

Supplementary Information

S1. Model Preparation

The land cover model is used to understand the transition types, for the identified land cover types, land cover fragmentation and which transitions occur in specific areas of the area of interest; *i.e.*, transitions which occur on the peat soil and transitions in protected forest areas. The categories used in this model are the seven of the original thirteen categories which occur in the area of interest reclassified to a contiguous number range, Table S1. The absence of the Oil Palm Plantation land cover category in the original model creates an issue as this will result in the model projects over estimating the overall growth of this land cover type. The classification of this land cover type in the 2010 land cover map is also an issue as the oil palm areas were identified by secondary classification of Plantation/Regrowth areas using ALOS radar images and only identified closed canopy oil palm plantations [1]. Koh *et al.* [1] estimate that these plantations must have been establish in 2002 at the latest meaning that significant oil palm plantations must have existed in the study area in 2000. Without accurate mapping of oil palm plantations in either 2000 or 2010 it was decided that this category could not be used for modeling purposes. The Oil Palm Plantation land cover category was classified as Plantation/Regrowth in the study.

Table S1. Land cover classification showing original source map land cover category, categories present in the study area with reclassification into 6 categories.

Original Category	Name	Comment	Area of Interest
1	Water		-
2	Mangrove		1
3	Peat Swamp Forest		2
4	Lowland Forest	<750 m above sea level	3
5	Lower Montane Forest	Between 750 and 1500 m above sea level	-
6	Upper Montane Forest	>1500 m above sea level	-
7	Plantation/Regrowth		4
8	Lowland Mosaic	<750 m above sea level	5
9	Montane Mosaic	>750 m above sea level	-
10	Lowland Open	<750 m above sea level	6
11	Montane Open	>750 m above sea level	-
12	Urban		-
13	Oil Palm Plantation	Large scale	4

Creation of a Dinamica EGO model requires a number of steps which have been undertaken independently but most of which could be amalgamated into a single model [2]:

1. Reclassification of the Land Cover images
2. Creation of Transition Matrices for the transition from initial to final land cover categorisation.
3. Understanding what land cover transitions have occurred and the mean land cover patch size, in hectares, and patch size variance for each individual land cover transition.
4. Assembling the ‘static’ weights of evidence factors into a ‘map cube’ [2]. These are the factors which do not change as the model runs; e.g., distance from rivers, soil type *etc.*

5. Calculating the Weight of Evidence Ranges for both static and dynamic weights of evidence factors. Dynamic weights-of-evidence factors change as the land cover changes and need to be recalculated for each new land cover map generated; e.g., distance from a nominated land cover type.
6. Calculation the Weights of Evidence coefficients for static and dynamic factors.
7. Determination of Weight of Evidence correlations. Use of weights of evidence requires that each of these factors is independent.
8. Preparation of a validation model from initial land cover image. This is to allow validation of the predicted model changes against the actual changes as shown in the final land cover image.
9. Validation of the model by comparison of the simulated changes from original land cover with the final land cover and modification and ‘tuning’ of the model.
10. Creation of a model from the final land cover image to predict future land cover changes.

S1.2. Reclassification of the Land Cover Images

Categorical map reclassification is easily achieved using Dinamica EGO. Reclassification is performed for both original and final land cover maps, Figure S1. Classifications were performed to reclassify the original land cover categories using simple code, Table S2.

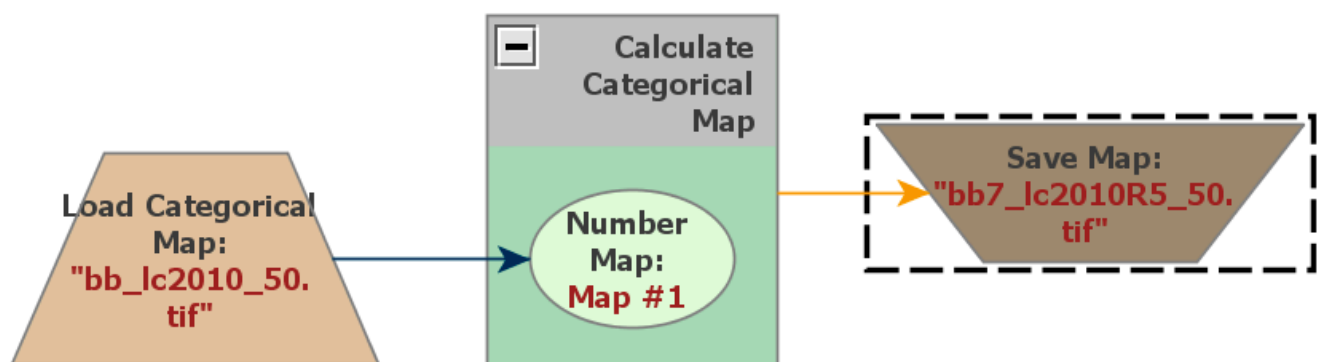


Figure S1. Land Cover Map reclassification.

Table S2. Land cover reclassification. ('i1' refers to the input map).

if i1 = 0 then
null
else if i1 = 1 then
null
else if i1 = 2 then
1
else if i1 = 3 then
2
else if i1 = 4 then
3
else if i1 = 7 then
4
else if i1 = 8 then
5
else if i1 = 10 then
6
else if i1 = 13 then
4
else
null

S1.3. Creation of Transition Matrices

Two transition matrices are produced, a single step matrix which treats the change from initial to final land cover as a single step and a multi-step matrix which calculates the changes per step for the number of steps specified by the user. In these models with a 10 year period between the initial and final land cover images 10 annual steps were chosen as an appropriate number of steps. This allows future simulations to be undertaken using yearly steps. It would be equally valid to specify 2 steps of 5 year each if the model was required to only provide land cover change outputs at 5 year intervals.

The original land cover transitions from 2000 until 2010 showed small areas of land cover transitions between Peat Swamp and Lowland forest. As the nature of these forests is dependent upon the nature of the soil it has been assumed that these transitions result from classification differences in the 2000 and 2010 land cover maps. As a result it was decided that the land cover categories in the 2010 map would be assumed as correct and reclassification was undertaken for this correction prior to determination of the transition matrices.

Dinamica provides tools for creation of single and multi-step transition rate matrices, Figure S2. The single step matrix is for the entire period between the original and final land cover map while the multi-step matrix is based upon the individual steps included in the land cover period, 10 steps, one for each year in this model, Table S3. The multi-step matrix showed transitions which would be classed as "impossible" so the permitted transitions and the associated transition values were modified. Transitions from 2000–2010 where transitions occurred between Peat Swamp and Lowland forest, were considered as classification errors in the original land cover maps and these were corrected. The correction assumes that the 2010 map showed the correct classification. There were other transitions where open or mosaic

areas transition directly to forest land cover types in a single year. These transition types were removed from the matrix and adjustments were made to the remaining transition rates. This was achieved by trial and error with using 10 steps from the 2000 until the output was less than 0.1% different from that in the observed 2010 land cover map. No individual land cover category was more than 0.7% different from the observed 2010 value.

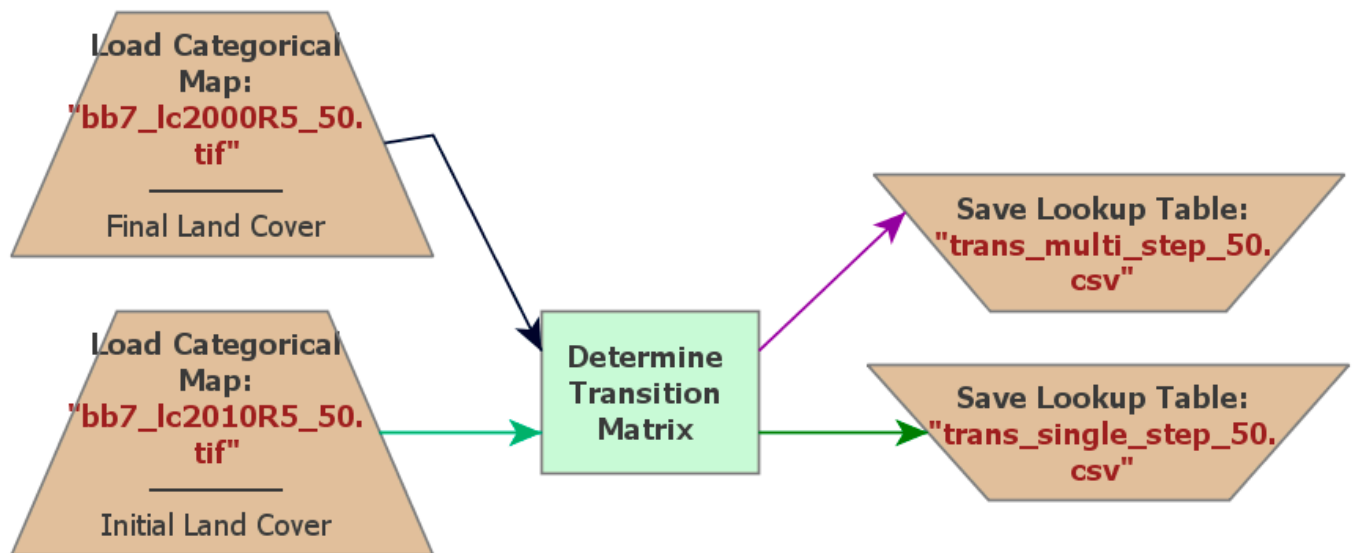


Figure S2. Create Transition Matrices.

Table S3. Single and Multiple transition matrices. Each transition shows: from category, left of the '!'; to category, right of the '!' in the Transition column and a transition rate. The multi-step case is 10 steps. And has been modified so that only transitions naturally expected will be included in the modelling. Shaded cells show multi-step transition excluded.

Transition	Single Step	Multi-Step (10 Steps)	
	Rate	Rate (Generated)	Rate (Modified)
1.004	0.218731118	0.03262484	0.0198
1.006	0.090634441	0.012917667	0.001002
2.004	0.105310147	0.009236003	0.00898
2.005	0.05530922	0.010740989	0.010740989
2.006	0.03369668	0.001949654	0.00187
3.004	0.174083662	0.019952488	0.01866
3.005	0.054452113	0.009244169	0.009022
3.006	0.032045142	0.001575287	0.001093
4.001	0.002116238	0.000281622	0.000281622
4.002	0.040865293	0.005463579	0.005463579
4.003	0.034954421	0.004757904	0.004757904
4.005	0.126991818	0.032646272	0.032646272
4.006	0.095624787	0.007964465	0.00767
5.001	0.001343436		
5.002	0.012579446		
5.003	0.011968793		
5.004	0.522352332	0.131014898	0.130015
5.006	0.245628948	0.059184639	0.05355
6.001	0.00325389	0.000443837	
6.002	0.038685139	0.004731749	
6.003	0.060739284	0.008207357	
6.004	0.206397871	0.024891312	0.028
6.005	0.064774108	0.011593562	0.011593562

S1.4. Transitions which have occurred

To determine which transitions occur Dinamica EGO is used to compare original and final land cover maps, Figure S3, using the initial and final land cover maps as input and producing an output map showing each transition occurring as a separate category, Figure S4. The map is controlled by a small code segment within Calculate Categorical Map which assigns a new category based upon the initial and final land cover type, Table S4. If either the initial or final land cover type is 'null' or no change has occurred then the output is set to 'null'. If a change in land cover category is identified then a new category with the first digit set as the initial land cover type and the second digit is set to the final land cover type; e.g., a transition from category 1(mangrove), to category 6 will become category 16 (lowland open).

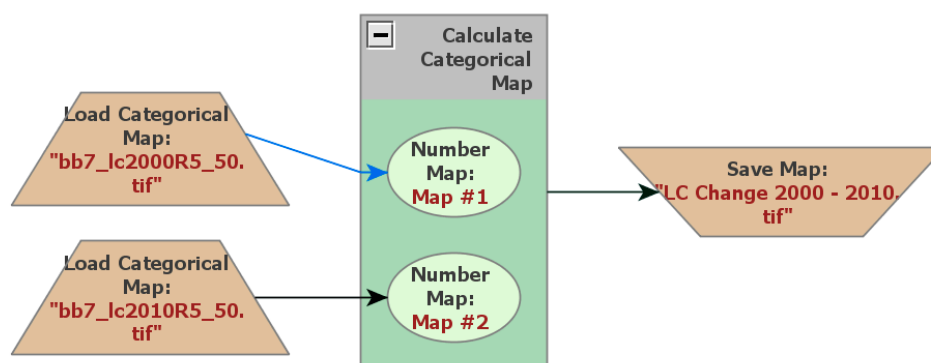


Figure S3. Determine Land Cover Transitions.

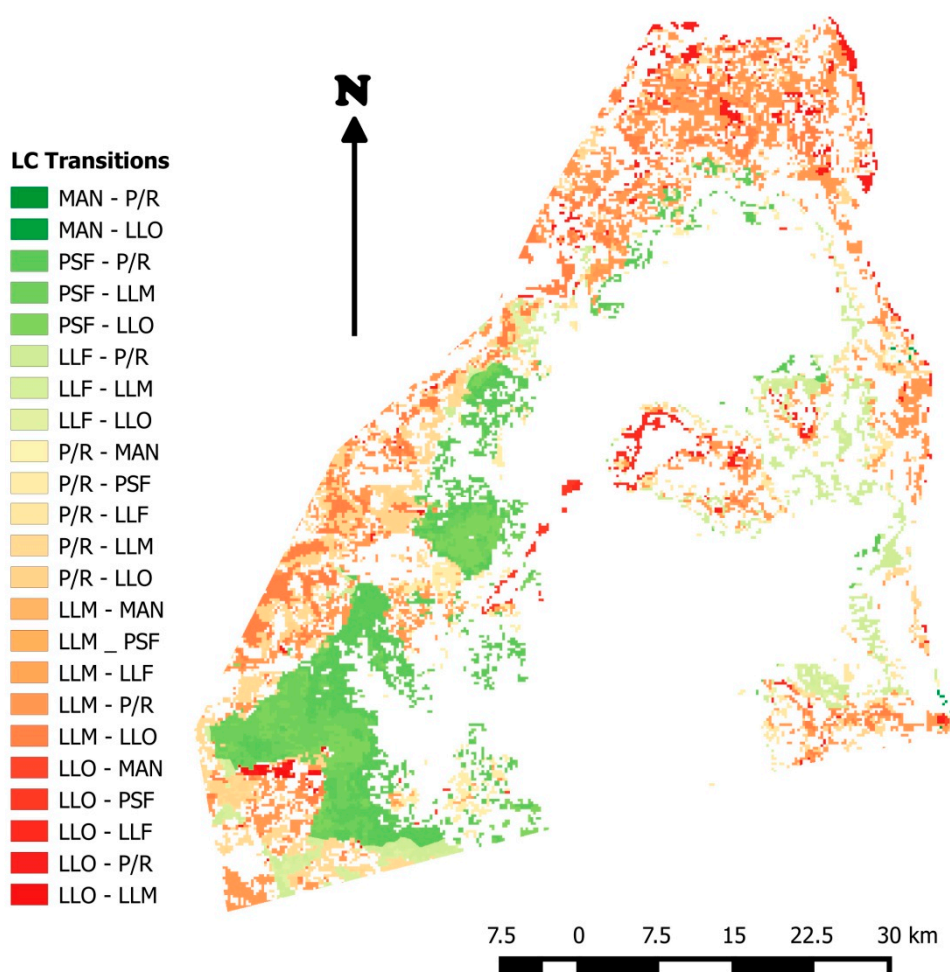


Figure S4. Three category land cover transition map, 2000–2010. (MAN—Mangrove, PSF—Peat Swamp Forest, LLF—Lowland Forest, P/R—Plantation/Regrowth, LLM—Lowland Mosaic, LLO—Lowland Open).

Table S4. Code to determine which transitions have occurred -. i1 and i2 refer to initial land cover and final land cover input maps respectively.

if isNull(i1) or isNull(i2) then	else if i1 = 4 and i2 = 1 then
null	41
else if i1 = 1 and i2 = 2 then	else if i1 = 4 and i2 = 2 then
12	42
else if i1 = 1 and i2 = 3 then	else if i1 = 4 and i2 = 3 then
13	43
else if i1 = 1 and i2 = 4 then	else if i1 = 4 and i2 = 5 then
14	45
else if i1 = 1 and i2 = 5 then	else if i1 = 4 and i2 = 6 then
15	46
else if i1 = 1 and i2 = 6 then	else if i1 = 5 and i2 = 1 then
16	51
else if i1 = 2 and i2 = 1 then	else if i1 = 5 and i2 = 2 then
21	52
else if i1 = 2 and i2 = 3 then	else if i1 = 5 and i2 = 3 then
23	53
else if i1 = 2 and i2 = 4 then	else if i1 = 5 and i2 = 4 then
24	54
else if i1 = 2 and i2 = 5 then	else if i1 = 5 and i2 = 6 then
25	56
else if i1 = 2 and i2 = 6 then	else if i1 = 6 and i2 = 1 then
26	61
else if i1 = 3 and i2 = 1 then	else if i1 = 6 and i2 = 2 then
31	62
else if i1 = 3 and i2 = 2 then	else if i1 = 6 and i2 = 3 then
32	63
else if i1 = 3 and i2 = 4 then	else if i1 = 6 and i2 = 4 then
34	64
else if i1 = 3 and i2 = 5 then	else if i1 = 6 and i2 = 5 then
35	65
else if i1 = 3 and i2 = 6 then	else
36	null

Table S5. Transitions from 2000–2010 showing total area, mean are per fragment and standard deviation. (MAN—Mangeove, PSF—Peat Swamp Forest, LLF—Lowland Forest, P/R—Plantation/Regrowth, LLM—Lowland Mosaic, LLO—Lowland Open)

Transition	Total Area /ha	Mean Patch Area /ha	Area StdDev
MAN-P/R	90.5	12.9286	8.8758
MAN-LLO	37.5	12.5	5.1031
PSF-P/R	18460	91.8408	444.637
PSF-LLM	9695.25	86.5647	487.1988
PSF-LLO	5906.75	67.8937	214.7095
LLF-P/R	7951.75	45.6997	92.0909
LLF-LLM	2487.25	40.7746	61.9989
LLF-LLO	1463.75	22.178	32.3954
P/R-MAN	181.25	18.125	10.625
P/R-PSF	3500	33.0189	68.1186
P/R-LLF	2993.75	23.7599	33.2963
P/R-LLM	10,876.5	32.0841	66.1781
P/R-LLO	8190	34.2678	78.5251
LLM-MAN	68.75	9.8214	6.5611
LLM-PSF	643.75	20.7661	17.9175
LLM-LLF	612.5	18.0147	27.5269
LLM-P/R	26,731.25	59.9355	241.0236
LLM-LLO	12,570	49.6838	103.2789
LLO-MAN	56.25	18.75	8.8388
LLO-PSF	668.75	35.1974	32.9605
LLO-LLF	1050	45.6522	112.3857
LLO-P/R	3568	23.9463	37.2233
LLO-LLM	1119.75	18.3566	21.8962

The output map is analysed with FRAGSTATS [3], to output the transitions which have occurred, Table S5. Some of the transitions cannot have occurred in a single year (step), e.g., from Lowland Open (Class 6) to Peat Swamp Forest (Class 2), but will have involved more than one transition over the 10 year period.

In addition to identifying the transitions which have occurred, the mean fragment area and standard deviation for each transition are collected as these are required later in the model preparation.

S1.5. Assembling ‘static’ Weights of Evidence

Some of the factors which impact the land cover change do not change during the period of the model. The factors which have been identified as static are:

- distance from rivers
- distance from roads
- distance from coast
- protected forests areas
- timber concession areas

- peat soil/mineral soil
- fire kernel density

To simplify handling of these factors Dinamica EGO allows the raster maps of these factors to be placed in a 'map cube' [2] for simplified handling. Dinamica EGO provides capability for easy creation of the map cube, Figure S5. For each of the factors which involve distance from the feature it is necessary to calculate this distance as input to the cube map creation. The output cube map contains all layers specified as input, Figure S6 and Figure S7.

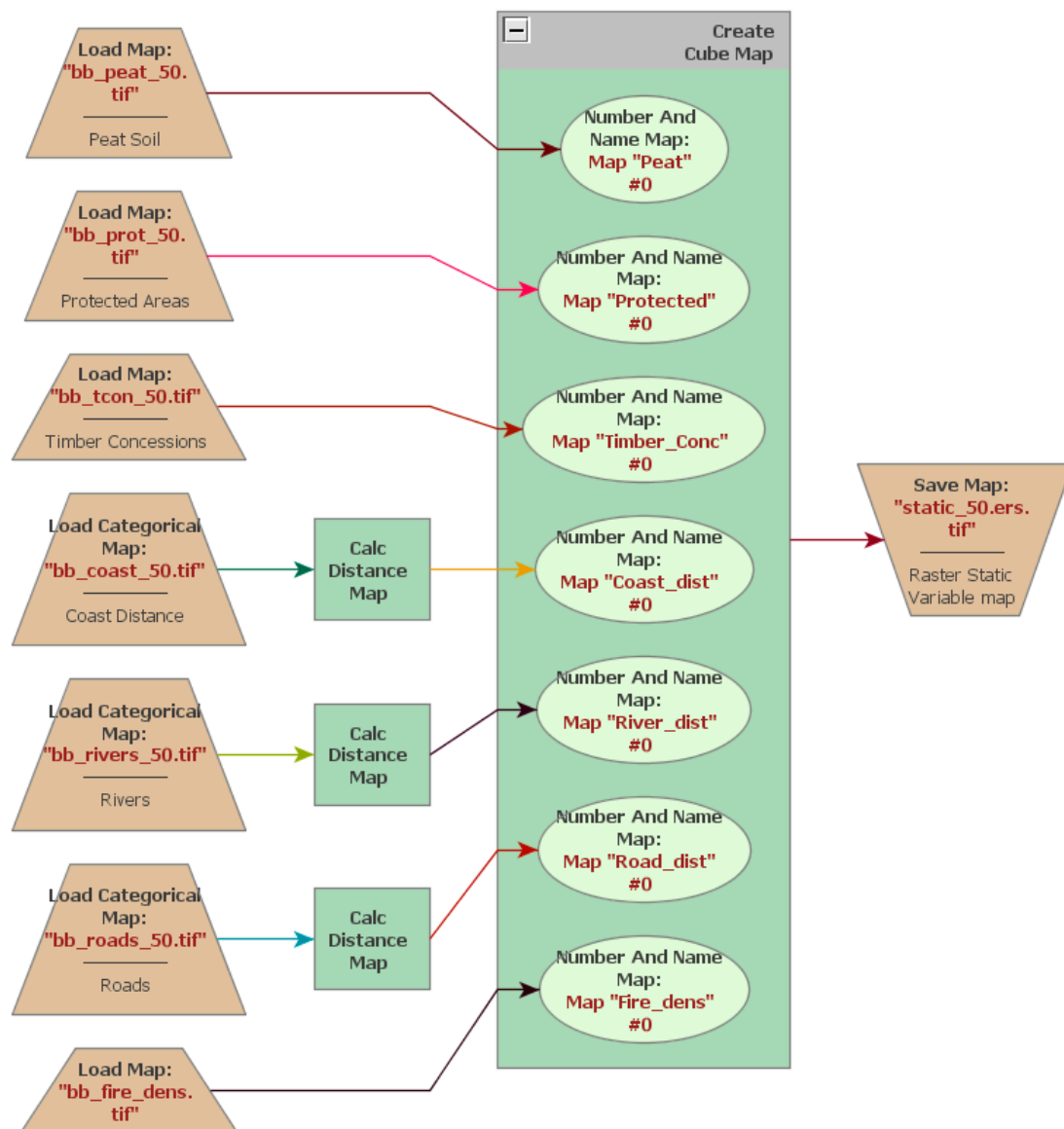


Figure S5. Create 'static' factors cube map.

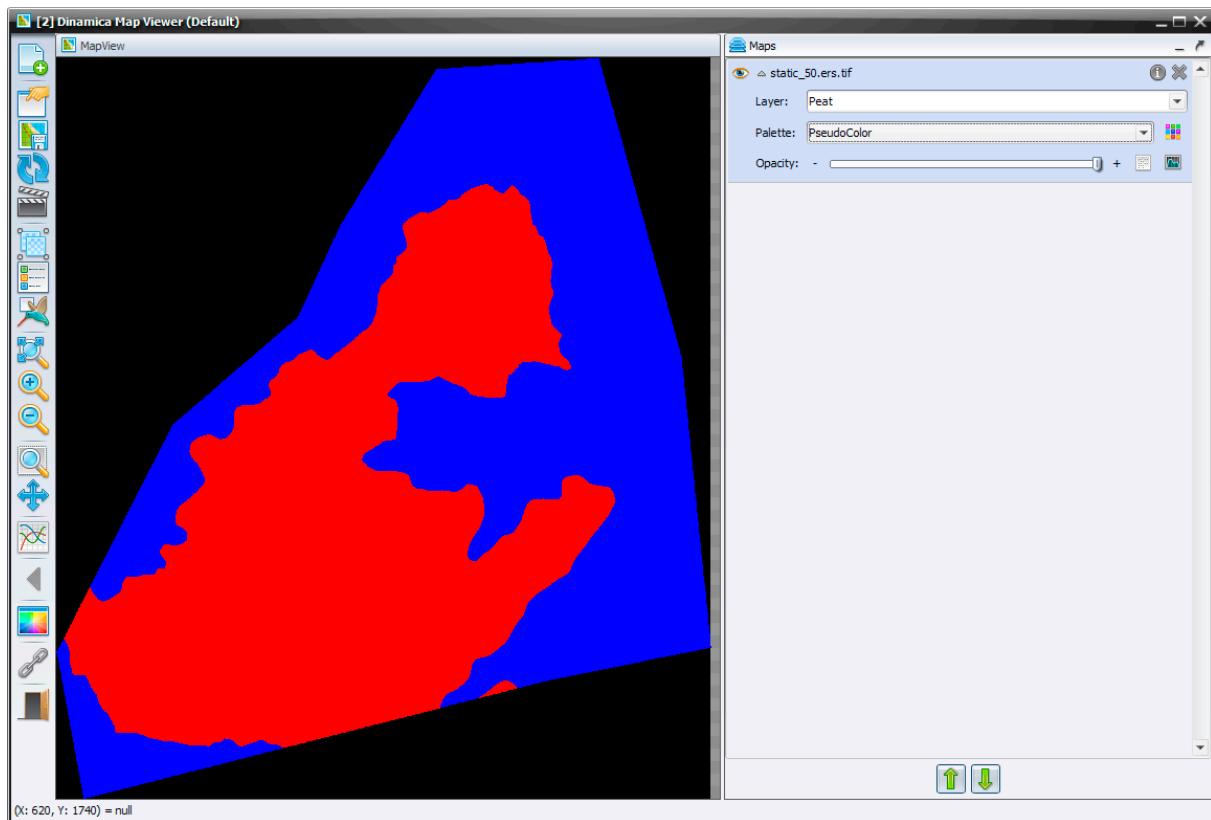


Figure S6. Static factor cube map showing map layers – Dinamica EGO Map Viewer. Layer shown soil type, peat (red)/mineral soil (blue).

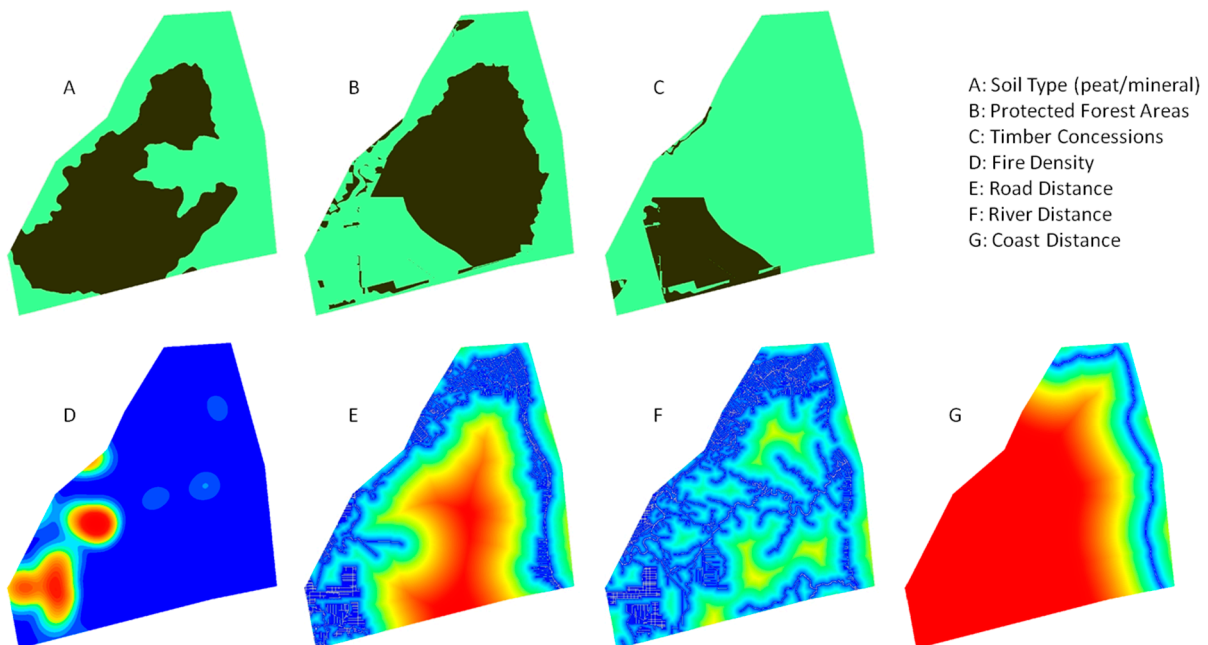


Figure S7. Static factors cube map layers: For A, B & C the dark areas show peat soil, protected forest and timer concessions respectively. For D, E, F & G low values are shown in blue with high values in red, i.e. low fire density or short distances are blue with high fire density or larger distances in red.

S3.5. Calculating the Weight of Evidence Ranges

Dinamica EGO uses categorical maps for all calculations [2]. For non-categorical maps, e.g., distance maps and fire density, ranges are calculated for which new coefficients are determined as impacts for each land cover transition.

For categorical maps, e.g., peat soil map, the range is simply the different categories specified in the input map and the coefficients are based upon the map categories.

The calculation is made for the static factors described above and the dynamic factors which will change as the model is run. Dynamic factor include items such as distance from specific vegetation types which will change as the land cover changes when the model is run.

For each transition it is necessary to identify parameters for each factor, Figure S8, file and layer name, if categorical or not, and if not categorical the increment to be used when calculating ranges, the maximum and minimum delta for the output and the graph angle change to be used to identify ranges. In developing the model for the distance maps the increment is set to the pixel resolution of the map and the angle to 5 degrees with the minimum and maximum delta set to a large value, 500,000 in the model. Fire density has values in the range 1–24.75 with the increment set to 1, minimum and maximum delta as 1 and 20 respectively and the angle at 5 degrees. The same parameter values are used for each transition.

Variable

Map Identifier: Layer Name:

☐ Categorical

☒ Non-Categorical

Increment: Maximum Delta:

Minimum Delta: Tolerance Angle:

Figure S8. Weights of Evidence parameters.

Calculation of the dynamic weights of evidence factors, Figure S9, produces a file containing the calculated ranges for each factor for each transition. This file is used as input for determining the Weight of Evidence Coefficients. Some factors will not produce any ranges. This always occurs when you are using a factor which is a distance from the initial land cover type of a transition but also may occur if it is determined that the factor has not impact on the particular transition. The weights of evidence ranges produced are edited so that the transitions included are the same as those included in the multi-step transition matrix, The Weights of Evidence Coefficients are used in the land cover transition model to create the probability maps which determine where land cover transitions may occur.

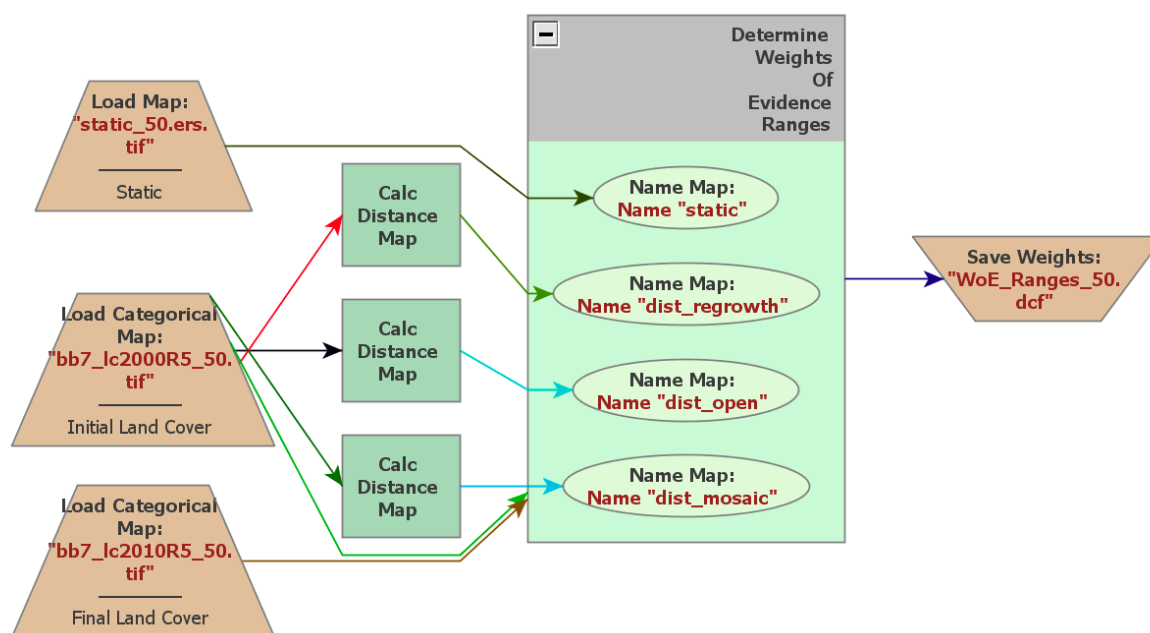


Figure S9. Determining Weight of Evidence Ranges.

S1.6. Calculation the Weights of Evidence Coefficients

The Weights of Evidence coefficients specify the weights to be placed on each range based upon the original and final maps dynamic and static factors and the calculated Weights of Evidence ranges, Figure S10. The output can be viewed as graphical output, Figure S11. The specific example shown, Figure S11, indicates that the transition from peat swamp forest to regrowth is positively correlated when the rivers are close and negatively correlated when the rivers are more distant with greater negative correlation at greater distances.

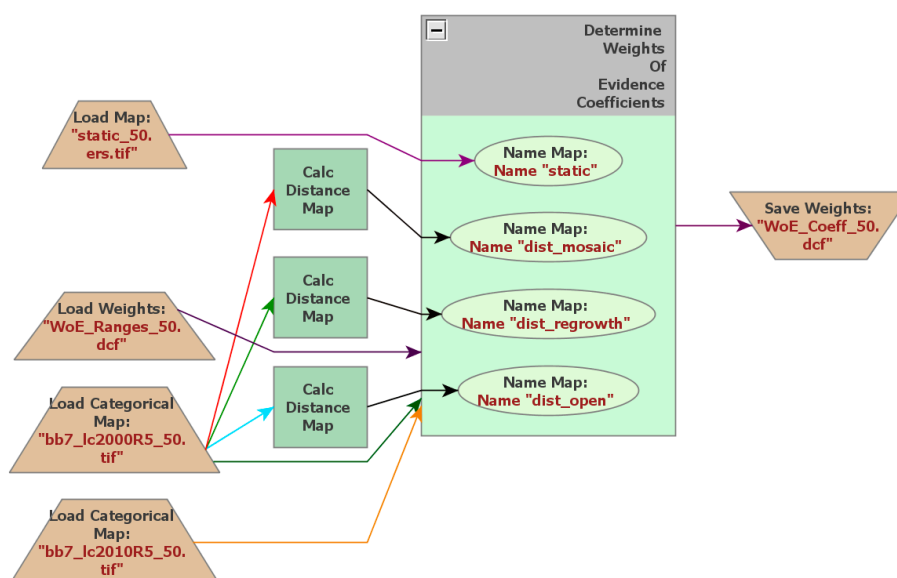


Figure S10. Determining Weight of Evidence Coefficients.

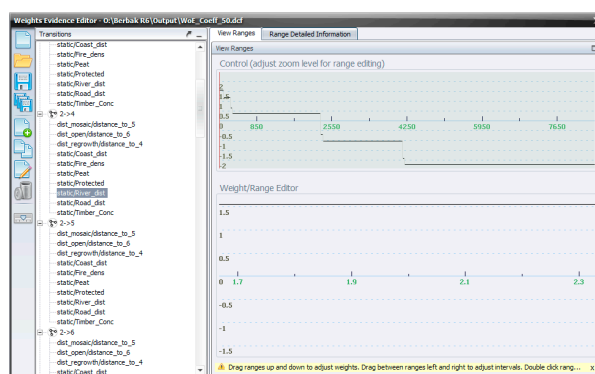


Figure S11. Weights of Evidence coefficient graph, transition peat swamp forest → regrowth; factor: river distance.

The Weight of Evidence coefficients, Table S6, show the ranges determined and the coefficient for each range. A negative coefficient shows negative correlation for the specified range and a positive coefficient a positive correlation.

Table S6. Weight of Evidence Coefficients for transition 2-> 4 (lowland forest—plantation/regrowth).

Transition: 2-> 4 Variable: static/Regrowth_Distance	
Range Interval	Coefficient
0.0–100.0	1.866979956626892
100.0–550.0	1.4061199426651
550.0–600.0	0.9042699933052063
600.0–2100.0	0.6383150219917297
2100.0–2150.0	0.32375600934028625
2150.0–2500.0	0.18167400360107422
2500.0–2550.0	−0.021397199481725693
2550.0–3200.0	−0.17880499362945557
3200.0–3250.0	−0.42249301075935364
3250.0–3350.0	−0.5808129906654358
3350.0–3400.0	−0.7425649762153625
3400.0–3750.0	−0.634922981262207
3750.0–3950.0	−0.8434540033340454
3950.0–4350.0	−1.1148899793624878
4350.0–4400.0	−1.805649995803833
4400.0–4950.0	−2.552839994430542
4950.0–11700.0	−5.7551798820495605

3.7. Determination of Weight of Evidence Correlations

As Dinamica EGO is a weights-of-evidence based model the weights-of-evidence are required to be conditionally independent of each other. Dinamica EGO provides the capability to determine if each weight-of-evidence factor is independent of each other factor for each transition, Figure S12. The output is provided to the Dinamica EGO message log allowing the user to determine if two factors are not independent for a transition, Table S7. If two factors are not conditionally independent then one of the two factors must be removed for that transition [2].

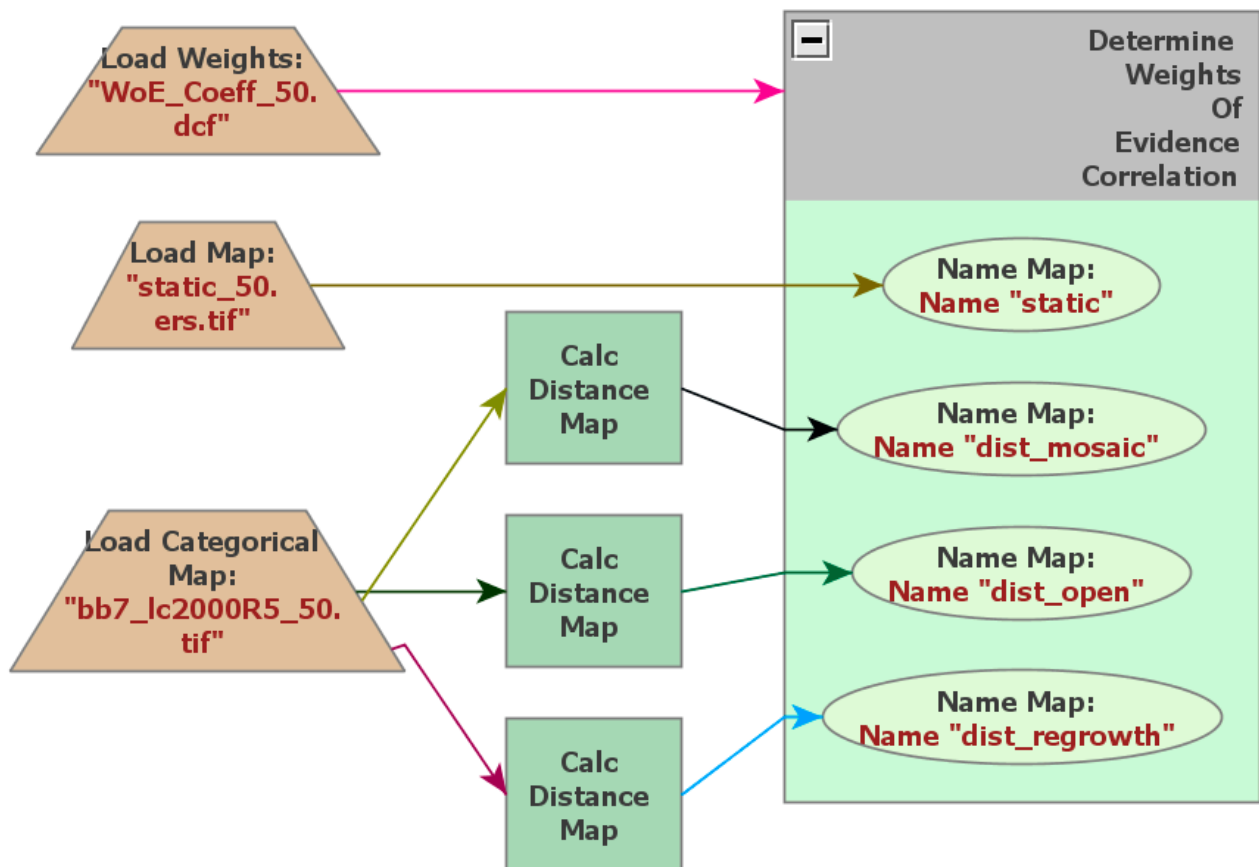


Figure S12. Weights of Evidence Correlation.

Table S7. Sample Correlation Output, 3 category model, transition 1 -> 2 (other -> regrowth).

Transition: 2->4		----- Crammer -----		----- Entropy -----		
First Variable	Second Variable	Chi^2	Crammer*	Joint Contingency	Joint Information* Entropy	Uncertainty
dist_mosaic/distance_to_5	dist_open/distance_to_6	771401.470262025	0.204632139993276	0.62112209425172	3.21647821223902	0.16603780517132
dist_mosaic/distance_to_5	dist_regrowth/distance_to_4	1294870.63986041	0.300703458182846	0.758691482218684	3.44768991291412	0.321071253770943
dist_mosaic/distance_to_5	static/Coast_dist	467936.305301486	0.155096691368195	0.514928657273051	4.33534569015473	0.0881894859134503
dist_mosaic/distance_to_5	static/Fire_dens	180593.946080208	0.0963364806855953	0.349570170799741	3.09932410291199	0.0464806650309289
dist_mosaic/distance_to_5	static/Peat	420937.363442895	0.569630914342046	0.494960965658126	2.40115769971913	0.142384808295167
dist_mosaic/distance_to_5	static/Protected	143848.10086539	0.332994360754182	0.315938302014992	2.54657281274468	0.0432622004235373
dist_mosaic/distance_to_5	static/River_dist	258268.513789639	0.171482049901012	0.413163897337065	3.30114318130399	0.0639016618769577
dist_mosaic/distance_to_5	static/Road_dist	799837.876578938	0.204829814278628	0.621490414456223	4.49111572932434	0.135825127122168
dist_mosaic/distance_to_5	static/Timber_Conc	33606.1610350019	0.16095121690038	0.158906121991237	2.40533984291278	0.0109544021344939
dist_open/distance_to_6	dist_regrowth/distance_to_4	610333.877090572	0.193187332640781	0.599083016707225	3.54039133190536	0.139527038459479
dist_open/distance_to_6	static/Coast_dist	305190.833299265	0.119167862118363	0.419055695275459	4.23062581455814	0.0525804280451347
dist_open/distance_to_6	static/Fire_dens	112671.926331328	0.072404617093862	0.270006580586391	2.91186742914891	0.0337795621137102
dist_open/distance_to_6	static/Peat	289053.440189662	0.449151756298359	0.409721101487011	2.2524544964785	0.0954350747533665
dist_open/distance_to_6	static/Protected	81073.8093690268	0.237872545857664	0.231415497610322	2.34806363884908	0.024330554580152
dist_open/distance_to_6	static/River_dist	321853.516415392	0.182433003025755	0.43468606065828	3.05426675986777	0.0727721776369965
dist_open/distance_to_6	static/Road_dist	491916.546174378	0.153354467550814	0.510659082850678	4.37509890541274	0.0791881681455974
dist_open/distance_to_6	static/Timber_Conc	77147.002120147	0.232040374717019	0.226034980809506	2.14019092246723	0.025273269770134
dist_regrowth/distance_to_4	static/Coast_dist	443525.099273813	0.154651591587843	0.526083296281851	4.4105772771783	0.088910511603552
dist_regrowth/distance_to_4	static/Fire_dens	208330.28857831	0.105974972919656	0.390282565167185	3.13890756381704	0.0622572156454717
dist_regrowth/distance_to_4	static/Peat	319111.385426117	0.524636192641104	0.464581327412051	2.54472907460432	0.117932503681253
dist_regrowth/distance_to_4	static/Protected	93811.7875686348	0.28445646167881	0.273602420787894	2.69264585304152	0.0303837243666646
dist_regrowth/distance_to_4	static/River_dist	241331.463595313	0.17592984905759	0.421991867038737	3.50930891960006	0.0607481838107224
dist_regrowth/distance_to_4	static/Road_dist	650296.543154211	0.189525598379891	0.604124294634044	4.50000038682219	0.128665513602404
dist_regrowth/distance_to_4	static/Timber_Conc	18052.7216244999	0.124783867121716	0.12382356173858	2.54162177921465	0.00609028996786581
static/Coast_dist	static/Fire_dens	1420361.79361484	0.201732939226204	0.678826867274009	3.50334342003244	0.178370342459235
static/Coast_dist	static/Peat	656799.973794613	0.628642206921034	0.532214495962846	3.10886757588815	0.146018968281249
static/Coast_dist	static/Protected	681849.878236258	0.640518025741262	0.539363120623906	3.11947166427219	0.138409507027138
static/Coast_dist	static/River_dist	252451.861404402	0.150165537975745	0.369227087786846	4.07885325416744	0.0446373429616267
static/Coast_dist	static/Road_dist	1664510.45142497	0.143384823359392	0.711964689520897	5.12549574061069	0.184214762887057
static/Coast_dist	static/Timber_Conc	677637.319594787	0.638536357749735	0.538178261351597	2.9127973047427	0.125081181287357
static/Fire_dens	static/Peat	185907.634207593	0.334211148428069	0.316976961492534	1.80951950797348	0.0725163496820845
static/Fire_dens	static/Protected	116320.908701422	0.264363330012769	0.255583057701197	1.8367386767782	0.0409972663125588
static/Fire_dens	static/River_dist	157078.68939125	0.118372075261347	0.298868794284425	2.61227383005524	0.0475934863458379
static/Fire_dens	static/Road_dist	372130.124082538	0.104536746305136	0.432032813669242	4.03447115313986	0.055234732645296
static/Fire_dens	static/Timber_Conc	88004.1809021201	0.229945001384356	0.224096785758357	1.60810296730553	0.0275892881152858
static/Peat	static/Protected	102497.115123694	0.248157920727606	0.240852576345237	1.35269497100563	0.0449877930437609
static/Peat	static/River_dist	145370.871895209	0.301285578992391	0.288476974801513	2.1560612505131	0.0428628071135368
static/Peat	static/Road_dist	327349.473907478	0.4493006384687	0.409834105047569	3.56761235710734	0.0580954540885433
static/Peat	static/Timber_Conc	216528.086663907	0.360686128102315	0.339290783331331	1.06514552440434	0.130079898014045
static/Protected	static/River_dist	163112.418204563	0.319141410587801	0.304033667191097	2.14893608784456	0.048461630336003
static/Protected	static/Road_dist	577333.964615093	0.596684513237727	0.512400720208296	3.4716005592428	0.109916151234118
static/Protected	static/Timber_Conc	283677.300347414	0.4128427034023	0.381601614016289	1.02034755740692	0.204911134732815
static/River_dist	static/Road_dist	597854.998843658	0.233503586236695	0.525582393234532	4.29620584835828	0.085434759516954
static/River_dist	static/Timber_Conc	3851.17743037294	0.0490384134569475	0.0489795566338158	1.95808732587475	0.00126408953842326
static/Road_dist	static/Timber_Conc	30879.2120095146	0.137995306916428	0.136699877254502	3.42170030824473	0.00597974476736817

S1.7. Validation Model

A validation model is produced using the initial land cover map as a starting point for the number of steps specified when the transition matrices were determined. The model output can then be compared with the final land cover to determine the accuracy of the model. The area of each land cover category will be correct as the transition matrix specifies the proportions for each transition in each step. This was set when modifying the land cover transition matrix, Section S1.3 above.

Location accuracy is the important factor in model validation. Dinamica EGO provides two mechanisms for making land cover transitions: the Expander creates transitions by expanding or contracting existing land cover areas and the Patcher creates new areas by ‘seeding’. The model has to be configured for the ratio of changes between expansion of existing areas and creation of new patches and the parameters specifying the size and shape of changed areas. The land cover changes have three parameters for each transition, mean area, variance and isometry. The mean and variance are obtained from the analysis performed in determining transitions which have occurred, Table S5. The mean calculated was for the entire 10 step transition and a good estimate of the per step transition is 1/10th of the calculated value. The annual variance is the standard deviation also squared and then divided by 10, Table S8. The isometry specifies the shape of the changes areas and is specified as a value between 0, circular, and 2, linear [2]. In the models an isometry value of ‘1’ has been chosen.

The same values are used for both the expansion of existing area and for creation of new patches. The proportional split between area expansion and new areas is the key modification used when tuning the model for best fit.

Table S8. Transitions for model, initial to final transition showing total area, mean area per fragment and standard deviation over 10 steps annual mean area and annual variance. (MAN—Mangrove, PSF—Peat Swamp Forest, LLF—Lowland Forest, P/R—Plantation/Regrowth, LLM—Lowland Mosaic, LLO—Lowland Open). Shaded rows are not used in the model as they are not permitted in the modified transition matrix.

TYPE	Area /ha	Mean Patch Area /ha	Patch Area Standard Deviation	Annual Mean Change /ha	Annual Variance
MAN-P/R	90.5	12.9	8.9	1.3	7.9
MAN-LLO	37.5	12.5	5.1	1.3	2.6
PSF-P/R	18,460.0	91.8	444.6	9.2	19,770.2
PSF-LLM	9695.3	86.6	487.2	8.7	23,736.3
PSF-LLO	5906.8	67.9	214.7	6.8	4610.0
LLF-P/R	7951.8	45.7	92.1	4.6	848.1
LLF-LLM	2487.3	40.8	62.0	4.1	384.4
LLF-LLO	1463.8	22.2	32.4	2.2	104.9
P/R-MAN	181.3	18.1	10.6	1.8	11.3
P/R-PSF	3500.0	33.0	68.1	3.3	464.0
P/R-LLF	2993.8	23.8	33.3	2.4	110.9
P/R-LLM	10,876.5	32.1	66.2	3.2	438.0
P/R-LLO	8190.0	34.3	78.5	3.4	616.6

Table S8. Cont.

TYPE	Area /ha	Mean Patch Area /ha	Patch Area Standard Deviation	Annual Mean Change /ha	Annual Variance
LLM-MAN	68.8	9.8	6.6	1.0	4.3
LLM-PSF	643.8	20.8	17.9	2.1	32.1
LLM-LLF	612.5	18.0	27.5	1.8	75.8
LLM-P/R	26,731.3	59.9	241.0	6.0	5809.2
LLM-LLO	12,570.0	49.7	103.3	5.0	1066.7
LLO-MAN	56.3	18.8	8.8	1.9	7.8
LLO-PSF	668.8	35.2	33.0	3.5	108.6
LLO-LLF	1050.0	45.7	112.4	4.6	1263.1
LLO-P/R	3568.0	23.9	37.2	2.4	138.6
LLO-LLM	1119.8	18.4	21.9	1.8	47.9

S1.8. Model Validation

Dinamica EGO provides two similar mechanisms for determining the accuracy of models by comparison of the final land cover map and the output from the model using an exponential, Figure S13, or constant, Figure S14, decay functions [2]. The main mechanism used for this model is the constant decay function as it allows comparison over a large number of cells.

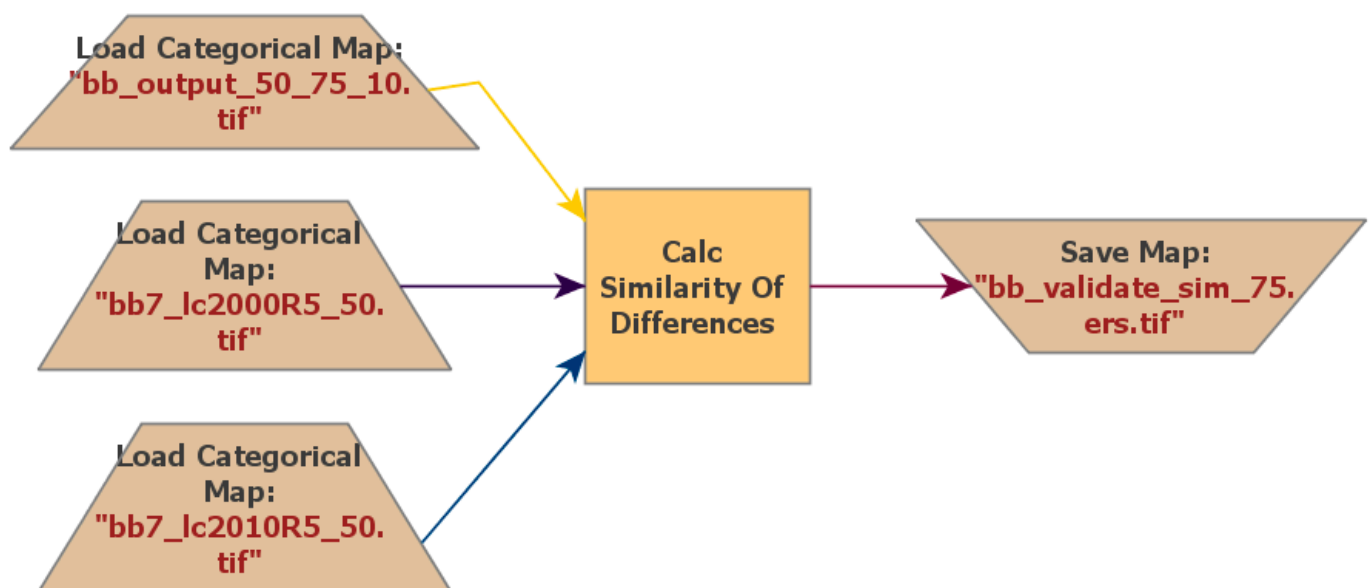


Figure S13. Exponential Decay model validation.

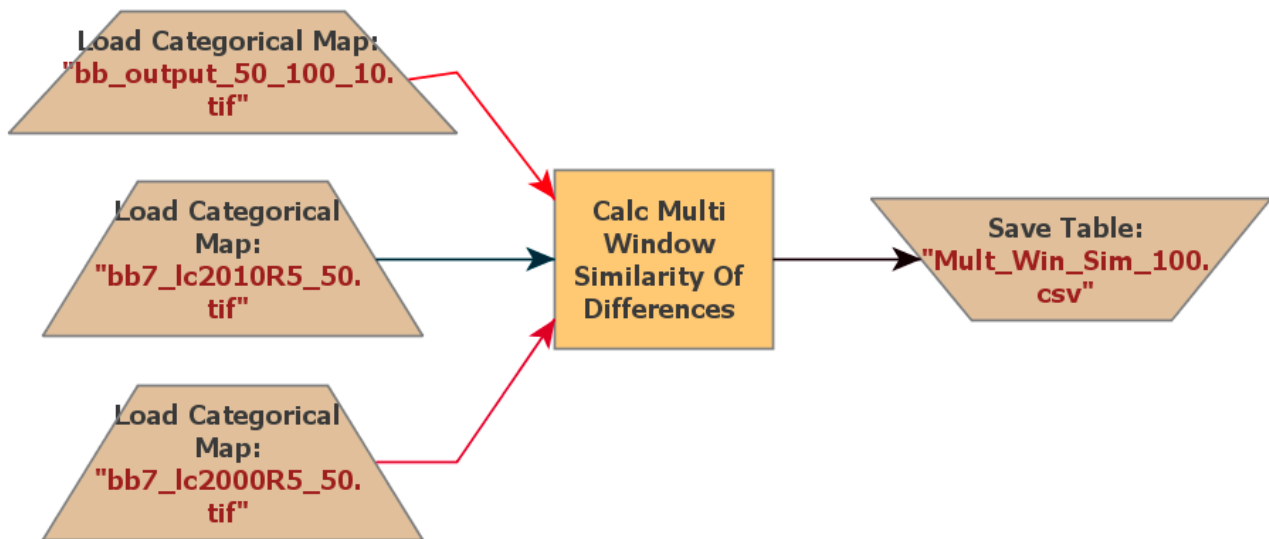


Figure S14. Constant Decay Simulation Validation.

It is also possible to view the output graphically which enables estimation of the distance at which a given accuracy is achieved.

S1.9. Future Simulation Model

The simulation model for future land cover changes is similar to that used for validation once the tuning has been performed. The initial land cover input in this scenario is the final land cover map provided.

The future simulation was run for 30 years into the future, from 2010, i.e. in yearly steps until 2040.

S2. Model Accuracy

Model accuracy is measured by two important aspects:

- land change area accuracy
- land change positional accuracy

Land change area accuracy is dependent upon the transition matrix used in the model. The setting of the values in this matrix is discussed in Section S1.3 above.

Model positional accuracy is dependent upon a number of input factors which impact the model output. The projected transitions from a Dinamica model are based upon the probability maps which are derived from the existing land cover map and the weights of evidence coefficients. The probability maps are then used by the expander and patcher functions to determine which pixels undergo transitions to produce the projection map.

The model positional accuracy can be tuned by modifying the weights of evidence coefficients from those which generated by the steps previously described. Changing the expander/patcher ratio will determine how much of the change results in expanding existing land cover areas with the remaining creating new patches.

To understand the positional accuracy of the model configuration changes are made to the expander/patcher ratio (the proportion of expansion of existing areas and the proportion of new areas created).

Model positional accuracy is measured using a constant decay function which implements fuzzy similarity based upon fuzziness of category and location on maps of changes between the original and final observed land cover and initial observed and final simulated land cover [2,4]. The mechanism uses and increasing window size to a user defined maximum and calculates the fuzzy similarity for each successive odd cell sized window. This allows comparisons based upon cell sizes from single cell to the maximum that the user has defined.

In assessing the similarities of the models used in this study, single pixel, (50m), 11 pixels (550m) and 21 pixels (1050m) are compared. The choice of these ranges is due to the requirement that window sizes are an odd number of pixels [2].

A comparison was performed for the land cover classification using a range of different expander/patcher ratios and the constant decay function accuracy using single pixel (50m), 11 pixel (550m) and 21 pixels (1050m) and largest peat swamp forest patch size was also determined, Table S9.

Table S9. Multiple Windows Constant Decay Function Validation Results for model with varying expander/patcher ratios.

Expander /Patcher Proportions	1 pixel (50m)	11 pixel (550m)	21 pixels (1050m)	PSF Largest Patch /ha
2010 (O)				144266
50–50	0.44063506	0.667828011	0.792627468	139959.8
55–45	0.444351736	0.666079504	0.790231466	141543.8
60–40	0.45209418	0.665599996	0.788647583	142461.0
65/35	0.457351734	0.670350323	0.7926706	140770.0
70/30	0.464051241	0.670427533	0.783309674	140789.0
75/25	0.463256885	0.665634657	0.781300358	139065.8
80/20	0.460776837	0.65977718	0.78035916	142221.8
85/15	0.458356157	0.656968132	0.774316083	142055.5
90/10	0.465235578	0.655124346	0.76970569	142670.0
100/0	0.456117879	0.64093161	0.75077668	141798.0

The simulations show constant decay function accuracy remaining relatively constant over most of the expander/patcher range examined but with an accuracy decrease as the expander/patcher ratio moves towards 100/0. There is no particular trend in the size of the largest Peat Swamp Forest patch size. An expander/patcher ratio of 70/30 was chosen for the land cover simulation as this ratio showed higher accuracy at the single and 11 pixel windows and had a comparable high value for the 21 pixel window.

S2.1. Accuracy Assessment

The model has a single pixel (50 m × 50 m) accuracy of 48%, using an 11 pixel window (550 m × 550 m) the accuracy increased to 67% and with 21 pixels (1050 m × 1050 m) this rose to 80%. The West Kalimantan study [5] using seven land cover categories showed accuracy figures a for 100 m resolution

model of 25% (single pixel) and 81% for 1100 m. The model proved more accurate at the single pixel level and showed similar accuracy at the greater distance.

Another study around the Xingu National Park in the Brazilian Amazon [6] based upon three land cover categories (Forests, Pastureland and Cropland) resulted in 30% accuracy at 100 m and 60% accuracy at 1.9 km with an estimate that at 1100 m the accuracy was approximately 50%.

Based upon comparison with these contemporary studies which also used the Dinamica EGO toolset the simulated model accuracy compares favourably.

S3. Simulation Results

Simulation of the model was performed for 30 years beyond 2010 based upon the 50 m resolution models with expander/patcher ratios of 70/30 with all incremental yearly changes captured. The models produced simulated land cover maps for each year from 2011–2040, Figure S16, from which land cover areas for each category were calculated (Table S10).

The overall transitions between land cover categories between 2010 and the simulated 2040 land cover were determined, (Table S11).

As Dinamica EGO builds stochastic models the output may change with multiple simulation runs. To examine the variations in output from different simulation runs a further 20 model executions were performed for each model for which only the final simulation output, 2040, was captured. The total land cover area for each land cover type remained the same as this is determined by the transition matrix used as input. There is variation in the way in which the land cover transitions are allocated which is highlighted by the range and variation of mean land cover area and standard deviation for each land cover type, (Table S12).

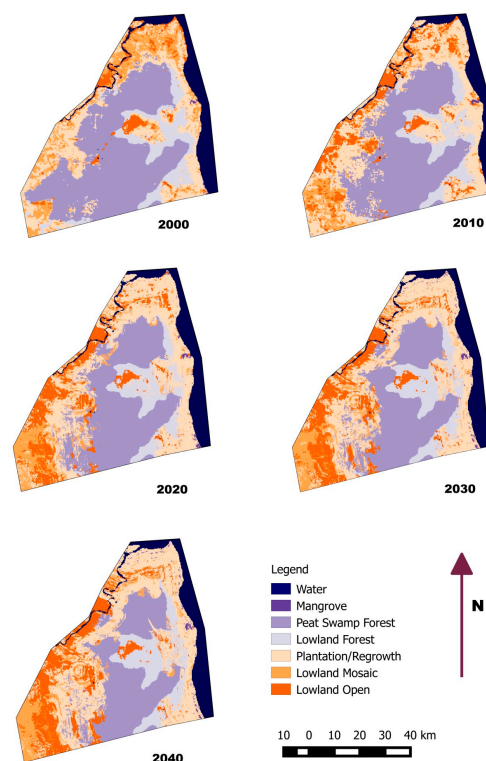


Figure S16. Observed and simulated land cover: 2000–2040.

Table S10. Observed and simulated land cover category areas in Berbak Area of Interest: 2000 - 2040. Total area 375,749 ha.

Year	Mangrove /ha	Peat Swamp Forest /ha	Lowland Forest /ha	Plantation /Regrowth /ha	Lowland Mosaic /ha	Lowland Open /ha	Total Forest	Total Forest %
2000	413.8	175,291.8	45,677.8	85,647.3	51,174.8	17,287.0	221,383.3	59.0%
2010	598.3	146,042.3	38,431.3	116,838.5	34,739.8	39,098.5	185,071.8	49.3%
2011	619.5	143,527.8	37,881.8	118,552.5	34,545.3	40,621.8	182,029.0	48.4%
2012	640.5	141,076.8	37,356.3	120,165.0	34,427.8	42,082.3	179,073.5	47.7%
2013	661.0	138,688.0	36,853.8	121,689.0	34,371.0	43,485.8	176,202.8	46.9%
2014	681.8	136,358.8	36,372.8	123,137.8	34,360.5	44,837.0	173,413.3	46.2%
2015	702.5	134,087.5	35,912.5	124,519.5	34,385.0	46,141.5	170,702.5	45.4%
2016	723.3	131,873.3	35,472.3	125,841.5	34,437.5	47,400.8	168,068.8	44.7%
2017	744.0	129,714.0	35,050.5	127,111.8	34,509.5	48,618.8	165,508.5	44.0%
2018	764.5	127,608.3	34,647.3	128,333.3	34,597.3	49,798.0	163,020.0	43.4%
2019	785.0	125,554.5	34,261.3	129,511.8	34,696.0	50,940.0	160,600.8	42.7%
2020	805.5	123,551.5	33,892.0	130,650.0	34,802.5	52,047.0	158,249.0	42.1%
2021	825.8	121,598.3	33,538.5	131,751.0	34,915.0	53,120.0	155,962.5	41.5%
2022	846.3	119,692.8	33,200.5	132,816.3	35,031.0	54,161.8	153,739.5	40.9%
2023	866.5	117,835.0	32,877.8	133,848.3	35,149.0	55,172.0	151,579.3	40.3%
2024	886.5	116,022.5	32,569.0	134,850.3	35,267.8	56,152.5	149,478.0	39.8%
2025	906.3	114,254.5	32,274.0	135,822.3	35,386.8	57,104.8	147,434.8	39.2%
2026	925.8	112,530.0	31,992.0	136,766.0	35,504.8	58,030.0	145,447.8	38.7%
2027	945.3	110,848.0	31,722.3	137,682.0	35,622.3	58,928.8	143,515.5	38.2%
2028	964.5	109,207.5	31,464.8	138,573.3	35,737.3	59,801.3	141,636.8	37.7%
2029	984.0	107,607.0	31,219.0	139,439.0	35,850.5	60,649.0	139,810.0	37.2%
2030	1003.0	106,046.0	30,984.5	140,280.5	35,962.3	61,472.3	138,033.5	36.7%
2031	1022.0	104,523.5	30,761.0	141,098.5	36,071.3	62,272.3	136,306.5	36.3%
2032	1040.8	103,038.3	30,547.5	141,894.0	36,178.3	63,049.8	134,626.5	35.8%
2033	1059.8	101,589.3	30,343.8	142,668.3	36,282.3	63,805.3	132,992.8	35.4%
2034	1078.3	100,175.5	30,149.8	143,421.0	36,384.0	64,540.0	131,403.5	35.0%
2035	1096.8	98,796.8	29,965.0	144,153.0	36,483.3	65,253.8	129,858.5	34.6%
2036	1114.8	97,451.8	29,789.0	144,865.8	36,579.8	65,947.5	128,355.5	34.2%
2037	1132.8	96,139.5	29,621.5	145,559.5	36,673.8	66,621.5	126,893.8	33.8%
2038	1150.5	94,859.5	29,461.8	146,234.3	36,765.8	67,276.8	125,471.8	33.4%
2039	1168.0	93,610.8	29,310.3	146,891.0	36,855.3	67,913.3	124,089.0	33.0%
2040	1185.0	92,393.0	29,166.3	147,529.8	36,942.3	68,532.3	122,744.3	32.7%
% Chg								
2010–2040	98.1%	–36.7%	–24.1%	26.3%	6.3%	75.3%	–33.7%	

Table S11. Land cover category transitions: 2010–2040.

2010 Category	2040 Category	Total Area /ha	Patch Mean Area /ha
Mangrove	Plantation/Regrowth	175.0	4.9
Mangrove	Lowland Open	19.8	1.6
Mangrove	Oil Palm Plantation	5.5	0.7
Peat Swamp Forest	Lowland Forest	9.3	9.3
Peat Swamp Forest	Plantation/Regrowth	39,344.5	84.6
Peat Swamp Forest	Lowland Mosaic	7250.5	6.3
Peat Swamp Forest	Lowland Open	8136.5	59.0
Lowland Forest	Mangrove	2.0	2.0
Lowland Forest	Peat Swamp Forest	15,944.3	82.6
Lowland Forest	Plantation/Regrowth	1023.5	1.9
Lowland Forest	Lowland Mosaic	1186.0	12.5
Lowland Forest	Lowland Open	561.3	5.8
Plantation/Regrowth	Mangrove	8397.3	26.2
Plantation/Regrowth	Peat Swamp Forest	16,310.5	8.0
Plantation/Regrowth	Lowland Forest	19,548.3	18.3
Plantation/Regrowth	Lowland Mosaic	100.0	2.7
Plantation/Regrowth	Lowland Open	61.8	1.5
Lowland Mosaic	Mangrove	10,960.0	9.4
Lowland Mosaic	Peat Swamp Forest	13,935.3	17.6
Lowland Mosaic	Lowland Forest	122.0	2.1
Lowland Mosaic	Plantation/Regrowth	3.0	0.6
Lowland Mosaic	Lowland Open	211.8	3.9
Lowland Open	Mangrove	2931.5	4.9
Lowland Open	Peat Swamp Forest	175.0	4.9
Lowland Open	Lowland Forest	19.8	1.6
Lowland Open	Plantation/Regrowth	5.5	0.7
Lowland Open	Lowland Mosaic	9.3	9.3

Table S12. Minimum and maximum mean and standard deviations for each land cover type over 20 identical simulations.

	Mangrove		Peat Swamp Forest		Lowland Forest		Plantation/Regrowth		Lowland Mosaic		Lowland Open	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Min	6.17	33.08	67.54	1763.72	32.63	681.09	49.57	1917.58	8.81	197.97	47.30	880.36
Max	9.78	48.21	72.81	1841.00	38.84	748.33	53.49	2632.20	9.46	243.78	52.31	1133.19
% Var	59%	46%	8%	4%	19%	10%	8%	37%	7%	23%	11%	29%

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