarizes

Fig. 8 Model fitness of Banjir Kanal Timur's flood based on the depth range

the *F* and *C* scores for each Manning's *n*. As for the *F* indexes, model evaluations provide measures of ft values higher than 0.6 for Manning's *n* same or higher than 0.05. Hence, Manning's *n* of 0.06 which produces the best *F* performances is selected as the final roughness coefficient for Banjir Kanal Timur.

The model fitness of Banjir Kanal Timur's flood model is further evaluated based on depth range data which are collected using primary survey in the same area and time period (Fig. [8](#page-18-0)). It can be seen that although there are a handful of over-predicted or underpredicted spots (represented by red dots), the ftted spots generally show accurate food depth. It implies that the DEM generated using the LiDAR can give accurate representation of the actual terrain in a particular time period while on the other hand still vulnerable to the micro-scale accuracy of water infrastructure such as levee and drainage channels which are not or hardly represented in the model.

On the other hand, the performance of the tidal food model is evaluated more straightforwardly by comparing the modelled food utilizing land cover Manning's *n* as stated in Table [1](#page-8-1) to the historical food as explained in Sect. [3.4.](#page-9-0) For the most part, the model (Fig. [9\)](#page-19-0) tends to overestimate the food event, especially in Mangunharjo, Karanganyar, and Tugurejo areas. Despite that, it still produces relatively good *F* scores of 0.79 and *C* scores of 0.95 (Table [6\)](#page-19-1).

Evaluations of both food models generally produce satisfactory results with an F score higher than 0.6, the minimum value accepted by other studies (Quiroga et al. [2016](#page-34-20), Horrit and Bates [2002](#page-33-22), Horrit et al. [2007,](#page-33-15) Baldasarre et al. [2009\)](#page-33-0). Despite that, the limitation of the model is generally divided into two categories: the uncertainties produced by using unsupervised satellite imagery as the benchmark observed food extent and detailed terrain and geometry factors that cannot be thoroughly depicted by the model. As for Banjir Kanal Timur's case, a remotely sensed food event cannot diferentiate whether the food surrounding the stream is caused by the overfowing of the river or is infuenced by local drainage problems which are also commonly found in the area. Not to mention because of the endogenic processes on the observed food cells, any additional precipitation will get ponded once the ground is saturated. Furthermore, the limitation of this performance evaluation is also due to the unavailability of several parts of river cross-sections in Semarang City including levees' technical geometry details. Although river geometry interpolation has already been carried out, the full availability of river cross-section will surely increase the representation of the riverbed in the DEM which in turn can increase the output of the

Fig. 9 Model fitness of tidal flood model in each administrative area

model including food extent and depth of inundation. On the other hand, the similar pattern of tidal food model overestimation in most administrative areas is most likely caused by mutable ponds and man-made emergency levees spreading across maritime wetlands that are hardly included in the model.

4.4 Model sensitivity

Outputs of hydrological modelling include food inundation, velocity, and food extent. The model is simulated for designed food events of 5-, 25-, and 50-year return periods with flood scenarios namely tidal, fluvial, and combined floods. Figure [10](#page-21-0) shows flood extent and inundation depth in the fuvial scenarios for 5-, 25-, and 50-year designed events and tidal scenarios. Using 5-year return period most of afected areas experience combined food with depths less than 0.5 m and between 1.0 and 1.5 m. Figure [10](#page-21-0)a) shows that food happens in Tugu district with most areas having food depth ranging from 1.0 to 1.5 m. In Semarang Utara district, the majority of food happens in center part of the area with <0.5 m food depth. In West Semarang and Gayamsari districts, the depth ranges around 0.5 m. In Genuk district, several areas have an inundation depth around 1.5 m such as Trimulyo, Terboyo Kulon, and Terboyo Wetan villages. The 25-year return period (Fig. [10](#page-21-0)b) and 50-year return period (Fig. [10c](#page-21-0)) show similarities. There are six areas that are inundated by combined food: Tugu, West Semarang, North Semarang, East Semarang, Gayamsari, and Genuk districts. Most areas have depth ranging from 1.0 to 1.5 m in Tugu, and <0.5 m food depth is found in Semarang Barat, Semarang Utara, Semarang Timur, Gayamsari, and Genuk districts, and only few areas have depth ranging 1.0–1.5 m (Terboyo Kulon, Terboyo Wetan and Trimulyo).

Details of food inundation depth areas against designed food events of 5-, 25-, and 50-year return periods are given in Table [7.](#page-22-0) In terms of the fuvial food, the food extent increases as the fow hydrograph scenario progresses from *Q*5 to *Q*50. The *Q*5 scenario has the highest ratio of food extent with a depth of less than 0.5 m, reaching 77%, while the *Q*25 and *Q*50 scenarios have a ratio that is 12% lower. However, in the food depth range of 0.5–1.0 m, the situation is reversed, with *Q*25 and *Q*50 ratios equalling slightly more than 30% and Q5 ratios reaching around 20%. Furthermore, in contrast to the tidal and combined food simulation results, only a minor extent of food with a depth of more than 1 m is found under the fuvial food event category by a maximum of only up to 1.69 km2 (5% ratio) under the *Q*50 scenario. This could indicate the signifcant contribution of tidal fooding as well as land subsidence on the overall food conditions in Semarang. The tidal food areas do not change in 5-, 25-, and 50-year return period scenarios because tidal food only considers the high highest water level (HHWL) factor, without considering food discharge in each return period. The inundation area with a depth of more than 0.5 m caused by tidal food is wider compared to its counterpart caused by fuvial food in 5-, 25-, and 50-year return periods.

As for the combined food, the total food extent in each return period is increasing. The extent reaches 39.09, 41.02, and 42.03 in 5-, 25-, and 50-year ARI (Annual Recurrent Intervals), respectively. It increases linearly with increase in each inundation depth. Figure [11](#page-22-1) shows that the average increases in inundation area according to the depth of 0.0–0.5 m, 0.5–1.0 m, 1.0–1.5 m, and 1.5–2 m are 1.9%, 1.2%, 0.4%, and 0.2%, respectively. The widest inundation area is at a depth of $0.0-0.5$ m reaching 21.53 km^2 under the 25-year-return-period.

Table [8](#page-23-0) shows that the flood velocity in 5- and 25-year return periods is less than 1.5 m/s. However, it reaches up to 1.53 m/s in 50-year return period. The velocity and extent of fooding at the 50-year return period have the highest values compared to other return periods.

Flood intensity refers to the severity or strength of a food event. It is a measure of the magnitude of fooding in terms of the volume of water, the rate of water fow, the depth

c. Combined Flood 50-vear return neriod scenario

Fig. 10 Simulated depth and inundation extent in combined food periods **a** 5-year, **b** 25-year, **c** 50-year return period scenario

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Inundation depth	Fluvial flood		Tidal flood		Combined	
	Area $(km2)$	$(\%)$	Area $(km2)$	$(\%)$	Area $(km2)$	$(\%)$
Q5						
$0.00 - 0.50$ m	22.58	76.64	12.57	46.82	20.18	50.88
$0.50 - 1.00$ m	6.46	21.93	5.54	20.61	10.16	25.62
$1.00 - 1.50$ m	0.41	1.39	8.70	32.4	9.16	23.11
$1.50 - 2.00$ m	0.01	0.04	0.05	0.17	0.15	0.39
Total	29.46	100	26.86	100	39.65	100
Q ₂₅						
$0.00 - 0.50$ m	21.60	65.8	12.57	46.82	20.99	50.99
$0.50 - 1.00$ m	10.61	32.32	5.54	20.61	10.51	25.54
$1.00 - 1.50$ m	0.59	1.79	8.70	32.4	9.44	22.95
$1.50 - 2.00$ m	0.03	0.09	0.05	0.17	0.21	0.52
Total	32.83	100	26.86	100	41.15	100
050						
$0.00 - 0.50$ m	22.24	64.45	12.57	46.82	21.55	51.11
$0.50 - 1.00$ m	11.56	33.5	5.54	20.61	10.85	25.72
$1.00 - 1.50$ m	0.63	1.83	8.70	32.4	9.48	22.49
$1.50 - 2.00$ m	0.08	0.22	0.05	0.17	0.29	0.69
Total	34.51	100.00	26.86	100.00	42.17	100.00

Table 7 Flood model sensitivity in various annual recurrent intervals based on inundation depth

of inundation, and the destructive potential it poses to the afected area. Flood intensity in 50-year return period scenario is shown in Fig. [12](#page-24-0). High zone of food intensity of tidal flood (Fig. [12a](#page-24-0)) has a higher value than its corresponding area in fluvial flood (Fig. [12](#page-24-0)b). Fluvial food with wider inundation can be found in northern Tugu and northern Genuk districts. Most of Tugu district is dominated by areas that have elevations lower than MSL (mean sea level). However, the Genuk district has experienced a high rate of land subsidence, which exacerbates the impact of food intensity, especially in the northern and western parts of the Genuk district. In combined flood (Fig. [12c](#page-24-0)), floodplain in urban areas

Fig. 11 Potential flood extent against inundation depth in combined flood

located on a river experiences a fairly high discharge, such as the Banjir Kanal Timur (BKT) and the Bringin River, indicating moderate and high food intensity food hazard. This condition is exacerbated because most foodplain areas are predominantly found in low elevations, especially areas adjacent to rivers.

4.5 Land subsidence and inundation depth

Low land subsidence rates are observed in terrains with low-elevation terrain below sea level, resulting in high water inundation in Mangkang. On the other hand, areas with low subsidence rates in high-elevation terrains have low water inundation heights, such as in Tambakharjo. Kemijen which has terrain elevation of approximately 0.4 m shows relatively high land subsidence rate, leading to moderate flood depths ranging from 50 to 70 cm. Areas with high flood water inundation heights $(>1 \text{ m})$ are found in Terboyo and Trimulyo, where not only are the terrains low below sea level, but they also experience high subsidence rates. Inundation depths related to land subsidence rate and terrain elevation are shown in Table [9.](#page-25-0)

The correlation between land subsidence, DEM, and food depth can be summarized and categorized into three types as follows:

- 1. Land subsidence and DEM: The terrain's elevation, represented by the DEM, plays a crucial role in land subsidence. Areas with low elevations below sea level are more susceptible to land subsidence. When the land subsides in such regions, it exacerbates the fooding problem since the relative sea level rises, increasing the chances of water inundation during floods.
- 2. Land subsidence and food depth: The rate of land subsidence directly impacts the food depth during inundation events. Higher subsidence rates in an area will lead to a more signifcant decrease in the land's elevation over time, resulting in a higher relative sea level during foods. Consequently, foodwaters can reach greater depths in areas experiencing substantial land subsidence.
- 3. DEM and food depth: The DEM, which provides information about the terrain's elevation, is directly related to food depth. Lower elevation areas, as represented by the DEM, are more likely to experience higher food depths during inundation events. Higher elevation areas, on the other hand, will generally have lower food depths during the same flooding events.

a. Tidal flood intensity

b. Fluvial flood intensity

Fig. 12 Flood intensity in 50-year return period **a** Tidal **b** Fluvial and **c** Combined food

N ₀	Location	District	Terrain eleva- tion(m)	Inundation depth(m)	Rate of land subsidence (m yr^{-1})
1	Mangkang	Mangkang	-0.22	1.50	0.03
2	Tugurejo	Mangkang	-0.37	1.30	0.06
3	Tambakharjo	Semarang Barat	1.18	0.30	0.05
3	Bandarharjo	Semarang Utara	0.36	0.70	0.10
$\overline{4}$	Kemijen	Semarang Timur	0.45	0.74	0.10
5	Tanjung Mas	Genuk	-0.50	1.50	0.09
6	Terboyo	Genuk	-0.40	1.50	0.09
7	Trimulyo	Genuk	-0.14	1.50	0.09

Table 9 Characteristics of inundation depth related to land subsidence and terrain elevation

4.6 Mapping food hazard induced by land subsidence

The food hazard map of the study area is divided into three classes as follows: areas with high, moderate, and low hazard levels as shown in Fig. [13.](#page-26-0) The boundary conditions for the categories are evaluated referring to Table [2](#page-11-0) with GIS method.

Tidal food extents are triggered by tidal factors and exacerbated by land subsidence (Fig. [13a](#page-26-0)). Genuk and northern part of Semarang Utara district area fall into the high-level hazard category due to the high rates of both food intensity caused by tidal factors and land subsidence. Contrastingly, there is no potential hazard of tidal fooding in Tawangsari and Tawangmas parts of Semarang Barat district, because most of the topographic elevation of those two areas is higher than the mean sea level elevation.

On the other hand, the areas labelled on the map as high-level hazard of fuvial food (Fig. [13](#page-26-0)b) are strongly infuenced by the river discharge according to inundation depth, velocity, and land subsidence rate, as referred to Table [3.](#page-13-0) High-level hazard of fuvial food can be found in foodplain areas of Genuk and the east part of Semarang. Comparatively to fuvial and tidal fooding, combined food modelling in Fig. [13c](#page-26-0) shows changes in the hazard levels. For example, for fuvial food the hazard level in Tugu and Semarang Barat district is low, but it changes into moderate level for combined food. For tidal food, there is a change in Tawang Mas and Tawangsari districts from no food found in that area into an area with low and moderate hazard levels. In the Genuk district area, both the moderate and high hazard levels expand when considering the combined food scenario. This means that when taking into account both fuvial (riverine) and tidal fooding, a larger area in Genuk district is classifed as having moderate to high food hazards. This suggests that the risks and potential damage from fooding are increasing when considering both types of floods together.

Concerning the food extent, the inundation area will cause damage to land use area. Potential land use damages are also analyzed against the simulated food extents shown in Fig. [14](#page-27-0). The most afected land cover type is pond, followed by settlement, industrial, farm, vacant land, river, and kaleyard. Furthermore, the exposure of the mentioned land use increases linearly concerning the food event.

Fig. 13 Flood hazard zone in 50-year return period **a** Tidal **b** Fluvial **c** Combined Flood

Fig. 14 Potential land use damages against tidal and flood recurrence events

5 Discussion

In terms of calibration and validation of the model, the result would be more accurate if it was calibrated and validated based on actual food events (e.g., upstream and downstream fow hydrographs, mapped and documented inundation extents, depths, or fow velocities). Unfortunately, such data are difficult to find. Therefore, we employ field survey data and satellite image data. Regarding input data, the DEM is crucial in ensuring model accuracy. This paper attempts to assess food inundation model sensitivity to diferent DEMs, namely DEMNAS, TerraSAR, and LiDAR under 50-year return period designed food. The assessment shows that LiDAR is more sensitive. LiDAR DEM with a resolution of 1 m enables the creation of high-quality rasters for fow velocity and depth compared to DEMNAS and TerraSAR. LiDAR provides detailed and high-resolution elevation data, which are crucial for accurately representing the terrain and surface features in food-prone areas.

In this study, the accuracy of the food inundation modelling results is improved by river geometry data during the process of hydro-enforcement. In addition, since the condition of the surface topography in the study area is dynamic due to land subsidence, the DEM used for food modelling is corrected using land subsidence rate. Land subsidence modelling using DinSAR is a quick assessment method that ofers the advantage of mapping relatively large areas. However, it also comes with certain limitations. One of these limitations is its sensitivity to variations in environmental conditions, which can afect accuracy. From the results in **4.2**, fooding behavior indicates that the contribution of fuvial foods should not be ignored, even in water catchment areas where overfow foods are the main cause of flooding damage. Fluvial floods also make a significant contribution to urban floods, e.g., Kemijen, Mlatiharjo, Muktiharjo, and Genuksari. The signifcant depth and extensive coverage of this fuvial food make it necessary to be cautious, especially for foodplain areas along major rivers such as the Kanal Timur, Tenggang, and Babon foods. On the other hand, tidal foods are characterized by higher food depths, particularly in coastal regions adjacent to the sea, like Mangkang, Terboyo, and Trimulyo, which have topographic elevations lower than mean sea level (MSL). These coastal areas are more susceptible to the impact of tidal surges, leading to more severe fooding during tidal events.

The analysis results reveal a remarkably strong correlation between the rate of land subsidence and food events. This correlation is particularly evident in the northern areas of Semarang City, such as Tambakharjo, Terboyo, and Genuksari, where the rate of land subsidence reaches more than 9 cm year¹, leading to flooding events with inundation depths more than 0.5 m. To determine categories of food hazard levels, we conduct the process based on food intensity and land subsidence which results in three categories: low, moderate, and high. Despite the diferent methodological basis, a similar pattern was also presented in another study conducted by BPBD [\(2022](#page-34-21)). It used fuzzy logic estimation based on slope and distance from river, which mentioned the high level is found in the northern part of Semarang's coastal area, e.g., Mangkang, Bandarharjo, Tawangmas Mlatiharjo, Kaligawe, and Gayamsari in the middle part Semarang.

Previous research proposed food hazard levels based on depth and fow velocity (Kourgialas & Karatzas [2011\)](#page-33-23). According to Vojtek and Vojteková [\(2016](#page-35-15)) defning food hazard levels will depend on the impact of food events and the characteristics of study areas. Baldassarre et al. [\(2009](#page-33-16)) proposed fve levels of hazard following the USBR ACER Technical Memorandum No. 11 (1988). However, to determine categories of food hazard levels, we conduct the process based on food intensity and land subsidence which results in three categories: low, moderate, and high. Utilizing this categorization may provide more rigorous insight into the underlying uncertainties contained in future food hazards, especially among "sinking" coastal cities around Indonesia or even the world.

In this paper, we have mapped food-prone areas with a more detailed hazard level, taking into account food intensity and the rate of land subsidence. Therefore, this paper can be studied further to analyze potential damage caused by foods. However, analyzing potential damage accurately requires more data processing (Budiyono et al. [2015\)](#page-32-15). This study can also be developed further to evaluate indirect food impacts. Related studied have been done such as (Hammond et al. [2013](#page-33-24); Mehvar et al. [2018;](#page-34-22) Mahya et al. [2021\)](#page-34-0).

6 Conclusions

To conclude, water bodies (mostly maritime wetlands and ponds) should be considered the most food-prone areas, followed closely by settlements. It is important to mention that the Genuk district falls in the high-level hazard category for both fuvial and tidal food scenarios. However, moderate hazard is also found in parts of the Tugu and Semarang Barat districts. This paper presents a hydrodynamic-based analysis that hopefully could give deeper insight into future flood adaptation and mitigation efforts.

Land subsidence, DEM, and food depth are interconnected factors infuencing food vulnerability in an area. Areas with low elevations below sea level (as indicated by the DEM) are more prone to land subsidence, which exacerbates fooding by raising the relative sea level during inundation. Consequently, higher land subsidence rates lead to greater decreases in elevation over time, resulting in deeper food depths during inundation events.

To complement the effort of Semarang coastal area flood risk reduction, strengthening the efort of reducing land subsidence, which is argued to contribute to 6.8% of fooding extension in Semarang (Irawan et al. [2021\)](#page-33-8), is also essential. According to (Abidin et al.

[2022\)](#page-32-16) several programs proposed land subsidence risk reduction, i.e., improvement of the subsidence monitoring system and its governance, the realization of zero groundwater policy, strengthening subsidence-adaptive urban development, and strengthening land subsidence risk governance. On the other hand, mitigation of land subsidence can be done if the causes are known. So far, the investigation into the causes of land subsidence in Semarang is still being carried out, so the mitigation itself is indeed still below the best expectation so far (Andreas et al. [2017\)](#page-32-17). Thus, we also encourage undergoing strategies proposed by the Coordinating Ministry for Maritime Afairs (2019) named "Coastal Land Subsidence Mitigation and Adaptation Road Map" to further study the groundwater basin's characteristics across Semarang as well as how to monitor them, so that the sustainability of groundwater and the healthy balance of "water supply versus demand" could be better planned, maintained, and regulated.

It was proven that assessment of food risk induced by tidal and fuvial food can be a useful tool for mapping food extent, especially in the coastal area, i.e., which area experiences in land subsidence and tidal fooding monitoring. The study result can also be applied to the prevention of susceptible areas and food risk management. Dissemination of food risk and increasing public awareness of food hazard should be proposed as the primary goals. Flood hazard level map can be used as reference in spatial planning, such as regulation in building expansion and density contraction in area with high-level food hazard.

Ultimately, more detailed studies on a fner scale regarding moderate–high hazard areas that incorporate more detailed technical considerations such as existing water infrastructure are encouraged to better depict what best solution fts for respected study areas. We also encourage further study by incorporating analysis, not only on a hazard but also vulnerability and capacity rate in the face of food disaster, to fully understand the food risk circumstances in Semarang whether stochastic-based or analytical-based.

Appendix 1: Flow accumulation from diferent DEMs

Flow accumulation is an important factor in understanding and forecasting food-prone locations. It is the amount of fow that builds in each raster pixel based on the cumulative weights of the pixels before it (Negese et al. [2022\)](#page-34-23). Researchers can identify food-prone places by examining fow accumulation patterns (Yunus [2021;](#page-35-18) Negese et al. [2022\)](#page-34-23).

As shown in Fig. [15](#page-30-0) and Table [10](#page-30-1) the fow accumulation determined from diferent DEM resolutions statistically shows that when the resolution goes from fne to coarse, the maximum, mean, and standard deviation fow accumulations drop dramatically. When the DEM resolution is reduced from 1 to 9 m, from LiDAR to TerraSAR, the mean fow accumulation is reduced by one-third, while the maximum and standard deviation of fow accumulation are reduced by one-fourth.

A high DEM resolution enables the collection of more values. In other words, the greater the value of max fow accumulation, the greater the number of rivers or water bodies derived from the DEM, and the greater the potential of inundation area as related to food extent fndings as mentioned in Table [5.](#page-17-0) A more accurate representation of

Fig. 15 Flow accumulation value and distribution diferences Between TerraSAR, DEMNAS, and LiDAR DEM

Table 10 Flow accumulation statistics of diferent DEMs tested in this study (TerraSAR, DEMNAS, and LiDAR)

Statistic	Flow accumulation/ $m2$					
	TerraSAR-9 m	DEMNAS-8.1 m	$LiDAR - 1 m$			
Mean	192	328	536			
Max	102,472	244,441	399,666			
Standard deviation	2186	4793	8532			

complicated topography will be possible with smaller grid cell sizes, and thus, high-resolution DEMs are better equipped to refne complex topographic characteristics (Wechsler [2006\)](#page-35-19). If the topography is complex, larger diferences between grid cells can be predicted. The surface would appear very varied over short distances, but observed slopes would be relatively consistent regardless of where they were tested over longer distances (Warren et al. [2004\)](#page-35-20).

Fig. 16 Elevation values and distribution diferences between TerraSAR, DEMNAS, and LiDAR DEM

This explains how the slope becomes comparable or a smoothing efect develops in the observed slopes at low DEM resolutions. As a result, most low DEM resolution values are smoothed according to the major flow accumulation value, resulting in a drop in flow accumulation mean and standard deviation concerning its limited measured slope variability. This consideration is highly relevant to the visualized digital elevation model depicted in Fig. [16,](#page-31-0) where the topography is becoming very complex in the LiDAR DEM with clearlybordered boxy pattern relevant to the Semarang's urban coastal landscape, thus resulting in higher accuracy of modelled food extent and depth, as opposed to the smoothed elevation diferences found in DEMNAS and TerraSAR that produce a less satisfying result.

Acknowledgements This research is funded by BUDI DN Doctoral Scholarship from the Lembaga Pengelola Dana Penelitian (LPDP), Ministry of Finance and Ministry of Research, Technology and Higher Education, Republic of Indonesia, and Research Doctoral Dissertation grand number FITB.PN-1-03-2021 from Ministry of Research and Technology/BRIN.

Author contributions "All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by BDY, HZA, P, HA, ASPP, and FG. The frst draft of the manuscript was written by BDY, and all authors commented on previous versions of the manuscript. All authors read and approved the fnal manuscript."

Funding The authors have not disclosed any funding.

Declarations

Confict of interest The authors have no relevant fnancial or non-fnancial interests to disclose.

Ethical approval Hereby, I, Bambang Darmo Yuwono, consciously assure that for the manuscript Mapping of food hazard induced by land subsidence in Semarang City, Indonesia, using hydraulic and spatial models, the following is fulflled: (1) This material is the author**'**s own original work, which has not been previously published elsewhere. (2) The paper is not currently being considered for publication elsewhere. (3) The paper refects the authors**'** own research and analysis in a truthful and complete manner. (4) The paper properly credits the meaningful contributions of co-authors and co-researchers. (5) The results are appropriately placed in the context of prior and existing research. (6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference. (7) All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

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