Supplemental Material

S1. Dyna-CLUE Baseline Calibration and Validation

S1.1. Location Characteristics

The model baseline simulations build on the TREND scenario computations referring to the LUC assessment period 1998 to 2008. Dyna-CLUE simulates LUC at locations with the highest 'preference' for a specific land-use type and year. The model quantifies the relation between land-use type occurrence, and the physical or socio-economic conditions of a location with a probability function derived from a logistic regression analysis [1,2]:

$$Logit(p_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{S1}$$

with p_i denoting the probability per grid cell to have the selected land-use type i, X the vector of LUC driving factors, and coefficients β estimated using the actual land-use pattern as dependent variable. The resulting *logit* model indicates the preference of land-use type i based on the relationship of its occurrence, and the biophysical and socio-economic conditions per grid cell. The relative operating characteristic coefficient (*ROC*) is used to evaluate the goodness-of-fit, comparing the observed values over the whole domain of predicted probabilities, instead of evaluating the percentage of correct observations at a fixed cut-off value only [1]. The effect of spatial autocorrelation is minimised by performing the regression on a random sample of pixels at a minimum distance to each other [2]. A completely random *logit* model would result in a ROC ≤ 0.5 while a value of >0.7 is preferable. A perfect model fit is received at $ROC=1$ [3].

The physical location factors representing potential limitations for agricultural production in MSMW included elevation, altitude, local soil types (Acrisol, Cambisol, Umbrisol), and distance-to-streams. The latter one was chosen as proxy for the availability of irrigation water during dry seasons. Socio-economic factors included distance-to-village as proxy of local consumption, while distance-to-road was selected as proxy for the costs to transport agricultural commodities to nearby markets. Elevation and slope maps were computed from a digital elevation model, whereas the distance-to-road and -stream map was derived from a base map of the Land Development Department, Thailand (Scale 1:50,000; reference year 1999). A local soil map was obtained from [4]. Adjusting all maps to the required spatial scale and conversion into raster format was done in ArcGIS 10. Regression coefficients (Eq. S1) were computed by converting all maps mentioned above (Fig. S1) and the land-use map 2008 into ASCII format. SPSS 21 was used for the statistical analysis of each land-use type's presence or absence in correspondence to its location factors, using land-use 2008 as dependent variable. The receiving regression coefficients (Table S1) were then used as inputs to Dyna-CLUE.

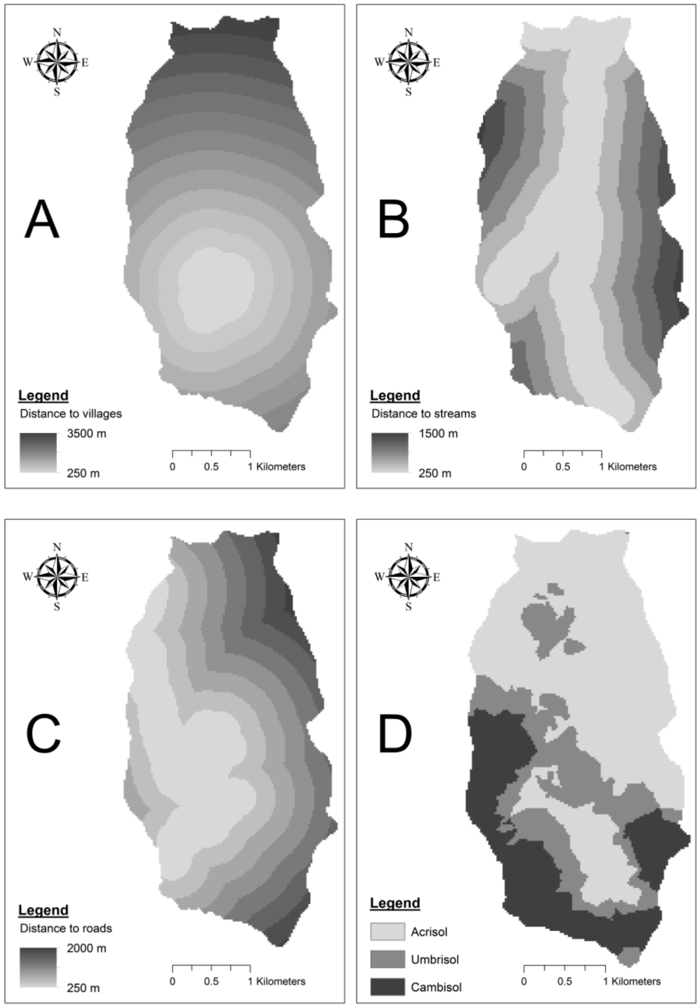

Figure S1. Dyna-CLUE input maps: (**S1A**) distance to village, (**S1B**) distance to streams, (**S1C**) distance to roads, and (**S1D**) soil types.

Table S1. β regression coefficients of significant location factors related to LUC using land-use map 2008 as dependent variable.

Variable	Secondary forests	Orchard	Vegetable	Urban	Field crops	Fallow
Distance-to-river	0.00022	n.s.	0.00108	0.00372	−0.00048	n.s.
Distance-to-road	0.00166	−0.00099	−0.00321	−0.04871	−0.00152	−0.00142
Distance-to-village	0.00062	−0.00138	−0.04768	−0.05371	−0.00270	0.00024
Elevation	0.00462	−0.01068	n.s.	n.s.	−0.04369	0.00274
Slope	0.05177	−0.03417	n.s.	n.s.	2.09721	n.s.
Soil 1[a]	−3.98030	n.s.	n.s.	n.s.	n.s.	1.85886
Soil 2[a]	−1.55347	−19.13110	n.s.	n.s.	n.s.	0.98312
Soil 3[a]	−0.75410	−19.70689	n.s.	n.s.	n.s.	n.s.
Constant	−2.48426	72.54214	0.92435	6.96827	0.42124	−7.10217
ROC[b]	0.82	0.85	0.74	0.98	0.75	0.75

Note: n.s., not significant at $p>0.05$; [a] Categorical variable: Soil 1-Acrisol, Soil 2-Cambisol, Soil 3-Umbrisol; [b] Relative operational characteristic, with 1 indicating a perfect fit

S1.2. Conversion Matrix and Land-use Elasticity

Land-use policies can influence the patterns of LUC and are reflected in Dyna-CLUE by a conversion matrix, with the rows representing land-use type *i* at time step t and the columns indicating land-use type *i* at time step (*t*+1). Each land-use type is assigned a relative elasticity to conversion, ranging from 0 (easy conversion) to 1 (irreversible change) [1]. Elasticity can be explained as the resistance of a specific land-use type to change its location. Elasticities are implemented in Dyna-CLUE as additional location suitability to assign a large influence to land-use history [5]. Following [6], a conversion elasticity of 1 was set to secondary forest and urbanized areas, given their low likelihood to be converted. An elasticity value of 0.5 was given to orchards, whereas fallow, field crops and vegetables were set to 0.2 given their higher likelihood of conversion as a result of the agricultural dynamics in MSMW.

S1.3. Land Use Allocation

Dyna-CLUE calculates for each year the most likely changes in land use based on the total probability per land-use type, grid cell and time step as the total probability of land use type *i* and grid cell [1]:

$$TROP_i = p_i + ELAS_i + ITER_i \tag{S2}$$

with $TROP_i$ the total probability of land use type *i*, p_i calculated in Eq. S2, $ELAS_i$ the conversion elasticity per land use type *i*, and $ITER_i$ an iteration variable that is specific for each land use type *i*, indicating its relative competitive strength. During an annual time step, Dyna-CLUE makes a preliminary allocation for all land use types with an equal value of *ITER* to allocate land use type *i* with the highest total probability to the considered grid cell. LUC trajectories that are not allowed by the conversion matrix or spatial restrictions, i.e. natural forest reserves are excluded. As next step, the allocated area for each land use type *i* is compared with its actual land use demand. If allocated area is smaller than its area demand, the value of $ITER_i$ will be increased, else $ITER_i$ will be decreased since too much land has been allocated to land use type *i*. The above steps are repeated until allocation of land use area equals annual land use demand [1].

S2. Calculation of Time-averaged Above-ground Carbon Stocks

Comparing above-ground carbon (AGC) sequestration potentials of land use systems with different rotation times requires the estimation of the average AGC stored in the system over its entire rotation time, referred to as 'time-averaged AGC stock' (AGC_{TA}) [7]. For systems that are increasing or decreasing in area, the spatial average will be lower or higher than the time-averaged AGC value. The advantage of time-averaged AGC stock data is that it takes into account the dynamics of the system itself, e.g. tree regrowth and wood harvesting and allows for a comparison of land use systems that have different growth and harvesting rotation times.

Four parameters are required to calculate a land use type-specific AGC_{TA} stock (i) the annual AGC increment rate AGC_{INC} (Mg ha^{-1} a^{-1}), (ii) the maximum AGC (AGC_{MAX}, in Mg ha^{-1}) stored in the land use system during its rotation period, (iii) the rotation time T_{MAX} (years) to reach AGC_{MAX}, and (iv) the rotation length per land use system T_R (years) (Figure S2). The calculation of AGC_{TA} differs between a crop- and a tree-based land use system. In case of tree-based systems, AGC_{MAX} is reached at the end of the establishment phase (T_{MAX}) after for example, fruit production would still continue during the production phase, although without a further build-up of AGC (Figure S2-A). In this case, AGC_{TA} is determined as the weighted average of the AGC_{TA} stock of tree establishment and tree production phase, with T_R extending the total land use rotation period [8]. This differs for long crop-fallow rotations, such as swiddening or short seasonal crop-fallow systems, usually found for field crops or vegetables production (Figure S2-B). Here, AGC is essentially the carbon stored in the fallow vegetation between crop harvest and plot clearing.

S3. Field Measurements and Literature References to Calculate Time-averaged Above-ground Carbon Stocks

Field measurements were conducted for the two most prominent agricultural land use systems in MSMW, namely 'orchards' and 'vegetables'. Given the variety of related cropping systems, *Litchi chinensis* (orchards) and *Brassica* spp. (vegetables) were chosen as specific benchmark crops. Crop selection followed their economic importance in MSMW [1] and their spatial occurrence in 2008. In case of *Litchi chinensis*, plot selection followed a stratified sampling design using all litchi farmers in MSMW (n=112 in 2008) as first strata. As next step, sixty households in MSMW (55 % of watershed) were randomly selected and interviewed for information on individual orchard planting density, and related management activities. Orchard location was identified during interviews with the cadastre map 2005. Based on this second strata, two orchards per identified age class (13, 17, 24 and 32 years) (Figure 1) were randomly selected, and four sub-plots of 20 m × 20 m per orchard demarcated (n=32). Within a sub-plot, diameter of trunk at breast height D (m) and tree height h (m) of all included trees was measured. Tree height h was determined from ground to the tip of crown using a pole of known length, and D was measured with a tape. Due to the absence of a Litchi-specific allometric equation, AGC (kg) per tree was computed using a formula of [9] for seasonal tropical forest stands and rainfall regimes of <1500 m year^{-1}:

$$\mathrm{AGC} = \left(0.112\left(0.59\,\mathrm{D}^{2}\mathrm{H}^{0.916}\right)\right)0.5 \tag{S3}$$

with AGC the above ground carbon content (kg), 0.59 the wood specific density (g cm^{-3}) of *Litchi chinensis* in MSMW [10], and 0.5 as conversion coefficient for biomass-to-carbon [11]

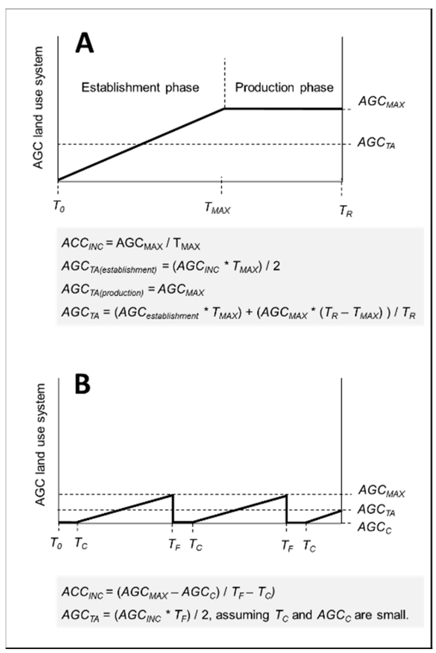

Figure S2. Schematic diagram of the build-up in above-ground carbon (AGC) stocks (bold line) and variables to calculate AGC_{INC} the annual AGC stock increment; with (S2A) tree-based land use system, and (S2B) crop-fallow rotation system; with AGC_{C} – above ground carbon stock remaining in cropping system after harvest, AGC_{MAX} - maximum AGC stock per land use type; AGC_{TA} - time-averaged above ground carbon stock per land use type, T_0 - time at start of land use rotation, T_{MAX} - time to reach maximum AGC stock during tree establishment phase, T_C - length of cropping period, T_F - length of fallow stage, T_R - land use rotation time [adapted from: 3, 8].

In contrast to literature recommendations [7], deadwood and under-storey vegetation in case of orchards were not measured in this study given the frequent application of herbicides, the burning of ground litter by orchard farmers once or twice a year, and the collection of deadwood and branches by local villagers as firewood source.

In case of *Brassica* spp., five farmer-managed plots were selected to determine AGC contents (Figure 1). Prior the beginning of annual field preparation in April 2008 and May 2009, destructive samples were collected from ten randomly selected 1 m^2 sub-plots per farmer plot and weighed to determine fresh biomass (kg) (n=100). Per sub-plot, a 1000 gram composite sub-sample was taken and oven-dried at 70° C for at least 48 hours until weight changes did not occur anymore. AGC per farmer plot was calculated on a hectare basis using the biomass-to-carbon conversion coefficient 0.5 [11].

Literature references were used to derive AGC input datasets for the remaining land use types, namely fallow, field crops, and secondary forests. In case of fallow and field crops, this was done because of the overall small in total land use area, and for secondary forests because of local restrictions to conduct surveys in the forest conservation areas. *Zea mays* was chosen as benchmark field crop given to its local importance as feed stock source. In case of field crop systems, literature references were selected for comparable study sites in North-eastern and Northern Thailand, with the considered AGC stock referring only to those AGC stocks remaining on the field after crop harvest [8]. In case of secondary forests, only those references were selected which comprised the above ground biomass strata: trees, deadwood and under-storey vegetation as recommended by [7].

References

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