Using public participation within land use change scenarios for analysing environmental and socioeconomic drivers

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Abstract

This paper aims to improve the understanding of environmental and socioeconomic drivers on land use change (LUC) through public participation (PP), and provide recommendations for long-term policy making to support sustainable land use (LU) management. PP was necessary to help understand and address the problem and concerns of stakeholders within the study area.

Through two collaboration workshops seven individual future LU scenarios were created. Using the future land use simulation model, LU was projected up till 2060, after which logistic regression analysis took place to find the most significant driver. Results found that LUC within the baseline scenario and the ones chosen by stakeholders were very different, however concluded that Paddy field extent would decrease in the future to be replaced by more drought resilient agriculture; Perennials & Orchards and Field Crops. Outcomes from future scenarios propose that future LUC was driven by environment spatial factors such as elevation and climate, not soil suitability. With, first hand interviews suggesting it is indirect external factors such as, crop price that drive LUC. Overall the study provides steps towards dynamic LUC modelling where future scenarios have been tailored to details specified by the public through their participation.

Acronyms

| Acronym | Description |
|---------|-------------|
| PP      | Public participation |
| PAR     | Participatory Action Research |
| LU      | Land Use |
| LUC     | Land Use Change |
| MRB     | Mun River Basin |
| CLUE    | The Conversion of Land Use and its Effects |
| FLUS    | Future Land Use Simulation |
| ANN     | Artificial neural network |
| CA      | Cellular automata |
| DF      | Driving factors |
| LR      | Logistic regression |
| LDD     | Land Development Department |
| ENRICH  | ENhancing Resilience to future Hydro-meteorological extremes |
| STAR    | Strengthening Thailand's Agricultural drought Resilience |
| BAU     | Business as usual scenario |
| FOR     | Conservation scenario |
| URB     | High urban growth scenario |
| COB     | Multi objective/combination scenario |
| PRO     | Productivity scenario |
| POL     | Policy driven scenario |
| WAT     | Water stressed scenario |

1. Introduction

1.1. Public participation in research

The concept of PP, PAR, ‘citizen science’ or ‘stakeholder engagement’ (Baum et al 2006, Trisurat et al 2016, 2019, Strasser et al 2019) in research is a powerful concept and one of gaining interest to academics, governments and policy makers, when considering environmental problems (Rowe and Frewer 2004, Shirk et al 2012). PAR was first observed within research in the late 1960s to address issues with disadvantaged members of society, and though initially used in low income countries (Baum et al 2006), it has since been used within various disciplines, especially within geographical teaching and higher education (Kindon and Elwood 2009, Jacobs 2016). First used
within Human Geography within undergraduate and postgraduate studies (Pain et al 2013, Whitman et al 2015). PAR has since become increasingly popular within physical geography and related studies due to its critical action-oriented nature, providing collaboration and co-production of research, whilst enriching the learning of those involved (Pain 2009, Whitman et al 2015).

Inspired by the work of Paulo Freire, PP seeks to connect scholars, governments and members of the public to produce innovative knowledge that can help in decision making, policy development and solve local environmental problems (Whitman et al 2015, Brown and Eckold 2020), by improving and empowering the lives of local people (Rowe and Frewer 2004, Baum et al 2006, Strasser et al 2019). The process of PP and PAR, through an collaborative interactive activity (usually a questionnaire survey) (Zaleczna 2018), enables increased cognitive knowledge and understanding of a subject area ‘democratizing science’ whilst providing social and practical learning (Haywood 2014, Rouillard et al 2014, Jacobs 2016, Srichaichana et al 2019, Strasser et al 2019). There are three known categories of PP in scientific research; Contributory, Collaborative and Co-created (Miller-Rushing et al 2012). The high flexibility within its methods (Patel et al 2007) means the degree at which the public or stakeholders may be involved can be through a number of different ways or levels, though this is usually down to the scope of the research (Rowe and Frewer 2004). Nevertheless, PP within LU planning is difficult (Zaleczna 2018). Local stakeholder opinions can be easily discouraged if in a minority group, and the law does not require decision-makers to take into account the interest of who will be immediately affected by the LUC. Ultimately, the effectiveness of PP within LU planning, largely depends on the willingness of groups to cooperate and compromise (Zaleczna 2018).

A paper by White (2001) provides steps that researchers can take to improve the PP process within LU management. White (2001) concluded that top-down approaches are neither workable nor welcome and can be faced with suspicion and antagonism (White 2001). Meanwhile, Rouillard et al (2014) research concluded that an inclusive PP process contributed to greater uptake of rural LUC and improved compliance with existing environmental policies. The work by Golobić and Marušić (2007) looked at the importance of PP within LU planning and decision making processes. Using expert knowledge Golobić and Marušić (2007) prepared three LU scenarios (settlement, industry and conservation) and evaluated the suitability via a questionnaire combined with drawing responses. The methodology proved to be effective in accruing local knowledge. Patel et al (2007) and Grieswald et al (2017) used a similar methodology asking stakeholders from different backgrounds to create visual images to illustrate potential LU scenarios. The results enabled stakeholders to visualise and raise awareness of the potential conflict and synergies between LU types and management.

Meanwhile studies such as Brown et al (2012), Zolkafli et al (2017), Jankowski (2019) and Kahilatani et al (2019), have used internet-based public participation geographic information systems (PPGIS) as a way to improve PP in LU planning. PPGIS are Web-based questionnaires that enable stakeholders to respond spatially to questions by marking a location and/or defining a LU features (Brown et al 2012, Zolkafli et al 2017, Jankowski et al 2019). While Zolkafli et al (2017) argue that PPGIS has significantly enhanced public knowledge in LU planning through capacity building, a clear disadvantage to this methodology is that it requires the participants to have knowledge and access of using Web technology (Internet) as well as basic literacy and map skills (Jankowski et al 2019). Further studies by Brown use participatory mapping and community surveys as alternatives to PP, finding that these generated increased descriptive information compared to formal styles of questioning, which is usually characterised by low participation. Nevertheless, Brown and Eckold (2020) and Brown et al (2020) conclude that despite PP research validity and its potential to improve social acceptance of LU decisions, social impact is still limited because there is as the large gap between the generation of useful information and actually using the information gathered to inform LU decisions.

Studies conducted by Olabisi are of particular interest (Olabisi et al 2010, 2014, 2020, Schmitt et al 2018). Olabisi et al (2014) provided three separate workshops to consider multiple futures. Using the (1)NSPECT process (Olabisi et al 2010), that was generated by Richard Bawden, they created a range of scenarios; capitalism, moderation of agriculture, sustainable development and environmental destruction (Olabisi et al 2014). Olabisi et al (2014) concluded that scenario visioning or planning helps promote social learning, as workshops provide a form in which stakeholders from different sectors can exchange information and perspectives on complex problems. Schmitt et al (2018) built on this idea using a transformative scenario planning and casual loop diagramming processes to create four future plausible LU stories up to 2035. Stakeholders were then asked to sketch out the timeline of events for each scenario. Using these methods they were able to incorporate local knowledge from stakeholders and provide recommendations to policy makers who ultimately would be in charge of implementing ideas.
1.2. Land use change modelling

LUC has direct and indirect impacts on the hydrological cycle, climate variability and watershed capacity, changing the frequency and intensity of hazards such as droughts and floods (Weng 2001, Shrestha et al 2020). Globally, changes in forest cover, through deforestation, and changes in agricultural areas, are the most significant types of LUC affecting water resources within a catchment. LUC Modelling is not only a highly dynamic field of research (Veldkamp and Lambin 2001) but an important tool, linking natural and human systems together over different spatial and temporal scales (Promper et al 2014, Islam et al 2018), to evaluate the influences of various planning policies. From using environmental, social and economic variables, they have the ability to predict the location and quantity of past and future change (Veldkamp and Lambin 2001, Ellis and Revitt 2010, Zhu et al 2010, Lourdes et al 2011).

Table 1 lists a variety of LUC Models, each with its own merit (Berbero et al 2016). The CLUE-s software package is one of the most widely used (Douglas-Mankin et al 2010, Zhang et al 2013, Wang et al 2018). More recently Olabisi et al (2020) conducted scenario exercises whereby communities identified drivers of change and actions that would improve adaption for the mid-term future. Workshop participants were asked to illustrate the impacts of climate change on the agricultural sector, as well as exacerbating or mitigating factors. Four scenarios were created looking at the combination of (high & low) flooding and (high & low) youth empowerment. The conclusion was that in areas with absence of data, participatory scenario exercises have the means to creating more climate-resilient systems, as they provide a flexible and adaptive approach to climate adaption (Olabisi et al 2020).

1.3. What this research will add

Although literature has expressed an interest in using PP as a methodology within LUC research, many have failed to use a calibrated LUC model within their research, rather a ‘soft version’ of getting participants to draw potential scenarios or annotate LU maps. Consequently, this research will be largely collaborative; designed by scientists but where members of the public contribute data, refine project aims, analyse data and or disseminate findings (Miller-Rushing et al 2012). The MRB was used as a case study for the research because LUC due to agricultural

| Model/framework | Spatial resolution | Scale | Availability | Reference |
|-----------------|--------------------|-------|--------------|-----------|
| SWAT            | 50 × 50 m DEM      | Globally | Freely available | (Douglas-Mankin et al 2010, Zhang et al 2013, Wang et al 2018) |
| CLUE/Dyna CLUE  | Depends on input   | Globally applicable | Dyna-Clue freely available (limited extent) | (Verburg et al 2006, Lourdes et al 2011, Pindozzi et al 2017, Khan et al 2018, Trisurat et al 2019) |
| (various versions) |                     | more suitable for smaller scale studies | | |
| DINAMICO EGO    | Depends on input   | National, subnational | Freely available | (Yi et al 2012, Pathirana et al 2014, Veerbeek et al 2015) |
| CAPRI           | NUTS-2 regions/1 × 1 km | EU (Regional) | Not available | (Paracchini et al 2010, Britz et al 2011) |
| SLEUTH          | Depends on input   | Globally applicable | Available | (Xian and Crane 2005, Le Roux 2012) |
| FLUS            | Depends on Input/1 × 1 km applicable | Globally applicable | Freely available | (Liu et al 2017, Liang et al 2018a) |
Figure 1. A working flowchart clarifying how PP was integrated in to the FLUS model.

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intensification and urban expansion are having significant impacts on the hydrological regime. In particular, agricultural development is having a profound effect on land and water degradation, through soil erosion, excessive nutrients and increased water demand (Akter and Babel 2012). PP was particularly essential to this study as the future LU scenarios chosen were developed from feedbacks and inputs from those the results primarily influenced, adding invaluable detail to our research direction. With outcomes better tailored to the needs of those living within the MRB. By using PP at its core, this study aims to constructive future LUC scenarios for the MRB. The specific objectives are: (a) to design future scenarios through workshops with stakeholders; (b) to develop an optimisation tool to find target values for future LU; (c) simulate future LU using the FLUS model; and (d) to quantify the influence of environmental and socio-economic drivers in the MRB (figure 1).

2. Methodology

2.1. Study area

The Mun, a tributary to the Mekong River, is one of the largest river basins in Thailand (Akter and Babel 2012) and an important agricultural region, especially for rice production (Prabnakorn et al 2016), with 60% of rice cultivated in Thailand from the north eastern region (Prabnakorn et al 2018, 2019). Most rice farming in the region is traditional and small scale, located in the lowland areas along the river (Prabnakorn et al 2016). Between 2000 and 2017 Paddy fields covered 60%–53% of the catchment, an area of 32,326.6 km$^2$ and 28,154.5 km$^2$ respectively (figure 2). Real differences in agricultural LU occurred with Perennial & Orchards, which increased from 1.7% to 6.3%, 909.2 km$^2$, and 3359.2 km$^2$ respectively 2000–2017 (figure 2). Poor consolidate sandy loam soils dominate the MRB with more than 40% suffering from erosion during monsoon rains (figure 3). The basin also suffers from moderate to poor drainage, with the poorest drainage found in the West along the river. In comparison, soil fertility values are of a low fertility grade, as sandy loam soils are quick to drain, thus lack the capacity to hold and absorb water and nutrients (figure 3). Worst soil fertility values are in the South and North of the catchment. On the other hand, areas alongside the river are associated with Clay or Silt clay soils; these are relatively fertile because although they suffer with bad drainage this fundamentally means they are better at holding water and nutrients.

2.2. Land use change model

The FLUS model was developed by Sun Yat-sen University and is freely available to download from www.geosimulation.cn/flus.html, it is based on Top down system dynamics combined with a Bottom up CA (Liu et al 2017, Liang et al 2018a). The output file provided by the ANN module within FLUS was used to calculate the LR. An LR algorithm was used to calculate the contribution of each driving factor (DR) on LU distribution or transition (Kamakura 2018). The contribution of each DF on LU is within the result section of this paper. In this study the LR measures the propensity for the event (Change in LU), or its log-odds. Where the dependant variable = whether
Figure 2. Past LUC in the MRB 2000–2017.

Figure 3. In descending order soil type, fertility, drainage and elevation maps for the MRB.
Table 2. Data sources within this study.

| Data type                                      | Observation period               | Spatial resolution | Organisation source        |
|------------------------------------------------|----------------------------------|--------------------|----------------------------|
| Land-use of North East Thailand                | Land use maps (Shape file) for the years 2000–2002, 2006–2007, 2008–2009, 2010–2013, 2015–2016 | 100 m              | Land Development Department |
| Population density map                         | 2000, 2008, 2017                 | 1 km (30′′ × 30′′) | LandScan https://landscan.ornl.gov |
| Soil Data; type, fertility, drainage and productivity | 2007                            | 100 m              | Land Development Department |
| Topographic map (DEM)                          | 2019                            | 30 m               | SRTM-USGS https://earthexplorer.usgs.gov |
| Temperature and precipitation data             | 1975–2015                       | 0.25 degrees grid. | Thailand Meteorological Department & Royal Irrigation Department |
| Crop moisture defect                           | 1961–1990                       | 0.083 decimal degree | Global Agro-Ecological Zones |

the LU changed or not (1 = yes, 0 = no) and the predictors explaining the propensity of the change are the DFs.

2.3. Data collection
The data origins and spatial resolutions are given in table 2. DF were chosen based on data availability: Elevation, Drainage, Fertility, River Distance, Road Distance, Slope, Soil Type, Suitability Map and Population Density. LU types were identified according to the LU maps supplied by the LDD: Paddy Fields, Field Crops, Perennials & Orchards, Other Agriculture, Forest, Water Bodies, Marsh & Swamp, Urban and Miscellaneous.

2.4. Stakeholder engagement
PP took place via two events:

(1) Stakeholder meeting, March 2019 in Nakhon Ratchasima and Field trip to Burirum Province for interviews with farmers.

The objectives were:

- To present overall objectives, scope of the study, methodology, work plan of the project.
- To provide an opportunity for the stakeholders to give feedback and suggestions on the research.

51 participants from related government departments, Universities, and headman of the village/community attended the meeting. Outputs helped determine DF and gave background information on the local area and problems facing the farming community.

(2) January 2020 Joint Mid-Term Science and Stakeholder Workshop between ENRICH (in the Mun river basin in Northeast of Thailand) and STAR projects.

The workshop provided an opportunity to share updates with stakeholders, government agencies, and academicians, as well as receive feedbacks, comments and suggestions from the participants. Two key questions were given to participants to derive the LU scenarios:

- Can LU be classified by anything other than its visual LU?
- Would different scenarios benefit the study?

Feedback and answers to these questions helped to create the scenarios.

2.5. Future scenario’s

2.5.1. Solver
An optimisation tool was used to find target values for future LU. The model worked by changing the decision variables (LU types) to satisfy the limits of the constraints until the best value for the objective cell was achieved (Chandrakantha 2008, Barati 2013).
In our case the Objective cell and the Constraints varied depending on scenario and in some cases this was a pre-defined value within a formula (appendix 1 available online at stacks.iop.org/ERL/17/025002/mmedia).

Seven future scenarios were created: (a) BAU, (b) Conservation (FOR), (c) Urbanization (URB), (d) COB, (e) PRO, (f) POL and (g) WAT.

2.5.2. Business as usual (BAU) scenario
BAU was developed following past trends observed from previous LDD maps 2000–2017. LU allocation was determined using an add-in of the FLUS model known as a Markov chain. This is a mathematical system that will transition one state, (in this case a
state is a particular LU type) to a future state according to past trends. The BAU scenario was used as the baseline for the optimisation, for FOR, PRO, URB, COB, POL and WAT scenarios.

2.5.3. Conservation (FOR) scenario
FOR aimed to improve the wildlife habitat of the area by increasing the forest cover to 25% of the total MRB catchment by the year 2050 (Shrestha et al 2020). Thus the target for the objective function was to obtain an increase in forest area by 5% each 5 year period up till 2050.

2.5.4. Increased urban growth (URB) scenario
Examples of URB are well documented within literature (Liang et al 2018b). A similar methodology is used by Huang et al (2018) where urban expansion is 10% higher than the BAU scenario. Results from this meant that the target for urban extent for 2060 was to reach 12% of the total catchment area. Objectives were set for every 5 year period that urban extent would increase by 10% of the previous time step.

2.5.5. Combination or multi objective (COB) scenario
COB was developed after workshop 2, where the participants’ suggested to combine the URB and FOR scenarios. Consequently, this scenario was multi-objective, having to find a solution that satisfied objectives of increased urban growth and conservation. Thus urban and forest extent by 2060 had the target of reach 12% and 25% of the total catchment respectively.

2.5.6. Productivity (PRO) scenario
PRO scenario was developed after interviews with farmers in workshop 1. The most common crop grown was Paddy rice and though farmers understood that there are alternatives to more water resilient crops there was a reluctance to change traditional farming practices. After questioning it became apparent that this was down to fluctuating crop prices. Where Paddy rice has a set price, crops such as sugar cane, papaya and cassava have a fluctuating price therefore farmers are at a high risk of no profit.

Soil productivity for different Crops varies within the MRB. The East of catchment is productive for rice growing whereas the West is productive for field Crops and fruit trees (figure 4). When compared to the actual LU in 2017, a significant amount of rice is grown in less productive soil regions, unsuitable for rice cultivation. In fact, 45% of the MRB’s soil is more suitable for growing Field Crops & Perennial and Orchards rather than Paddy Fields (figure 4). This scenario demonstrates what the catchment could look like if farmers deferred away from traditional rice farming in favour of Crops more productive and drought resilient. Subsequently, the target for the objective function was for every 5 year interval the total area covered by Field Crops plus Perennial & orchard combined increased by 5% with the aim that by 2060 the area identified by the LDD (figure 4) would be covered by Crops more productive and suitable to soil conditions.

2.5.7. Policy based (POL) scenario
POL scenario was created after comments made at Workshop 2 to reflect spontaneous changes that occur when policy changes. An academic commented:

‘We have dynamic modelling for floods and droughts, why not dynamic modelling for LUC?’
‘Policy hasn’t a 1 km² resolution—how do we model this. Changing policy is a problem.’
Changes in government affect LU policy; a simple methodology was used to try to depict this. A randomisation method was applied to make LU simulations more dynamic by changing the constraints and objectives of the optimisation tool over time. Policy objectives were assigned numbers based on previous scenarios used in the study. Every 5 year period a scenario was randomly generated to represent a change in LU policy, with the objectives and constraints set to the scenario chosen. The interval time for scenario change was 5 years because Local government elections occur every 5 years.

2.5.8. Water-stressed (WAT) scenario
Comments made during the stakeholder meeting revealed that it would be valuable to try and define LU change based on water scarcity.

‘Thailand LU depends on the water available, and changes to LU are down to water stress, this needs to be a control’
‘is drought the availability of water or the use/misuse of water?’

Consequently, four additional drivers that are related to water stress were added: Rainfall, Temperature max, Temperature min and Crop Water Defect. WAT scenario also aims to restore the wetland area of the MRB, to fall in line with the 2018 Water Resources Act and National Water Resources management plan (Chantanumate 2019, Pattanee 2019, Ruangrassamee & Koontanakulvong 2019, Ruangrassamee et al 2019). Objectives meant that Marsh & Swamp area would increase by 0.0025% each 5 year period up till 2050, and by 0.001% from 2050 to 2060. This meant that by 2037 the total Marsh and Swamp area would increase by 1% to cover the target restoration area of watershed/wetlands.

3. Results and discussion

3.1. Agricultural LU
Though LUCs have occurred throughout the study, figures 5 and 6 confirm that the greatest differences in the extent and distribution of future LU was between: COB vs WAT, COB vs PRO, COB vs BAU, COB vs URB and URB vs FOR. Within scenarios where urban growth (URB & COB) and conservation (FOR and COB) took place, the new forest and urban area has largely encroached upon agricultural land (figures 6(b)–(d)). When comparing URB and COB scenarios it is also evident that some previous forest area has transitioned to urban (figures 6(d) and (e)). Whereas, in scenarios where agricultural growth and land productivity was encouraged (PRO scenario) Paddy Fields and Forest area have been significantly replaced by Perennials & Orchards and Field Crops (figures 5 and 6(e)). This is seen to a lesser extent for the BAU scenario (figure 6(a)). When water stress (WAT scenario) was accounted for Marshland has encroached onto areas that were previously covered by Paddy Fields, though paddy field extent within the WAT scenario has remained high (figure 6(g)).

All future scenarios compared to 2017 found a decrease in Paddy Fields replaced by an increase in Field Crops (figure 5). This is observed mainly in the west of the catchment (figure 6). Increases in Perennials & Orchards, has occurred in the center and South East corner (figure 6), this is least significant in the

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Figure 5. % coverage for LU in 2060 for future scenarios.
FOR (figure 6(b)) and COB (figure 6(c)) scenarios. Visual links to DFs would suggest that the increased in Perennial & Orchards was influenced by elevation (figure 3), with Field Crops and Perennials found in higher elevations and Paddy Field in lower elevations. This analysis is supported by LR, which calculated the contribution of each DF on the nine LUs future distribution (figure 7). On the other hand, the contribution of elevation to Paddy Field distribution was negative, i.e. areas of lower elevations, in the east or along the north of the Mun river, would remain Paddy Field (figures 3, 6 and 7). This was the case especially in the PRO scenario (figure 6(e)), where 2060 Paddy Field area was reduced to 30% or 16 258 km$^2$ compared to 43% in 2060 for the BAU scenario and the original 53% that was recorded in 2017 (figure 5).

Fertility, Drainage, and Soil suitability (figure 7) according to LR analysis had little contribution to the distribution and future transition of LU. This suggests that the current LU, especially agriculture, does not take these factors into account, especially when
it comes down to choosing a more productive Crop, which is an argument that can be speculated from interviews with farmers.

Comments made during the first workshop:

'people are using land for the wrong practice'

'We are reluctant to change crops as prices increase and then decrease… there is a guaranteed market for paddy rice and not others…. it is a big risk for us to change crops, some crops take a long time to establish, we can't afford to have years with no food or income'
Figure 6. (Continued.)

'We have three main problems: Transportation costs, fluctuating crop price and Unevenness of rainfall'

Arguably, Crop choice is driven by external factors like policy, economics or social development, i.e. the need for certain Crop type and a livelihood, not what would be productive. For example, in figure 7 no agricultural LU is driven by soil suitability and in fact there is an increasingly negative association with suitability in future years compared to 2017; this is most significant for Paddy Fields. This highlights that Paddy Fields are situated in locations that are increasingly not suitable to be agriculturally productive (figures 4 and 6).

A positive association was found between Paddy Fields and soil fertility, with future extent remaining in areas of increased fertility alongside the river, areas known for their poor drainage, and water logged environments (figures 3 and 7). This increased capacity to hold water and thus nutrients create prime growing conditions for Paddy Fields (Abd-Elmabod et al 2017). Essentially, these results find that drainage and soil type directly drive soil fertility within the MRB, thus indirectly LUC. This analysis concurs analysis for fertility (figure 7) that future Paddy Field LU distribution was associated with areas of a higher fertility, areas of poor drainage (figures 3 and 6). The future distribution of Perennial and Orchard was found in areas of fair-moderate drainage, in the SE and centre, areas of a lower fertility 3 and 6), with future Field Crops found in the remaining areas.

3.2. Climatic drivers
In the WAT scenario, Paddy Fields were positively driven by rainfall and temperature (figure 8), with Paddy Fields found in the west of the catchment where lower minimum temperatures (figures 6 and 8) and increased annual rainfall were observed (figure 8). These results concurred with the simulated results (figure 6).
Figure 7. Logistic regression analysis for; elevation (top left), soil fertility (top right), soil suitability (bottom left) and drainage (bottom right).

Figure 8. Logistic regression analysis for additional climate drivers for different LU types. Followed by annual averaged minimum and maximum temperature for the MRB 1973–2015 and annual averaged rainfall (mm) for the MRB 1973–2015.
Field Crops were positively driven by maximum temperature, and negatively by rainfall (figure 8). The lowest annual rainfall and highest temperatures were spatially observed in the west of the catchment, primarily an area where increases in Field Crops were observed (figure 6). This implies that Field Crops are potentially more drought resistant compared to Paddy Fields, because they are driven by a climate that is less wet and hotter.

LR analysis found that Perennial & Orchard transition was driven by rainfall, with future distributions more negatively driven by maximum temperature than in 2017 (figure 8). Perennial & Orchard distribution was increasingly observed in the southeast and centre of the catchment, an area of increased rainfall and lower max temperatures (figures 6 and 8). Inferring that Perennial & Orchard Crop types are less drought tolerant than Field Crops, but more drought tolerant than Paddy Fields. This inference was reinforced by the opinions of stakeholders who ranked agricultural crops in terms of their risk to drought (figure 9).

4. Conclusions

Through PP and the contributions of local stakeholders and academics, seven plausible future LU transitions for the MRB were created via the FLUS model and an optimization tool. These contributions added invaluable detail to scenarios created, as well as providing additional analysis. Findings from this research will be used to propose suitable LUC scenarios and possible policy recommendations to the Thailand Government and local stakeholders to help with effective water resources management. Steps within the study were also made in trying to create a more interchangeable/dynamic way of modeling LUC. Arguably, future study needs to investigate and build on the idea of dynamic LUC modelling through PP.

Overall, in the future, Paddy Field extent was replaced in favor of other LUs such as Field Crops and Perennial & Orchards, with the greatest similarity observed between BAU and PRO scenarios. The COB scenario proved to be the most divergent, attributed to the two objectives that needed to be met.

Secondly, an investigation of the influence of DFs on LU transition and distribution took place. Outcomes propose that agricultural LU was mainly driven by Elevation instead of soil related drivers (Fertility, Drainage, Soil type). The additional climate drivers in the WAT scenario inferred that Paddy Fields are at a greater risk from drought than other LU such as Field Crops and Perennials and Orchards. Arguably, though LU is driven by environmental constraints interviews with stakeholders, infer that LU in terms of agricultural choice is driven instead by external factors like policy or social-economic development. In conclusion, PP in LUC research adds invaluable detail to research directions, where outcomes are tailored to the practical needs of the public, and should be included throughout the field of research.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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