Fine scale profile of CORINE Land Cover classes with LUCAS data.

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1 Objectives and context.

CORINE Land Cover (CLC) and LUCAS (Land Use/Cover Area frame Survey) provide different types of information on the European Union. The target of CLC is mapping land cover with a relatively coarse scale, while LUCAS aims at computing statistical estimates at EU level with fine scale. The total area of a class in a land cover map should not be interpreted as statistics (Gallego et al, 1999). The scale difference can be described by the ratio of the CLC minimum mapping unit of 25 ha (CEC, 1993, Perdigão and Annoni, 1997) and the size of the LUCAS "point" defined in the survey manual as 3x3 m. (Delincé, 2001).

Both sources of information are complementary and the idea of overlaying them is natural. However interpreting the results of this overlay is not straightforward. We discuss some of the issues related to this overlay: some targets that can be reached and others that are more problematic. The result of overlaying CLC and LUCAS is not a measure of the CLC accuracy.

It would be more meaningful to overlay LUCAS with CORINE Land Cover 2000 (CLC2000) than with the first version of CLC, but CLC2000 will not be available before 2004. However some reflections can be made on the possible use of LUCAS as auxiliary information to assess the accuracy of CLC2000.

At this stage we focus mainly on the estimation of fine scale profiles of CLC classes.

1.1 Fine scale land cover profile of a CLC class.

When we consider the part of territory covered by a given CLC class, for example the class 231="pasture", we know that this area is not 100% pasture for several reasons: scale, change in land cover since the CLC reference date, photo-interpretation inaccuracy and possible mislocation. We would like to estimate the proportion of pasture, arable land, forest or artificial land in the area labelled by CLC as "pasture". This is what we call the fine scale land cover profile of a CLC class.

One of the possible applications of these profiles is the use of CLC for the spatial disaggregation of statistical data available for administrative regions or for variables that can be computed from such statistical data. Important examples of spatial disaggregation for agri-environmental indicators are the nitrogen surplus in agriculture (Crouzet and Steenmans, 2001) or the results of the EU Farm Structure Survey (Kayadjanian and Vidal, 2001). A disaggregation method can make assumptions on the proportion of agriculture or the proportion of different crop types in each CLC class. For example we can arbitrarily assume that arable land represents 90% of the CLC class 211='non irrigated arable land' or 40% of the class 242='complex cultivation patterns', but more reliable results can be obtained by estimating such coefficients with an objective approach from ground survey data.

2 Overlay matrices

A first approximation to computing fine scale profiles is a simple GIS overlay of CLC with the point observations of the LUCAS 2001 ground survey. This has been done with a raster version of CLC with 100 m pixels in Lambert Azimuth coordinates. For this exercise only the Land cover classes of LUCAS were used. Land use codes should be included for future analyses. This operation produces a contingency table with 44 columns (CLC) and 57 rows (LUCAS land cover classes).

At this stage we assume that the co-location errors are less than 100 m. A more in-depth assessment of the overlay co-location accuracy seems necessary. Some problems are apparent along the coast line in Greece and Portugal, but inland mislocations have been also found in Italy, as reported below. The presence of co-location errors means that LUCAS points close to the border between CLC polygons might jump to another class.

The contingency table is not a measure of thematic accuracy of CLC, because it mixes several sources of disagreement. Tese can include:

- Co-location inaccuracy, that can be accumulated in the different steps of CLC processing: photo-interpretation, digitisation, merging tiles, projection, etc.
- Rasterisation (conversion from polygon format to raster format): If the polygon borders are irregular, conversion to raster format with 1 ha pixels modifies the class borders.
- Scale effect: objects with a size < 25ha are not represented in CLC.
- Land cover change from CLC (around 1990) to LUCAS 2001. In particular aforestation has been important in some countries, and urban growth is always considerable.
- Different concepts in nomenclature. This is important for example for different types of semi-natural areas.
- Photo-interpretation or observation errors. CLC probably contains more errors than LUCAS, but some observation mistakes can also appear in LUCAS.

2.1 Simplification of nomenclatures for the overlay.

The 57 x 44 contingency table produced by the overlay is too large for an easy visual inspection. In order to produce a smaller contingency table, the LUCAS land cover nomenclature has been simplified by grouping:

- All annual crops (except rice), open field vegetables and flowers, as well as fallow (set aside) in a class "arable land". Temporary pastures are kept as a single class.
- All citrus and other fruits are included in a class "fruits and citrus". Nurseries and permanent industrial crops are kept as single classes.

This leaves a nomenclature in 31 land cover classes further re-aggregated in a second step into 13 classes.

Table 1: Reduced LUCAS and CORINE Land Cover nomenclatures.

CLC 15	CLC code	CORINE Land Cover 30 classes	LUCAS 13	LUCAS 31 classes
1	11	urban fabric	1	Buildings with 1 to 3 floors
2	12	industrial, commercial transport	1	Buildings with more than 3 floors
2	13	mine. dump and construction	3	Greenhouses
2	14	artificial non-agricultural veget.	2	Non built-up area features
3	211	non-irrigated arable land	2	Non built-up linear features
3	212	permanently irrigated arable land	3	Annual crops
3	213	rice fields	3	Rice
4	221	vineyards	3	Fallow
5	222	fruit trees and berry plantations	4	Vineyards
6	223	olive growes	5	Fruits and citrus
7	23	pastures	6	Olive groves
14	241	annual crops with permanent crops	5	Nurseries
14	242	complex cultivation patterns	5	Permanent industrial crops
14	243	agriculture with natural vegetation	7	Temp. pasture
14	244	agro-forestry areas	8	Broadleaved forest
8	311	broad-leaved forest	9	Coniferous forest
9	312	coniferous forest	10	Mixed forest
10	313	mixed forest	8	Other broadleaved wooded area
7	321	natural grassland	9	Other coniferous wooded area
11	322	moors and heathland	10	Other mixed wooded area
11	323	sclerophyllous vegetation	8	Poplars, eucalyptus
11	324	transitional woodland-shrub	11	Shrubland with sparse tree cover
12	33A	sand, rock and sparse vegetation	11	Shrubland without tree cover
15	334	burnt areas	7	Perm. grass with sparse tree/shrub r
12	335	glaciers and perpetual snow	7	Perm. grass without tree/shrub
13	4	wetlands	12	Bare land
13	511	water courses	13	Inland water bodies
13	512	water bodies	13	Inland running water
13	52A	coastal water	13	Coastal water bodies
13	523	sea and ocean	13	Wetland
			12	Glaciers, permanent snow

The 44 classes of the CLC level 3 nomenclature have been regrouped to reduce the number of classes to 30:

- Artificial surfaces are reduced to level 2.
- Classes 331, 332 and 333 merged into “sand, rock and sparse vegetation”.
- All wetlands are combined into one class.
- Classes 521 and 522 are merged into “coastal water”.

This nomenclature has been reduced to 15 classes, corresponding approximately one-to-one with the LUCAS nomenclature in13 classes. The CLC classes “heterogeneous agricultural landscape” and “burnt areas” have no equivalent in LUCAS. Table 1 describes two different levels of aggregation for the LUCAS and the CLC nomenclatures used in this paper.

Table 2a: Raw contingency table LUCAS-CORINE (continues in next page)

LUCAS / CORINE	Urban	Industrial, commercial and transport	Mine. Dump and construction sites	Artificial non-agricultural vegetated areas	Non-irrigated arable	Permanently irrigated arable land	Rice fields	Vineyards	Fruit trees and berry plantations	Olive growes	Pasture	Annual crops with permanent crops	Complex cultivation patterns	Agriculture, with natural vegetation	Agro-forestry areas	continues in next page
Build 1-3 floors	423	61	3	6	216	16		16	7	9	77	7	122	40	9	.
Build >3 floors	89	21		2	16					1	4		7	5		.
Greenhouses	3				21	9			2				5	3		.
Artif Non built	215	54	5	3	176	21		13	4	12	56	2	90	34	3	.
Artif Non built	196	54	3	3	442	38		27	13	23	131	8	178	68	11	.
Annual crops	125	25	5	3	9712	522	12	111	62	75	565	65	1555	407	49	.
Rice	1				11	14	52				3		7	4		.
Fallow	14	6			1066	84		38	15	46	58	32	235	137	53	.
Vineyards	7	1			147	17		404	10	37	5	44	207	53	2	.
Fruit.citrus	28	4	3		176	40		29	229	27	27	22	266	59	1	.
Olive	10	2	1		158	15		19	17	600	2	51	208	97	16	.
Nurseries	1				18	1		1			3		5	5		.
Perm.ind.crops					9								5	2		.
Temp. pasture	27	3	1	1	928	54		22	7	19	494	19	426	153	22	.
Blv forest	48	8	11	8	456	4	1	36	24	32	239	12	235	392	272	.
Conif forest	26	3	2	1	238	6		16	8	9	129	7	107	157	8	.
Mixed forest	23	2	2	3	176			3	5	22	83	5	88	105	13	.
Blv woodland	68	12	2		182	7		12	9	5	118	5	111	101	14	.
Conif woodland	9				17			3	3		13	2	21	12		.
mixed woodland	7	1		3	24	1		2	2	1	6	1	19	14	2	.
Poplars,	8	1			86	14	3	7	5	11	20	16	35	68	12	.
Shrub+tree	24	3	2	2	219	7		28	14	52	68	29	132	173	59	.
Shrub no trees	26	1	4	2	213	23	1	38	22	33	45	19	139	267	45	.
Perm.grass	236	21	22	17	474	8		28	22	40	464	12	374	232	230	.
Perm.grass	227	35	11	13	1170	16	1	28	11	23	2235	15	1105	401	50	.
Bare	32	4	18		177	23		12	3	13	37		68	48	2	.
Inl water bodies	5		5	1	66			2	1	5	23		17	29	3	.
running water	15	6	2		78	19	3	7	6	4	42	4	38	35	5	.
Coastal water	1	1			4						1					.
Wetland	2			1	42	3	1	1			41	1	10	16	2	.
Glacier																.
	1896	329	102	69	16718	962	74	903	501	1099	4989	378	5815	3117	883	.

2.2 Overlay contingency tables with 30x31 classes

Table 2 shows the raw contingency table of the LUCAS-CLC overlay. It cannot be interpreted as an accuracy assessment of CLC because it mixes several sources of disagreement, but it may give useful information on the fine scale composition of the different CLC classes. For example it suggests that for the CLC class “non irrigated arable land”, in 2001 approximately 60% of the area was covered by annual crops, about 7% by fallow (set-aside agricultural land), 6% by temporary pasture, 9% by permanent grassland and another 9% by different types of forest, woodland, and shrub. The CLC class “broadleaved forest contains about 73% of forest, the class “complex agricultural landscapes“ contains about 50% of agricultural land, and so on.

Table 2b: Raw contingency table LUCAS-CORINE (from previous page)

LUCAS \ CORINE	Broad-leaved forest	Coniferous forest	Mixed forest	Natural grassland	Moors and heathland	Sclerophyllous vegetation	Transitionazl woodland-shrub	Sand, rock and sparse vegetation	Burnt areas	Glaciers and perpetual snow	Wetlands	Water courses	Water bodies	Coastal water	Sea and ocean	Total
Build 1-3 floors	18	17	14	5		6	10						4		3	1089
Build >3 floors	1						2					2		1		151
Greenhouses	1		1													45
Artif Non built	12	31	22	7	2	9	6	3			4		6	1		791
Artif Non built	58	148	92	29	15	30	37	6			9	3	1	1		1624
Annual crops	170	143	121	81	11	61	64	13	4		5	9	9	1		13985
Rice						3							2			97
Fallow	52	40	25	39	6	61	27	5	1		2	1	1			2044
Vineyards	23	7	11	10	1	12	9	5	1		1					1014
Fruit.citrus	31	13	4	11	14	18	14	8				1				1025
Olive	25	21	11	27	7	59	24	5	1				1			1377
Nurseries	1	3	4								1					43
Perm.ind.crops		2			1			1								20
Temp. pasture	53	54	78	22	13	12	33	2	1		6	1	2			2453
Blv forest	3563	538	814	156	103	322	399	21	2		20	13	8			7737
Conif forest	459	5340	1792	144	93	171	812	60	12		16	1	27		1	9645
Mixed forest	673	1568	1426	39	29	69	330	13	3		8		14		1	4703
Blv woodland	86	46	40	24	13	21	25	1			3	1	4			910
Conif woodland	8	56	22	5	4	5	12	3			2		1			198
mixed woodland	25	21	18	9	1	8	7	1			1		4			178
Poplars,	130	384	177	10	20	9	38	3	1		1	1	3			1063
Shrub+tree	281	241	72	202	171	389	282	46	11		4	1	5			2517
Shrub no trees	214	174	122	275	347	680	220	203	7		17	6	6	2	5	3156
Perm.grass	207	118	83	332	51	162	103	40	3		13	4	4			3300
Perm.grass	212	198	145	427	115	102	59	99	2		30	3	9	2		6744
Bare	74	101	44	372	189	152	126	727		25	12	5	6	2	14	2286
Inl water bodies	24	112	70	4	8	5	23	6		5	30	15	1104	11	5	1579
running water	28	30	17	11	6	14	16	14			4	41	6	7		458
Coastal water								1			22	9	26	46		111
Wetland	21	258	226	18	113		618	13			301	5	28	7	2	1730
Glacier								19		23						42
	6450	9664	5451	2259	1333	2380	3296	1318	49	53	512	122	1281	81	31	72115

2.3 Restricting to "pure pixels"

A first step to separate different sources of apparent disagreement between LUCAS and CLC is eliminating points that are close to the borders between CLC classes, so that we can reasonably assume that co-location inaccuracy does not occur.

In Figure 1 we see an example of a LUCAS PSU in the south of Finland overlaid on CLC. CLC reports forest and arable land in this area. It may happen that the CLC class "arable land" (in yellow) contains small patches of other land cover types, below the 25 ha threshold. This is consistent with the specifications of CLC.

Table 3a: Table LUCAS-CORINE. Only pure pixels (continues in next page)

LUCAS / CORINE	Urban	Industrial, commercial and transport	Mine. Dump and construction sites	Artificial non-agricultural vegetated areas	Non-irrigated arable	Permanently irrigated arable land	Rice fields	Vineyards	Fruit trees and berry plantations	Olive growes	Pasture	Annual crops with permanent crops	Complex cultivation patterns	Agriculture, with natural vegetation	Agro-forestry areas	continues in next page
Build 1-3 floors	221	20	0	1	120	13	0	11	4	7	31	5	56	15	5	.
Build >3 floors	68	10	0	0	7	0	0	0	0	0	2	0	3	1	0	.
Greenhouses	2	0	0	0	15	8	0	0	2	0	0	0	4	2	0	.
Artif Non built	105	22	3	0	115	14	0	8	2	7	36	1	41	11	3	.
Artif Non built	92	21	0	2	269	27	0	16	6	13	59	4	88	24	5	.
Annual crops	22	3	0	0	7574	422	7	57	32	42	226	41	818	149	25	.
Rice	0	0	0	0	6	14	43	0	0	0	0	0	3	0	0	.
Fallow	1	1	0	0	784	53	0	22	7	28	26	20	137	65	36	.
Vineyards	0	0	0	0	85	9	0	263	6	25	1	33	123	23	1	.
Fruit.citrus	12	0	0	0	104	31	0	14	160	16	10	7	154	31	1	.
Olive	3	1	0	0	86	4	0	11	7	416	1	25	122	47	10	.
Nurseries	0	0	0	0	8	0	0	1	0	0	1	0	1	1	0	.
Perm.ind.crops	0	0	0	0	4	0	0	0	0	0	0	0	4	1	0	.
Temp. pasture	6	0	0	1	617	43	0	12	4	8	340	8	235	62	13	.
Blv forest	19	2	2	3	180	0	0	11	10	12	62	5	61	115	189	.
Conif forest	4	2	2	0	76	2	0	7	0	2	20	1	30	47	1	.
Mixed forest	9	2	0	2	65	0	0	0	0	11	18	3	27	29	6	.
Blv woodland	28	5	1	0	104	4	0	4	4	4	40	2	40	32	6	.
Conif woodland	5	0	0	0	8	0	0	1	1	0	2	2	9	5	0	.
mixed woodland	5	1	0	1	17	0	0	2	2	1	2	0	6	6	2	.
Poplars,	5	0	0	0	44	8	0	4	2	2	8	6	7	34	4	.
Shrub+tree	12	0	1	0	111	1	0	8	5	26	27	20	57	77	30	.
Shrub no trees	11	1	0	0	95	10	0	20	10	12	14	8	59	112	16	.
Perm.grass	97	7	16	7	259	2	0	9	12	17	207	7	153	81	163	.
Perm.grass	68	15	5	4	663	12	0	7	3	8	1197	12	479	140	30	.
Bare	13	1	10	0	93	13	0	8	0	9	18	0	41	17	2	.
Inl water bodies	2	0	3	0	31	0	0	0	0	3	12	0	6	8	1	.
running water	6	1	0	0	42	13	2	2	3	4	22	4	12	9	5	.
Coastal water	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	.
Wetland	0	0	0	0	29	1	0	0	0	0	26	0	6	5	1	.
Glacier	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.
	816	115	43	21	11612	704	52	498	282	673	2408	214	2782	1149	555	.

We can also see SSU 22, for which the Lucas ground survey reports an annual crop. This point falls in the CLC class “coniferous”, probably due to a co-location problem or to the modification of borders when polygons are transformed into raster format. To avoid, at least partially, this source of apparent disagreement, we disregard the border CLC pixels. For this purpose we define as border pixel a pixel for which by a 3x3 window contains more than one CLC class. The CLC pixel corresponding to SSU 22 is a border pixel because the 3x3 window contains arable land and coniferous, while the CLC pixel corresponding to SSU 24 is a pure pixel because the 3x3 window only contains arable land in CLC.

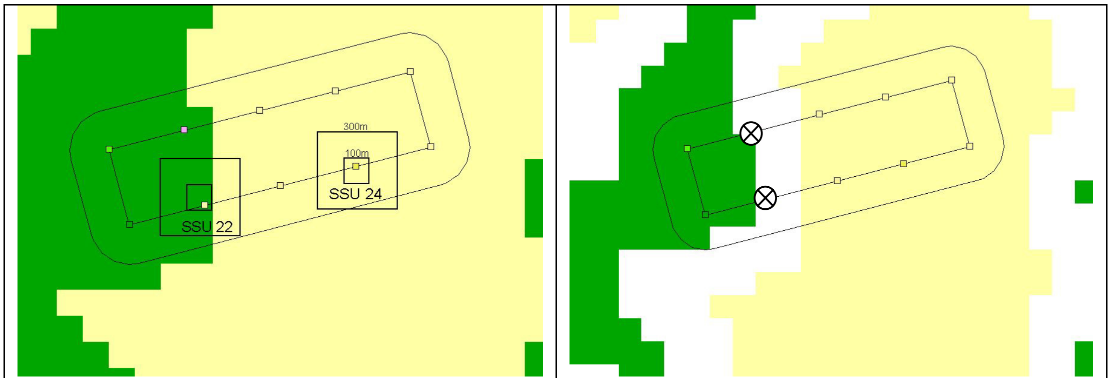
Table 3b Table LUCAS-CORINE. Only pure pixels (from previous page)

LUCAS / CORINE	Broad-leaved forest	Coniferous forest	Mixed forest	Natural grassland	Moors and heathland	Sclerophyllous vegetation	Transitionazl woodland-shrub	Sand, rock and sparse vegetation	Burnt areas	Glaciers and perpetual snow	Wetlands	Water courses	Water bodies	Coastal water	Sea and ocean	Total
Build 1-3 floors	5	7	4	0	0	2	3	0	0	0	0	0	1	0	0	531
Build >3 floors	0	0	0	0	0	0	2	0	0	0	0	1	0	1	0	95
Greenhouses	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34
Artif Non built	4	13	4	4	1	4	5	2	0	0	1	0	0	1	0	407
Artif Non built	23	89	44	10	9	14	12	3	0	0	6	0	0	0	0	836
Annual crops	17	35	32	36	3	13	9	5	1	0	0	2	0	0	0	9571
Rice	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	67
Fallow	14	15	10	20	3	26	10	0	1	0	0	0	0	0	0	1279
Vineyards	5	3	1	4	0	4	3	1	0	0	0	0	0	0	0	590
Fruit.citrus	15	2	3	6	10	5	3	1	0	0	0	0	0	0	0	585
Olive	7	5	4	9	3	23	7	3	0	0	0	0	0	0	0	794
Nurseries	0	1	2	0	0	0	0	0	0	0	1	0	0	0	0	16
Perm.ind.crops	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	10
Temp. pasture	15	12	43	16	8	4	10	1	1	0	2	0	0	0	0	1461
Blv forest	2127	252	371	53	42	185	188	1	1	0	9	1	0	0	0	3901
Conif forest	256	3510	896	47	45	94	274	12	8	0	3	0	8	0	1	5348
Mixed forest	387	913	737	8	10	40	146	2	1	0	2	0	3	0	0	2421
Blv woodland	40	25	15	7	3	7	9	0	0	0	3	0	1	0	0	384
Conif woodland	6	37	8	3	3	3	6	3	0	0	1	0	0	0	0	103
mixed woodland	14	12	9	5	1	4	4	1	0	0	0	0	2	0	0	97
Poplars,	81	301	122	4	8	4	15	1	0	0	0	0	1	0	0	661
Shrub+tree	148	131	33	101	101	223	158	17	4	0	2	0	0	0	0	1293
Shrub no trees	105	90	62	151	209	423	79	130	3	0	9	0	1	0	4	1634
Perm.grass	60	42	31	170	24	98	50	15	0	0	7	0	0	0	0	1534
Perm.grass	46	55	43	265	56	73	17	69	0	0	11	0	1	0	0	3279
Bare	37	47	19	207	120	93	44	533	0	8	7	0	3	1	8	1352
Inl water bodies	3	56	24	1	6	2	14	1	0	4	16	3	780	7	3	986
running water	8	11	4	4	0	5	6	2	0	0	1	12	5	2	0	185
Coastal water	0	0	0	0	0	0	0	0	0	0	15	8	21	39	0	84
Wetland	4	143	80	12	79	0	269	9	0	0	145	2	4	0	0	815
Glacier	0	0	0	0	0	0	0	11	0	14	0	0	0	0	0	25
	3428	5807	2601	1143	745	1349	1343	823	20	26	241	29	832	51	16	40378

For this segment two SSUs (points) out of 10 are excluded. Globally nearly 32,000 SSUs out of 72,000 are eliminated when we only keep “pure CLC pixels”.

The fine scale profile of CLC classes changes if we only look at pure pixels showing a better agreement (table 3). For example in the CLC class “non irrigated arable land” the proportion of annual crops increases to 65% and the total of typycal land cover types in arable land (including set aside and permanent pasture) is above 77%. The proportion of forest in the CLC class “broadleaved forest” grows from 73% of forest to 81%. The proportion of agricultural land in the CLC class “complex agricultural landscapes” also grows from 50% to 57%.

Figure 1: CLC-LUCAS overlay : eliminating a buffer of border pixels.



a) Example of LUCAS PSU on CLC b) Removing CLC border pixels.

2.4 Overlay tables with 15x13 classes.

The second level of nomenclature simplification leads to table 4 (raw overlay) and table 5 (pure pixels), easier to read than the previous tables, although there is no additional information.

Table 4: Raw overlay table LUCAS-CORINE with 15x13 classes

LUCAS 13 classes / CLC 15 classes	Buildings	Other artificial	Arable	Vineyard	Fruits	Olive	Grass	Broadleaved forest-& wood	Coniferous	Mixed forest	Shrub-heath	Bare land	Water	Total
Urban	512	411	143	7	29	10	490	124	35	30	50	32	23	1896
Other artificial	93	122	39	1	7	3	124	42	6	11	14	22	16	500
Arable	248	677	11503	164	244	173	2651	753	261	201	463	200	216	17754
Vineyard	16	40	149	404	30	19	78	55	19	5	66	12	10	903
Fruits	7	17	79	10	229	17	40	38	11	7	36	3	7	501
Olive	10	35	121	37	27	600	82	48	9	23	85	13	9	1099
Pasture	86	223	746	15	41	29	3974	567	291	137	590	409	140	7248
Broadleaved forest	19	70	223	23	32	25	472	3779	467	698	495	74	73	6450
Coniferous	17	179	183	7	18	21	370	968	5396	1589	415	101	400	9664
Mixed forest	14	114	147	11	8	11	306	1031	1814	1444	194	44	313	5451
Woddland-shrub	18	99	233	22	47	90	650	950	1097	444	2089	467	803	7009
Bare land	0	9	18	5	9	5	141	25	63	14	249	794	39	1371
Water	10	25	30	1	2	1	74	54	48	28	46	39	1669	2027
Heterogeneous	190	394	2552	306	365	372	3039	1273	314	247	863	118	160	10193
Burnt	0	0	5	1	0	1	6	3	12	3	18	0	0	49
Total	1240	2415	16171	1014	1088	1377	12497	9710	9843	4881	5673	2328	3878	72115

We can notice strong differences in the total number of points for some classes, such as water, even if no major errors are expected. This does **not** give any indication of inconsistency, it is simply a confirmation that the total area of a class in CLC must not be interpreted as land cover area estimates (Gallego et al, 1999).

Table 5: Overlay LUCAS-CORINE, pure pixels, 13x15 classes

LUCAS 13 classes / CLC 15 classes	Buildings	Other artificial	Arable	Vineyard	Fruits	Olive	Grass	Broadleaved forest-& wood	Coniferous	Mixed forest	Shrub-heath	Bare land	Water	Total
Urban	289	197	25	0	12	3	171	52	9	14	23	13	8	816
Other artificial	31	48	4	0	0	1	55	13	4	6	2	11	4	179
Arable	140	425	8926	94	147	90	1596	340	86	82	217	106	119	12368
Vineyard	11	24	79	263	15	11	28	19	8	2	28	8	2	498
Fruits	4	8	41	6	160	7	19	16	1	2	15	0	3	282
Olive	7	20	70	25	16	416	33	18	2	12	38	9	7	673
Pasture	33	109	308	5	17	10	2195	174	72	33	293	225	77	3551
Broadleaved forest	5	27	32	5	15	7	121	2248	262	401	253	37	15	3428
Coniferous	7	102	50	3	3	5	109	578	3547	925	221	47	210	5807
Mixed forest	4	48	42	1	5	4	117	508	904	746	95	19	108	2601
Woddland-shrub	7	45	64	7	19	33	340	461	425	205	1193	257	381	3437
Bare land	0	5	5	1	1	3	85	2	15	3	147	566	16	849
Water	3	8	3	0	1	0	21	15	13	7	16	19	1063	1169
Heterogeneous	85	177	1300	180	200	204	1383	501	95	79	379	60	57	4700
Burnt	0	0	2	0	0	0	1	1	8	1	7	0	0	20
Total	626	1243	10951	590	611	794	6274	4946	5451	2518	2927	1377	2070	40378

3 Discussion and possible ways forward.

Contingency tables computed for all pixels are biased because of mislocation: the profile of a CLC class includes pixels from neighbouring classes. The bias is likely in the sense of increasing apparent disagreement. Restricting contingency tables to pure pixels is expected to avoid jumping from one CLC class to another, but it may be biased in the opposite sense because more conflictive border areas are avoided. Now we try to tackle the next question: can we use the spatial structure of CLC to reduce the bias of the profile estimation?

3.1 Overlaying CLC and LUCAS: a possible formal scheme to deal with co-location inaccuracy.

Let us make a first simplification assuming that the territory is divided into pixels of 1 ha. The information provided by LUCAS is a ground observation $L(i,j)=g$ available for a sample of cells in row j and column i. CLC also gives a value for each cell $C(i,j)=c$

The location accuracy requested in LUCAS is of the order of a few meters, better than the 100 m. location accuracy requested to CLC, therefore we take the orthophotos used for LUCAS as reference geometry and we consider the location error of CLC by writing the observation as $C'(i,j)=C(i',j')=c'$, where $i'=i+\varepsilon_1$; $j'=j+\varepsilon_2$. ε_1 and ε_2 are the vertical and horizontal location error, that we assume for the moment within the CLC specifications (100 m maximum error) and isotropic (i.e. the same in any direction):

$$p(\varepsilon_1) = p(\varepsilon_2) = \begin{Bmatrix} 1 \\ 0 \\ -1 \end{Bmatrix} = \begin{cases} q \\ 1-2q \\ q \end{cases}$$

where we generally expect a parameter $q < 1/3$ (the probability of staying in the same pixel is higher than the probability of jumping to each of the neighbouring pixels).

Under this assumption table 6 shows the probability scheme of the apparent location of a LUCAS point that would fall on the central cell of the table.

Table 6 : Mislocation probability scheme

q^2	$q(1-2q)$	q^2
$q(1-2q)$	$(1-2q)^2$	$q(1-2q)$
q^2	$q(1-2q)$	q^2

We call H the GIS overlay matrix:

$$H_{g,c} = \#\left(L(i,j) = g, C'(i,j) = c\right)$$

$H1_{g,c}$ is the overlay matrix restricted to the 1 ha pixels that are CLC-pure, i.e. surrounded by pixels of the same CLC class. $H2_{g,c}$ is the overlay matrix for the CLC border pixels. The marginals and conditional proportions are:

$$H_{+c} = \sum_g H_{g,c} \qquad H1_{+c} = \sum_g H1_{g,c} \qquad H2_{+c} = \sum_g H2_{g,c}$$

$$H(g/c) = \frac{H_{g,c}}{H_{+,c}} \qquad H1(g/c) = \frac{H1_{g,c}}{H1_{+,c}} \qquad H2(g/c) = \frac{H2_{g,c}}{H2_{+,c}}$$

The confusion matrix A is the overlay matrix that would have been obtained without location error, i.e assuming $C'(i,j) = C(i,j)$:

$$A_{g,c} = \#\left(L(i,j) = g, C(i,j) = c\right)$$

Notice that even with location errors the marginals $A_{+,c}$ $A1_{+,c}$ and $A2_{+,c}$ coincide with those of the overlay matrix H (the total number of pixels with each CLC class).

Our target is estimating the proportion of each ground class g in each CLC class c, i.e. the conditional proportions associated to the overlay matrix:

$$A(g/c) = \frac{A_{g,c}}{A_{+,c}}$$

In order to make the link between the confusion matrix A and the overlay matrices G, $G1$, and $G2$, we need to consider the number of cases in which mislocation causes jumping from class c to class c'. Let us call $B1(c,c')$ the number of pairs of contiguous pixels (with a common side) with CLC classes c and c'. $B2(c,c')$ is the number of pairs of corner-contiguous pixels (with a common corner) with CLC classes c and c'. According to the model specified in table 7 the probability that mislocation causes a jump from class c to class c' is:

$$p[C'(i,j) = c' / C(i,j) = c] = \frac{B1(c,c')\, q(1-2q)}{B1(c,+)} + \frac{B2(c,c')\, q^2}{B2(c,+)}$$

Under this model, we are sure that the $H1_{g,c}$ pure pixels did not change CLC class by mislocation, While the $H2_{g,c}$ border can actually come from the same class or from other classes. The expected confusion matrix is

$$E[A_{g,c}] = H1_{g,c} + p(\varepsilon_1 = \varepsilon_2 = 0)\, H2_{g,c} + \sum_{c'} p[C'(i, j = c') / C(i, j = c)]\, H2_{g,c}$$

$$= H1_{g,c} + (1-2q)^2\, H2_{g,c} + \sum_{c'} \frac{B1(c,c')\, q(1-2q)}{B1(c,+)} + \frac{B2(c,c')\, q^2}{B2(c,+)}\, H2_{g,c'}$$

Because of the very large number of CLC pixels, $E\lfloor A_{g,c} \rfloor$ can be approximately identified with $A_{g,c}$. $H1$, $H2$ are known. $B1$ and $B2$ can be computed from CLC, but q has to be estimated.

A reliable estimation of q would require knowing the distribution of the co-location inaccuracy. Alternatively some indirect method could be designed using the comparison of $H1$ and $H2$, but this would require additional hypothesis. This problem remains anyway out of the scope of this paper.

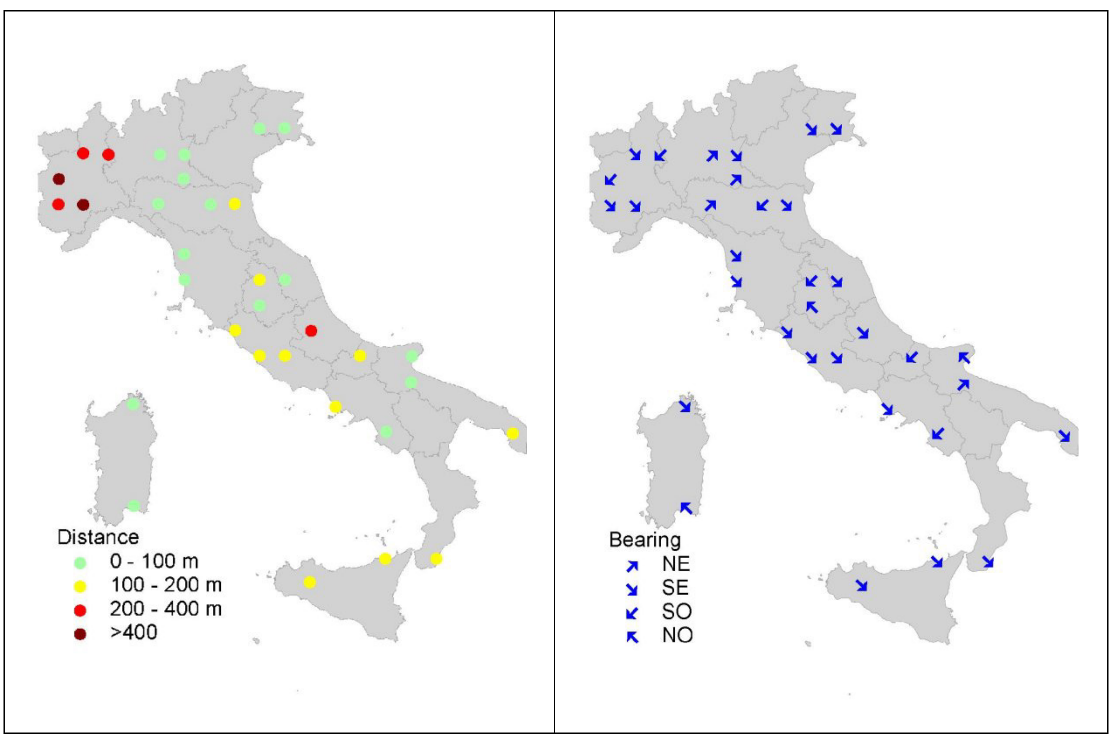
3.2 Co-location inaccuracy CLC-Orthophotos in Italy

The approach suggested in the previous paragraph assumes that the co-location inaccuracy is less than 100 m. At the time being a visual co-location accuracy assessment between CLC and Lucas has not been possible. Such assessment could be carried out in Italy by the ITA consortium between CLC and a sample or ortho-photos used for the so-called “mini-sites” pilot study in the context of the MARS Project. For 33 of these mini-sites, with a size of 6x6 km each, physical features could be identified both in CLC and the orthophoto, so that a good overlay could be obtained with a shift. Figure 2 shows an example of visual shift correction. The line in cyan is the CLC polygon indicating an urban settlement, and the line in yellow after the shift that seems to give an approximately correct overlay.

Figure 3a shows the general layout of the shifts. In 17 cases out of 33, the required shift was more than 100 m, and in some cases, mainly in Piemonte, far above 200 m. The average shift was 139 m. The bearings do not indicate any homogeneous direction that would suggest a general projection problem. These results for Italy do not lead to any general conclusion, but give strong indications on the need to undertake a proper co-location assessment.

Figure 2: Co-location inaccuracy between CLC and an ortho-photo

Figure 3: Location disagreement between CLC and ortho-photos.



3.3 Can LUCAS be used to assess the accuracy of CLC?

Assessing the thematic accuracy of geographic information is more complex than evaluating the geometric accuracy. Standard criteria are difficult to establish and a large scientific literature on the issue has been produced in the last 20 years (Lowell and Jaton, 1999, Mowrer and Congalton, 1999). There is still much to do from the methodological point of view, in particular for the case of land cover information.

When two land cover information layers are available for the same area and one of them is assumed to be more precise, an indicator of the agreement between both can be seen as an accuracy measure of the less precise layer.

The more precise layer is usually known only for a sample, and improved information may be obtained combining it with less precise but exhaustive information. This is the case of CLC and Lucas.

The disagreement between two layers can be thematic, i.e. different land cover types are reported by both layers for the same area, but it can come as well from a co-location problem. Thematic disagreements can come from an error (in principle of the layer assumed to be less precise), from differences in the classification nomenclature, from different scales or from different reference dates. Co-location inaccuracy may be due to mislocation in the data collection (systematic shift for example), or to further manipulation (co-ordinates projection, elaboration of mosaics, reference geoid, etc).

The complex problem of measuring thematic inaccuracy or disagreement becomes easier to manage if we assume that there is no co-location error, the reference date and the scale are the same and both layers have the same nomenclature. Under these implicit assumptions several agreement indicators can be computed such as the kappa index (Congalton and Green, 1999).

Unfortunately these simplification assumptions are far from being acceptable when CLC and LUCAS data are overlaid: co-location inaccuracy is not negligible, scale and reference dates are substantially different, and nomenclature criteria are necessarily different, since the targets and scales are different. The confusion matrices and disagreement indicators reported below cannot be directly interpreted as an indication of errors in CLC.

If we read the overlay tables given above as accuracy measures and we compute indexes, the results may be worrying at first sight, but a more nuanced discussion is needed.

For example a previous assessment of CLC in Arezzo (Italy) shows that the values of accuracy indicators computed by straightforward overlay can be drastically distorted by the effect of scale (Gallego, 2001). In the Arezzo study two land cover maps at different scales were compared; co-location and nomenclature problems were minimal, still a simple pixelwise overlay gave low values for agreement indicators, but after removing the scale effect, the agreement became satisfactory except for the class “pasture”, with a minor presence in that test site. The conclusions of this study might be specific for the Arezzo test site, but the warning about negative distortions of agreement indicators has a general validity.

When CLC and Lucas are compared, besides the different scales, we have indications of possible strong co-location inaccuracy and significant nomenclature differences. Therefore the negative distortion of agreement indicators can be very high. A major step to improve the interpretation of such indicators is assessing the possible co-location inaccuracy. This can be done by selecting a subsample of LUCAS PSUs (Primary Sampling Units) for which the shift may be visually identified. This can be done if there are objects that can be identified both in CLC and in the ortho-photos used as ground survey documents for Lucas. It is difficult to determine a priori if it will be possible do identify common objects in CLC and an ortho-photo, but some hints can be given by the presence of CLC categories usually easier to identify, such as water. In any case a basic condition for the feasibility of co-location accuracy assessment is the availability of the ortho-photos used for LUCAS ground work.

Because of the different scales of CLC and LUCAS, nearly any combination of classes is possible without any thematic error, so that a certain amount of disagreement is perfectly normal. If one point is forest in LUCAS and arable land in CLC, there is a disagreement, although this does not mean that there is an error. If there is a disagreement in 2 points out of 10 in a LUCAS Primary Sampling Unit (PSU), there is no significant indication of thematic inaccuracy, but suspicions appear if more than 5 points are in disagreement.

Beyond the question of scale, it is sometimes difficult to decide if a certain combination of classes can be considered to be fully in agreement or in disagreement. For example the CLC class 311=”broad-leaved forest” is not in fully agreement with the LUCAS class C23=”mixed wooded area”, but the level of disagreement is not the same as with LUCAS G01=”inland water bodies”.

This suggests the introduction of intermediate levels of disagreement, corresponding to some degree of compatibility (Congalton and Green, 1999). Table 6 illustrates a possible definition. A value $\varphi_{ij} = 0$ means disagreement, a value $\varphi_{ij} = 1$ means complete agreement and intermediate values correspond to different levels of agreement. Some CLC classes, such as 2.4.2 “complex cultivation patterns” are more or less in agreement with almost any Lucas class, but the level is not necessarily the same. The definition given by table 6 is certainly subjective and needs to be discussed.

A traditional synthetic agreement indicator is the kappa index (Bishop et al, 1975):

$$K = \frac{\sum_i p_{ii} - \sum_i p_{i+} p_{+i}}{1 - \sum_i p_{i+} p_{+i}}$$

The kappa index has a value 0 if the agreement is the same that would be obtained at random, and a value 1 if the agreement is perfect. The application of the kappa index assumes that the nomenclature is the same in both layers and any pair of non-coinciding classes is a complete disagreement. To adapt the kappa index to a fuzzy disagreement scheme, we can write,

$$K' = \frac{\sum_{ij} \varphi_{ij} \left(p_{ij} - p_{i+} p_{+j} \right)}{1 - \sum_{ij} \varphi_{ij}\, p_{i+}\, p_{+j}}$$

Table 7: Example of fuzzy agreement definition

LUCAS 13 classes / CLC 15 classes	Buildings	Other artificial	Arable	Vineyard	Fruits	Olive	Grass	Broadleaved forest &-wood	Coniferous	Mixed forest	Shrub-heath	Bare land	Water
Urban	1	0.7	0	0	0	0	0.5	0.3	0.3	0.3	0	0.3	0.1
Other artificial	0.7	1	0	0	0	0	0.5	0	0	0	0	0.5	0
Arable	0	0	1	0	0	0	0.7	0	0	0	0	0	0
Vineyard	0	0	0	1	0	0	0	0	0	0	0	0	0
Fruits	0	0	0	0	1	0	0	0	0	0	0	0	0
Olive	0	0	0	0	0	1	0	0	0	0	0	0	0
Pasture	0	0	0.3	0	0	0	1	0.2	0.2	0.2	0.2	0	0
Broadleaved forest	0	0	0	0	0	0	0	1	0.2	0.7	0.3	0	0
Coniferous	0	0	0	0	0	0	0	0.2	1	0.7	0.3	0	0
Mixed forest	0	0	0	0	0	0	0	0.8	0.8	1	0.3	0	0
Woddland-shrub	0	0	0	0	0	0	0	0.8	0.8	0.8	1	0	0
Bare land	0	0	0	0	0	0	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	0	0	0	0	0	0	1
Heterogeneous	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Burnt	0	0	0.3	0.3	0.3	0.3	0.3	0.8	0.8	0.8	0.8	0.5	0

This adapted kappa index also ranges between 0 for random attribution and 1 for perfect agreement. The value of the “fuzzy kappa” index for the raw Table 4 with the definition given in Table 7 is 0.502, while for the “pure pixels” (Table 5), the value reaches 0.590.

4 Conclusions

The matrices obtained from a GIS overlay of CLC and LUCAS have a rich information, but its interpretation in terms of CLC accuracy is hazardous because many sources of disagreement are confounded. Computing fine scale profiles of CLC classes is feasible, but a better knowledge of the distribution of the co-location inaccuracy is needed in order to estimate the probability of jumping between raster cells.

The situation will improve when CLC2000 is available, although the co-location problems will never disappear completely. A formal model is outlined that may be applied in the future when such co-location inaccuracy is sufficiently known. This target can be achieved by a visual comparison of a sub-sample of LUCAS Primary Sampling Units (PSU’s) on CLC and on the ortho-photographs used as ground documents for LUCAS.

This research indicates that the direct use of LUCAS to assess the thematic accuracy of CLC2000 is not adequate, but an enhanced photo-interpretation of LUCAS PSUs can provide a good assessment. A fuzzy disagreement matrix might provide a useful tool for computing a numerical accuracy indicator.

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