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Research Article

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Posted Date: July 21st, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-685721/v1>

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Version of Record: A version of this preprint was published at Water Resources Management on November 8th, 2021. See the published version at <https://doi.org/10.1007/s11269-021-03010-2>.

Multiple Kernel Learning with Maximum Inundation Extent from MODIS

Imagery for Spatial Prediction of Flood Susceptibility

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Abstract:

This paper proposes a new technology of spatial prediction for flood susceptibility. Multiple kernel learning was used to build the flood susceptibility model and predict the flood inundation risk of the Sanhuajian Basin of the Yellow River. Based on the historical flow records of the Huayuankou Site and the MODIS remote sensing images of the study area, the maximum inundation range was extracted by the open water

likelihood index method, and the flooded and non-flooded sample sites were selected. Considering the availability of pertinent literatures and data, ten flood conditioning factors were defined as the sample characteristics. The model performance was evaluated in terms of accuracy, F1 score, and AUC. According to the results, multiple kernel learning significantly outperforms the support vector machine adopting single kernel, and NLMKL demonstrates the best comprehensive performance. The flood susceptibility map generated by MODIS remote sensing images and multiple kernel learning, therefore, can provide effective help for researchers and decision makers in flood management.

Keywords: Flood susceptibility; Multiple kernel learning; Support vector machine; Nonlinear combination; Maximum inundation extent

1. Introduction

Flood is one of the most destructive natural disasters. It inflicts massive losses all over the world on a yearly basis (Chen et al. 2020). From 1980 to 2016, flood accounted for 23% of global economic loss (Mateo et al. 2017). Such losses can be mitigated or even averted by effective flood risk management methods.

Hydrodynamics-based flood inundation models, such as HEC-RAS (Pappenberger et al. 2005), Mike21 (Beilicci et al. 2016), Delft3D (Hoch et al. 2018), LISFLOOD-FP (Rajib et al. 2020), etc., can provide detailed and high-precision information on the spatial distribution of flood risks in a river basin so as to facilitate decision-making. These models, however, have some limitations in that they require high-standard data and intensive calculation (Teng et al. 2017).

Compared with flood risk maps generated by hydraulic models, the flood susceptibility map (FSM), which has been widely studied in recent years, exhibits

superior cross-regional portability and convenience (Tehrany et al. 2013; Shafapour et al. 2019; Zhao et al. 2019; Tien et al. 2020; Yariyan et al. 2020). FSM adopts the geographic information system (GIS) in conjunction with machine learning to predict flood probability and evaluate the risk in the study area. Essential to the construction of an FSM machine learning model are flood conditioning factors (including altitude, slope, soil, rainfall, etc.) and historical records of flood inundation of the study area.

In the actual modelling process, however, insufficiency and poor availability of the historical data (labeled data) is a commonplace issue. Moreover, since the majority of studies only focus on a single flood outbreak in the study area, the findings are prone to have limitations. In view of this, we employed the open water likelihood index (OWL) method to extract the inundation range from MODIS remote sensing images in the study area (Huang et al. 2014), worked out the historical maximum inundation range by synthesizing multiple inundation ranges throughout a long time series, and used this as the base map for the sampling of the machine learning model.

In terms of machine learning algorithms, the support vector machine (SVM) has been proved to be suitable for FSM (Shafapour et al. 2019; Zhao et al. 2019), and the kernel function selection and parameter optimization are the key to performance. Studies in this field have mostly adopted SVM with a single kernel function, which has a relatively narrow variation space as well as limited generalization ability and robustness.

In recent years, multiple kernel learning (MKL) has become a hotspot in machine learning researches and been widely used in imaging (Gu et al. 2016), bioinformatics (Qi et al. 2020), and finance (Arratia et al. 2020). MKL learns through a combination of multiple kernel functions instead of one, and the kernel combination can be linear, nonlinear, or data dependent (Gönen et al. 2011). The MKL obtained by optimizing the

combination of base kernels shows better generalization performance as it can eliminate the heterogeneous information in sample features and uneven distribution of data in high-dimensional feature space (Rakotomamonjy et al. 2008; Gönen et al. 2011, 2013; Zheng et al. 2017).

This research focuses on using different combinations of MKL to classify the flood susceptibility in the study area and draw the FSM. Central to MKL is the combination of multiple kernel functions and the learning method for the base kernel weight coefficient. EasyMKL, a scalable MKL algorithm (Aioli et al. 2015), is adopted for the linear kernel function combination. Combining the basic kernels by solving a quadratic programming problem, it features a low memory consumption and a short computing time. For the nonlinear kernel combination, NLMKL (Cortes et al. 2009) is used, which can be integrated with SVM and transform the min-max problem into a simpler minimization problem. A momentum-based gradient descent algorithm is proposed to solve the optimal weight of each kernel matrix. We applied the two MKL algorithms to FSM research, investigating the area between Sanmenxia and Huayuankou in the Yellow River Basin of China. According to the results, multiple kernel learning significantly outperforms the support vector machine adopting single kernel or other baseline methods, and NLMKL has the best comprehensive performance.

The remaining part of this paper is organized as follows. The section 2 is an introduction to multiple kernel learning. The section 3 introduces the method of extracting the maximum inundation range from MODIS Imagery. The section 4 exhibits the data of the study area. The section 5 shows the experimental results and discussions with regard to the comparison between the several algorithms. Finally, the conclusion is drawn in the section 6.

2. Proposed Method

Support vector machines often use a single kernel function to measure the similarity between different instances. The selection of the kernel function and its parameters determines the structure of feature space as well as the classification effect (Damasevicius et al. 2010). However, a single kernel function cannot fully describe data similarity. MKL, in contrast, combines multiple kernel functions and thus often outperforms single kernel SVM. The kernel combination of MKL can be linear (weighted addition of multiple kernels), nonlinear (product or power of multiple kernels) or data dependent (kernel combination in relation to sample characteristics). By finding the best kernel combination parameters, MKL combines several base kernels and makes use of their respective advantages to obtain a kernel function with stronger learning and generalization abilities. Common methods of determining the kernel combination parameters include the fixed rule-based method, heuristic method, and optimization method (Gönen et al. 2011).

2.1. EasyMKL

EasyMKL (Aiolli et al. 2015), a highly scalable MKL algorithm, can effectively handle hundreds of thousands of kernels. Compared with other MKL algorithms (e.g. Simple MKL, generalized MKL, etc.), it shows better performance and maintains good robustness even in the presence of data noise. This algorithm has a linear combination of the base kernels in the following form:

$$\mathbf{K} = \sum_{r=1}^R \eta_r \mathbf{K}_r, \eta_r \geq 0 \quad (1)$$

Where $\mathbf{K}_r$ is the base kernel function, R is the number of base kernels, and η_r , the weight coefficient of each base kernel. EasyMKL obtains the best combination parameters by solving a min-max problem about the variables γ and η :

$$\max_{\eta: \|\eta\|=1} \min_{\gamma \in \Gamma} (1-\lambda) \gamma^T \mathbf{P} \left(\sum_r \eta_r \mathbf{K}_r \right) \mathbf{P} \gamma + \lambda \|\gamma\|^2 \quad (2)$$

Where γ is the probability distribution of positive and negative training samples, η is the base kernel combination vector, a unitary norm vector. $\mathbf{P}$ is the label vector of training set, and $\mathbf{K}_r$, the r -th base kernel. Define the vector of the r -th entry $d_r(\gamma) = \gamma^T \hat{\mathbf{Y}} \hat{\mathbf{K}}_r \hat{\mathbf{Y}} \gamma$, and then the optimization problem can be written as:

$$\min_{\gamma \in \Gamma} \max_{\|\eta\|=1} (1-\lambda) \eta^T d(\gamma) + \lambda \|\gamma\|_2^2 \quad (3)$$

By maximizing the distance between positive and negative samples, the min-max problem can be simplified as a quadratic problem, of which the analytical solution is as follows:

$$\eta^* = \frac{d(\gamma^*)}{\|d(\gamma^*)\|_2} \quad (4)$$

The weight parameters of each base kernel $\mathbf{K}_r$ are obtained through the following formula:

$$\eta_r = \gamma^{*T} \mathbf{Y} \left(\mathbf{K}_r / T_r(\mathbf{K}_r) \right) \mathbf{Y} \gamma^* \quad (5)$$

2.2. NLMKL

NLMKL is a nonlinear polynomial kernel combination method (Cortes et al. 2009):

$$\mathbf{K} = \sum_{k_1 + L + k_r = d}^R \eta_1^{k_1} \mathbf{L} \eta_r^{k_r} \mathbf{K}_1^{k_1} \mathbf{L} \mathbf{K}_r^{k_r}, \eta_r \geq 0 \quad (6)$$

Where d is the degree of the combination of polynomials, $\mathbf{K}$ is a positive semidefinite matrix. In order to reduce the complexity, only the case where $d = 2$ is taken into consideration, and thus the nonlinear kernel combination can be given the following expression:

$$\mathbf{K} = \sum_{k=1}^R \sum_{l=1}^R \eta_k \eta_l \mathbf{K}_k \mathbf{K}_l \quad (7)$$

Apply (7) to SVM, and then the weight coefficient η_r of each base kernel is obtained by solving a min-max problem:

$$\min_{\boldsymbol{\eta} \in \Omega} \max_{\alpha \in \mathbb{R}^m} \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j \mathbf{K} \quad (8)$$

Where Ω is a positive, bounded, and convex set. Norm-1 and norm-2 bounded sets constitute the two possible choices for the set Ω , and the norm-2 bounded set is adopted in this paper.

$$\Omega_2 = \left\{ \boldsymbol{\eta} \mid \boldsymbol{\eta} \geq 0 \wedge \|\boldsymbol{\eta} - \boldsymbol{\eta}_0\|_2 \leq \Lambda \right\} \quad (9)$$

In equation (9), $\boldsymbol{\eta}_0$ is the bias parameter of the base kernel weight vector $\boldsymbol{\eta}$. In actual implementation, $\boldsymbol{\eta}_0$ is initially taken as 0 and Λ as 1. The min-max optimization problem of equation (8) can be solved by a two-step method. This paper proposes a momentum-based gradient descent algorithm (Algorithm 1). In each iteration, firstly, given the fixation of the base kernel weight vector $\boldsymbol{\eta}$, the support vector machine problem is solved to obtain α . Then, considering the constraint Ω_2 , the base kernel weight vector $\boldsymbol{\eta}$ is updated by the gradient descent method with momentum term while the SVM parameters are fixed. Repeat these two steps until convergence. Because the momentum term increases gradually in the gradient direction while decreasing gradually where the gradient direction changes, we can get faster convergence speed and weaker oscillation.

As the focus of this paper is to develop a machine learning model for spatial prediction of flood susceptibility, we have compared the two proposed MKL models with other algorithms, selecting SVM (linear kernel), SVM (RBF kernel), RMKL (Do et al. 2009), and GMKL (Varma et al. 2009) as baseline methods. The setting particulars

of the four MKL algorithms (EasyMKL, NLMK, RMKL and GMKL), all of which use linear and RBF kernels as the base kernel, will be covered in Section 5.1.

Algorithm 1 Momentum-Based Gradient Descent

Input: $\eta_{\text{init}} \in \Omega_2, \delta \in [0,1], \beta \in [0,1], \delta > 0, (K_k)_{k=1}^P, \eta' \leftarrow \eta_{\text{init}}, v_t \leftarrow v_{\text{init}}$

Repeat:

$$\eta \leftarrow \eta', K = \sum_{k=1}^R \sum_{l=1}^R \eta_k \eta_l K_k K_l$$

$$\alpha \leftarrow \text{SVM}_{\text{step}}$$

$$v_t \leftarrow \delta \alpha^* K \alpha + \beta v_t$$

$$\eta' \leftarrow -v_t + \eta$$

$$\forall k, \eta'_k \leftarrow \max(0, \eta'_k)$$

$$\text{normalize } \eta', \text{ s.t. } \|\eta' - \eta_0\| = \Lambda$$

Until:

$$\|\eta' - \eta\| < \delta$$

3. MODIS Imagery Maximum Inundation Extent

MOD09A1 is a synthetic product of the MODIS surface reflectance by the Terra satellite following an exclusion of interferential factors like atmospheric radiation and aerosol. Its spatial resolution is 500 meters, and its temporal resolution is once every eight days (Chen et al. 2013). MODIS remote sensing imagery is widely used in flood detection and suitable for large-scale spatial research. This study adopts the open water likelihood (OWL) index to extract flood inundation ranges from MOD09A1 remote sensing images (Huang et al. 2014). The OWL index contains five parameters sensitive to water bodies, namely, the short-wave infrared band (band 6 and band 7), NDVI (Townshend et al. 1986), NDWI (Gao et al. 1995) and the multi-resolution valley bottom flatness index (MrVBF) (Gallant et al. 2003). Modeled by nonlinear logistic regression, the OWL index adopts the expression below:

$$\text{OWL} = \frac{1}{1 + \exp(f)} \quad (10)$$

Where

$$f = a_0 + \sum_{i=1}^5 a_i x_i \quad (11)$$

Where x_1 = SWIR Band 6 (reflectance $\times 1000$); x_2 = SWIR Band 7 (reflectance $\times 1000$); x_3 = NDVI; x_4 = NDWI; x_5 = MrVBF; $a_0 = -3.41375620$; $a_1 = -0.000959735270$; $a_2 = 0.00417955330$; $a_3 = 14.1927990$; $a_4 = -0.430407140$; $a_5 = -0.0961932990$. The OWL index value ranges from 0 to 100, representing the probability of water existence in each pixel of the MOD09A1 remote sensing images. Whether the pixel is a flooded or non-flooded one is determined by setting the corresponding threshold. In this study, the threshold is set as 0, so if the value exceeds 0, it is judged to be a flooded pixel.

The flood inundation range of a single image is obtained through the OWL index. ArcGIS can help synthesize multiple flood inundation ranges of the same study area throughout a long time series into the maximum flood inundation range, which is used as the base map for the sampling of the machine learning model. The chosen sample sites are labeled “flooded” or “non-flooded”.

4. Data Description

4.1. Study area and historical daily flow data

This paper examines the area between Sanmenxia and Huayuankou (A.K.A. the Sanhuajian Basin) in the middle reaches of the Yellow River, the longitude between 109.73° E and 113.58° E , and the latitude between 33.64° N and 36.97° N . Sanhuajian is surrounded by mountains in the north, west and south; the Yellow River runs from west to east across it in the middle. A semi-humid area, Sanhuajian witnesses frequent rainstorms from late June to early August (Wang et al. 2014).

We obtained the historical daily flow data of the Huayuankou Site from the YRCC

website¹, which cover ten complete water years (from 2007 to 2017) as shown in **Fig. 1**. Flooding is usually caused by flood peaks, and the major peaks are represented by red dots in the **Fig. 1**.

Fig. 1 Historical data of the daily flow of the Huayuankou Site.

4.2. Flood inventories

According to the time points of flood peak occurrences in **Fig. 1**, we pinpointed the corresponding dates of the MOD09A1 remote sensing images, along with the dates before and after the occurrences. The flood inundation range of each remote sensing image was extracted by OWL index and synthesized via ArcGIS into the maximum flood inundation range of the study area.

In the maximum flood inundation range, 310 flooded sites were randomly selected; in the non-flood inundation range, 310 non-flooded sites were randomly selected. In **Fig. 2**, the red dots stand for flooded sites, and the blue dots, non-flooded sites. We used 70% (434) of the total sample sites as the training set and 30% (186) as the test set, marking the flooded sites as “1” and the non-flooded sites as “-1”.

¹ <http://www.yrcc.gov.cn/>

Fig. 2 Location of flooded and non-flooded sites in Sanhuajian.

4.3. Flood conditioning factors

Flood disasters involve an extremely complex process and can be attributed to many interplaying factors. Drawing reference from previous studies (Zhao et al. 2019; Dodangeh et al. 2020; Tien et al. 2020), this paper selects out ten flood conditioning factors, including elevation, slope, aspect, curvature, Stream Power Index (SPI), Topographic Wetness Index (TWI), distance from river, soil type, vegetation, and annual average rainfall. **Table 1** lists the data source, format, spatial and temporal resolution of these flood conditioning factors. Stream Power Index (SPI) represents the river erosivity of the catchment area, while Topographic Wetness Index (TWI) takes into account the influence of the terrain and soil characteristics on soil moisture distribution (Regmi et al. 2010). They are calculated using the following formulas:

$$SPI = A \tan \beta / b \quad (12)$$

$$TWI = \ln(A / b \tan \beta) \quad (13)$$

Where A (m^2) is the upstream catchment area or flow accumulation, b (m) is the unit width of water flow, and β (radian) is the slope.

Because the resolution of each factor is different, we used ArcGIS to preprocess

all the data and resampled them into raster data with a resolution of 90m, so that all raster data share the same coordinate system and pixel size, making it convenient for machine learning and statistical analysis. Flood conditioning factors are shown in **Fig. 3**.

Table 1 Data source of flood conditioning factors.

name	data format	spatial resolution	temporal resolution	source
DEM	TIF	30m	2015	ASTER GDEM V2
slope	TIF	30m	2015	DEM
aspect	TIF	30m	2015	DEM
curvature	TIF	30m	2015	DEM
SPI	TIF	30m		DEM
TWI	TIF	30m		DEM
Distance from river	shapefile			DEM
Soil types	shapefile	1:1000000	1995	CAShEarth Data Sharing and Service Portal ²
vegetation	shapefile	1:1000000	2007	CAShEarth Data Sharing and Service Portal
rainfall	TIF	0.5 ° × 0.5 °	2007- 2017	0.5 ° × 0.5 ° raster data set of monthly surface precipitation in China (V2.0) ³

² <http://data.casearth.cn/>

³ http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_PRE_MON_GRID_0.5.html

Fig. 3 Flood conditioning factors:(a) Elevation (meter), (b) Slope (degree), (c) Aspect, (d) Curvature, (e) SPI, (f) TWI, (g) Distance to rivers (meter), (h) Soil Types, (i) Vegetation, (j) Rainfall (mm).

5. Experimental Results and Discussions

5.1. Experiment settings

The historical flood inundation data set includes 620 instances (positive and negative instances are equal in number), among which 434 are used for training (70%) and 186 for testing. The dimension (feature length) of each instance is 10. In order to get the best performance, the data set has been standardized.

SVM (linear kernel), SVM (RBF kernel), RMKL and GMKL were adopted as the baseline methods. EasyMKL, NLMK, RMKL and GMKL all used linear and RBF kernels as the base kernels.

We implemented these algorithms in Python using Sklearn Library and PyTorch Library and found the best hyper parameter configuration through 5-fold cross-validation and grid search: C for SVM and γ for RBF kernel function. The value range of C is $C = \{10^{-2}, 10^{-1}, \dots, 10^2\}$, and that of γ is $\gamma = \{0.01, 0.1, 0.2, 0.5, 0.8, 1\}$.

Accuracy is the evaluation criterion of the cross-validation.

5.2. Performance evaluation

The performance of each model was evaluated in terms of accuracy (ACC), F1 score, and Area Under Curve (AUC) – common indicators for machine learning model evaluation (Choubin et al. 2019; Hu et al. 2021). TP, TN, FP, and FN were true positive (correctly classified flooded sites), true negative (correctly classified non-flooded sites), false positive (misclassified flooded sites) and false negative (misclassified non-flooded sites), respectively.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (14)$$

$$F1 = \frac{2 \times P \times R}{P + R} \quad (15)$$

P and R are precision and recall:

$$P = \frac{TP}{TP + FP} \quad (16)$$

$$R = \frac{TP}{TP + FN} \quad (17)$$

As to the receiver operating characteristic (ROC) curve, false positive rate (FPR) is defined as the X-axis, and true positive rate (TPR), the Y-axis. Area Under Curve

(AUC), which is widely applied in FSM model evaluation, was used to assess the model performance. When AUC is 0.5, it means the model works like a random model; when AUC exceeds 0.8, it shows the model has good performance (Tien et al. 2016); when AUC is 1, the model features perfect classification.

5.3 Experiment results and analysis

Table 2 presents a detailed comparison of the classification algorithms used in the training set. The performance of the multiple kernel method is better than that of the single kernel support vector machine. In terms of accuracy, NLMKL is the best (0.938), followed by EasyMKL (0.917) and GMKL(0.912). In terms of F score, NLMKL (0.941) and EasyMKL (0.92) are the best performers. **Fig. 4** shows the ROC curve and AUC value of each model in the training set. EasyMKL (0.973) and NLMKL (0.987) have higher AUC values, similar ROC curves, and therefore similar performances, followed by GMKL(0.970). **Table 3** presents a detailed comparison of the classification algorithms used in the test set. In general, the multiple kernel method again outperforms the single kernel support vector machine. In terms of accuracy, NLMKL is the best (0.833), followed by EasyMKL (0.823) and GMKL (0.817). With regard to the F score, the ranking remains unchanged. **Fig. 5** shows the ROC curve and AUC value of each model in the training set. All classification algorithms show similar performance, yet NLMKL (0.889) has a higher AUC value.

Table 2 Performance of different models in training set.

	SVM(linear)	SVM(RBF)	EasyMKL	NLMKL	RMKL	GMKL
ACC	0.800	0.876	0.917	0.938	0.901	0.912
F	0.811	0.884	0.92	0.941	0.904	0.916
P	0.786	0.851	0.908	0.919	0.878	0.9
R	0.838	0.919	0.933	0.964	0.933	0.933

Table 3 Performance of different models in test set.

	SVM(linear)	SVM(RBF)	EasyMKL	NLMKL	RMKL	GMKL
ACC	0.806	0.801	0.823	0.833	0.812	0.817
F	0.816	0.810	0.833	0.841	0.821	0.821
P	0.734	0.731	0.762	0.759	0.741	0.757
R	0.919	0.908	0.92	0.943	0.919	0.897

Fig. 4 ROC and AUC of different models in training set. **Fig. 5** ROC and AUC of different models in test set.

The trained machine learning model was used to predict the probability of flood inundation for each pixel in the study area. The classification methods commonly used in GIS include natural discontinuity classification method, quantile method, equal interval method, and geometric interval method (Tehrany et al. 2013). The natural discontinuity method, based on the inherent natural grouping of data, can identify the similar values and group them in the most appropriate manner (Smith et al. 2007). It

can also maximize the difference between classes and set the boundary at the point where the difference of data values is relatively large. Therefore, we used the natural discontinuity classification method in ArcGIS to divide the model-obtained probability values into five categories (very low, low, moderate, high, and very high) and completed the flood susceptibility map of the study area (**Fig. 6**). As can be seen from all the figures, the most flood-vulnerable areas are mainly located in the east of the basin. These areas are low and flat, and placed in proximity of the river and most of the vegetation there is cultivated.

Fig. 6 Flood susceptibility maps derived from (a) SVM (linear), (b) SVM (RBF), (c) EasyMKL, (d) NLMKL, (e) RMKL, (f) GMKL.

Table 4 Flood density on flood susceptibility maps by the five models

Model	Flood susceptibility level	Pixels of class	%class	Number of flooded sites	% flooded sites	Flood density($1/10^6$)
SVM(linear)	Very low	1484188	33.09	5	1.61	3.37

	Low	978770	21.82	8	2.58	8.17
	Moderate	759848	16.94	43	13.87	56.59
	High	661781	14.75	79	25.48	119.37
	Very high	600682	13.39	175	56.45	291.34
SVM(RBF)	Very low	1520086	33.51	5	1.29	3.32
	Low	979929	21.39	11	1.61	6.26
	Moderate	718286	16.00	25	8.39	33.42
	High	610514	13.60	37	10.32	52.45
	Very high	702172	15.49	232	78.39	349.76
EasyMKL	Very low	1074818	25.30	1	0.32	0.88
	Low	1051054	23.66	5	0.32	4.71
	Moderate	875703	19.66	21	7.10	23.82
	High	733620	16.36	40	13.87	54.50
	Very high	672667	15.02	243	78.39	360.66
NLMKL	Very low	1410757	30.78	1	0.32	0.72
	Low	1053870	23.34	3	1.61	2.87
	Moderate	754324	16.73	19	5.81	25.32
	High	641797	14.19	43	13.55	67.57
	Very high	670924	14.96	244	78.71	363.68
RMKL	Very low	1591920	35.49	2	0.65	1.26
	Low	952649	21.24	9	2.9	9.45
	Moderate	702084	15.65	28	9.03	39.88
	High	611987	13.64	48	15.48	78.43
	Very high	626629	13.97	223	71.94	355.87
GMKL	Very low	1682734	37.52	2	0.65	1.19
	Low	957130	21.34	8	2.58	8.36
	Moderate	612461	13.65	25	8.06	40.82
	High	568702	12.68	38	12.26	66.82
	Very high	664242	14.81	237	76.45	356.80

Fig. 7 Flood density in different flood susceptibility areas by the six models.

Fig. 8 Flooded sites in different flood susceptibility areas by the six models.

Flood density was taken into consideration to further evaluate the performance of the flood susceptibility map (Chapi et al. 2017). FD is the ratio of flooded site number to class pixel number in each susceptibility category. Ideally, density values should increase from very low susceptibility areas to very high susceptibility areas (Pradhan et al. 2010). **Table 4** lists the distribution of the categories of flood susceptibility maps by each model, the number of flood sites in each category, and flood density. **Fig. 7** shows flood density in different flood susceptibility areas by the six compared models. The results show that the flood susceptibility map obtained by the NLMKL (363.68) model

has the highest FD in extremely high susceptibility area. Also a multiple kernel learning method, EasyMKL (360.66) shows great performance, which is superior to other baseline methods. Likewise, in very low and low susceptibility areas, the multiple kernel learning method outperforms the single kernel SVM. Among those in comparison, NLMKL (0.72 and 2.87) is the best performer. In terms of flood site coverage, **Fig. 8** shows the inundation sites in different flood susceptibility areas by the six compared models. EasyMKL and NLMKL cover 283 and 287 flood sites respectively in the high and very high susceptibility areas, outperforming the linear kernel SVM (254), RBF kernel SVM (269), RMKL (271), and GMKL (275); in low and very low susceptibility areas, EasyMKL and NLMKL cover six and four flood sites respectively, outperforming the linear kernel SVM (11), RBF kernel SVM (16), RMKL (11), and GMKL (10) .

6. Conclusion

In this study, two multiple kernel learning methods were developed for flood susceptibility mapping of Sanhuajian of the Yellow River. The performance of the two MKL methods (EasyMKL and NLMKL) is compared with that of the linear kernel SVM, RBF kernel SVM, RMKL, and GMKL. The results show that the MKL method has better performance and is more suitable for flood susceptibility mapping, especially for flood inundation sites extracted from historical MODIS remote sensing images alone. To summarize, the major contributions of this study are as follows:

(1) In the absence of any historical records of the inundation sites, the sites are pinpointed using MODIS remote sensing images to provide data sets for machine learning models and complete the flood susceptibility map of the study area. This data acquisition method can provide reference to other areas in need of a flood susceptibility map when lacking a record of the inundation sites.

(2) The two MKL models have higher prediction accuracy and higher quality in generating the flood susceptibility map. Their performance is better than that of the single kernel support vector machine.

(3) Between the two MKL methods, NLMKL has the higher prediction accuracy, F1 score, and AUC than EasyMKL. In terms of the flood susceptibility map performance, NLMKL is also slightly better than EasyMKL.

Authors Contributions Q. Hu: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Roles/Writing - original draft. Y.L. Zhu: Funding acquisition, Project administration, Writing - review & editing. H.X. Hu: Conceptualization, Methodology, Supervision, Writing - review & editing. Z. Guan: Data curation, Software, Visualization. Z.Y. Qian: Data curation, Software, Visualization. A. Yang: Resources, Project administration.

Funding This work was supported by National Key Research and Development Program of China (Grant No: 2018YFC0407904).

Declarations

Ethical Approval All authors have seen and agreed with the contents of the manuscript and are looking forward to publishing this paper on “Water Resources Management” journal.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Conflict of Interest The authors declare that there is no conflict of interest.

Competing Interests The authors declare no competing interests.

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