Pontius Jr. Methods Based on a Cross-Tabulation Matrix to Validate Land Use Cover Maps

Martin Paegelow, Jean-François Mas, Marta Gallardo, María Teresa Camacho Olmedo, and David García-Álvarez

Abstract

Several validation techniques based on the cross-tabulation matrix can be applied to validate Land Use Cover (LUC) maps. The exercises in this chapter focus, in particular, on the cross-tabulation techniques proposed by Robert Gilmore Pontius Jr., who has developed many indices and techniques in this field. Given his major contribution to this family of validation techniques, we have associated his name here with cross-tabulation techniques without this in any way implying that his scientific activity is limited to this field. The null model (Sect. 1) is especially useful for validating simulations, comparing the modelled map to a reference map with full persistence. LUCC budget (Sect. 2) only focusses on changes, which it splits into different components. This method can be used to compare the changes we want to validate with a reference set of changes, so providing interesting information as to how well our maps capture the dynamics of the landscape. Quantity and allocation disagreement (Sect. 3) analyse the differences between the reference map and the map being validated using two indices: disagreement in quantity and disagreement in allocation. The Figure of Merit (FoM) (Sect. 4) technique is used to validate a set of LUC changes by comparing them with a reference, distinguishing between different components of agreement: correctly simulated change, wrongly simulated or missing change. Incidents and States (Sect. 5) allows us to identify illogical transitions in a time series of maps by providing the number of states and transitions that a cell undergoes over the course of the series. Intensity analysis (Sect. 6) and Flow matrix (Sect. 7) also enable us to validate the logic of LUC changes in a time series of maps. Intensity analysis provides information on the speed of changes, identifying those transitions or changes that do not follow a logical trend, while the flow matrix enables us to spot unstable changes in a series of maps. In this chapter, we present examples of how these techniques can be used in different cases: to validate single LUC maps, to validate a series of maps with two or more time points, to validate simulated changes against a reference map of changes and to validate changes simulated by various models. All these techniques are illustrated by exercises using datasets from the Asturias Central Area and the Ariège Valley.

Keywords

LUCC budget • Change matrices • Cross-tabulation • Error Analysis • Figure of Merit • Intensity Analysis • Flow matrix

1 Null Model

Description

The null model is a method specifically developed by Pontius and Malanson (2005) to validate LUCC modelling simulations. It assumes that the land use/land cover at the simulation start time (t_1) is exactly the same at the end time (t_2) and that no changes take place. The aim is to evaluate

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whether a landscape with no changes more closely resembles the reference landscape for the year of the simulation (t_2) than the simulated landscape. In other words, we change the date of the initial LUC map while leaving the content unchanged. It then becomes a reference map (no change) with which we can measure the predictive power of the model.

If the agreement between the observed LUC at t_2 and the simulation map at t_2 is higher than that between observed LUC at t_2 and the so-called *null model*, the simulation has greater predictive power than the hypothesis of complete persistence (no change). The agreement between the null model, the simulation and the reference map is usually assessed using common cross-tabulation techniques and Kappa indices (see Sect. 1 in Chapter "Basic and Multiple-Resolution Cross-Tabulation to Validate Land Use Cover Maps" and Sect. 3 in Chapter "Metrics Based on a Cross-Tabulation Matrix to Validate Land Use Cover Maps").

Utility

Exercises
1. To validate simulated changes against a reference map of changes

The null model helps to measure the relative success of a simulation compared to persistence in time. The usefulness of this method depends on the spatiotemporal dynamics of the study area.

The method is based on the hypothesis that a simulation is successful if it gets better validation scores than a landscape in which no changes occur. When simulating change in a study area in which little change is taking place, it may be difficult to correctly simulate these changes in the same positions as on the reference map of changes. As a result, the null model may provide better validation scores than the simulation, in that the null model avoids possible errors when allocating changes and always simulates persistence correctly. This is why the null model is especially useful for validating whether an LUCC model simulates persistence correctly.

QGIS Exercise

Available tools
• Processing Toolbox GRASS Raster (r.*) *r.kappa* • Semi-Automatic Classification Plugin Tab: Postprocessing Section: *Cross-classification*

To calculate the null model, we must use the same techniques as cross-tabulation and Kappa. Please see Sect. 1 in Chapter "Basic and Multiple-Resolution Cross-Tabulation to Validate Land Use Cover Maps" and Sect. 3 in Chapter "Metrics Based on a Cross-Tabulation Matrix to Validate Land Use Cover Maps" for details about how to compute cross-matrices and kappa indices between two raster layers.

Exercise 1. To validate simulated changes against a reference map of changes

Aim

To find out if the prediction score obtained by the simulation map for 2018 is higher than that obtained by the null model.

Materials

CORINE Land Cover Map Val d'Ariège 2012
CORINE Land Cover Map Val d'Ariège 2018
Simulation LCM Val d'Ariège 2018

Requisites

All maps must be rasters and must have the same resolution, extent and projection.

Execution

Step 1

The first step is to calculate the Kappa indices measuring the agreement between the simulation, the null model and the reference map showing observed LUC in 2018. We use the GRASS *r.kappa* raster tool to calculate the kappa values for agreement: (i) between observed LUC in 2012 duplicated in 2018 (null model) and observed LUC in 2018 and (ii) between observed LUC in 2018 and simulated LUC in 2018.

Step 2

We then generate the cross-matrices between the simulation, null model and reference map (CLC_2012 against CLC_2018 and CLC_predict_2018 against CLC_2018) using the *Cross-classification* tool (see Exercise 2 of Sect. 1 in Chapter "Basic and Multiple-Resolution Cross-Tabulation to Validate Land Use Cover Maps"). This method complements the kappa agreement indices and provides additional information about the similarity between the different maps.

Step 3

Once the cross-tabulations are obtained, on a spreadsheet we calculate the sum of cells on the diagonal (pixel-to-pixel correspondence).

Results and Comments

The resulting Kappa values are 0.9849 for the simulation (CLC_predict_2018 related to CLC_2018) and 0.9875 for the null model (CLC_2012 related to CLC_2018). The quantity and allocation correspondence (the proportion of diagonal pixels in the cross-matrices) are 98.22% for the simulation and 98.53% for the null model. Therefore, with both techniques, the null model obtains a slightly higher score than the simulation.

Interpretation of these results is difficult and has to be done carefully due to the limitations of this technique and the criticisms often levelled against it. The results show that persistence is the dominant process (98.5% of the study area did not change between 2012 and 2018; null model). Taking into account that most models simulate persistence better than change, it would be difficult to obtain a higher prediction score for a study area in which so little land use change is taking place. The low proportion of changes makes it difficult to simulate the changes between land use categories correctly. The slightest error diminishes the performance of the simulation compared to the null model.

Other methods, such as the Figure of Merit (see Sect. 4), can provide a better picture on how the model correctly simulated the change.

2 LUCC Budget

Description

LUCC budget is a technique for analysing land use/cover change (LUCC) using the cross-tabulation matrix obtained by overlaying two maps of the same area at two different dates. For each category, the changes are characterized in four components: gross gains, gross losses, net change and swap (Pontius et al. 2004).

Gross gains are the areas gained by each category, and gross losses are the areas lost. Net change is the difference between gains and losses. In categories in which gains and losses are occurring in different places, swap is a measure of the real changes taking place which are not revealed by the net change indicator. It measures the total area in which an equivalent amount of gains and losses have taken place, i.e. if in one category there are gains of 5 ha in one place and losses of 3 ha in another, the 3 ha that it losses in one place and recoups in another are the swap (swap = 3 + 3 = 6 ha), while the remaining 2 ha (5–3) are the net change.

Utility

Exercises
1. To validate a series of maps with two or more time points

When monitoring landscape changes, the LUCC budget technique helps to identify the most critical land use transitions and should ultimately facilitate linking patterns to process (Pontius et al. 2004). It also allows LUCC simulation models to compare observed LUCC with simulated LUCC in both the calibration and validation steps (Paegelow 2018). In short, LUCC budget enables a more detailed analysis of land use change in a particular area.

QGIS Exercise

Available tools
• Processing R provider plugin *LUCCBudget.rsx* R script

The components of change computed by the LUCC budget are derived from the cross-tabulation matrix. This matrix can be obtained by overlaying the two maps in QGIS and then calculating the LUCC budget values using a spreadsheet programme. However, we suggest using the *LUCCBudget.rsx* R script with the QGIS Processing R provider plugin. This script will carry out the entire LUCC budget calculation and will generate a table containing the values for the four components of change.

See Chapter "About this Book" for more detailed information about how to integrate R into QGIS and how to use R scripts such as the one applied in this exercise.

Exercise 1. To validate a series of maps with two or more time points

Aim

To carry out LUCC budget analysis in the Ariege study area using the CORINE Land Use maps dated 2000 and 2018.

Materials

CORINE Land Cover Map Val d'Ariège 2000
CORINE Land Cover Map Val d'Ariège 2018

Requisites

All maps must be in raster format and have the same resolution, extent and projection.

Execution

If necessary, install the Processing R provider plugin, and download the *LUCCBudget.rsx* R script into the R scripts folder (processing/rscripts). For more details, see Chapter "About this Book".

Step 1

Then, run the script and fill in the required parameters (names of the two maps and the output table) as shown in Fig. 1.

Results and Comments

The script will generate the cross-tabulation or change matrix as shown in Table 1. This matrix is saved as an intermediate product. The script will also generate a table in CSV format that indicates, for each category, the value of the four components assessed by the LUCC budget technique (Table 2).

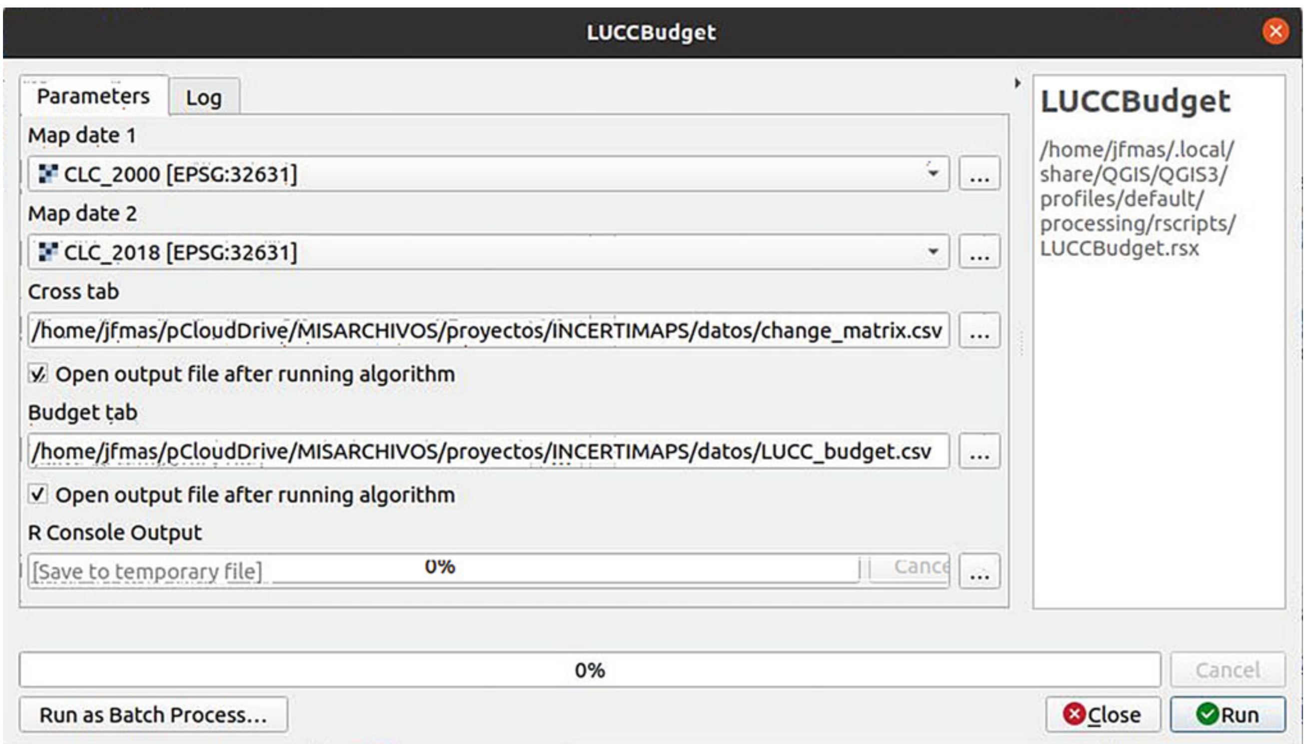


Fig. 1 Exercise 1. Step 1. LUCCBudget R script

Table 1 Result from Exercise 1. Cross-tabulation or change matrix

	0	1	2	3	4	5	6
0	**74,437**	0	0	0	0	0	0
1	0	**3,302**	3	0	8	0	37
2	0	1,853	**52,059**	235	409	0	2
3	0	23	109	**39,232**	127	0	0
4	0	12	399	877	**11,418**	22	0
5	0	0	0	0	10	**921**	0
6	0	0	0	0	0	0	**76**

Table 2 Results from Exercise 1. LUCC budget components

	Gains	Losses	Swap	Net
0	0	0	0	0
1	1,888	48	96	1,840
2	511	2,499	1,023	1,987
3	1,112	258	517	854
4	554	1,310	1,108	756
5	22	10	20	12
6	38	0	0	38

As can be seen in Table 2, the only class in which there are no losses, and consequently no swap is Category 6 (water). Therefore, for this category, the gross change is equal to the net change. Similar behaviour could be expected for Category 1 (built-up) because it is a "definitive" class (with no return), in the sense that it is very unlikely that a built-up area will be converted into another land cover. However, the change matrix (Table 1) shows small areas of transition from Category 1 (built-up) to Categories 2 (agriculture), 4 (scrublands) and 6 (water). These transitions are probably erroneous changes, resulting from misclassifications in the maps. The other categories appear to be more dynamic with both gross losses and gains and significant swap values.

3 Quantity and Allocation Disagreement

Description

Pontius Jr. and Millones (2011) proposed a set of metrics, obtained from the cross-tabulation matrix, which classify the overall change detected between a pair of maps into various components, namely, differences in the quantity of each category and differences in their location.

When analysing a time series (or single maps evaluated against a reference map), this method can differentiate between the changes that are due to differences in the relative importance of certain categories (some increase and others decrease) and those derived from changes in the location of the elements that make up these categories. It also identifies the categories that undergo net changes and swaps. As regards differences in location, this method distinguishes between exchanges between classes and changes in the location of two or more classes.

Utility

Exercises
1. To validate a series of maps with two or more time points

Quantity and allocation disagreement assess how similar a simulation or simulation is to a reference map, differentiating between (dis)agreement that is due to the quantities of different classes and (dis)agreement caused by the allocation of these classes in different places. By providing the same information, this method can also be used to validate an LUC map against a reference map or to assess the LUC changes in a time series of maps and understand whether or not these changes follow a logical trend.

QGIS Exercise

Available tools
• Processing Toolbox GRASS Raster *r.cross* *r.kappa* SAGA *Confusion matrix* • Pontius matrix (Excel sheet) http://www2.clarku.edu/~rpontius/PontiusMatrix41.xlsx • Semi-Automatic Classification plugin (SCP) Tab: Postprocessing Section: *Cross-Classification*

For more information about the use of *r.cross*, *r.kappa, SAGA Confusion matrix* and *SCP*, please refer to Chapters

"Basic and Multiple-Resolution Cross-Tabulation to Validate Land Use Cover Maps" and "Metrics Based on a Cross-Tabulation Matrix to Validate Land Use Cover Maps". QGIS *Raster Calculator* is a generic tool performing all kinds of raster calculations. It is intended for detailed analysis of the differences in quantity and allocation, rather than global studies.

Exercise 1. To validate a series of maps with two or more time points

Aim

To detect quantity and allocation changes between CORINE LUC maps of the Ariège Valley (southern France) between 2012 and 2018.

Materials

CORINE Land Cover Map Val d'Ariège 2012
CORINE Land Cover Map Val d'Ariège 2018

Requisites

All maps must be in raster format with the same resolution, extent and spatial reference system (SRS).

Execution

Step 1

In order to be able to make this analysis, the CORINE LUC map for 2018 must be polygonized. To this end, use the tool *Polygonize*.

Step 2

After polygonizing the CORINE raster, the next stage is to cross-tabulate the two maps we are going to compare. To this end, open the SAGA *confusion matrix* tool and select the CORINE LUC map for 2012 as Classification 1 layer and the CORINE LUC map for 2018 as Classification 2 layer. Then, fill in the parameters for the following lines—*Value*, *Value (Maximum)* and *Name*—into the function. Do not change any default options (the "Report unchanged classes" box must be ticked; output as "cells" and open the results generated) (Fig. 2). Rather than saving these results in a file, they can be handled as temporary layers.

Step 3

Import the SAGA-generated confusion matrix obtained in the previous stage into a spreadsheet software such as Excel. Then translate the obtained matrix into percentages (Table 3). This is done by dividing each pixel score in the original table by the total number of pixels multiplied by 100.

Step 4

Finally, use the SAGA-generated confusion matrix obtained in Step 2 to calculate the quantity and allocation disagreements in a spreadsheet software such as Excel. For a pixel resolution of 15 × 15 m, 1 ha corresponds to 44.44 pixels. Quantity disagreement is calculated by subtracting column total from row total (quantity disagreement = row total – column total) (Table 4). Allocation disagreement corresponds to all not-diagonal cell values.

Results and Comments

Table 3 shows the SAGA-generated confusion matrix reformatted in Excel and converted into a per cent of the study area. The sum of the diagonal corresponds to the overall persistence between 2012 and 2018. This value is 98.52%, which means that the change rate is 1.48%.

Although the net balance values (2018–2012) provided in Table 4 mask the changes that have taken place in certain classes, we can see from Table 3 that built-up gains (1.01%) result almost exclusively from the conversion of agricultural and pasture land (1.00), whose losses are partially compensated by the conversion of scrubland into agriculture and pasture (0.08). Scrubland is the only category with net losses and no net gains.

Table 4 expresses the amount of change (2018–2012) in ha (for a pixel resolution of 15 × 15 m; 1 ha corresponds to 44.44 pixels). As can be seen, no significant changes took place in mineral and water areas, while losses in scrubland were matched by gains in forest (about 400 ha) and losses in agriculture and pasture were matched by gains in built-up areas (about 1,000 ha).

Allocation disagreement corresponds to all not-diagonal cell values. These may be expressed as gains (2018—intersection 2012 against 2018) and losses (2012—intersection 2012 against 2018). While in some classes there are net changes (e.g. scrubland is the only category with net losses and no net gains), the changes in agriculture and pasture land are almost all losses (1.05), with just a few small gains (0.08%) from scrubland. This means that quantity disagreement shows a negative net balance for agriculture and

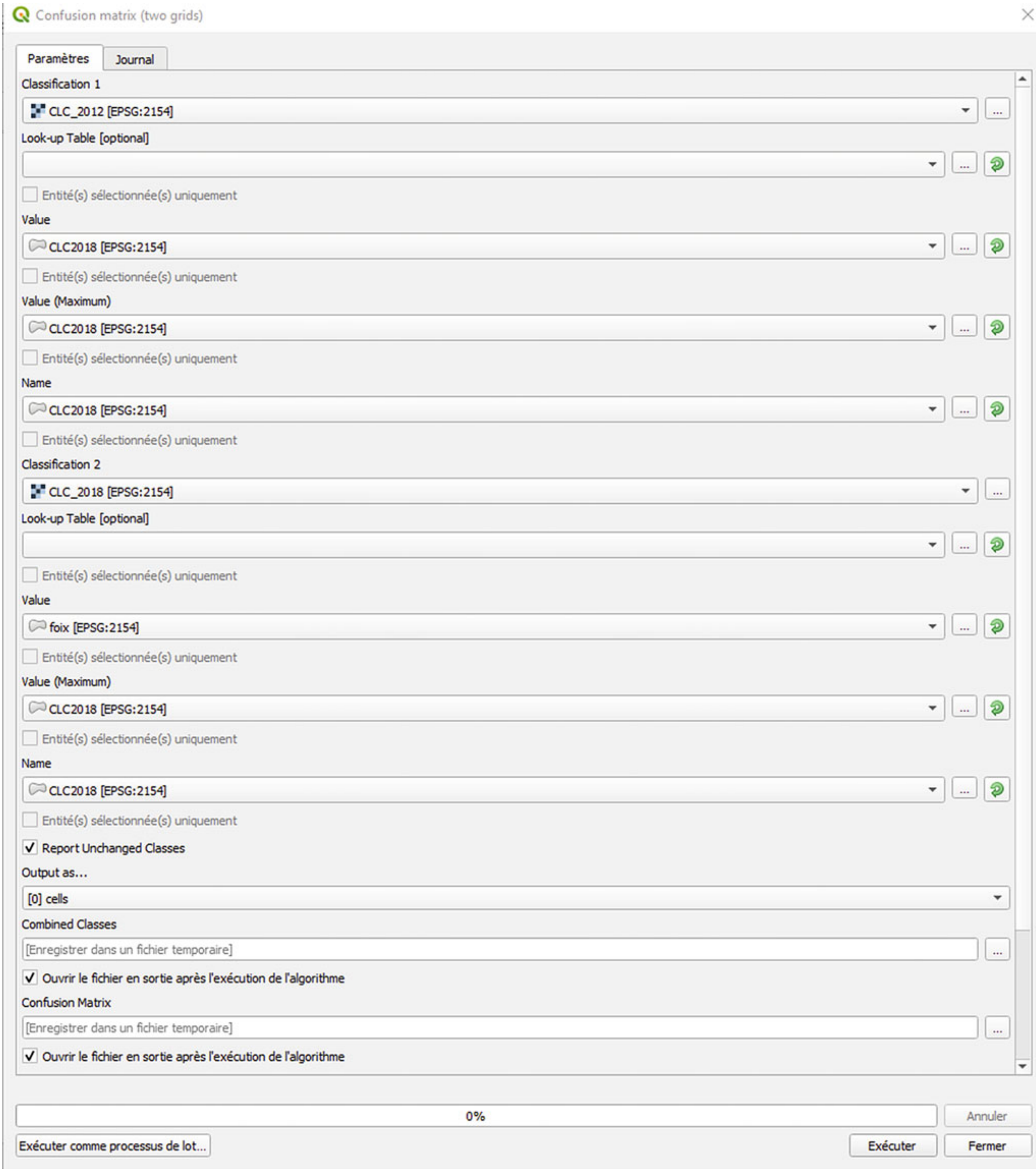


Fig. 2 Exercise 1. Step 2. Confusion matrix (two grids)

Table 3 Result from Exercise 1. Confusion matrix between 2018 and 2012 maps

	2018								
%		Built-up	Agriculture	Forest	Scrubs	Mineral	Water	**Total 2012**	***Losses***
2012	Built-up	*3.63*	0.00	0.00	0.00	0.00	0.03	**3.66**	***0.03***
	Agriculture	1.00	*47.21*	0.04	0.00	0.00	0.00	**48.25**	***1.04***
	Forest	0.01	0.03	*36.03*	0.00	0.00	0.00	**36.07**	***0.04***
	Scrubs	0.00	0.08	0.28	*10.74*	0.00	0.00	**11.11**	***0.37***
	Mineral	0.00	0.00	0.00	0.00	*0.85*	0.00	**0.85**	***0***
	Water	0.00	0.00	0.00	0.00	0.00	*0.06*	**0.06**	***0***
	Total 2018	**4.63**	**47.32**	**36.36**	**10.74**	**0.86**	**0.09**	100	
	Gains	***1.01***	***0.11***	***0.33***	***0.00***	***0.00***	***0.03***		

Table 4 Result from Exercise 1. Net change (ha) per category

Quantity disagreement (ha)	2018–2012
Built-up	1,083.04
Agriculture	–1,037.43
Forest	322.58
Scrubs	–406.55
Mineral	4.30
Water	33.59

pasture of about 1,037 ha (see Table 4), while allocation disagreement shows that more agriculture and pasture land is affected with losses of about 1,160 ha (1.04% converted into ha) and gains of about 123 ha between 2012 and 2018. Unlike allocation disagreement, quantity disagreement hides the real amount of land in which changes take place (for more details, see Sect. 2).

4 Figure of Merit (FoM) and Complementary Producer's and User's Accuracy

Description

The Figure of Merit (Pontius et al. 2008) is a measure that examines how simulated change overlaps with a reference map of changes. A Figure of Merit of 0% means there is no overlap, whereas a Figure of Merit of 100% means perfect overlap. The overlap between real changes and simulated changes leads to four possible combinations. These are the four components of the Figure of Merit:

- MISSES (A) = the real maps show change but the simulation shows persistence.
- HITS (B) = the real maps show change and the simulation shows change.
- WRONG HITS (C) = the real maps show change and the simulation shows change but allocates it to the wrong category.
- FALSE ALARMS (D) = the real maps show persistence but the simulation shows change.

The Figure of Merit is calculated via the following ratio of the four components: B/(A + B + C + D).

The overlap between real changes and simulated changes also produces a fifth combination:

- CORRECT REJECTIONS (E) = the real maps show persistence and the simulation shows persistence.

Two complementary measures can be obtained using the same components of the Figure of Merit:

- Producer's accuracy: A measure calculated using the ratio B/(A + B + C), which expresses "the proportion of pixels that the model predicts accurately as change, given that the reference maps indicate observed change" (Pontius et al. 2008).
- User's accuracy: A measure calculated using the ratio B/(B + C + D), which measures the number of pixels that the model predicts accurately as change as a proportion of all the changes it predicts.

Utility

Exercises
1. To validate simulated changes against a reference map of changes
2. To validate simulated changes against a reference map of changes in a binary format
3. To validate the changes simulated by various models

The Figure of Merit and the complementary Producer's and User's accuracies are very useful measures for validating the change simulated by a model. The different components of the Figure of Merit can give users a better picture of how accurate the simulation is, e.g. if the model estimated more or less changes than those appearing on the reference map. They can also differentiate between quantity and allocation errors (Pontius et al. 2018).

These measures are also highly recommended for comparing several simulations using a standard measure. They can be applied, for example, to assess the congruence of model outputs. This is a form of validation that evaluates the agreement between simulations obtained through different models or between simulations obtained using the same model but parametrized in different ways. The agreement between the simulation maps is measured and the degree of congruence is considered an indicator of the stability of the model and the plausibility of the simulations. The congruence of model outputs provides useful information about model robustness (Paegelow et al. 2014; Camacho Olmedo et al. 2015).

Complementary analyses to the Figure of Merit and the Producer's and User's accuracies include spatial metrics, Kappa indices, the Land Use and Cover budget (LUCC budget) technique and Quantity and Allocation disagreement. These indices are described in Sects. 2 and 3 of this chapter.

QGIS Exercises

Available tools
• Processing Toolbox
SAGA
Image analysis
Confusion matrix (two grids)
Confusion matrix (polygons/grid)
Raster analysis
Cross-classification and tabulation
• Processing Toolbox
GRASS
Raster
r.cross
• Semi-Automatic Classification Plugin
Tab: Postprocessing
Section: *Cross-classification*
Section: *Accuracy*
Section: *Land cover change*

The Figure of Merit and the complementary Producer's and User's accuracy indices are not calculated directly in QGIS. Producer's and User's accuracy per category can be calculated using the SAGA *Confusion matrix (two grids)* and *Confusion matrix (polygons/grid)* tools and in the "Semi-Automatic Classification Plugin" (*Accuracy*).

Users can calculate the Figure of Merit from the cross-tabulation matrices. As commented in Sect. 1 in Chapter "Basic and Multiple-Resolution Cross-Tabulation to Validate Land Use Cover Maps", QGIS includes many tools for cross-tabulating spatial data in the GRASS and SAGA toolboxes. The "Semi-Automatic Classification Plugin" also includes cross-tabulation tools.

Of all the tools available in QGIS, in this book, we recommend the "Semi-Automatic Classification Plugin", which is the most efficient, most stable tool of all those assessed.

Exercise 1. To validate simulated changes against a reference map of changes

Aim

To validate the change simulated by a model against a reference map of changes for the same simulation period. The initial map is the CORINE map for 2005 in both cases. The changes from 2005 to 2011 are calculated for the simulation and for the CORINE data as reference.

Materials

CORINE Land Use Map Asturias Central Area 2005
CORINE Land Use Map Asturias Central Area 2011
Simulation LCM Val d'Ariège 2018

Requisites

The maps must have the same extent, spatial resolution, projection and legend. If they do not have the same legend, the maps must be reclassified to meet this requirement. For a proper validation, the latest reference map must refer to the same date as the simulation.

Execution

Step 1

We begin by obtaining two rasters showing the areas that changed in the study area during the period analysed and those that remained the same. This procedure must be done twice: once for the reference map (CORINE 2005–CORINE 2011) and once for the simulated map (CORINE 2005–Simulation 2011).

To obtain these maps, open the "Semi-Automatic Classification Plugin" and the "Postprocessing" tab. Then select *Land cover change* and fill in the required parameters: the earlier map in the reference classification (CORINE 2005) and the more recent map in the new classification (CORINE 2011; Simulation 2011) (Fig. 3). Leave the "Report unchanged pixels" option unmarked so as to obtain a map

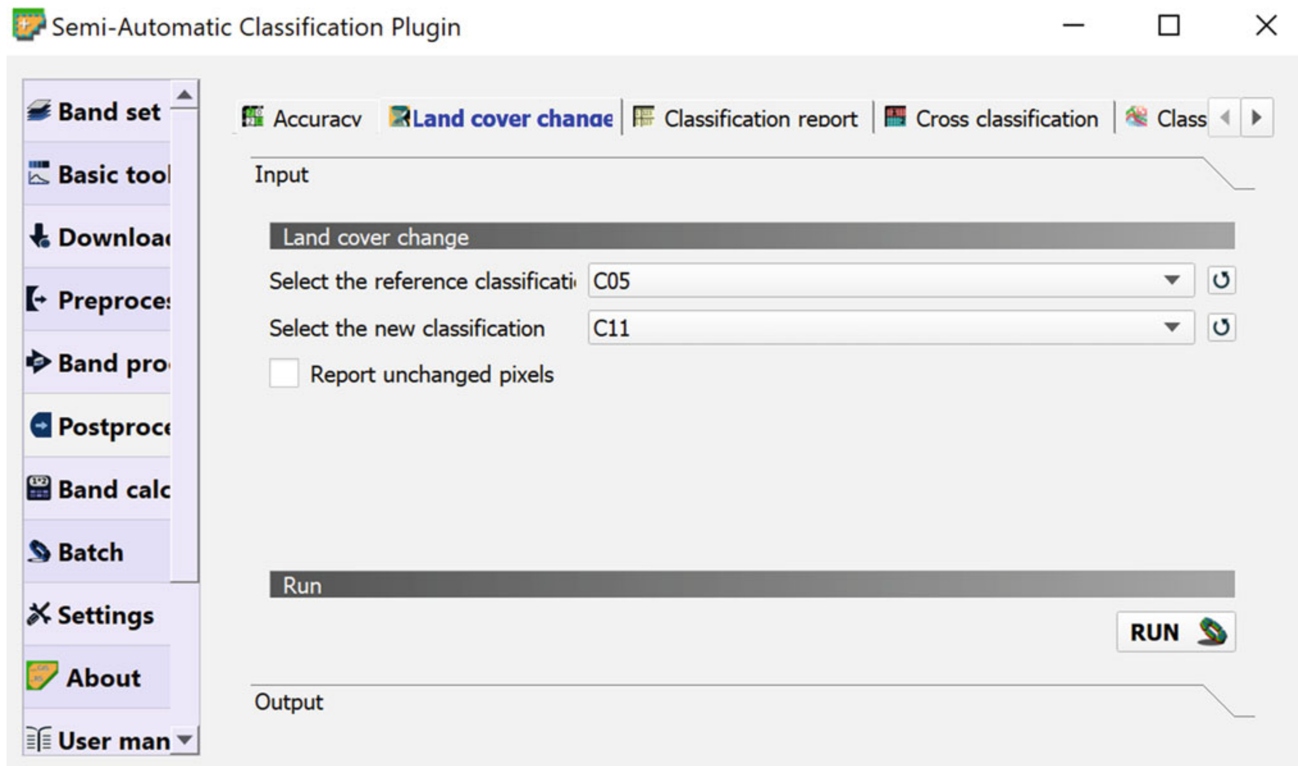


Fig. 3 Exercise 1. Step 1. Semi-Automatic Classification Plugin

that only shows the areas that changed during the study period. If this option is marked, a map showing both change and persistence areas will be obtained.

Run the tool to obtain two output maps showing the changes on the reference map (CORINE) and the changes simulated by the model. Both will refer to the same period (2005–2011).

Step 2

The next stage involves cross-tabulating the two maps of changes. To obtain these maps, open the Semi-Automatic Classification Plugin and in the "Postprocessing" tab, select *Accuracy*. Select the required parameters: classification to assess (simulated changes) and reference raster (CORINE 05–11 changes) (Fig. 4).

Results and Comments

Step 1 produces two maps of changes, which are stored in the folder specified by the user. The function also generates a matrix for each pair of cross-tabulated maps. These matrices appear in the "output" window, stored in CSV format. They show each possible combination between the two cross-tabulated maps and the code under which each combination is represented in the output raster.

Only four transitions (new codes *3, 4, 16* and *17*) are simulated by the model, as expressed in Table 5. Twenty-eight transitions occur between the CORINE maps (Table 2).

Most of the changes predicted in the simulation refer to the transition from agricultural areas (Category 0) to urban fabric (Category 2) and to the transition from agricultural areas to industrial and commercial areas (Category 3). Together, they represent 1,546 of the 1,632 pixels simulated. That is, almost 95% of the simulated pixels. In the reference map, these transitions represent 751 and 503 pixels, respectively, a less significant proportion of total change (in italics in Table 6).

After completing *Step 2*, we now have a cross-tabulation raster and a table showing every possible combination between the two cross-tabulated maps (Table 7).

Following the definitions provided by Pontius et al. (2008), in our case, HITS were only obtained in new codes 12 (old code 3 in the CORINE map of changes and old code 3 in the simulated map of changes), 18 (old codes 4 and 4) and 55 (old codes 17 and 17). HITS are obtained when both the reference map and the simulation show the same change or transition, which is why they both have the same codes.

The WRONG HITS correspond to combinations where both the reference map and the simulation show change, but to different gaining categories. For example, new code 13 (old codes 3 and 4) refers to areas that were agricultural

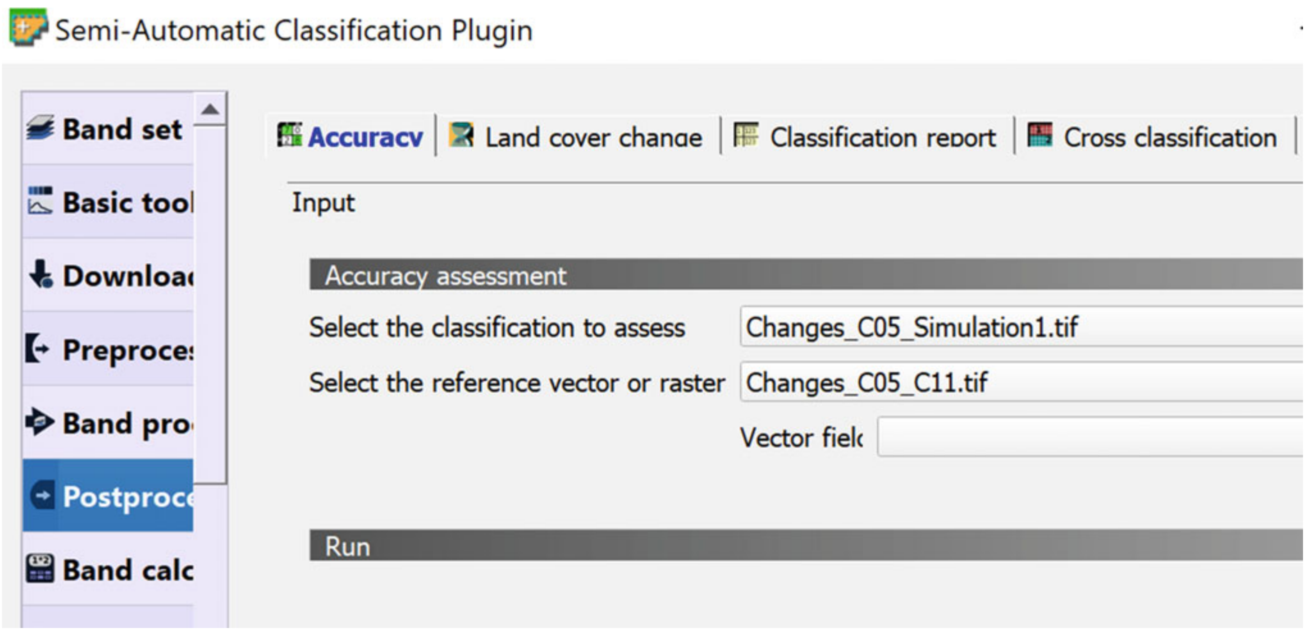


Fig. 4 Exercise 1. Step 2. Semi-Automatic Classification Plugin

Table 5 Result from Exercise 1. Variety and size of the simulated transitions

New codes	CORINE 05 category	Simulation category	Pixel sum
3	*0*	*2*	*874*
4	*0*	*3*	*672*
16	*1*	*2*	*38*
17	*1*	*3*	*48*

Table 6 Result from Exercise 1. Size of transitions between CORINE 2005 and CORINE 2011 maps

New codes	CORINE 05 category	CORINE 11 category	Pixel sum
2	0	1	374
3	*0*	*2*	*751*
4	*0*	*3*	*503*
5	0	4	148
6	0	5	11
7	0	6	301
10	0	9	132
14	1	0	588
16	*1*	*2*	*61*
17	*1*	*3*	*82*
18	1	4	157
19	1	5	109
20	1	6	225
24	1	10	180
27	2	0	21
28	2	1	22
30	2	3	26
36	2	9	4
40	3	0	51
42	3	2	11
53	4	0	211
54	4	1	327
55	4	2	89
56	4	3	21
79	6	0	44
80	6	1	111
147	11	3	88
151	11	7	657

areas that changed to urban fabric in the simulation and to industrial and commercial areas in the reference map (Tables 5 and 6).

FALSE ALARMS refer to areas that are marked as persistence in the reference map and as change in the simulation. Examples include new code 2 (old codes 0 and 3). Areas with that code refer to pixels that were simulated as urban fabric in the simulation, but do not show change in the reference map. Code 0 does not appear among the codes in Table 6 summarizing all the possible transitions between the original (CORINE 2005) and the reference map (CORINE 2011). It must therefore refer to persistence.

Table 7 Result from Exercise 1. (Dis)agreement between the simulated changes and the changes in the reference maps classified in five categories: misses, hits, wrong hits, false alarms and correct rejections

New codes	Changes CORINE 05–11	Changes simulation	Pixel sum	Interpretation
1	0	0	577,949[1]	CORRECT REJECTION
2	0	3	600	FALSE ALARMS
3	0	4	525	FALSE ALARMS
4	0	16	38	FALSE ALARMS
5	0	17	33	FALSE ALARMS
6	2	0	374	MISSES
11	3	0	543	MISSES
12	3	3	204	HITS
13	3	4	4	WRONG HITS
16	4	0	364	MISSES
17	4	3	2	WRONG HITS
18	4	4	137	HITS
21	5	0	148	MISSES
26	6	0	11	MISSES
31	7	0	280	MISSES
32	7	3	15	WRONG HITS
33	7	4	6	WRONG HITS
36	10	0	79	MISSES
37	10	3	53	WRONG HITS
41	14	0	579	MISSES
45	14	17	9	WRONG HITS
46	16	0	61	MISSES
51	17	0	76	MISSES
55	17	17	6	HITS
56	18	0	157	MISSES
61	19	0	109	MISSES
66	20	0	225	MISSES
71	24	0	180	MISSES
76	27	0	21	MISSES
81	28	0	22	MISSES
86	30	0	26	MISSES
91	36	0	4	MISSES
96	40	0	51	MISSES
101	42	0	11	MISSES
106	53	0	211	MISSES
111	54	0	327	MISSES
116	55	0	89	MISSES
121	56	0	21	MISSES
126	79	0	44	MISSES
131	80	0	111	MISSES
136	147	0	88	MISSES
141	151	0	657	MISSES

[1] The result of 577,949 pixels classified as CORRECT REJECTIONS was calculated by subtracting the 339,103 pixels of no data from the 917,052 pixels coded as 1.

MISSES refer to the areas where the reference map shows change but the simulation shows persistence. Examples include code 16 (old code 4 and 0). Finally, CORRECT REJECTION refers to the pixels marked as persistence in the reference map that were correctly simulated as persistence (new code 1, old codes 0 and 0).

In total, HITS account for 347 pixels, WRONG HITS for 89 pixels, FALSE ALARMS for 1,196 pixels and MISSES for 4,869 pixels (Table 7). Therefore, the simulation produced a lot more FALSE ALARMS than HITS and the vast majority of the predictions were MISSES. This makes sense because most of the landscape remained unchanged over the simulation period.

With all the above information, we can finally calculate the Figure of Merit (B/(A + B + C + D)) for the model. It is 5.340%. This is a very low Figure of Merit, far below the 100% that would mean perfect overlap. However, perfect overlap is almost impossible. In most cases, low Figures of Merit are the norm.

We must also consider that the Figure of Merit compares the simulated changes with all the changes in the reference map. In our simulation, we only modelled two categories actively (urban fabric and industrial and commercial areas). This means that the changes in all the other categories were not even simulated and no agreement can therefore be expected. This limitation must be borne in mind when evaluating the Figure of Merit.

The best way to obtain a Figure of Merit that offers objective information about the validity of our modelling exercise is to repeat the same exercise, focusing exclusively on the actively modelled transitions (from agricultural and vegetation areas to urban fabric and industrial and commercial areas).

Producer's accuracy (B/(A + B + C)) is 6.54% and expresses the number of pixels that the model accurately predicts as change as a proportion of total observed change. For its part, User's accuracy (B/(B + C + D)) measures the number of pixels that the model predicts accurately as change as a proportion of total predicted change, in this case 21.26%.

As regards the four simulated changes, shown in Table 5, the Producer's and User's accuracy values for Categories 3 and 4 are higher than for Category 17, and are zero in Category 16 (Table 8).

Exercise 2. To validate simulated changes against a reference map of changes in a binary format

Aim

To validate the change simulated by a model against a reference map of changes for the same simulation period. To do this, we overlay two maps that show change versus non-change over the same period. The initial map in both cases is the CORINE dataset for 2005. The changes from 2005 to 2011 are calculated for the simulation and for the CORINE dataset as reference. In this exercise we do not evaluate the WRONG HITS.

Materials

CORINE Land Use Map Asturias Central Area 2005
CORINE Land Use Map Asturias Central Area 2011
Simulation CORINE Asturias Central Area 2011

Requisites

The maps must have the same extent, spatial resolution, projection and legend. If they do not have the same legend, the maps must be reclassified so as to meet this requirement. For a proper validation, the latest reference map must refer to the same date as the simulation.

Execution

Step 1

The first step is to obtain two rasters showing the areas that changed and those that remained the same over the period being analysed: one for the reference map (CORINE 2005–CORINE 2011) and one for the simulation (CORINE 2005–Simulation 2011). To obtain these maps, follow the instructions in Exercise 1 *Step* 1 above.

Step 2

Once the two maps have been obtained, they must be reclassified into binary format, i.e. into a map with two possible values: 0 (persistence) and 1 (changes). This is done using the *Reclassify by table* tool.

Table 8 Results from Exercise 1. Producer's and User's accuracy values

Categories in changes simulation	3	4	17	16
Producer's accuracy %	27.1638	27.2366	7.3171	0.000
User's accuracy %	23.3410	20.3869	12.5000	-

Fig. 5 Exercise 2. Step 2. Intermediate map showing the areas of change in the reference maps

Fig. 6 Exercise 2. Step 2. Intermediate map showing the areas of change in the simulation

Figures 5 and 6 show the change areas (value 1) in black and the persistence areas (value 0) in white, for both the reference map (Fig. 5) and the simulation (Fig. 6).

Step 3

Finally, the two binary maps must be cross-tabulated. To do so, open the "Semi-Automatic Classification Plugin" and, in the "Postprocessing" tab, select the *Cross-classification* option. Fill in the required parameters: classification (binary changes from the simulation) and reference raster (binary changes from CORINE) (Fig. 7).

Results and Comments

Once we have completed *Step 3*, the QGIS creates an output raster that shows all possible combinations between the two binary change maps. The function also generates a table showing all possible combinations between the two input maps. This table appears in the "output" window, stored in CSV format. This table also lists the codes with which each combination is represented in the output raster.

Table 9 presents the four possible combinations obtained from the two binary maps crossed in *Step 3*. As 0 was used to represent persistent areas and 1 areas that changed, new code 1 (0/0) refers to pixels that the model correctly simulated as persistence (CORRECT REJECTIONS). New code 4 (1/1) refers to pixels that the model correctly simulated as change (HITS), while codes 2 and 3 refer to pixels in which the model does not agree with the reference map. Code 2 (0/1) corresponds to FALSE ALARMS: the model simulated change but the reference map shows persistence. Code 3 (1/0) stands for MISSES: the model simulated persistence but the reference map shows change.

The sum of MISSES plus HITS (5,305 pixels) represents the change in the reference map (CORINE) for the period 2005–2011. These pixels cover just 0.9077% of the total study area. Very little change therefore took place in the reference map for our study area.

HITS plus FALSE ALARMS (1,632 pixels) gives all the pixels in which the simulation predicted change. These pixels cover 0.2792% of the total study area. This means that fewer changes were simulated than actually took place on

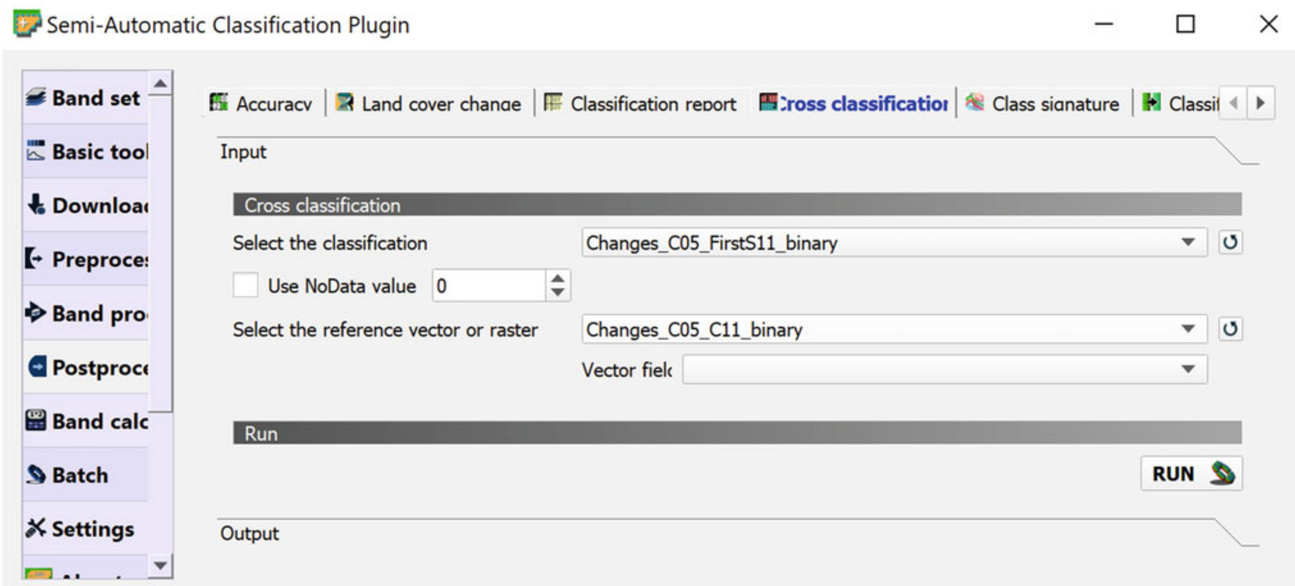


Fig. 7 Exercise 2. Step 3. Semi-Automatic Classification Plugin

Table 9 Result from Exercise 1. (Dis)agreement between the simulated changes and the changes in the reference maps classifiedin five categories: misses, hits, wrong hits, false alarms and correct rejections

New codes	Binary CORINE changes	Binary simulated changes	Pixel sum	Interpretation
1	0	0	577,949[2]	CORRECT REJECTIONS
2	0	1	1,196	FALSE ALARMS
3	1	0	4,869	MISSES
4	1	1	436	HITS

the reference map. This makes sense given that in our simulation we only simulated the transitions from agricultural and vegetation areas to urban fabric and industrial and commercial areas, while the reference map also considered many other changes between all the other categories represented on the map, which were not simulated in our modelling exercise.

The Figure of Merit (B/(A + B + C + D)) for our simulation is very low at 6.7%. This indicates that the simulation did not simulate most of the changes that took place in the reference map correctly. This is partly due to the fact that we only actively modelled two categories, while the reference map showed the changes that took place between all categories. As a result, overlap between the two maps is impossible in many areas. Even so, the general level of overlap between the simulated changes and those observed on the reference maps is still quite low. Other metrics and tools must therefore be used in order to interpret the simulation and the performance of the modelling exercise better.

The Figure of Merit in this exercise is a bit better than in the previous one because we did not take WRONG HITS into account. In this case, we only compared changes, without taking into account the type of change that happened in the simulation period.

Exercise 3. To validate the changes simulated by various models

Aim

To compare and validate the change simulated by two models. For this purpose, we overlay three maps that show change versus non-change over the same interval. The initial map in all cases is the CORINE dataset for 2005. The changes from 2005 to 2011 are calculated for the simulation from model 1, for the simulation from model 2 and for the CORINE dataset as reference. WRONG HITS are not evaluated in this exercise.

[2] There are 339,103 pixels of no data. If we subtract them from the 917,052 pixels coded as 1, the result is 577,949 pixels in which there were CORRECT REJECTIONS.

Materials

CORINE Land Use Map Asturias Central Area 2005
CORINE Land Use Map Asturias Central Area 2011
Simulation CORINE Asturias Central Area 2011
Simulation CORINE 2 Asturias Central Area 2011

Requisites

The maps must have the same extent, spatial resolution, projection and legend. If they do not have the same legend, the maps must be reclassified so as to meet this requirement. For a proper validation, the latest reference map must refer to the same date as the simulation.

Execution

Step 1

The first step is to obtain three rasters for the study area showing the areas that changed and those that remained the same over the period being analysed. In this way, we obtain: (i) the map of changes for the reference map (CORINE 2005–CORINE 2011), (ii) the map of changes for the first simulation (CORINE 2005–Simulation 1 2011) and (iii) the map of changes for the second simulation (CORINE 2005–Simulation 2 2011).

To obtain these maps, open the "Semi-Automatic Classification Plugin" and, in the "Postprocessing" tab, select *Land cover change*. Then, fill in the required parameters: the earliest map in the reference classification (CORINE 2005) and the more recent maps in the new classifications (CORINE 2011, Simulation 1 2011, Simulation 2 2011). The three output maps will show the change areas and the persistence areas for each of the three maps (the reference CORINE map and the two simulations) under consideration.

Step 2

Once these three maps have been obtained, they must be reclassified into binary maps in which persistence areas are reclassified as 0 and change areas as 1. The maps are reclassified using the *Reclassify by table* tool.

Step 3

The three binary maps must then be cross-tabulated, so as to be able to assess the congruence between the simulations and the reference map.

To do this, open the "Semi-Automatic Classification Plugin" and the "Postprocessing" tab, and then select *Cross-classification*. Start by cross-tabulating the two simulations you want to compare. To this end, fill in the following parameters: classification (binary map of changes from simulation 1) and reference raster (binary map of changes from simulation 2) (Fig. 8).

Step 4

The procedure is repeated again, this time cross-tabulating the raster obtained in the previous step with the reference map. In this case, open the tool and fill in the parameters as follows: classification (raster obtained after running the tool

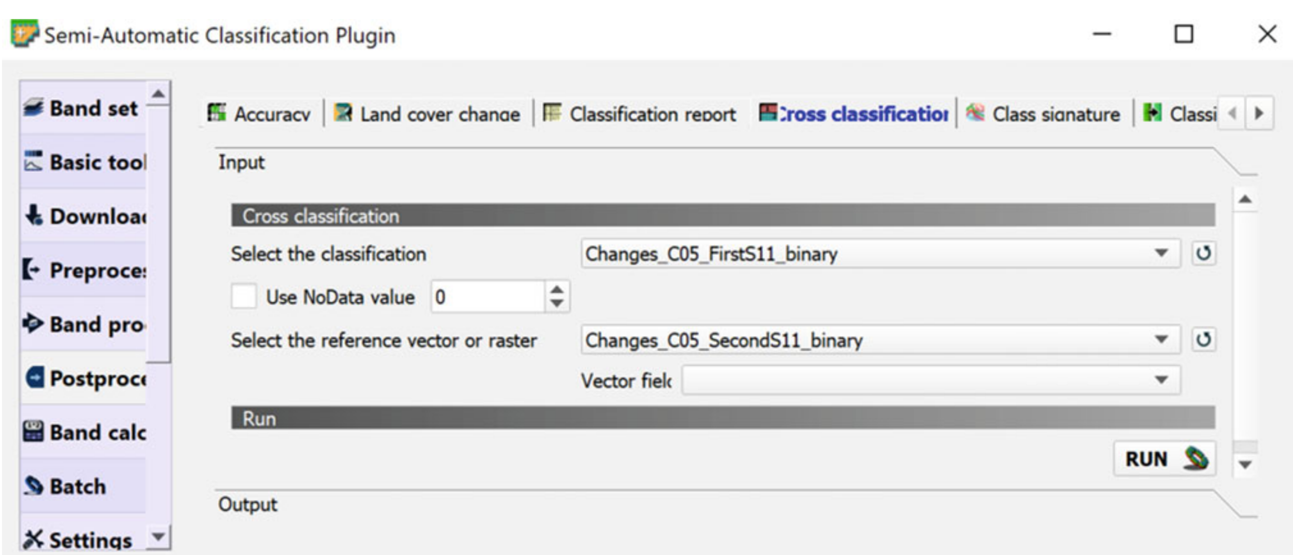


Fig. 8 Exercise 3. Step 3. Semi-Automatic Classification Plugin

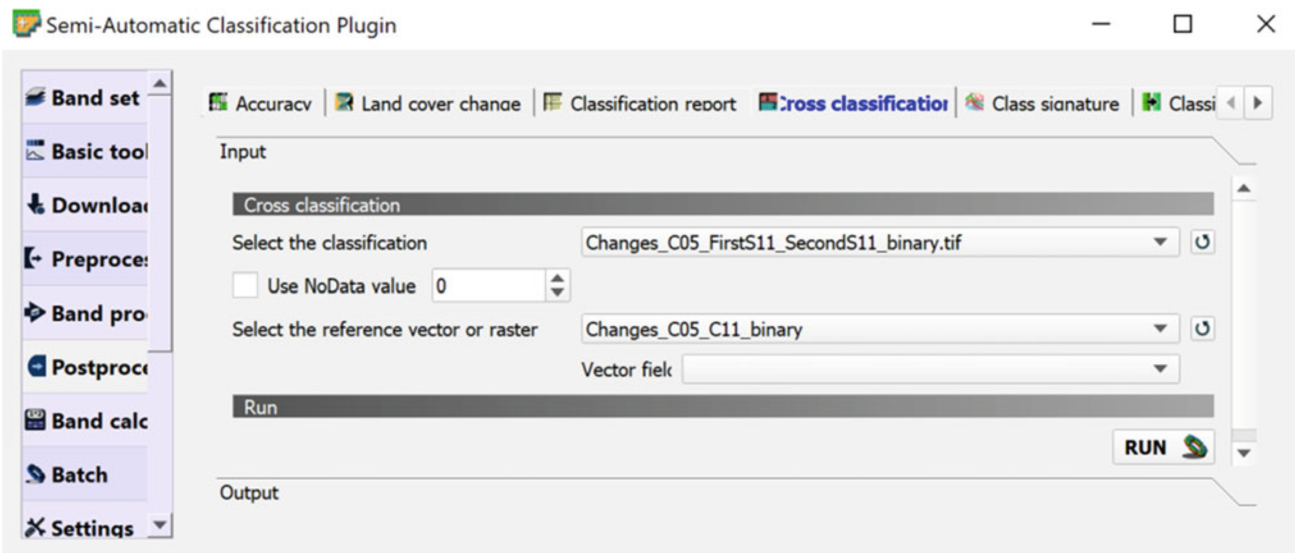


Fig. 9 Exercise 3. Step 4. Semi-Automatic Classification Plugin

as explained in the previous step) and reference raster (CORINE 05–11 binary map of changes) (Fig. 9).

Results and Comments

After carrying out *Steps 3* and *4*, QGIS creates two output rasters. The function also generates a table for each raster, which appears in the “output” window in CSV format. This table shows every possible combination between the values of the cross-tabulated maps. It also lists the codes under which each combination is represented in the output raster.

The raster obtained in *Step 3* measures the agreement between the two simulations (Table 10). In the binary maps, 0 was used to refer to persistent areas whereas 1 referred to areas that changed. New code 1 (previous codes 0/0) therefore refers to the pixels in which both models predicted persistence, while new code 4 (1/1) refers to the pixels where both models predicted change. Finally, new codes 2 and 3 represent areas in which the simulations do not agree: one shows persistence, whereas the other shows change.

The raster obtained in *Step 4* was produced by cross-tabulating a reference change map with the raster obtained after cross-tabulating the change maps produced by the two simulations. This cross-tabulation therefore produces eight possible combinations (Table 11).

In order to interpret the results of this second cross-tabulation correctly, we need to understand the values of the two rasters that were cross-tabulated. In the reference change map, 0 refers to persistent areas and 1 to areas that changed during the period under consideration. The meanings of the new codes in the raster obtained in *Step 3* are detailed in Table 9.

This enables a better interpretation of the results of the last raster generated. New code 1 (previous codes 0/1) refers to areas in which persistence was observed on the reference map of changes (code 0) and was also simulated by the two

Table 10 Results from Exercise 3. (Dis)agreement between the changes in the two simulations that have been compared

New codes	Binary changes from simulation 1	Binary changes from simulation 2	Pixel sum	Interpretation
1	0	0	581,158[3]	Both models predicted persistence
2	0	1	64	First model predicted persistence/Second model predicted change
3	1	0	1,660	First model predicted change/Second model predicted persistence
4	1	1	1,568	Both models predicted change

[3] There are 339,103 pixels of no data. If we subtract them from the 920,261 pixels coded as 1, the result is 581,158 pixels.

Table 11 Results from Exercise 3. (Dis)agreement between the changes in the two simulations and the changes in the reference maps

New codes	Binary changes CORINE	Cross-tabulation from binary changes simulation from models 1 and 2	Pixel sum	Interpretation
1	0	1	576,588[4]	DOUBLE CORRECT REJECTION Both models correctly predicted persistence
2	0	2	54	CORRECT REJECTION/FALSE ALARMS First model correctly predicted persistence/Second model wrongly predicted change
3	0	3	1,361	FALSE ALARMS/CORRECT REJECTION First model wrongly predicted change/Second model correctly predicted persistence
4	0	4	1,142	DOUBLE FALSE ALARMS Both models wrongly predicted change
5	1	1	4,570	DOUBLE MISSES Both models wrongly predicted persistence
6	1	2	10	MISSES/HITS First model wrongly predicted persistence/Second model correctly predicted change
7	1	3	299	HITS/MISSES First model correctly predicted change/Second model wrongly predicted persistence
8	1	4	426	DOUBLE HITS Both models correctly predicted change

models (code 1) (see Table 9 to understand the meaning of this code). Those cases in which the two models and the reference map all simulated persistence are referred to as DOUBLE REJECTIONS (Camacho Olmedo et al. 2015).

New code 4 (previous codes 0/4) refers to areas where the two models simulated change (code 4) and the reference change map showed persistence. These are known as DOUBLE FALSE ALARMS.

New code 5 (1/1) corresponds to areas where both models simulated persistence and the reference map showed change (DOUBLE MISSES). New code 8 (1/4) refers to areas where the two models and the reference map also showed change (DOUBLE HITS). Finally, the other four combinations refer to areas where each simulation shows a different agreement with the reference map (Table 11).

These eight possible combinations are expressed as two maps. The first map (a zoomed area is shown in Fig. 10, on the left) shows the four possible combinations for the areas on the CORINE map in which persistence was observed. Pixels simulated as persistence are therefore CORRECT REJECTIONS, while those simulated as change areas are FALSE ALARMS. The areas that changed are masked in white. The second map (a zoomed area is shown in Fig. 11, on the right) shows the four possible combinations for the areas on the CORINE map in which change was observed. Pixels simulated as change are HITS, while those simulated as persistence are MISSES. The persistence areas are masked in white.

According to all the above results, it seems that the two simulations are very similar in terms of predictive accuracy. The vast majority of the pixels on the map are DOUBLE CORRECT REJECTIONS, which means that both models are very accurate when predicting persistence. This makes sense in that persistence is very easy to simulate in a highly stable area like the one we simulated. The most challenging task is to correctly simulate change. The best

[4] There are 339,103 pixels of no data. If we subtract them from the 915,691 pixels coded as 1, the result is 576,588 pixels classified as DOUBLE CORRECT REJECTIONS.

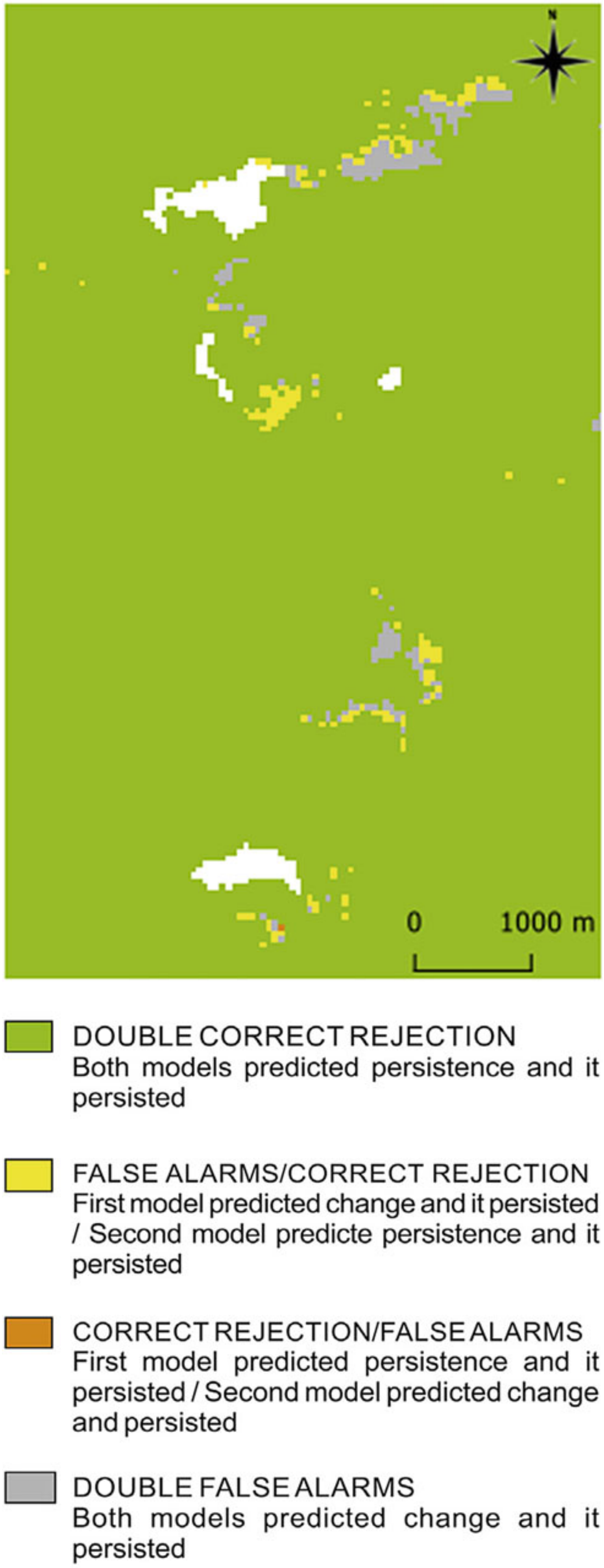


Fig. 10 Result from Exercise 3. (Dis)agreement between the simulations and the reference maps for the areas where persistence was observed

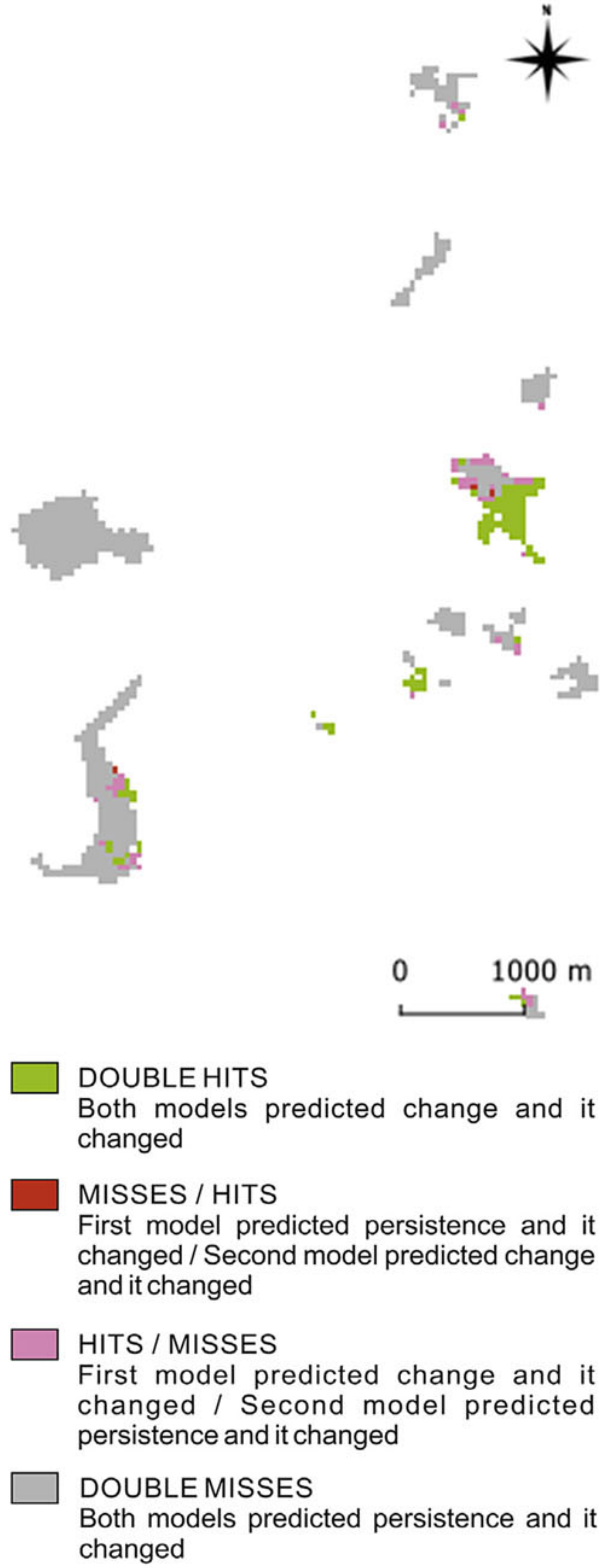


Fig. 11 Result from Exercise 3. (Dis)agreement between the simulations and the reference maps for the areas where change was observed

models are therefore those that simulate change most accurately.

If we focus exclusively on the areas that changed, the accuracy is very low. 86.1451% of the pixels were DOUBLE MISSES, while in the remaining pixels there were HITS in one or both models. This means that in the vast majority of cases, our models incorrectly simulated change. These simulations cannot therefore be validated, although other validation tools can be used to check whether the simulated pattern is valid. In this regard, even if a hard comparison does not show a high level of agreement between a simulation and the reference map, the pattern of the simulated changing areas may be logical or correct. The models can therefore be considered valid in a qualitative sense.

5 Incidents and States

Description

Incidents and states are terms proposed by Pontius Jr. et al. (2017) to characterize land use cover changes in a series of three or more maps. States refer to the number of land uses or land covers a pixel is assigned in the series of maps. There can be as many states as there are maps in the series. Hao and Gen-Suo (2014) used the term "land use classification variety" for this metric when applying it to validate Land Use Cover maps (MODIS Land Cover product).

Incidents refer to the number of times a pixel changes category over the course of a time series. There can be as many incidents as there are stages in the time series. In a series of 5 maps, there are 4 time-stages. The series may therefore have between 0 and 4 incidents, i.e. the pixel may change category between 0 and 4 times. The number of incidents can also be referred to as "Transition frequency".

Utility

Exercises
1. To validate a series of maps with two or more time points

The number of incidents and states assigned to the pixels in a time series of Land Use Cover maps can help us identify the changes that take place for technical reasons, i.e. erroneous or spurious changes which do not really happen on the ground.

When obtained from satellite imagery classification, Land Use Cover maps usually have important sources of uncertainty. Various different Land Use and Cover categories can have very similar levels of reflectance. If the imagery is obtained at different times of the year, or under different atmospheric conditions, the reflectance of a pixel can vary to a similar extent to the difference in reflectance between two Land Use Cover categories. The same pixel could therefore be classified under different categories over the course of the time series. The number of incidents and states of the pixel can potentially help us to identify these errors.

For example, in a time series of six maps, if a pixel has five incidents, but only two states, it means that it alternates between these two categories at each stage in the time series. If we discover which categories are involved in the transitions we can determine to what extent these changes are logical. Incidents and states can also be used to validate a series of simulations, when working with modelling exercises to obtain scenarios for more than two time points.

QGIS Exercise

Available tools
• Processing Toolbox GRASS Raster *r.series*

The GRASS toolbox associated with QGIS has a tool for calculating the number of states in a time series of Land Use Cover maps. QGIS does not provide any specific tool to calculate the number of incidents in the time series, so this metric must be calculated manually. This is done using the raster calculator and a raster reclassification tool.

QGIS offers several raster calculators and reclassification tools. Although they are all valid, in this exercise we will be using the ones from the core QGIS toolbox.

Pontius et al. (2017) also developed a tool in Excel to automatically calculate the incidents and states of a series of Land Use Cover raster maps in .rst format. It is available online free of charge.[5]

Exercise 1. To validate a series of maps with two or more time points

Aim

To find out if technical changes may have taken place in the last series of CORINE Land Cover maps produced for the Asturias Central Area.

[5] The tool is available on R. G. Pontius Jr's personal website: http://www2.clarku.edu/~rpontius/.

Materials

CORINE Land Use Map Asturias Central Area 2005
CORINE Land Use Map Asturias Central Area 2011
CORINE Land Use Map Asturias Central Area 2018

Requisites

All maps must be rasters and have the same resolution, extent and projection.

Execution

Step 1

In order to calculate the number of states per pixel, we must open the *r.series* tool and select all the maps that form part of the series of Land Use Cover maps we are analysing ("Input raster layer(s)"). In this case, we select the three maps in our series: CORINE Land Cover 2005, 2011 and 2018.

In the "Aggregate operation [optional]" option, select "Diversity". This will count the number of different categories to which a pixel is assigned over the course of the time series.

In "Advanced parameters", indicate the range of values of the Land Use Cover maps introduced as input, i.e. the minimum and maximum values. In our case, the minimum value for a category is 0 and the maximum value is 12 (Fig. 12).

The final stage is to indicate where the new map will be saved.

Step 2

There is no specific tool for calculating the number of incidents in a pixel over the course of a time series. This operation must therefore be carried out manually. The first

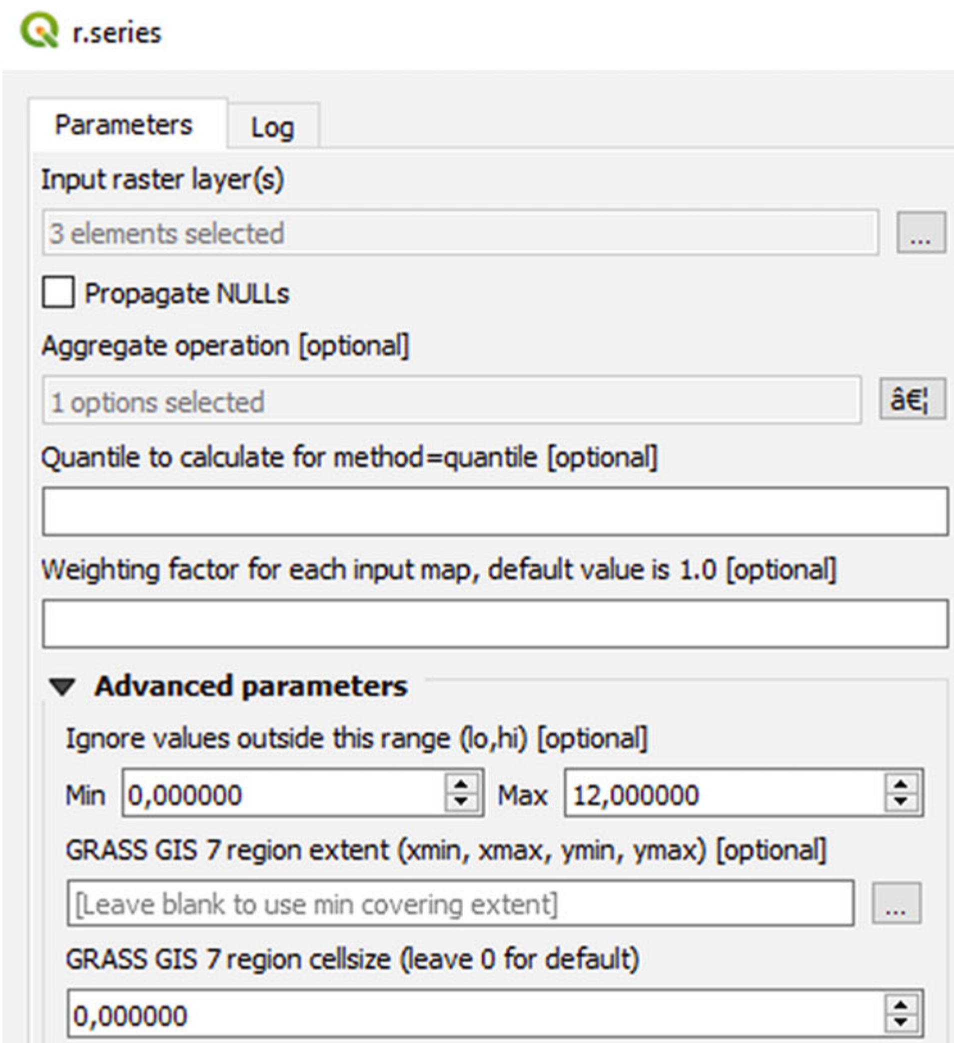


Fig. 12 Exercise 1. Step 1. R.series

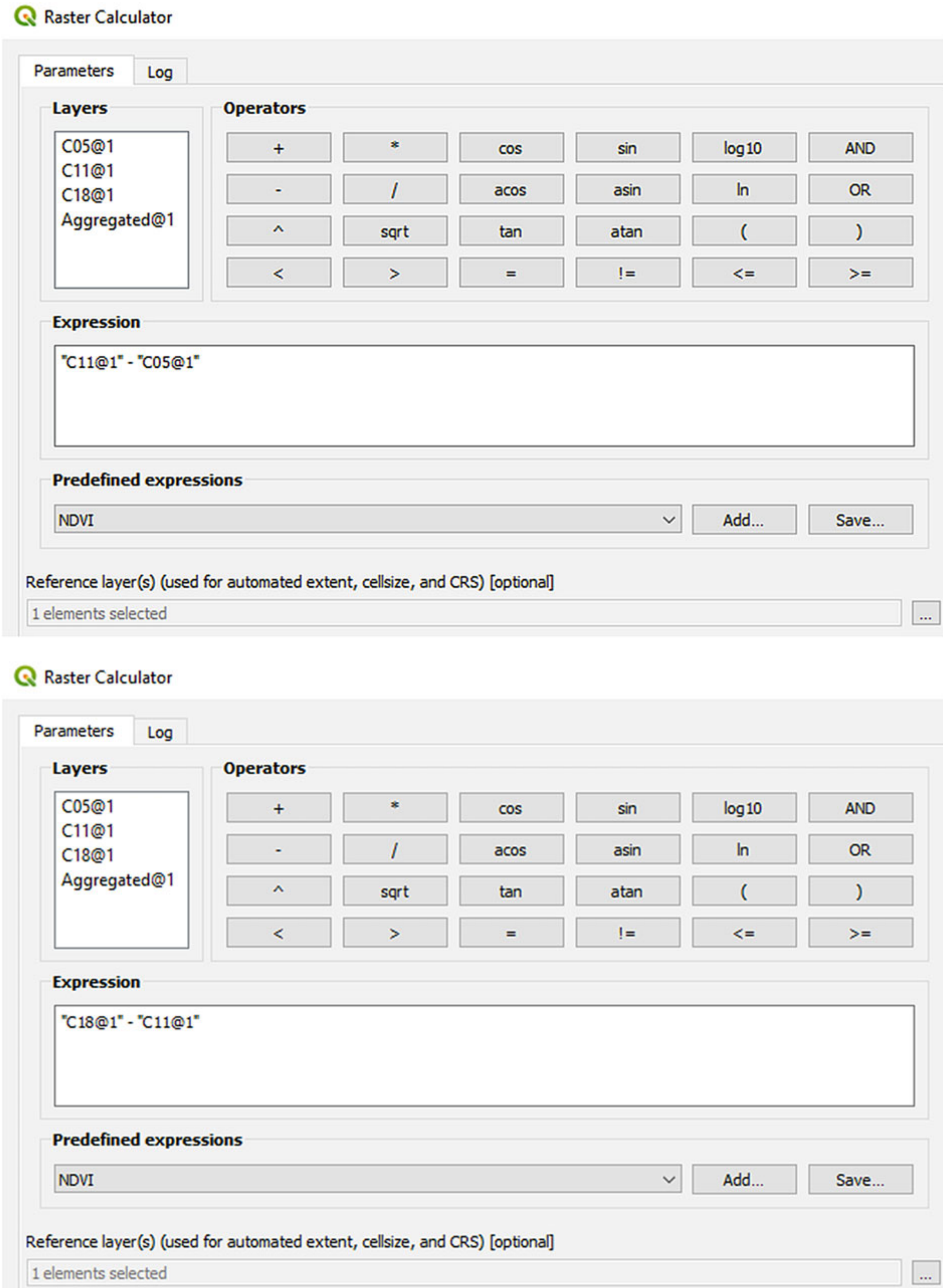


Fig. 13 Exercise 1. Step 2. Raster Calculator

step is to identify where the changes happened. For each pixel, we must then calculate the number of times it underwent change (or not). To carry out these operations, we have to work with pairs of maps: first 2005 and 2011 and then 2011 and 2018.

To identify where the changes happened, for each pair of rasters we must subtract one raster from the other. If a pixel does not change, the result of the subtraction will be a value of 0 for that pixel. If the pixel changes, the result of the subtraction will be a value other than 0.

The subtraction operation is carried out using the *Raster calculator*, in which we must write the following subtraction expression for each pair of maps:

$$\text{t2 map} - \text{t1 map}$$

We also need to indicate which raster is the reference map that will be used to define the characteristics (extent, spatial resolution and projection) of the new raster obtained after the calculation. In this case, we will be using the first map in our series (CORINE 2005). This must be indicated in the "Reference layer(s) (used for automated extent, cell size and CRS) [optional]" option (Fig. 13).

Step 3

Once the previous step has been completed, the maps obtained must be reclassified to enable us to identify the pixels where an incident took place (values other than 0) and the pixels that were incident-free at each stage (0 values).

To identify all pixels in which incidents took place with a value of 1, we reclassify all values other than 0 as 1 using the *Reclassify by table* tool (Fig. 15). The first stage in the reclassification process is to indicate the two rasters that must be reclassified. Then, detail the reclassification criteria using the "Reclassification table" option. In the window that opens for selecting the reclassification criteria, add two rows using the "Add row" button. Then, introduce the following values (Fig. 14):

That means that all values between −999 and −1 will be reclassified with the value 1. The same will be true for all values between 1 and 999. If as a result of the raster subtraction we get bigger negative values than −999 or bigger positive values than 999 we will need to adjust the values in the reclassification table accordingly.

Step 4

The last step is to count the number of incidents for each pixel over the course of the time series. This is done using the *Raster calculator*, which adds together the rasters we reclassified in the previous step using the following expression:

$$\text{Incidents\_C05\_C11} + \text{Incidents\_C11\_C18}\ (\text{Fig. 5})$$

The CORINE 2005 map will be used as a reference to define the characteristics of the output raster (Fig. 16).

Results and Comments

After completing all the operations described above, two different maps will be obtained: one with the number of states per pixel and another with the number of incidents per pixel.

The above maps (Fig. 17) show the number of incidents and states for a specific part of the Asturias Central Area. Most of the areas that change over the period 2005–2018 underwent just one LUCC transition (one incident and one state). However, we discovered a couple of cases in which there were two incidents and two states. This means that, for

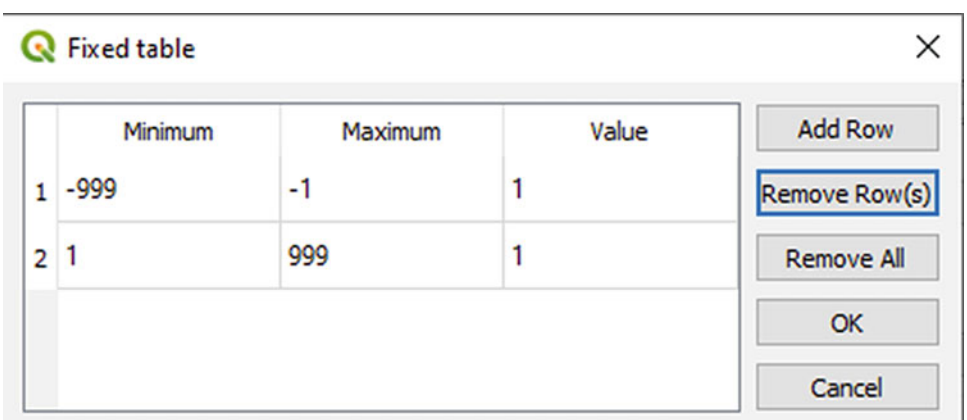


Fig. 14 Exercise 1. Step 3. Reclassification table of the Reclsify by Table tool

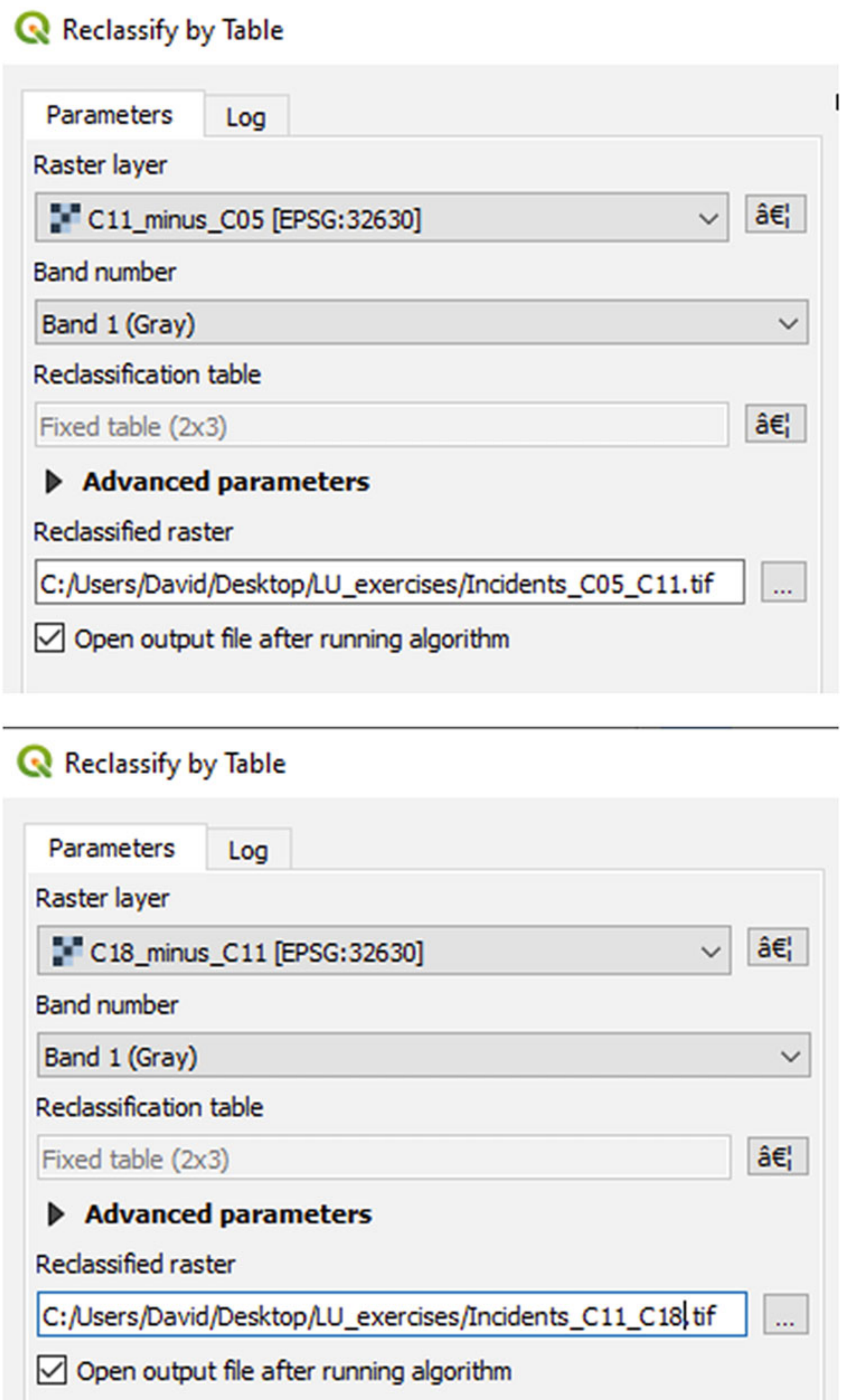


Fig. 15 Exercise 1. Step 3. Reclassify by Table

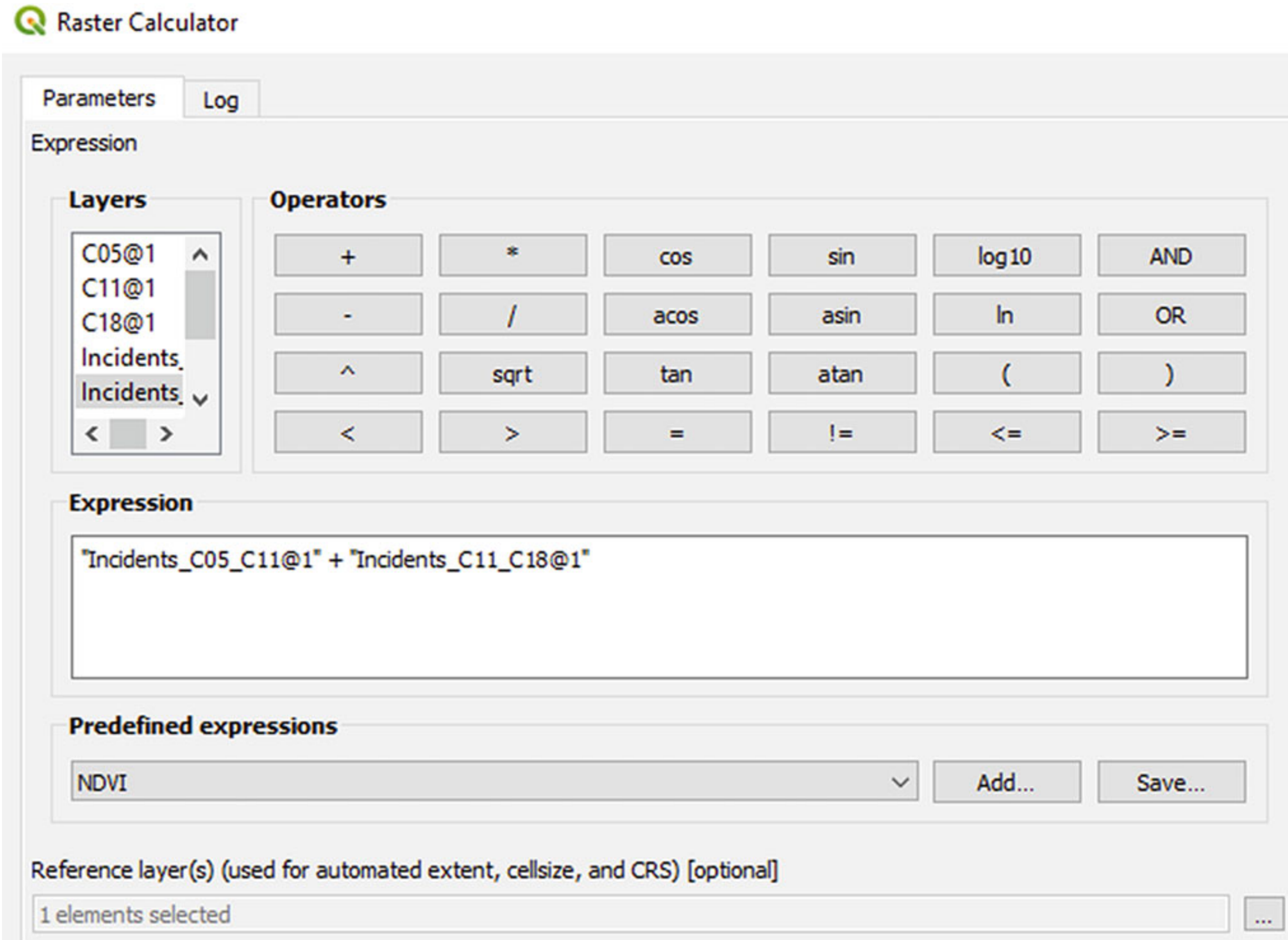


Fig. 16 Exercise 1. Step 4. Raster Calculator

the 3 years analysed (2005, 2011 and 2018), there were two changes or transitions, but these only involved two land uses or covers. In other words, the area changed from its original land use or cover in 2005 to a different one in 2011 and then reverted to the original in 2018.

If we refer back to the original maps, we can identify the transitions that took place. The changing area on the right (1) (Fig. 17) underwent a transition from "Agricultural areas" in 2005 to "Urban fabric" in 2011 and then changed back to "Agricultural areas" in 2018. It is highly unlikely that an agricultural cover could change to an artificial cover and then revert to its original state a few years later. It must therefore have been an error (technical or spurious change).

The changing area on the left (2) (Fig. 17) underwent a transition from "Agricultural areas" in 2005 to "Vegetation areas" in 2011, before changing back to "Agricultural areas" in 2018. This transition, although unlikely, seems more logical. So, before labelling it as an error or technical change, we should confirm whether these changes really took place in the area in question during the timeframe analysed. This can be done by photointerpretation of aerial imagery.

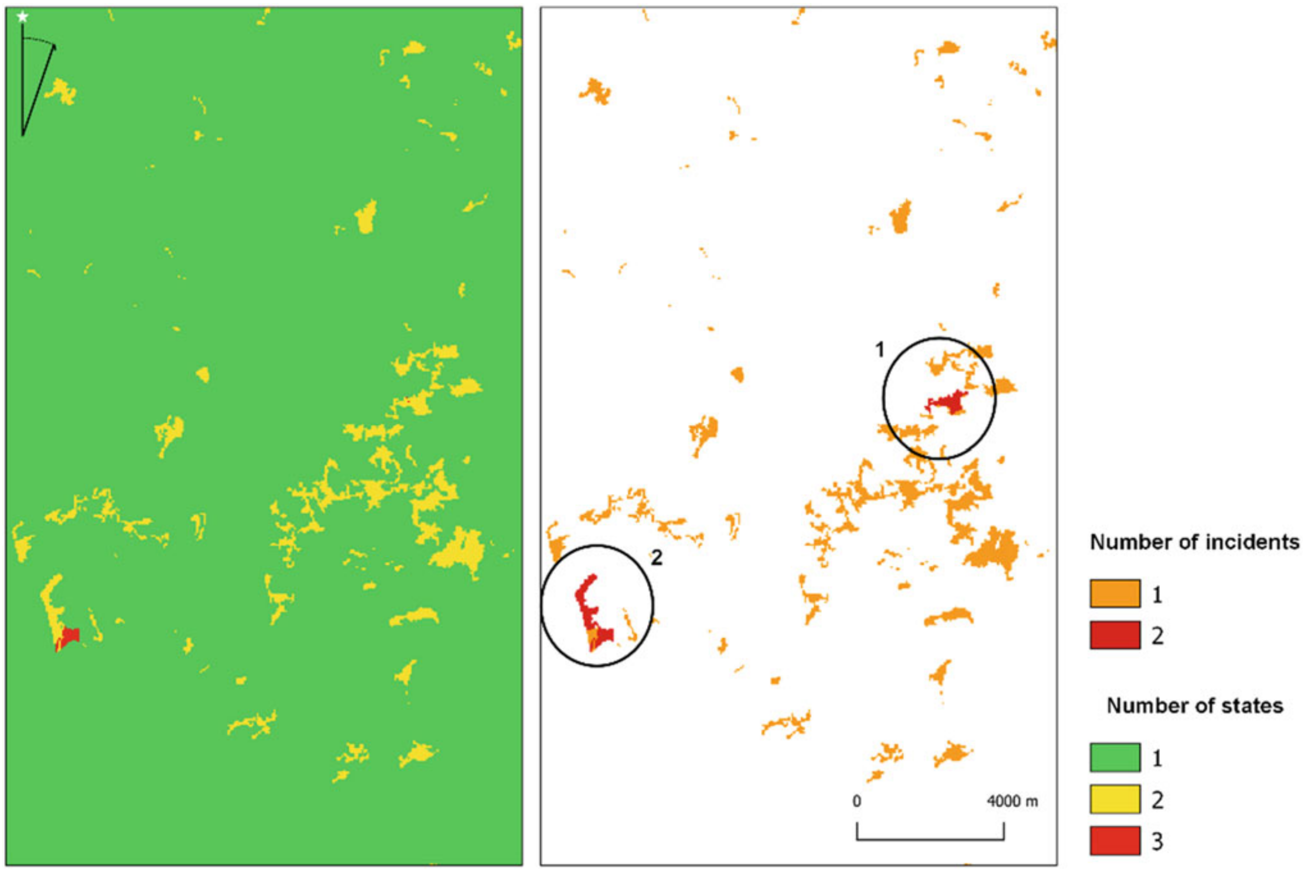


Fig. 17 Result from Exercise 1. Number of incidents and states for an example area of the Asturias Central Area

6 Intensity Analysis

Description

Intensity analysis, proposed by Aldwaik and Pontius (2012), enables us to assess the rate or intensity at which change takes place during each time interval in a time series of LUC maps. It also helps identify apparently random or uniform processes. It is a three-stage analysis process, which identifies: (i) periods of relatively slow/fast change; (ii) relatively dormant/active land use categories and (iii) the transitions that are actively avoided/targeted by a given land use category. A series of maps with three or more time points are needed for this analysis.

During the first stage of this process, the overall rate of land use change over each time interval is analysed to assess whether change was relatively fast or slow. To this end, the average annual rate of change for each time interval is compared with the average annual rate of change for the whole period.

The second stage analyses the intensity of change at category level within each time interval relative to the overall change rate for the interval calculated in stage one. It measures the gross losses and gross gains in area for each category so as to analyse whether the category shows a similar, stable pattern across the various time intervals in terms of the intensity of gains and losses. These observed intensities for each category are compared with an average annual rate of gains/losses that would exist if the changes within each interval were distributed uniformly over the entire time interval. This shows which categories are relatively dormant or active.

The final stage is at transition level. It examines the intensity of a particular transition over a given time interval, taking into account the different sizes of the categories and relative to the results of the category-level analysis. The gains made by a specific category may vary in size and intensity among the different categories from which it makes these gains. By comparing the observed rate of gains from each category with a uniform rate of gains that would exist if the gains were made uniformly from among all the available categories, we can identify those categories that are intensively avoided or targeted. Losses can be analysed in a similar way.

Intensity analysis also allows us to determine whether a particular transition occurs at a stable rate or occurs more intensely over a particular time interval within the series. If the same category is targeted (or avoided) over all the different time intervals, then this transition is said to be stationary.

Utility

Exercises
1. To validate a series of maps with two or more time points

Intensity analysis analyses the size and intensity of land changes. It also checks for stationarity and takes the relative size of the categories into account, rather than just the absolute gains or losses they may undergo.

At the interval level, users can identify how quickly or slowly LUC change is taking place during each time interval as compared to the average annual rate of change over the whole time series. At the category level, intensity analysis allows users to identify which categories are dormant versus active in terms of gains or losses in the size of each category. At the transition level, when a given category makes gains or losses, users can identify which other categories are most intensively targeted or avoided.

QGIS Exercise

Available tools
• Aldwaik and Pontius matrix (Excel sheet) https://sites.google.com/site/intensityanalysis/ • R Package *Intensity.analysis* • Processing R provider Plugin *Intensity_analysis.rsx* R script

There is not any specific tool available in QGIS to make intensity analysis, although this has been implemented in an R package (intensity.analysis) (Pontius and Khallaghi, 2019). Based on this package, we have developed an R script that allows to integrate this analysis in QGIS. This package will carry out the entire analysis and will generate three tables containing the results at each level of analysis (overall, category and transition) and a plot showing the results at the interval level.

See Chapter "About this Book" for more detailed information about how to integrate R into QGIS and how to use R scripts such as the one applied in this exercise.

Exercise 1. To validate a series of maps with two or more time points

Aim

To study land change in the Ariège study area using the CORINE Land Use maps dated 2000, 2012 and 2018. The results of this exercise can also be used to validate land change.

Materials

CORINE Land Cover Map Val d'Ariège 2000
CORINE Land Cover Map Val d'Ariège 2012
CORINE Land Cover Map Val d'Ariège 2018

Requisites

All maps must be in raster format and have the same resolution, extent and projection.

Execution

If necessary, install the Processing R provider plugin and download the *Intensity analysis.rsx* R script into the R scripts folder (processing/rscripts). See Chapter "About this Book" of this book for further information about how to use the QGIS R script.

Step 1

The land use maps need to be stacked into a multilayer file in chronological order. The first map is the oldest map. The second map is the next oldest and so on. This can be done with the *Merge* tool in the Raster tab.

Step 2

Run the script and fill in the required parameters (path and name of the time-series stack, null value, the path to the folder where the results will be saved, the path and name of the output plot) as shown in Fig. 18.

Results and Comments

The script will generate three files in the results folder: IntervalLevel.csv, CategoryLevel.csv and TransitionLevel.

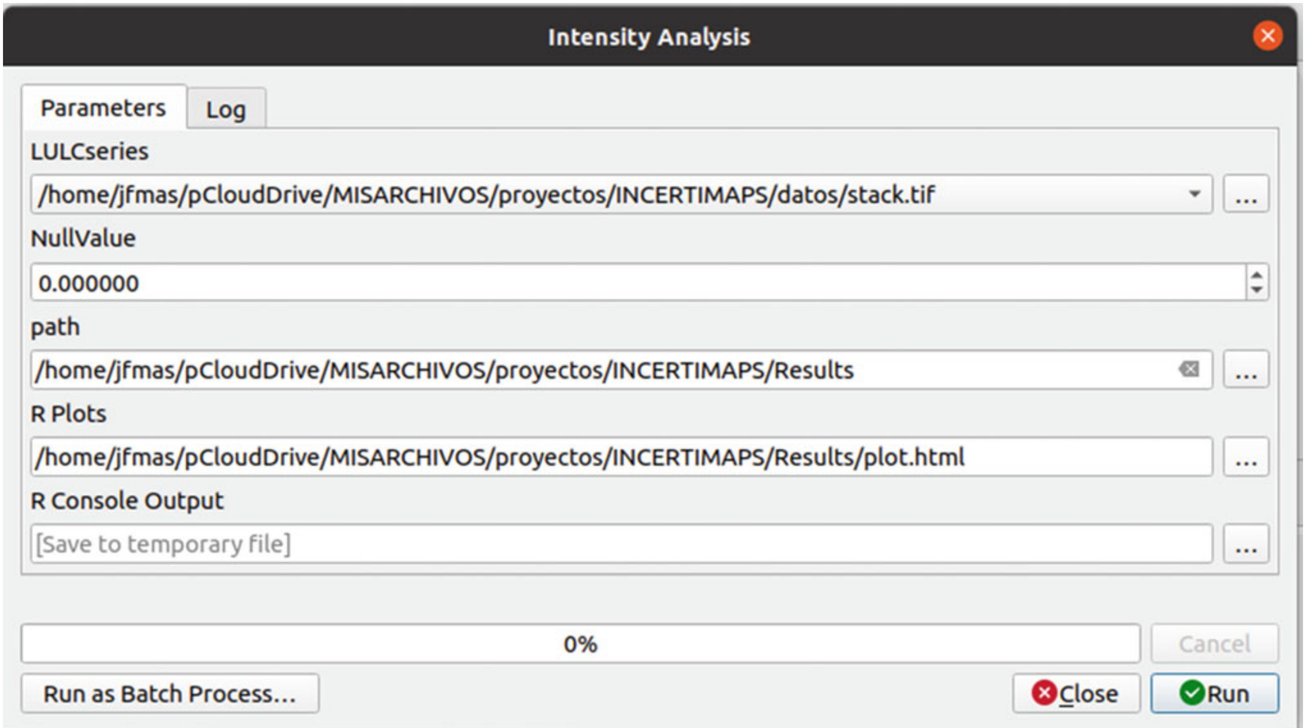


Fig. 18 Exercise 1. Step 2. Intensity Analysis R script

	A
1	,"Change Size","Annual change","Uniform Change across Intervals","Interval Behavior"
2	1_2,112424,0.0227104877429948,0.0187202341993798,Fast
3	2_3,72918,0.0147299806557647,0.0187202341993798,Slow

Fig. 19 Result. from Exercise 1. Average annual rate of change for each time interval and for the entire period

csv. A plot of the interval level is also produced. Plots of both the category and transition level have to be created from the Excel data sheet.

The first Excel file, called IntervalLevel.csv (Fig. 19), shows the average annual rate of change for each time interval (in this case there are two) and the average annual rate of change for the entire period. When the average rate for each interval is compared with the overall average rate, we can assess whether the interval in question was one of slow or fast change.

The automatically generated plot is shown in Fig. 20. The results show that land use change was more intense in the first time period than in the second. The average change rate over the entire period was 1.8, which means that change was relatively fast over the first period and relatively slow over the second.

The CategoryLevel.csv document (Fig. 21) contains information regarding gross losses and gross gains and the amount of loss intensities and gain intensities for each land use category (in this case there are six categories). If these gains or losses are compared with the average annual rate that would exist if the change within each interval were distributed uniformly over the entire time series, we can see which land categories are relatively dormant/active.

This table may be used to calculate the plots at the category level for each time interval. Figure 22 shows the result for the first time interval.

This figure shows the intensity of change in the different categories, regardless of their relative size within the study area. The categories with short bars to the left of the blue line representing average, uniform intensity are relatively inactive or dormant, whereas those that extend to the right are relatively active. For example, Category 1 showed the highest intensity in terms of land use gains, while Category 4 underwent more intense gains and losses than the average. At the other end of the scale, Category 3 was relatively

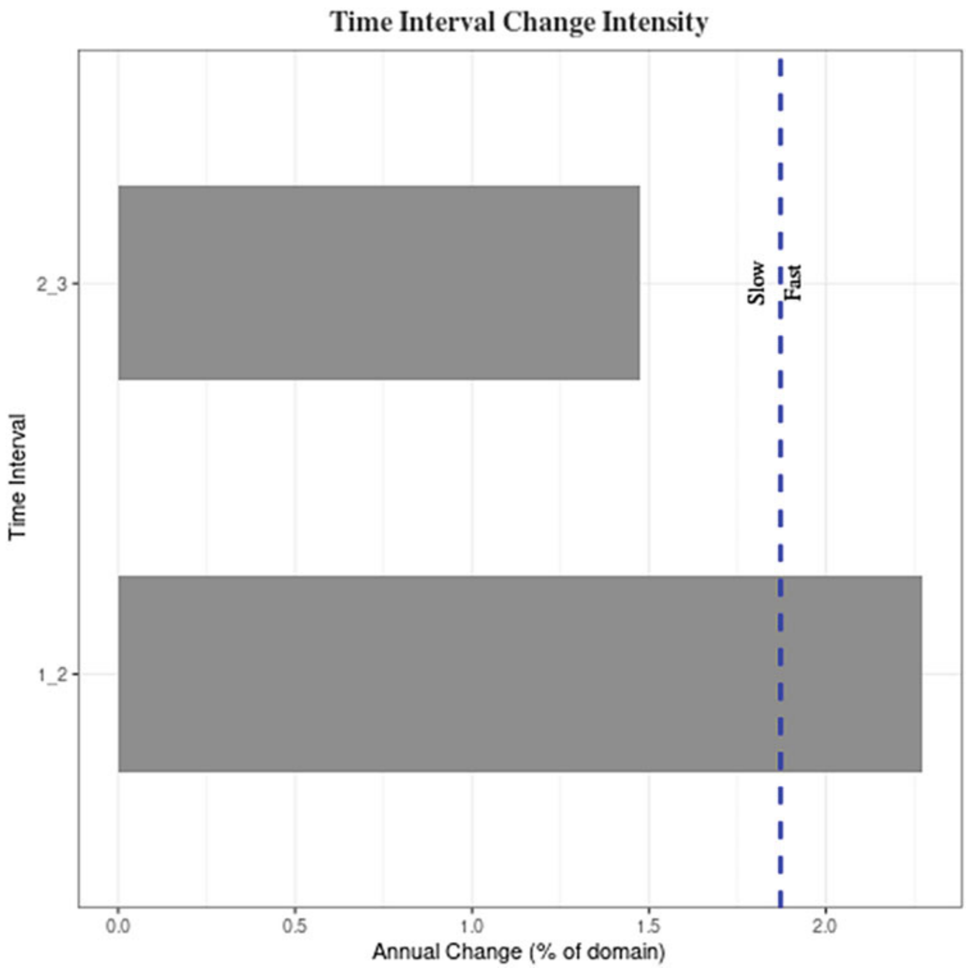


Fig. 20 Result from Exercise 1. Time interval change intensity plot

A	B	C	D	E	F	G	H	I	J
Category level Intensity Analysis for interval: 1 - 2									
,"Gross Loss","Gross Gain","Loss Intensity","Gain Intensity","Uniform Category Intensity","Loss Behavior","Gain Behavior"									
1,"516","33840","0.00345807420115805","0.185384025419086","0.0227104877429948","Dormant","Active"									
2,"60134","18721","0.0247443942018108","0.00783700896770504","0.0227104877429948","Active","Dormant"									
3,"10483","33408","0.00595948030921306","0.0187477798460244","0.0227104877429948","Dormant","Dormant"									
4,"40844","25480","0.0720383226097754","0.0461918885013379","0.0227104877429948","Active","Active"									
5,"447","975","0.010780436040903","0.0232187083253953","0.0227104877429948","Dormant","Active"									
6,"0","0","0","0","0.0227104877429948","Dormant","Dormant"									

Fig. 21 Result from Exercise 1. Gross gains and losses and amount of loss and gain intensities for each category

dormant compared to the other land use categories, as both gain and loss intensity are located to the left of the blue line.

Finally, the TransitionLevel.csv (Fig. 23) shows which transitions are intensively avoided or targeted taking into account the relative size of all the individual categories in the landscape. It compares the observed rate of gains from each category with a uniform rate of gains that would exist if the gains were made uniformly from among all the available categories, so allowing us to identify those categories that are intensively avoided or targeted. This information may be used to calculate different plots showing the intensity for each transition and time interval.

Figure 24 shows the first level of information in Fig. 23, that is, the annual transition size for gains in Category 1 in the first interval or period of time. The vertical blue line shows the uniform transition intensity. Categories on the left

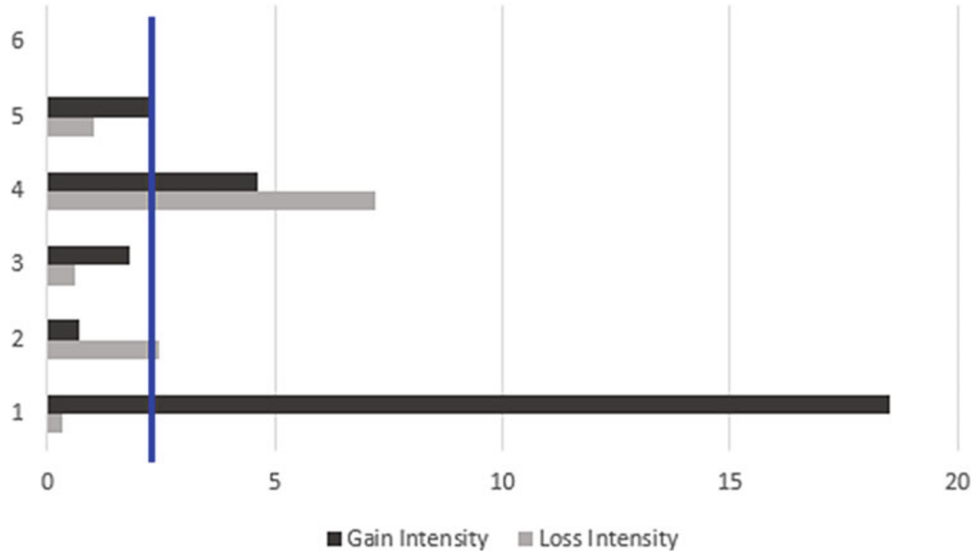


Fig. 22 Result from Exercise 1. Plot of gain and loss intensities per category

	A
1	Transition level Intensity Analysis for interval: 1 - 2
2	,"Annual Transition Size for Gain of 1","Transition Intensity for Gain of 1","Uniform Transition Intensity","Transition Behavior for Gain of 1"
3	2,"33352","0.0137239338048158","0.00704839061747568","Target"
4	3,"488","0.000277423103204805","0.00704839061747568","Avoid"
5	4,"0","0","0.00704839061747568","Avoid"
6	5,"0","0","0.00704839061747568","Avoid"
7	6,"0","0","0.00704839061747568","Avoid"
8	
9	,"Annual Transition Size for Gain of 2","Transition Intensity for Gain of 2","Uniform Transition Intensity","Transition Behavior for Gain of 2"
10	1,"152","0.0010186575166202","0.00742865872652132","Avoid"
11	3,"4405","0.00250419829839583","0.00742865872652132","Avoid"
12	4,"14164","0.0249816570719043","0.00742865872652132","Target"
13	5,"0","0","0.00742865872652132","Avoid"
14	6,"0","0","0.00742865872652132","Avoid"
15	
16	,"Annual Transition Size for Gain of 3","Transition Intensity for Gain of 3","Uniform Transition Intensity","Transition Behavior for Gain of 3"
17	1,"0","0","0.0104685726605053","Avoid"
18	2,"7703","0.00316968883720605","0.0104685726605053","Avoid"
19	4,"25705","0.0453370160288972","0.0104685726605053","Target"
20	5,"0","0","0.0104685726605053","Avoid"
21	6,"0","0","0.0104685726605053","Avoid"
22	
23	,"Annual Transition Size for Gain of 4","Transition Intensity for Gain of 4","Uniform Transition Intensity","Transition Behavior for Gain of 4"
24	1,"364","0.00243941668453785","0.00581292422027424","Avoid"
25	2,"19079","0.00785077155978894","0.00581292422027424","Target"
26	3,"5590","0.00317785890761242","0.00581292422027424","Avoid"
27	5,"447","0.010780436040903","0.00581292422027424","Target"
28	6,"0","0","0.00581292422027424","Avoid"
29	
30	,"Annual Transition Size for Gain of 5","Transition Intensity for Gain of 5","Uniform Transition Intensity","Transition Behavior for Gain of 5"
31	1,"0","0","0.000198620939169434","Avoid"
32	2,"0","0","0.000198620939169434","Avoid"
33	3,"0","0","0.000198620939169434","Avoid"
34	4,"975","0.00171964950897392","0.000198620939169434","Target"
35	6,"0","0","0.000198620939169434","Avoid"
36	

Fig. 23 Results from Exercise 1. Comparison of the observed rate of gains with an uniform rate of gains, differentiating between transitions that are intensively avoided and transitions that are intensivily targeted

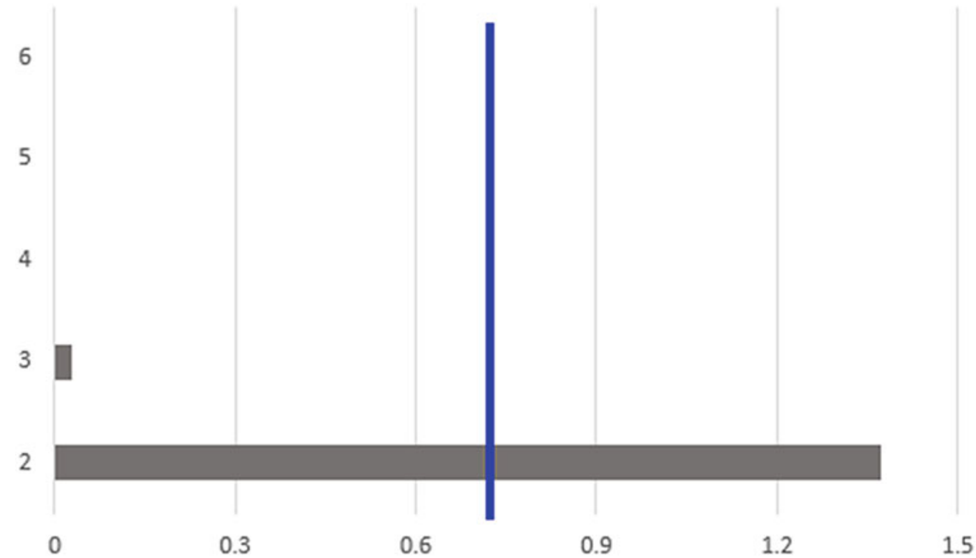


Fig. 24 Result from Exercise 1. Graph with the annual transition size for gains in category 1 in the first period of time

of this line tend to avoid this transition (for example, the change from Category 3 to Category 1) while the categories that extend to the right of the blue line tend to target this transition (for example, the transition from Category 2 to Category 1).

These analyses can also be used to validate land change in a series of maps with two or more time points. If there are large differences at the interval, category and/or transition level between the different time intervals, this means it would be difficult to validate the time series for simulating future trend scenarios, as the intensity of change over the time series has not been sufficiently stable or uniform to provide a base for future predictions. These differences may also be due to errors in the maps, which must be verified.

Utility

Exercises
1. To validate a series of maps with two or more time points

7 Flow Matrix

Description

The Flow Matrix was developed by Runfola and Pontius (2013) to quantitatively measure the instability of annual land use change between time intervals. The aim was to identify anomalies relative to the total amount of change over the time series. Flow Matrix exercises require a series of maps with at least three time points.

The Flow Matrix is a cross-tabulation matrix that shows the proportion of the study area that transitions from one category to another, excluding persistence. It assumes linear change over time during each time interval. It allows us to calculate: (a) the annual proportion of the study area that changes during each time interval and (b) the uniform annual proportion of the study area that changes over the entire time series, and the proportion of change that would have to be reallocated to different time intervals in order for change to be perfectly stable (R). When change is perfectly stable, R is zero. This value increases as change becomes more unstable.

A vertical bar chart is produced showing the amount of annual land use change during each time interval as compared to the uniform annual change.

The Flow Matrix provides an analysis of the temporal extent at which phenomena are stable. It can be used to find out whether land use change takes place at a uniform rate over the course of the entire study period or if more change takes place during certain intervals. It can also be used to detect errors. If one particular interval is very different from the others in terms of its annual change rate, this may be due to errors in the mapping or the methodology.

The Flow Matrix can also be used in the selection of particular calibration intervals when developing future historical trend simulations, as the data should show the greatest possible uniformity in past land use change. It can also be used to assess whether the results of a trend scenario are consistent, i.e. whether the model simulates much more or much less change than actually happened in the historical series.

QGIS Exercise

Available tools
• Processing R provider Plugin *Stable_change_flow_matrix.rsx* R script *Flow_matrix_graf.rsx* R script

No specific tool is available in QGIS to calculate the Flow Matrix. We have developed two R scripts (*Stable_change_flow_matrix.rsx* and *Flow_matrix_graf.rsx)* to this end. See Chapter "About this Book" for more detailed information about how to integrate R into QGIS and how to use R scripts such as the one applied in this exercise.

The first script will generate two tables in CSV format with the stable and unstable data that would exist for the whole study period, respectively. The second script will generate two tables, in CSV format, presenting the annual change for each interval and the uniform rate, respectively. It also produces a plot showing this annual change and the uniform rate for the entire time series.

Exercise 1. To validate a series of maps with two or more time points

Aim

To study and validate land change in the Ariège Valley study area using CORINE Land Use maps dated 2000, 2012 and 2018.

Materials

CORINE Land Cover Map Val d'Ariège 2000
CORINE Land Cover Map Val d'Ariège 2012
CORINE Land Cover Map Val d'Ariège 2018

Requisites

All maps must be in raster format and have the same resolution, extent and projection.

Execution

If necessary, install the Processing R provider plugin and download the *Stable_change_flow_matrix.rsx* and *Flow_matrix_graf.rsx* R scripts into the R scripts folder (processing/rscripts). See Chapter "About this Book" of this book for further information about how to use the QGIS R script.

Step 1

Then, run the stable and unstable change script (*stable_change_flow_matrix.rsx*) and fill in the required parameters: number of time points (in this case, 3), background value (in this case, 0), land use maps and number of years between the time points. Make sure you save the files in the correct folder (Fig. 25).

Step 2

Now, run the Annual Change Rates script (*Flow_matrix_graf.rsx*). Fill in the parameters as in the previous section (Fig. 25) to generate the plot.

Results and Comments

Step 1

generates two CSV files containing the data regarding unstable change (Fig. 26) and stable change (Fig. 27). The first file shows the proportion of change that would have to be reallocated to different time intervals in order for change to be perfectly stable (R). If change is perfectly stable, then R is zero. The R value increases as change becomes more unstable. In our case, R is 0.06, which means that 6% of change is unstable.

Stable change is the percentage of change that is stable in our study area between the first and the second intervals. This data is used to calculate the R value (R = 1 – stable change). In this case R = 1 − 0.94; R = 0.06.

Step 2

produces a chart showing the annual amount of land use change (expressed as a proportion of the study area) during each time interval and the uniform rate that would exist if the annual changes were distributed uniformly across the entire time period. This is shown as a horizontal line in Fig. 28. It also generates a CSV file showing the uniform change

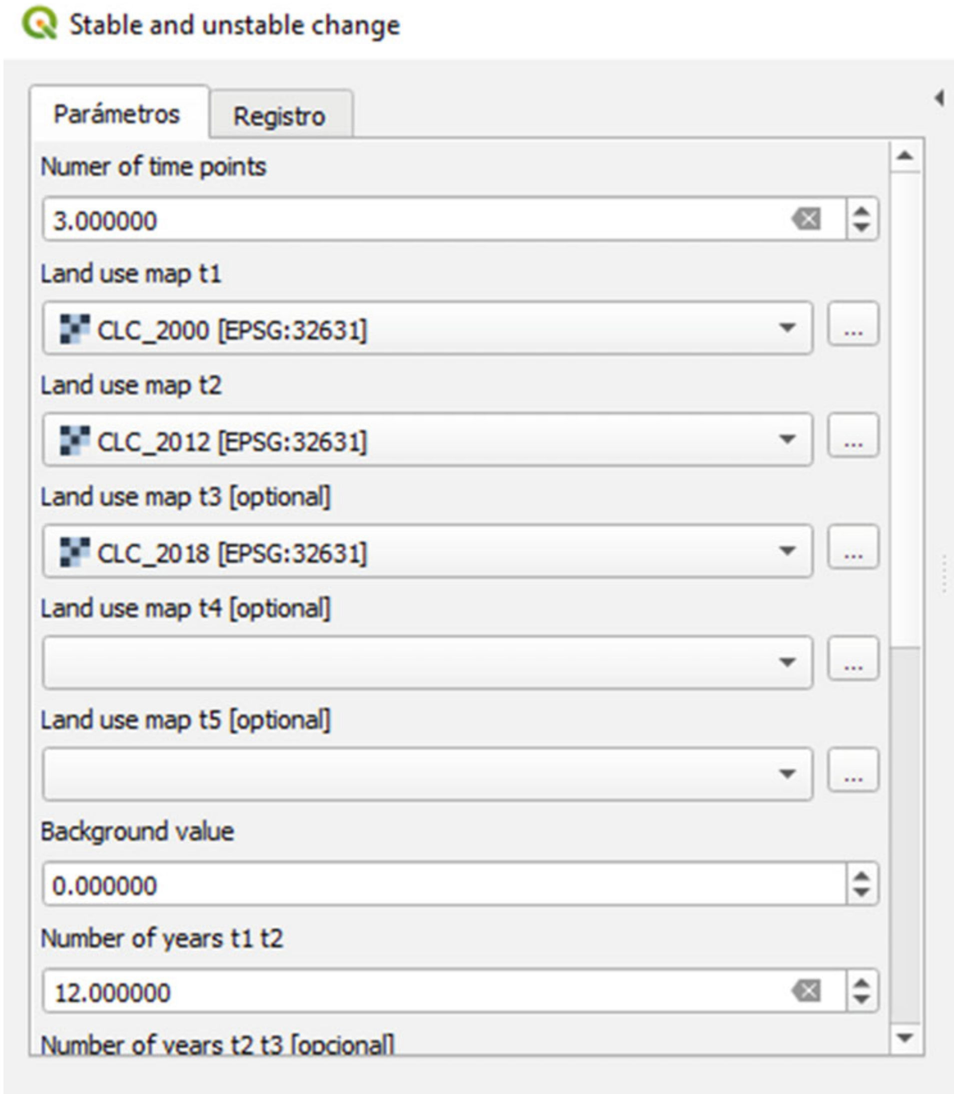
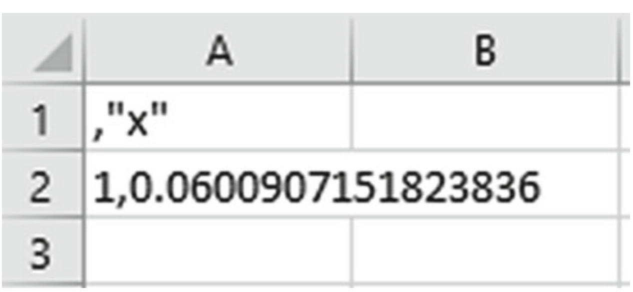
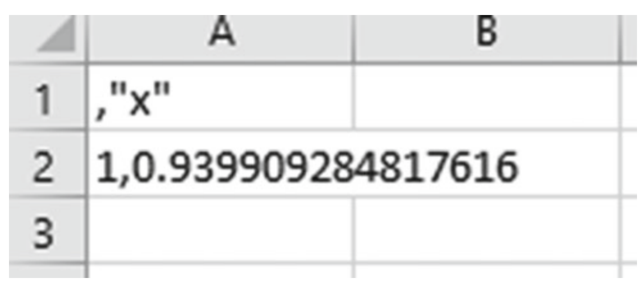


Fig. 25 Exercise 1. Step 1. Stable and unstable change R script



	A	B
1	,"x"	
2	1,0.0600907151823836	
3		

Fig. 26 Result from Exercise 1. Rate of unstable changes



	A	B
1	,"x"	
2	1,0.939909284817616	
3		

Fig. 27 Result from Exercise 1. Rate of stable changes

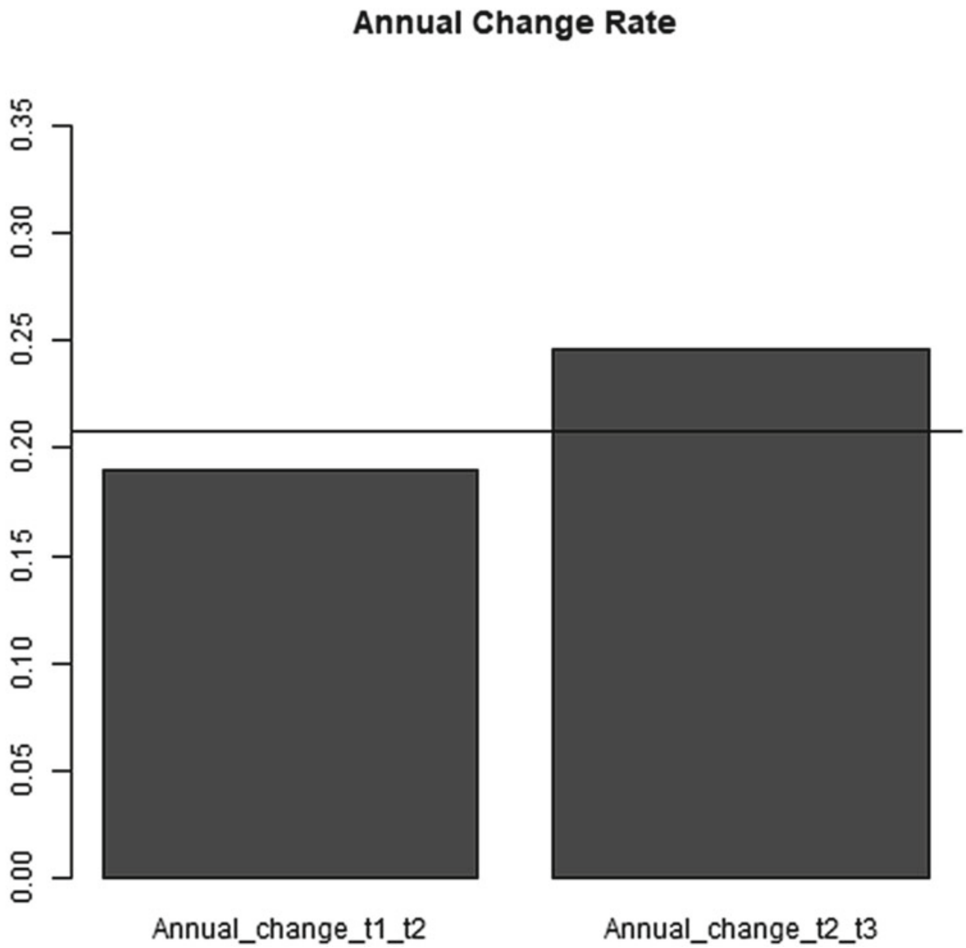


Fig. 28 Result from Exercise 1. Graph with the annual change rate for the two time periods that have been analysed

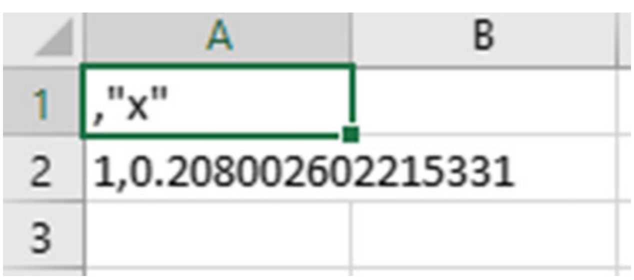


Fig. 29 Result from Exercise 1. Rate of uniform change

calculation, which is also expressed as a proportion of the study area (Fig. 29).

The tool also provides us with data about the annual land use change during each interval, as a percentage of the study area (Fig. 30). In our example, this is 0.19 for the first time interval and 0.24 for the second.

These results show that land use change did not occur at the same uniform rate over the course of the study period and there was more change in the second interval. It should

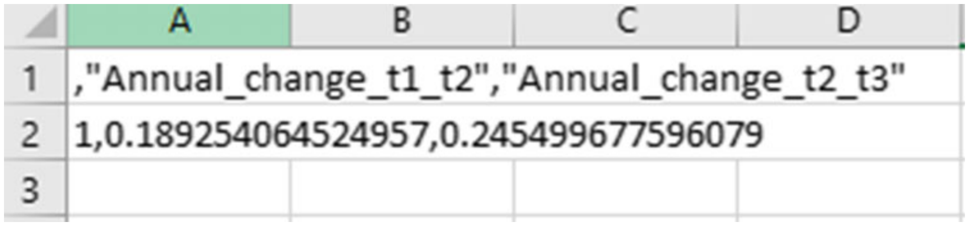


Fig. 30 Result from Exercise 1. Annual land change rates for each time period

be noted than if one time interval is very different from the others in terms of the amount of annual change (this did not happen in our case), this may be due to potential mapping errors.

The maps validated here could be used for simulating future trend scenarios, as there is not much difference between the intervals in terms of the annual rate of land use change.

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