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Evaluation of Loss of Rice Production due to Climate Change Reinforced Flood in Vietnam Using Hydrological Model and GIS

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Abstract

This study aimed to evaluate the effects of future floods triggered by climate change reinforced extreme precipitation upon rice production with the case study of the highly rice cultivated District of Duc Tho in the North Central Region of Vietnam. 24 hour - extreme precipitation and its recurrence interval were identified by applying Probability Weighted Moment to Generalized Extreme Value distribution using historical daily observations and output of ensemble median of eight selected GCMs. The calculation was run under RCP2.6 with low climate sensitivity (best case) and RCP8.5 with high climate sensitivity (worst case). The predicted future precipitation data was then used for flood modeling and inundation calculation using hydrological models and GIS. An integrated method taking into account flood depth, inundation duration and crop calendar was then used for potential damage calculation. The results show that under the impact of climate change, extreme precipitation and floods would be intensified, and as floods become more intensified, deeper and longer, the loss they would cause to rice production would increase significantly. The loss in 2050s under the worst case would be 30.1% and under the best case would be 10.3% greater than that in the baseline period (1986-2005). The results of this study provide valuable scientific information for policy maker in long-term agricultural and infrastructural planning to minimize potential damages of future floods.

Keywords: Climate change; Flood damage; GIS, Hydrological modeling; Rice

1. Introduction

Floods are among the world's most frequent and damaging types of disaster. According to Daniell *et al.* (2016), over the 1900-2015 period, over $7 trillion (2015-adjusted) in losses have occurred due to natural disasters, of which floods account for approximately 40%. In developing countries, flood damage to agriculture is a great concern since large populations live in rural areas and mainly rely upon agriculture. Estimating flood damage to crops is therefore important for post-flood relief and recovery planning as well as for long-term adaptation and mitigation actions in the agricultural sector; however, this is a challenging task due to the complex interaction between flooding processes and crop systems, especially when climate change is considered.

A number of methods have been introduced to estimate flood damage to agricultural crops for different areas in the world. Dutta *et al.* (2003) developed a mathematical model for flood loss estimation in Japan combining a physically based distributed hydrologic model and a distributed flood loss estimation model. Flood damage curves were established for 8 types of crop (including dry crops, melon, paddy, vegetable with root, sweet potato, green leave vegetable, bean, and cabbage) based on depth and duration of inundation. A similar method using MIKE FLOOD hydrological model combined with damage curves was also applied by Vozinaki et al. (2012) and Kourgialas and Karatzas (2013) to study flood loss in Greece. Messner *et al.* (2007) introduced a set of methods for flood damage evaluation that included formulas to calculate total flood damage from a single event. The formulas used an approach for "what-if" analyses which estimated the flood damage when inundation and susceptibility data were available. Banerjee (2010) estimated the short-term and long-term impacts of extreme floods on agricultural productivity in Bangladesh using rice and jute productivity data. The short-term impact was assessed by comparing average annual yield rates in "normal" flood years with those in "extreme" flood years. The long-term impact was analyzed by comparing the cultivation area and the agricultural productivity in "more" and "less" flood-prone districts over a period of 20 years. Penning-Rowsell *et al.* (2013) used a depth-loss relationship to assess flood damage to the Taihu Basin, China. The depth-loss rate was established by asset categories and flood depth based on an existing "flood loss rate", which is a percentage of the pre-flood property value at varying flood depths, and its associated flood damage data from past floods. The approaches are diversified and have led to different results. These studies, however, take into account floods alone; meanwhile the impacts of climate change were not considered.

Vietnam is a developing country where agriculture plays an important role in poverty alleviation and food security, and remains an important sector of the country's economy as it contributes about 20% of GDP. However, agricultural production is frequently threatened by annual flooding, of which intensity, frequency and potential damage is predicted to increase under climate change impact (Pham *et al.*, 2014). According to the United Nation Office for Disaster Risk Reduction (2009), Vietnam is among the countries most affected by floods. It is also ranked as the world's second most vulnerable country to climate change (Standard and Poor's, 2014). These pose a great concern for agricultural production in the near future. Among Vietnamese agricultural crops, rice is the most popular as it is grown throughout the country and is a major product for export. However, it is likely the most flood-affected crop due to its low-land cultivation location. The objective of this study is therefore to evaluate the loss of rice production due to climate change reinforced floods in Vietnam with a case study of the highly rice cultivated District of Duc Tho in the North Central Region, which would be valuable for policy makers in long-term agricultural and infrastructural planning to minimize potential damages of future floods to rice production.

2. Materials and Methods

The approach for predicting future (2050s) economic losses of rice production due to climate change triggered flood damage involves prediction of extreme precipitation under different Representative Concentration Pathways (RCPs), simulation of flood inundation using hydrological model and calculation of flood damage based on inundation depth and duration using GIS. RCPs are four greenhouse gas concentration trajectories adopted by the Intergovernmental Panel on Climate Change (IPCC) for its fifth Assessment Report (AR5) in 2014. RCPs supersede Special Report on Emissions Scenarios (SRES) projections published in 2000. The four RCPs, RCP2.6, RCP4.5, RCP6, and RCP8.5, are named according to radiative forcing target level for 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively) (Weyant *et al.*, 2009). The four RCPs include one mitigation scenario leading to a very low forcing level (RCP2.6), two medium stabilization scenarios (RCP4.5/RCP6) and one very high baseline emission scenarios (RCP8.5) (IPCC, 2014). In this study, RCP2.6 and RCP8.5 was used as they represent the best case and the worst case of climate change.

2.1. Prediction of extreme precipitation

Future extreme precipitation was predicted for the decade of 2050s using historical precipitation data combined with Generalized Extreme Value (GEV) distribution and pattern scaling method following the approach introduced by Ye and Li (2011). The GEV function is a three-parameter function as the followings:

$$F(x;\sigma,\gamma,\mu) = \begin{cases} \exp\left(-\{1+\gamma\frac{x-\mu}{\sigma}\}^{-1/\gamma}\right), \text{ if } 1+\gamma\frac{x-\mu}{\sigma} > 0, \gamma \neq 0 \\ \exp\left(-\exp -\frac{x-\mu}{\sigma}\}\right), \text{ if } x \in R, \gamma = 0 \end{cases} \quad (1)$$

where σ and μ ($\mu \in R$ and $\sigma > 0$) are the scale and location parameters, respectively. γ is the shape parameter which determines the type of GEV distribution. There are three types of distribution called Fréchet, Gumbel, and Weibull corresponding to $\gamma < 0$, $\gamma = 0$, and $\gamma > 0$, respectively. In this study, long-term historical rainfall daily data date back to more than 50 years with volume resolution of 0.1mm were employed for GEV analysis. The GEV function parameters for the General Circulation Model (GCM) baseline and future periods were estimated using the Probability Weighted Moments (PWM) method (Landwehr *et al.*, 1979) for each GCM grid (x,y). In this study, eight GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive (which is also the data source for IPCC AR5 climate change projections) were employed and ensemble

Table 1. List of GCMs used for climate change projection in this study

No	CMIP5 Models	Developer	Resolution (long*lat) atmospheric variable	Resolution (long*lat) ocean variable	Vintage	Reference
1	ACCESS1-3	CSIRO and Bureau of Meteorology, Australia	192*145	360*300	2011	Bi *et al.*, 2013; Dix *et al.*, 2013
2	CESM1-BGC	NSF-DOE-NCAR, USA	288*192	320*384	2010	Long *et al.*, 2012; Hurrell *et al.*, 2013
3	CMCC-CM	Centro Euro-Mediterraneo per I Cambiamenti Climatici, Italy	480*240	182*149	2009	Fogli *et al.*, 2009; Scoccimarro *et al.*, 2011
4	CNRM-CM5	CNRM and CER-FACS, France	256*128	362*292	2010	Voldoire *et al.*, 2013
5	HadGEM2-ES	Met Office Hadley Centre, UK	192*145	360*216	2009	Collins *et al.*, 2011; Martin *et al.*, 2011
6	INMCM4	Institute for Numerical Mathematics, Russia	180*120	360*340	2009	Volodin *et al.*, 2010
7	MIROC5	UTokyo, NIES, and JAMSTEC, Japan	256*128	256*224	2010	Watanabe *et al.*, 2010
8	MRI-CGCM3	Meteorological Research Institute, Japan	320*160	360*368	2011	Yukimoto *et al.*, 2012

median of the selected GCMs was used. Employing multiple ensemble members helps to reduce bias prediction of each single member GCM. The selection of GCMs was principally based on the spatial resolution of the GCMs. In each GCM family, only one GCM with highest resolution was selected. A list of GCMs employed is presented in Table 1.

2.2. Inundation modeling

The predicted extreme precipitation derived from GEV analysis and pattern scaling method was then used for inundation modeling using MIKE FLOOD model. The Model integrates the one-dimensional model MIKE 11 and the two-dimensional model MIKE 21 into a single, dynamically coupled modeling system. This coupled tool exploits the best features of both MIKE 11 and MIKE 21. Lateral links are used, enabling the overbank flow simulation between the river channel and the floodplain area. A lateral link allows a string of MIKE 21 cells to be laterally linked to a given reach in MIKE 11, either a section of a branch or an entire branch. The maximum floodwater depth and duration, which were estimated at every MIKE FLOOD model grid node, was subsequently used as input to a flood loss model for the estimation of damage to rice production. In this study, the MIKE FLOOD model was previously calibrated and validated for the study area by Pham *et al.* (2016).

2.3. Prediction of economic loss of rice production

The flood loss model for rice uses the equation below:

$$LOSS_{Rice(xy)} = A_{Rice(xy)} \times Y_{Rice} \times C_{Rice} \times E_{Rice(Ht)} \times LF_{Rice} \quad (2)$$

$$TLOSS_{Rice} = \sum_{x=1,y=1}^{m,n} LOSS_{Rice(xy)} \quad (3)$$

Where: $LOSS_{Rice\,(xy)}$ is economic loss of rice due to flood in grid xy (VND)

$TLOSS_{Rice}$ is the total economic loss of rice (VND)

$A_{Rice(xy)}$ is cultivation area of rice in grid xy (m^2)

Y_{Rice} is estimated yield of rice per unit area (kg/m^2)

C_{Rice} is estimated cost per unit weight of rice product (VND/kg)

$E_{Rice(Ht)}$ is loss coefficient for rice corresponding to depth *H* and

duration t at grid xy (%)

LF_{Rice} is loss factor, taking into account of growing season of rice (%). In this study, the loss factor is assumed to be 100% as the flood season in the study area (August-November) covers the haversting season of rice (August-September).

The loss coefficient E is calculated based on a stage-damage function, which is the exponential function $E = F(t) = a.e^{b*t}$, where *E* is the loss coefficient in percentage ($E \leq 100\%$), t is the duration of inundation (days), e is Euler's number equal to 2.71828; *a* and *b* are coefficients determined for each water depth level. In this study, flood water depth (H) was devided into three levels: $0.2m < H \leq 0.5\ m$; $0.5 < H \leq 1.0\ m$; and $H > 1.0\ m$. Our assumption is that the flood water shallower than 0.2 m caused no damage to rice. The coefficient a and b are shown in Table 2.

Table 2. Coefficients of Stage-damage function

Flood depth	a	b	R^2
$0.2m < H \leq 0.5$ m	12.17	0.195	0.988
$0.5 < H \leq 1.0$ m	28.07	0.163	0.964
$H > 1.0$ m	39.16	0.130	0.956

2.4. The study area

The introduced approach was applied to the case study of Duc Tho, a rural district of Ha Tinh Province in the North Central region of Vietnam and is a part of the Ca River Basin (CRB), which is one of the largest river basins in Vietnam. The district covers an area of approximately 203.5 Km^2 and has a population of more than 105,000 people (as 2016). The North Central Region in general and Duc Tho in particular is well-known as a hotspot of flooding in Vietnam due to high frequency and severity of floods occurring in the region. Geographic location of Duc Tho district is presented in Figure 1. In Duc Tho district, rice is the leading crop in terms of both cultivation area and production. Approximately one third of the area of the district is used for rice cultivation, producing more than 56,000 tons of rice annually (DSO, 2016). Rice is grown three crops a year which are called Winter-Spring crop (early November to mid April), Summer-Autumn crop (early May to late September) and October crop (mid May to mid November) and the main flood season is from early August to late November. The haversting time of the Summer-Autumn rice and October rice falls into the flood season, the risk of damage is therefore very high. A characteristic of floods in Duc Tho is that because the district is located in the downstream area and its topography is generally flat, the velocity of flood is weak and is therefore neglected in calculation of damage in this study.

3. Results and Discussion

3.1. Change in extreme precipitation

Figure 2 shows both the baseline GEV distribution and the 2050s GEV distribution under RCP2.6 and RCP8.5 projected by the ensemble median of the eight selected GCMs for 24-hour extreme precipitation at Linh Cam meteorological station.

From Figure 2 it can be clearly seen that compared to the baseline period, extreme precipitations at all level become more intensified or more frequent in the future under climate change impact. However, all the projected changes under RCP8.5 (with high climate sensitivity) are clearly much larger than those under RCP2.6 (with low climate sensitivity). The distance between the lines of observed GEV and GCM projected GEV functions becomes enlarged towards the upper tail of the distribution indicates an even stronger climate change effects when the precipitation event becomes more extreme, especially under RCP8.5. This pattern of precipitation change derived from application of GCMs in combination with Pattern Scaling and GEV methods was discussed in Ye and Li (2011). For Duc Tho district specifically, for an average extreme precipitation (EP) level, the baseline intensity of the 20 year-return period EP was 446 mm and changed to 470 mm and 575 mm under low and high RCP projection scenarios respectively, which represent a potential range of intensity increase between 5.4% and 28.9%. The frequency of the 20 year-EP level of baseline changed to 16 years and 10 years under the low and high RCP projection scenarios respectively, which are significant frequency increases between 20 to 50%.

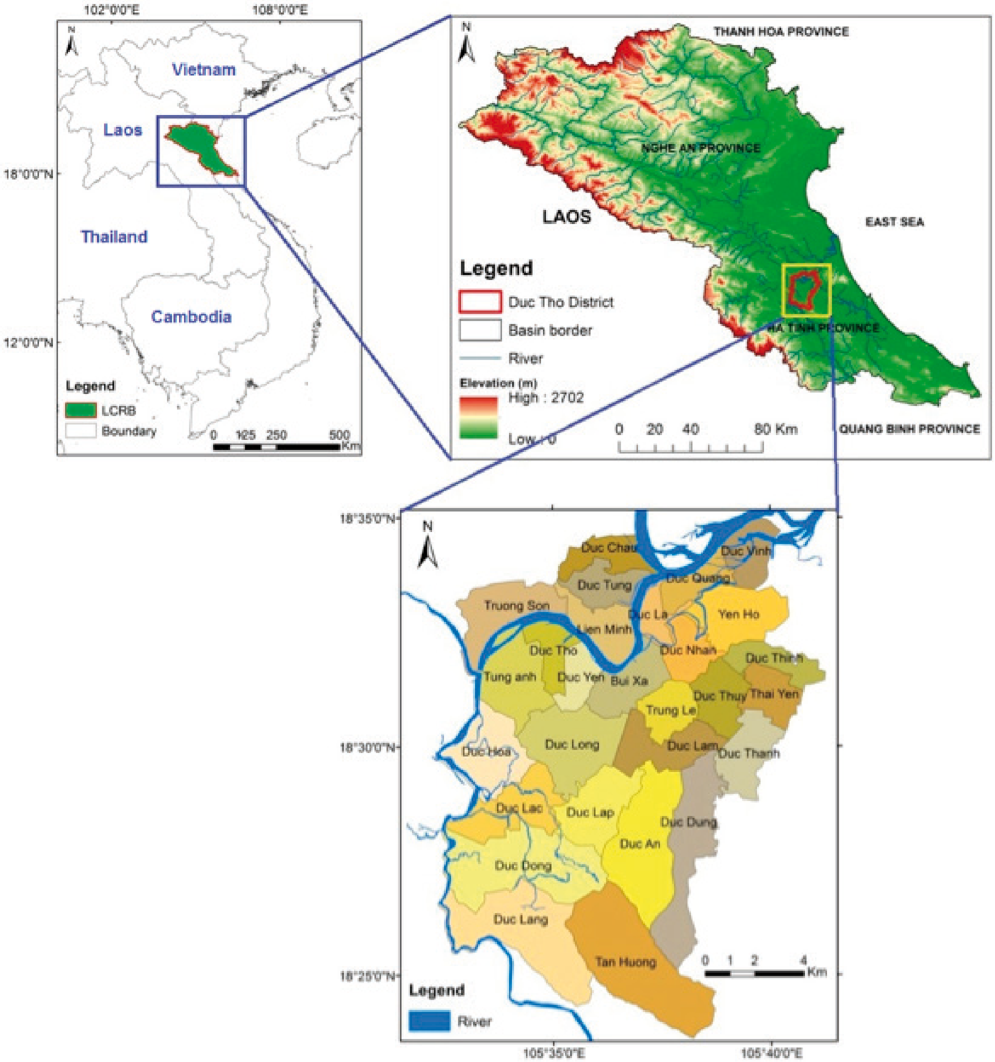

Figure 1. Geographic location of the study area

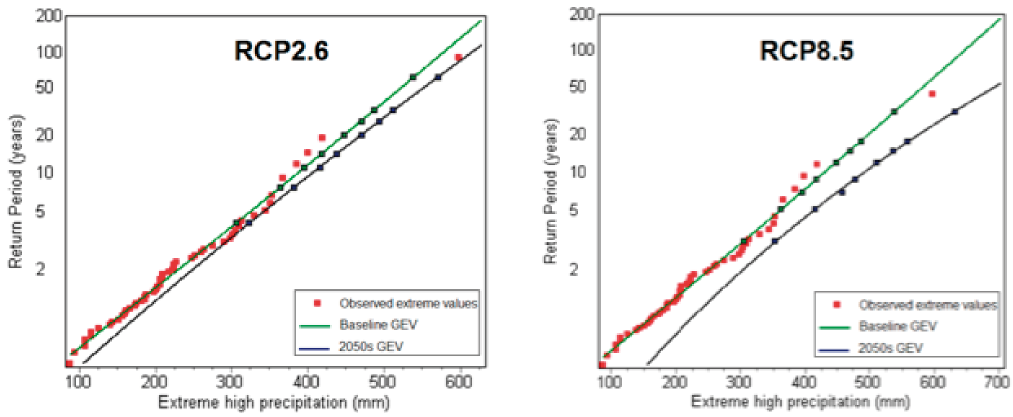

Figure 2. Prediction of extreme precipitation under RCP2.6 and RCP8.5

3.2. *Change in flood water level*

The change in water level was calculated for Linh Cam, the main hydrological station in Duc Tho district. Figure 3 shows an obvious increase in water level under both RCP projection scenarios (in 2050s) compared with the baseline period. The peak water level was predicted to increase from 6.49m in the baseline period to 6.64m and 7.09m in 2050s under RCP2.6 and RCP8.5 scenarios respectively, meaning that a potential range of increase between 0.15 to 0.6m is expected. The enlarged distance between both of RCP2.6 and RCP8.5 curves and the baseline curve also indicates that the flood event would last longer under the impact of climate change, especially under RCP8.5 scenario. A similar pattern of change in flow regime of rivers in the Ca River Basin under climate change impacts was also previously found and discussed in Pham *et al.* (2014).

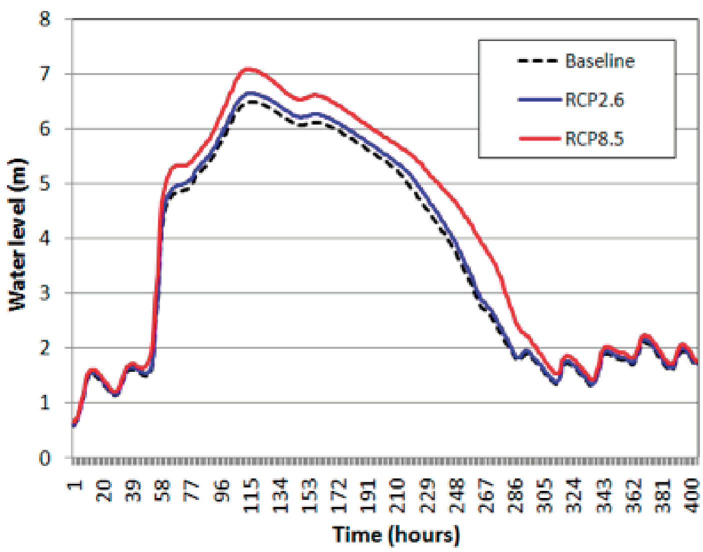

Figure 3. Water level at Linh Cam in the baseline period and in 2050s

3.3. *Economic loss of rice production*

Maps of inundation depth and inundation duration were interpolated from data of maximum depth and total duration at mesh grid of the MIKE flood model and are presented in Figure 4 and Figure 5. The area of inundation in the baseline period was 1170.26 ha, accounting for 57.74% of the total area of the district. Under climate change reinforcement, the area of inundation would increase to 12261.32 ha and 12982.38 ha according to scenarios RCP2.6 and RCP8.5, respectively. The increase in area of flood inundation due to climate change reinforcement was a common prediction among the scientific community and was reported by recent studies (Pham *et al.,* 2012; Shrestha and Lohpaisankrit, 2017).

The area of inundation upon rice cultivation was calculated by overlaying the map of inundation and land use map. The loss of rice production was calculated using the stage-damage function for every map grid (previously presented in Table 2) and is shown in Figure 6.

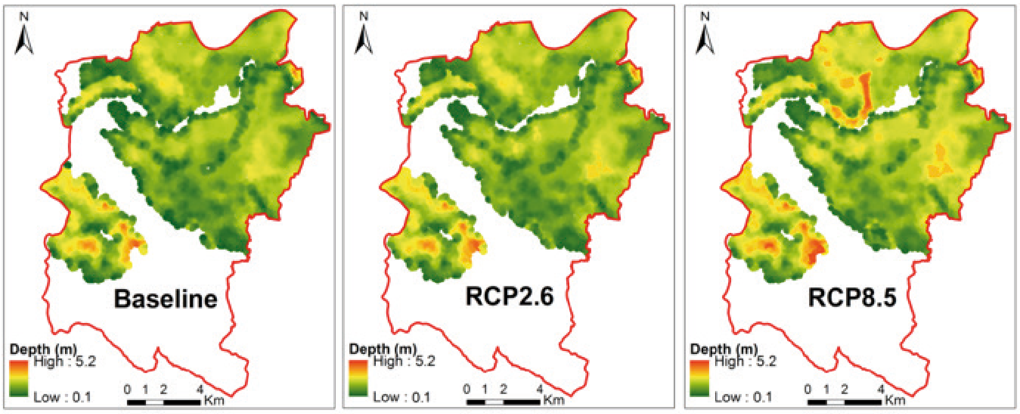

Figure 4. Inundation depth under baseline, RCP2.6 and RCP8.5 scenarios

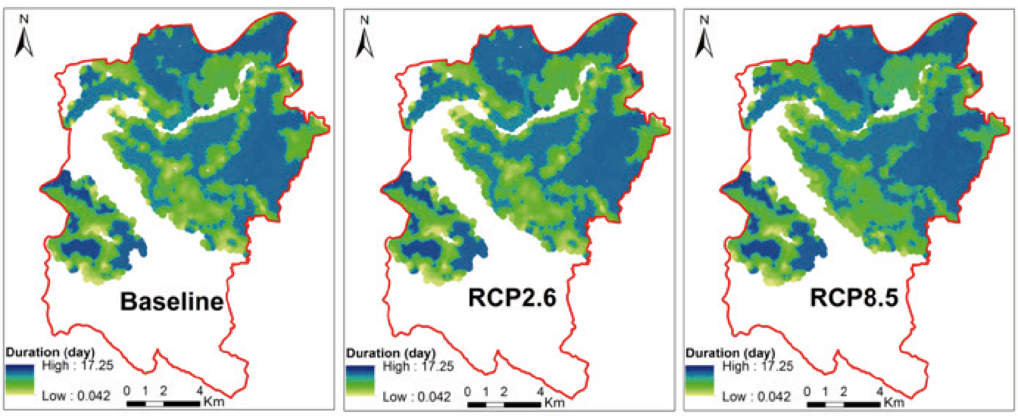

Figure 5. Inundation duration under baseline, RCP2.6 and RCP8.5 scenarios

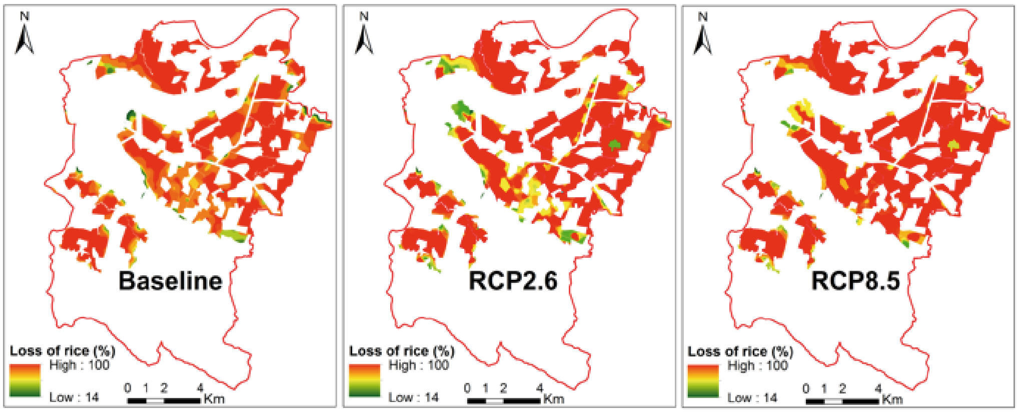

Figure 6. Loss of rice in percentage due to flooding under baseline, RCP2.6 and RCP8.5 scenarios

Figure 7 shows the area of rice inundated, the corresponding rice production affected, and the consequent economic loss of rice production. The area of rice cultivation inundated in the baseline period was 5565.21 ha and would increase to 5855.12 ha (an increase of 5.2%) and 6649.15 ha (an increase of 19.5%) ha in 2050s under scenarios RCP2.6 and RCP8.5, respectively. With a yield of 5 tons/ha and a price of 6 million VND/ton (as in 2016), the production of rice affected by floods would increase from 27827.05 tons in the baseline period to 29275.6 tons and 33247.75 tons; and the economic loss would increase from 150.87 to 166.23 billion VND (an increase of 10.3%) and 196.28 billion VND (an increase of 30.1%) under scenarios RCP2.6 and RCP8.5, respectively (Figure 7).

The increase in the economic loss of rice production was found to be not proportionate to the increase in the area of inundation due to additional effect by the increase in inundation duration. The results clearly indicate that as floods become more intensified, deeper and longer under the impact of climate change, the loss they would cause to rice production would increase significantly, especially under the high concentration scenario RCP8.5.

It is obvious that in addition to flood season, depth and duration, flood damage depends on many other factors such as flood flow velocity, sediment concentration, contamination of flood water, availability and information content of flood forecast, and the quality of external response in a flood situation. Although a few previous studies provided some quantitative hints about the influence of these factors (Penning-Rowsell and Green, 2000; Thieken *et al.*, 2005), there is no comprehensive approach for including all of such factors in damage evaluation. Most of studies on crop damage take into account flood season, depth and duration (Bremond *et al.*, 2013) while other factors are neglected since they are very heterogeneous in space and time, difficult to predict, and there is limited information on their effects. This is also a limitation of the present study and more investigations on the effect of those factors are recommended for further research.

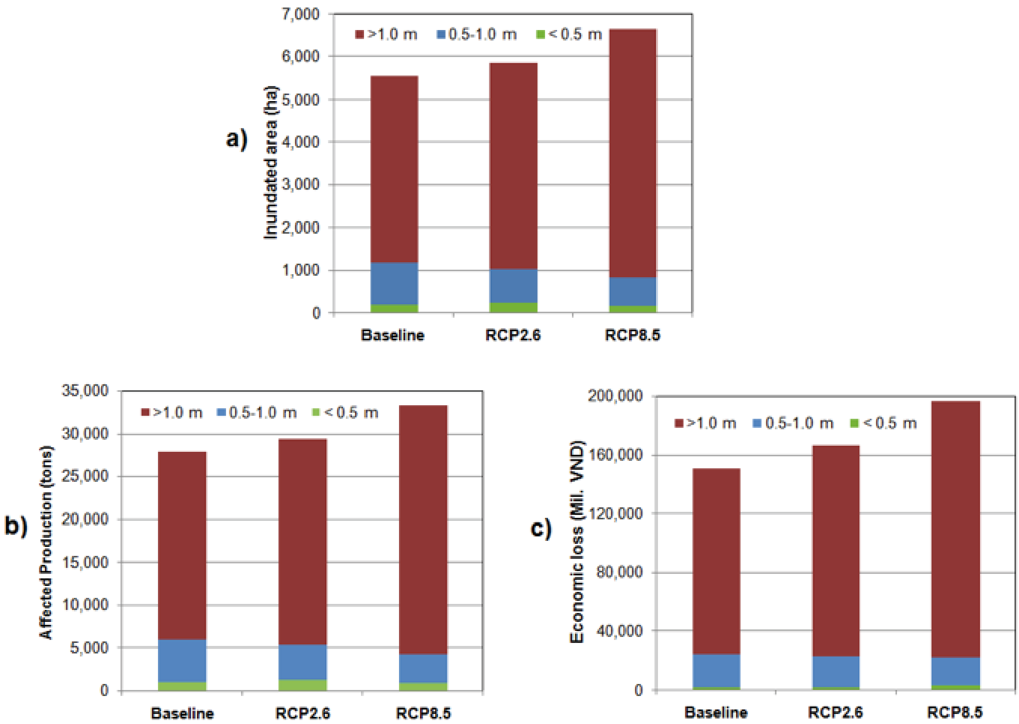

Figure 7. (a) Inundated area, (b) production affected and (c) economic loss of rice production under the baseline period and in 2050s RCP2.6 and RCP8.5 scenarios.

4. Conclusion and Recommendation

Vietnam is among the countries most affected by floods and most vulnerable to climate change. In Vietnam, flood damage to rice production is a great concern since large populations mainly rely upon rice production and rice is a major product for export. Projection of the effects of climate change on economic loss due to flood damage to rice production in Vietnam with the case study of Duc Tho, a district in its north-central region, was conducted using an integrated methodology. Extreme precipitation was estimated by applying Probability Weighted Moment to Generalized Extreme Value distribution using historical daily observations and output of ensemble median of eight selected GCMs. The calculation was run under two Representative Concentration Pathways: RCP2.6 with low climate sensitivity (best case) and RCP8.5 with high climate sensitivity (worst case). The predicted future precipitation data was then used for flood modeling and inundation calculation using hydrological models and GIS. An integrated method taking into account flood depth, inundation duration and crop calendar was then used for potential damage calculation. The results show that under the impact of climate change, extreme precipitation and floods would be intensified, and as floods become more intensified, deeper and longer, the loss they would cause to rice production would increase significantly. The loss under the worst case (RCP8.5) is much larger compared to the best case (RCP2.6).

The results of this study prove that the integrated approach introduced is a powerful tool for the prediction of flood damage under climate change impact and is capable of providing useful information for flood risk management and decision-making. The results are valuable for long-term agricultural and infrastructural planning in order to minimize potential damages of future floods, especially in the worst case of climate change.

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