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FILTERING LPIS DATA FOR BUILDING TRUSTWORTHY TRAINING DATASETS FOR CROP TYPE MAPPING: A CASE STUDY IN GREECE

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ABSTRACT:

The need for effective crop monitoring in large geographical scales has become increasingly important in recent years and constitutes a technological and scientific challenge for remote sensing applications. In Europe, member states of the European Union collect geospatial data in the framework of the Land Parcel Information System (LPIS) for agricultural management and subsidizing farmers. These data can be exploited as training datasets of machine learning classifiers for crop-type mapping applications. However, the way the LPIS data are being generated, concerning primarily errors in the farmers' declarations in terms of crop-type labels, exact geometries, etc, constrains their direct use in such classification frameworks. In this study, we present and assess a methodology for filtering LPIS data based on geometric and spectral criteria in order to build a trustworthy training dataset for machine learning crop-type classifiers. A new nomenclature was developed, oriented towards the spectral discrimination of crop-type classes and sub-classes in Greece. The filtering methodology was applied at national scale for the agricultural year of 2019 and resulted in the selection of a sub-set of the LPIS parcels that were assessed as the most suitable and reliable to represent the different levels of the nomenclature. The developed filtering procedure was validated against actual crop-type labels derived from field visits, while the resulted filtered data were successfully utilized on various crop-type mapping experiments in Greece.

1. INTRODUCTION

Regular monitoring and mapping plays a key role for agricultural areas, given the projected population growth and dietary changes in many of the fastest growing regions in the world that create pressing challenges for humanity. For Europe detailed information of agricultural land holdings on the parcel level exists in the form of the Land Parcel Information System (LPIS) and the Geospatial Aid Application (GSAA) data, which records individual claims for subsidies made by the farmers (Griffiths et al., 2019). The Paying Agency of every member state is obliged to check, at least, only a 5% of the declared parcels, in most cases by field inspection or/and photo interpretation on very high resolution images (David et al., 2021). In this sense the vast majority of crop parcels is currently declared by the farmers without any extra supervision and thus, under quite error-prone protocols and practices.

Aiming at reducing the uncertainty and error rates of the declaration procedures, the new rules for 2020+ CAP payments provide the increased use of modern technologies during verification phases and in particular the integration of Sentinel data for monitoring and cross-compliance assessment (Beriaux et al., 2021; Campos-Taberner et al., 2019; David et al., 2021). In this regard, the development of efficient remote sensing techniques towards monitoring and regularly updated crop type mapping arises as essential to achieve the new CAP goals. To this end many recent crop mapping studies have documented the employment of Sentinel data along with LPIS data for developing crop classification models in Austria, Belgium, Germany, France, Spain and the Netherlands (Beriaux et al., 2021; Blickensdörfer et al., 2022; Campos-Taberner et al., 2019; David et al., 2021; Griffiths et al., 2019; Reuß et al., 2021; Sitokonstantinou et al., 2018). In most cases LPIS data were utilised after the application of some basic preparation steps in order to fit the desired nomenclature and to exclude erroneous geometries and field boundaries from the analysis.

This paper presents a pipeline for filtering LPIS data towards building trustworthy training datasets for crop type monitoring and mapping. The filtering pipeline was developed at national scale, i.e., the entire Greek territory constitutes our case study. The developed methodology is based not only on geometric rules, but also on spectral criteria, in order to filter outlier records and declaration errors. Spectral analysis is performed on annual multitemporal Sentinel-2 data, accessed via the Google Earth Engine Python API. Validation of the filtered training data was performed by comparing them with crop-type information from field surveys, as well as, by assessing their performance on various crop type mapping experiments in Greece. Overall, the experimental results and their evaluation demonstrated the efficiency of the proposed methodology and raised expectations for its integration in operational classification frameworks towards annual crop type mapping.

2. MATERIALS AND METHODS

2.1 Cultivated Land and LPIS Dataset in Greece

The filtering pipeline was employed at national scale i.e., for the entire Greek territory and for the agricultural year of 2019. For this year, the Hellenic Statistical Authority has recently documented a total area of 32 km^2 of cultivated agricultural land. This total area consists of four main groups of crops, distributed as follows: 52.80% of the cultivated area was used for arable crops, 1.90% for horticultural cultivations, 33.80% for permanent crops and 11.50% were uncultivated for this very year, i.e., fallow-lands.

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	L1 code	Description & L2 sub-classes
1	OLG	Cultivated areas occupied by Olive Groves. It includes a single homonymous L2 class.
2	VNY	Cultivated areas occupied by Grape Vineyards. It includes a single homonymous L2 class.
3	CTR	Cultivated areas occupied by Citrus Fruit trees including Orange, Tangerine, Grapefruit, Lemon/Lime, Citron, Pomelo, Kumquat, Bitter Orange and Bergamot trees L2 classes.
4	POM	Cultivated areas occupied by Pome Fruit trees including Apple, Pear and Quince trees L2 classes.
5	STN	Cultivated areas occupied by Stone Fruit trees including Peach, Nectarine, Apricot, Cherry, Sour Cherry, Plum and Cherry Plum trees L2 classes.
6	NUT	Cultivated areas occupied by Nut trees including Almond, Walnut, Hazelnut, Pistachio and Carob trees L2 classes.
7	KWI	Cultivated areas occupied by Kiwi plants. It includes a single homonymous L2 class.
8	RIC	Cultivated areas planted or prepared for Rice production. It includes a single homonymous L2 class.
9	CRL	Cultivated areas planted with Cereal crops including, Hard and Soft Wheat, Barley, Oat, Rye, Triticale, Millet, Zea, Buckwheat, Tritordeum Bulel and Triticum Monococcum L2 classes.
10	MAI	Cultivated areas planted with Maize, Silage Maize and Fodder Maize L2 classes.
11	GRF	Cultivated areas planted with Grass-fodders crops including Medicago and Clover L2 classes.
12	CTN	Cultivated areas where Cotton is planted. It includes a single homonymous L2 class.
13	TBC	Cultivated areas where Tobacco is planted. It includes a single homonymous L2 class.
14	SUN	Cultivated areas where Sunflower is planted. It includes a single homonymous L2 class.
15	RAP	Cultivated areas where Rapeseed is planted. It includes a single homonymous L2 class.
16	BNS	Cultivated areas planted with the common Bean legume crop. It includes a single homonymous L2 class.
17	LEG	Cultivated areas planted with Legume crops (except from common bean), including Chickpea, Lentil, Lathyrus and Broad Beans L2 classes
18	POT	Summer and spring cultivations of Potatoes. It includes three L2 class for Summer Potato, Spring Potato and Small Islands Potato.
19	TOM	Cultivated areas planted with Tomato plants. It includes two L2 classes, Horticultural Tomato and Industrial Tomato.
20	MEL	Cultivated areas planted with Melon plants, including the Melons and Watermelons L2 classes.
21	HRF	Cultivated areas planted with Horticultural (uncovered) crops that are mainly cultivated during autumn months like, cauliflower, white/red/Brussels cabbage, some zucchini varieties, okra, autumn potato, broccoli, leek. It includes two L2 class for Horticultural Autumn and Autumn Potato.
22	HRP	Cultivated areas planted with Horticultural (uncovered) crops that are cultivated during spring or/and autumn months e.g., onion, carrot, dill, raive, parsley, lettuce, peas, radic, radish, rocket, celery, spinach, beet, fennel, eggplant, garlic, strawberry. It includes two L2 class for Horticultural Spring and Horticultural Spring/Autumn.
23	HRS	Cultivated areas planted with Horticultural (uncovered) crops that are mainly cultivated during summer months, like cucumber, pumpkin, zucchini and peppers. It includes a single homonymous L2 class.
24	GRH	Installations of glass, plastic or any other material which is translucent, namely Greenhouses, under which crops are being cultivated. Cultivated areas with plastic films, covering crops for most part of the year are also included in this class. It includes a single homonymous L2 class.
25	FLW	Agricultural land not used during the reference year for crop production, namely Fallow. It includes a single homonymous L2 class.

Table 1. The Level 1 (L1) classes of the nomenclature along with their description and included Level-2 (L2) sub-classes.

The employed LPIS data consisted of 6,145,720 parcel entries and correspond to cultivations practised between the start of November 2018 to the end of October 2019. Each polygon entry included among else descriptive fields, information about the general crop type of the cultivation in the Crop Code (CC) field, as well as more specific information on the so-called POI code field, referring mainly to different sub-species, varieties, clones and seeds. The LPIS nomenclature consists of 69 CC categories and 2,700 POI sub-categories.

Nonetheless, the Greek LPIS nomenclature in many cases defines separate crop classes (CC) and sub-classes (POI) based on the region of cultivation (e.g., grape vines in small Aegean islands), the plantation purposes (e.g., seed production, table or wine production grapes), agricultural practices and even different policies applied regarding subsidy applications. In this sense, the LPIS nomenclature cannot be used as is for the definition of distinct, agronomically and phenologically homogeneous classification classes.

2.2 Nomenclature

A nomenclature of three levels was developed by aggregating and grouping the LPIS codes based on their agronomical and phenological behaviour. The first coarser level was designed to depict crops presenting similar spectral characteristics that could serve as the categories for a machine learning classifier using multispectral satellite data of high spatial resolution.

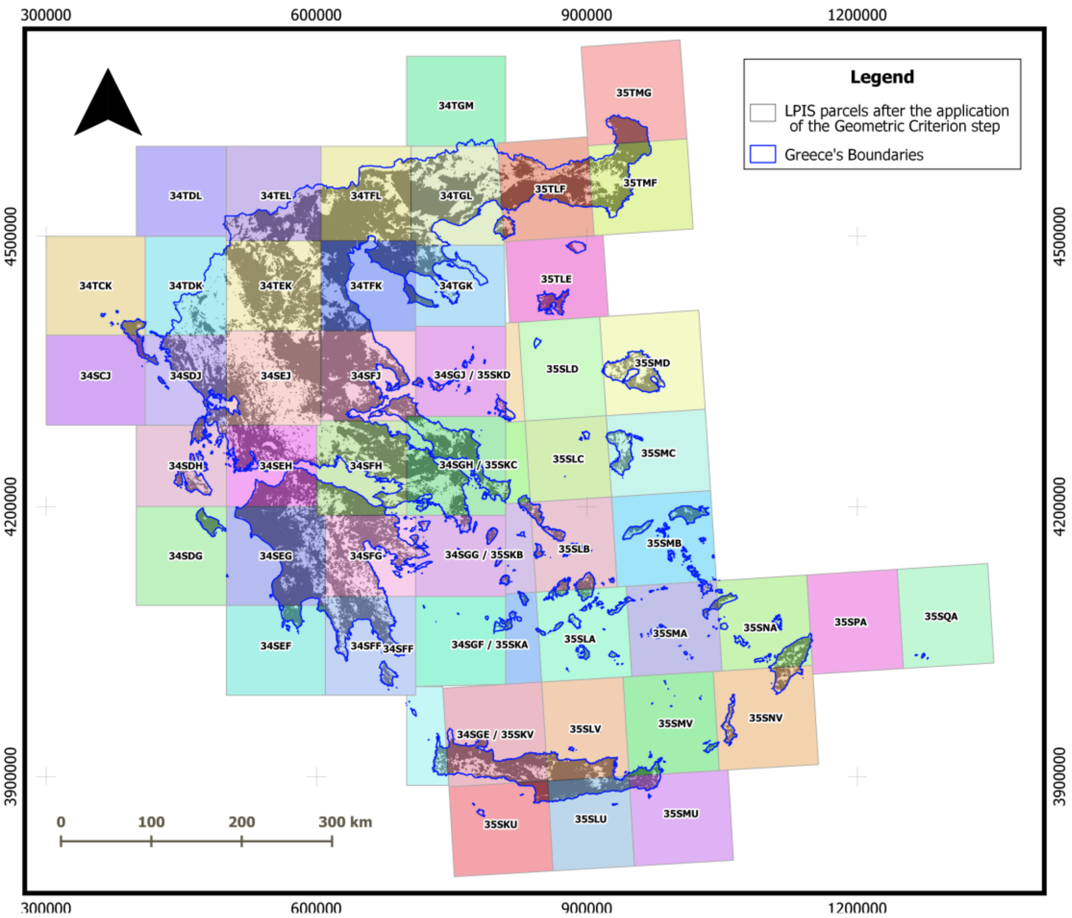

Figure 1. The distribution of the filtered parcels after the application of the geometric criterion overlaid by the Sentinel-2 tighter boundaries' tiles.

The cultivation extent and importance in the agricultural production of Greece was also taken into consideration for setting a specific crop category at this level. Level 1 (L1) includes 25 categories, incorporating crop families, like Cereals, Nut Trees, Citrus Trees, Grass Fodders, and separate crops like Olive Groves, Maize, Tobacco and Tomato. The second level analysed the categories of the first to their sub-categories and sub-species, accounting for a total of 67 classes. Level 3 consists of more than 1,500 POI codes that were grouped under the corresponding Level 2 (L2) classes. Level 1 classes, their definitions and included L2 subclasses (when applicable) are presented in Table 1.

2.3 Filtering Methodology

At first, parcels whose CC or POI code was not included in the developed nomenclature were erased from the LPIS dataset. Parcels corresponding to combined cultivations or sequential cropping i.e., having more than one CC or POI code on the same reference year were excluded from further processing, since the spatio-temporal information for their separation was not available. These parcels accounted for approx. 2.5% of the total number of parcels. Then a negative buffer of 15 m was applied to all parcel boundaries to ensure that spectral analysis would not include heterogeneous pixels on the boarders of the parcels but also to account for the multitemporal registration error of Sentinel-2 data. After buffering, geometries covering less than one Sentinel-2 pixel, i.e, 100 m^2, were erased. Remaining geometries, the so called from now on 'cleaned LPIS' parcels, summed up to approximately 3 million parcels/polygons.

The application of the two following criteria of the filtering methodology, i.e., the geometric and the spectral homogeneity, was performed on a per Sentinel-2 tile basis. This decision was made in order to account for the local spectro-temporal variability of the crop types, associated with the respective differences on the phenological cycles, local micro-climates and agricultural practices of different regions, but also to ensure a sufficient number of training polygons for all tiles, in the case of experimenting with smaller study areas than the entire country. It should be also noted that we used tighter boundaries for the Sentinel-2 tiles, by applying inside buffers to exclude overlapping regions.

A geometric criterion was defined in order to eliminate very small or very elongated parcels. For this purpose, the minimum rotated rectangle bounding box (MRRBB) of every parcel was calculated. Parcels having both MRRBB sides shorter than 10 meters, were eliminated. In order to ensure that under-represented L2 classes would not end up with no or very few parcels, we did not apply this check for the L2 classes that corresponded to less than 1000 polygons. Additionally, for each L2 class that had more than 1000 polygons before the application of the geometric criterion and ended up with less than 1000 polygons, we retained the 1000 polygons having the longest MRRBB sides. After the application of the geometric criterion the remaining geometries summed up to approx. 2

million polygons. The distribution of these polygons over the country is presented in Figure 1 with a grey colour along with the tighter boundaries of Sentinel-2 tiles.

These polygons were then filtered applying a spectral homogeneity criterion. Spectral analysis was performed on multitemporal Sentinel-2 L2A data accessed via the Google Earth Engine Python API. In particular, the Normalized Difference Vegetation Index (NDVI) was calculated for scenes acquired between 01/11/2018 and 31/10/2019, adhering to certain criteria. Two thresholds were applied, regarding the percentage of clouds' presence in the scene (less than 5%) and one regarding no data pixels (less than 15%). The above criteria led to the retrieval of 27 acquisitions per tile on average (median 27, min 13, max 56) for the 53 Sentinel-2 tiles depicting Greece. NDVI was computed at parcel level, for each available date as the mean value from all Sentinel-2 pixels contained in the parcels' buffered boundaries. It should be noted that the presence of pixels labelled as saturated or defected, dark area, cloud shadow, cloud medium or high probability, thin cirrus or snow/ice, based on the Scene Classification map (SCL) of the L2A data, marked the parcel as unreliable for the specific date.

The spectral homogeneity criterion was then applied based on the formation of multitemporal NDVI profiles at parcel level for each L2 class. The median NDVI of each L2 class was calculated from the parcels that were marked as reliable, for each date, per Sentinel-2 tile. The spectral homogeneity criterion was then employed; parcels whose NDVI profile fell into specific defined ranges above and below the computed median, using the standard deviation (std) value for each date, were selected as trustworthy from the general pool. NDVI standard deviation was used as a measure expressing the intra-class spectral homogeneity and varies depending on the type of cultivation but also the respective phenological state of the cultivated plants. Rules and intervals were designed in order to exclude outlier records that could probably correspond to erroneous declarations, but also aiming to produce a set of training data that was not highly unbalanced between the classes.

L1			
# of L2 categories ≤ 3		# of L2 categories > 3	
1st set of rules (wider)		**2nd set of rules (narrower)**	
L2			
# of L2 parcels	std range	# of L2 parcels	std range
<100	No filter	<100	No filter
100-1000	± 3	100-500	+3, -2
1000-5000	+3, -2	500-1000	± 2
5000-10000	± 2	1000-10000	+2, -1
>10000	+2, -1	>10000	± 1

Table 2. The rule-set of the spectral homogeneity criterion.

To this end both levels of the nomenclature, i.e., L1 and L2, were utilised to form two set of rules, as presented in Table 2. The first set (wider) was applied to the L2 classes belonging to L1 classes that contain three or less L2 categories for the studied tile. The second set of narrower standard deviation ranges was applied to the L2 classes of L1 classes that contained four or more L2 classes for the studied tile. If the application of the 2nd set of rules resulted into less than 1000 parcels for the L1 class, this class would re-pass the spectral homogeneity criterion under the first set of wider rules.

3. RESULTS AND DISCUSSION

3.1 Filtered Parcels per Crop-Type

The application of the first cleaning steps resulted into approx. 3 million cleaned LPIS parcels. Then, the application of the geometric criterion eliminated about 27% of the cleaned parcels, the spectral homogeneity criterion a 41% and the remaining 32% composed of the, accepted as trustworthy part, of the dataset. Table 3 presents the number of cleaned parcels for each L1 class before the application of the two filtering criteria, the corresponding percentages of rejected and accepted parcels from the two applied criteria and the final number of accepted parcels, aggregated for the entire country. It can be easily observed that the developed methodology that defines stricter rules for the over-represented classes resulted into accepting larger proportions for the under-represented classes on the top rows of Table 3.

L1	**# of Cleaned Parcels**	**Rej. by GC** (%)	**Rej. by SC** (%)	**Acc.** (%)	**# of Acc. Parcels**
HRS	1538	7.2	7.5	85.2	1311
TOM	3628	7.6	10.6	81.7	2965
GRH	4721	10.5	18.0	71.6	3379
HRF	4875	15.7	9.6	74.7	3641
MEL	5067	10.3	7.4	82.2	4167
POT	7269	14.1	11.9	74.0	5379
HRP	7717	10.0	7.4	82.6	6374
BNS	8945	20.0	10.9	69.2	6187
RAP	10175	14.6	17.3	68.1	6929
POM	11412	16.7	22.7	60.6	6916
KWI	12159	23.5	15.8	60.8	7388
RIC	17802	16.2	25.9	57.9	10315
TBC	22593	27.7	19.6	52.6	11890
LEG	27632	15.7	32.8	51.5	14227
CTR	33999	26.1	34.6	39.3	13365
NUT	40446	20.7	34.2	45.2	18276
STN	66911	31.4	30.5	38.1	25517
VNY	96129	18.2	28.1	53.7	51588
SUN	96728	24.4	36.0	39.6	38343
MAI	105320	34.8	21.7	43.5	45799
GRF	207897	15.9	49.3	34.8	72305
CTN	218211	21.7	40.3	38.0	82848
FLW	291118	29.0	35.6	35.4	103087
CRL	556354	21.9	54.6	23.5	130887
OLG	1095496	34.4	41.9	23.7	259829
Tot.	2954142	27.2	41.2	31.6	932912

Table 3. Ascending sorted number of cleaned parcels aggregated for the entire country for each Level 1 class and the percentages of rejected (Rej.) parcels by the geometric (GM) and spectral homogeneity (SC) criteria along with the percentage and the number of accepted (Acc.) parcels.

In Figures 2, 3 and 4, the NDVI profiles of Cotton (CTN) parcels, are presented for three representative S2 tiles. Cotton is one of the most widely-grown crops in Greece, cultivated

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predominantly in the north and central parts of the country. Cotton is planted during spring, usually from early March to late April. NDVI peak for this cultivation is expected from mid-July to mid-September, depending on the geographic latitude of the area of cultivation. Cotton corresponds to one L1 class and one homonymous L2 category. All selected tiles, contain large numbers of CTN parcels and they are located on different geographic and climatic zones of the country. In particular tile 35TLF depicts a northern part of the country on the Thrace Region and NDVI profiles from this area are presented in Figure 2. 34SEJ depicts a central region of the country that includes a significant part of the Thessalian Plain, the largest agricultural zone of the country. NDVI profiles from this area are presented in Figure 3. 34SFH depicts a south/central region of the country including the Thebes agricultural plain and NDVI profiles from this area are presented in Figure 4. It can be observed that for the northern 35TLF tile, the NDVI peak occurs slightly later compared to the other two tiles, i.e. on mid-August compared to early August for 34SEJ and 34SFH.

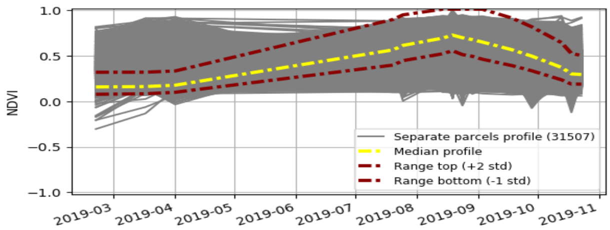

Figure 2. NDVI profiles of Cotton (CTN) parcels for the 35TLF Sentinel-2 tile. The accepted parcels within standard deviation (std) range, above and below the median curve, were 13341 out of 31507.

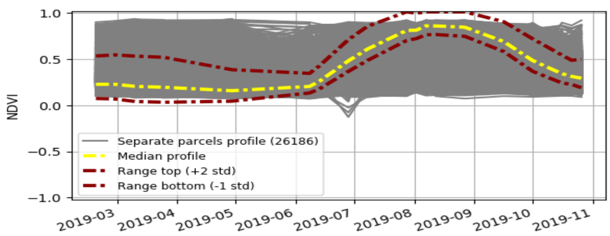

Figure 3. NDVI profiles of Cotton (CTN) parcels for the Sentinel-2 34SEJ tile. The accepted parcels within standard deviation (std) range, above and below the median curve, were 9129 out of 26186.

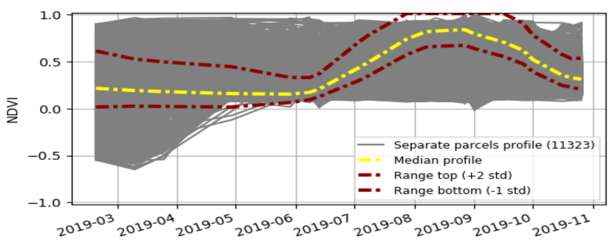

Figure 4. NDVI profiles of Cotton (CTN) parcels for the Sentinel-2 34SFH tile. The accepted parcels within standard deviation (std) range, above and below the median curve, were 4401 out of 11323.

CTN contains one homonymous category and no other sub-classes and thus the 1st set of rules was applied. For these three tiles, large numbers of CTN parcels, i.e., more than 10,000, were available and to this respect, the strictest filtering range of the 1st set was employed (see also Table 2), corresponding to +2 standard deviation (std) above and -1 std below the median curve. The application of this strict range resulted on the rejection of parcels having outlier NDVI values that may correspond to incorrect LPIS declarations or undetected clouds. At the same time, since the applied range is quite tight, it is very probable that correctly declared CTN parcels whose spectro-temporal behavior is not very typical, are also rejected from this process. As already mentioned in sub-section 2.3, the definition of the rule-set targeted also the production of a training dataset that is not highly unbalanced between the different crop types. In this sense, for classes having a large number of parcels, the accepted ones will correspond to the most representative and trustworthy cases.

We also hereby present in Figure 5 and Figure 6 the median NDVI profiles for seven L2 sub-categories of the Stone Fruit Trees (STN) L1 category. STN are primarily cultivated on the north-west of the country. NDVI values for STN are expected to raise and peak during spring and summer months respectively, while lower NDVI values are expected in autumn and winter months when the tree leafs are shed. The Sentinel-2 34TEL tile that contained a large number of STN polygons was selected for further analysis. For the studied tile, the STN L1 class contained seven L2 sub-classes and thus the 2nd set of rules was applied. Figure 5 presents the median NDVI of accepted parcels and Figure 6 the median NDVI of rejected parcels. The median NDVI profiles from the accepted parcels appear to have a significantly more consistent behaviour across the different L2 sub-classes, compared to the rejected ones. In both cases the profile of Peaches and Nectarines, that are the agronomically closest species, presented the most spectro-temporal similarities. Sour Cherry and Cherry Plum L2 classes that accounted for less than 100 parcels did not undergo a filtering procedure, and thus there are no rejected parcels for these categories.

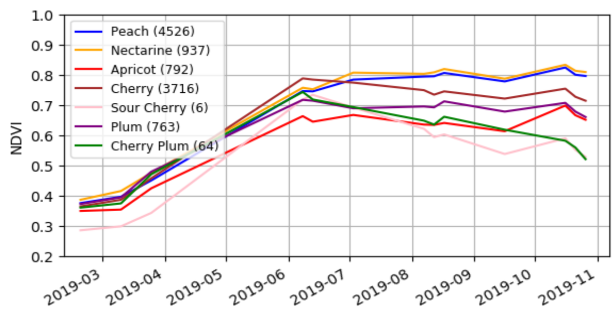

Figure 5. Median NDVI profiles for the accepted parcels of the L2 sub-classes of the Stone Fruit Trees (STN) L1 class from the 34TEL Sentinel-2 tile.

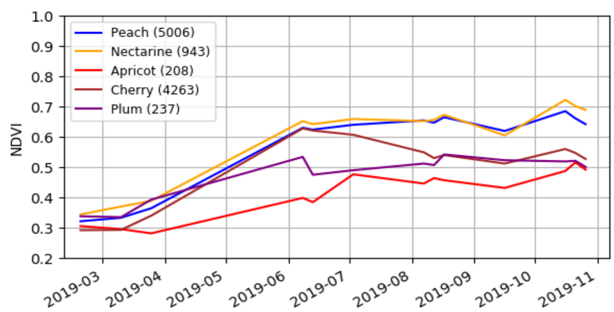

Figure 6. Median NDVI profiles for the rejected parcels of the L2 sub-classes of the Stone Fruit Trees (STN) L1 class from the 34TEL Sentinel-2 tile.

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3.2 Accuracy Assessment based on Field Data

The developed filtering methodology was evaluated using geospatial data from Rapid Field Visits (RFVs) of the Greek Paying Agency (OPEKEPE) and data collected from field campaigns of our laboratory. These data included crop type information at a thematic analysis similar to the defined L1 classes, and thus the evaluation was performed at this level. The validation of the classification experiments was quantitatively implemented by forming confusion matrices, expressing the agreement between the LPIS parcels and the validation points' labels. The standard accuracy metrics of overall accuracy (OA), user's and producer's accuracy (UA and PA) were calculated. Per class F-measure (F1) scores were also calculated as the harmonic mean between UA and PA. Comparison with the validation points was performed for the LPIS cleaned parcels before the application of the two filtering criteria, as well as for the accepted and the rejected parcels from the spectral homogeneity rules. A total of 9635 validation points was employed.

In Table 4 aggregated results from the entire country are presented for OA, average UA, PA and F1 metrics. OA for the unfiltered LPIS parcels reached a high rate of 91.76%. A higher OA rate of 92.79% is recorded for the accepted, after the filtering methodology, parcels and a lower rate of 91.50%, for the rejected ones. The avF1 calculated from all L1 categories as a single-number indicator of the methodology's efficiency, comparable to OA but without the bias of class sample size, highlighted largest discrepancies for the studied datasets. In particular the unfiltered parcels reported an avF1 of 78.35%, while the accepted parcels an increased, by more than 4%, rate of 82.49%. On the other hand the rejected by the spectral homogeneity criterion parcels, resulted into a lower avF1 rate of 69.27%, i.e., decreased by more than 13% compared to the accepted ones. These results underlined the fact that the filtering methodology produced a more reliable subset of the initial LPIS dataset, excluding most of the less trustworthy parcels.

Accuracy Metric	**OA** (%)	**avF1** (%)	**avPA** (%)	**avUA** (%)
Cleaned LPIS	91.76	78.35	77.36	79.36
After the application of the SC rules				
Accepted	92.79	82.49	84.75	80.34
Rejected	91.50	69.27	62.89	77.09

Table 4. Overall accuracy (OA) and average rates of F1 score (avF1), producer's accuracy (avPA) and user's accuracy (avUA) for the cleaned LPIS parcels and the accepted and rejected parcels from the spectral homogeneity (SC) criterion.

Further analysis was performed at a per L1 class level. In particular in Table 5, the F1 rates for the cleaned, the accepted and the rejected, from the spectral homogeneity criterion, parcels are presented for the entire country, along with the respective number of validation points per class per L1 class. For five classes (POM, POT, HRF, HRP, HRS) no validation points intersected with the rejected from the spectral homogeneity criterion parcels and thus the respective F1 rates could not be retrieved. These classes are rather under-represented in terms of number of parcels (see also Table 3).

All, but two (TBC, GRF) L1 classes, presented higher F1 rates on the accepted filtered parcels, compared to the cleaned LPIS parcels and the rejected parcels. Class TBC presented a large difference of almost 18% between the accepted and the rejected parcels, in favor of the latter. Nonetheless TBC was one of the classes with a small number of validation points, i.e., 18 and thus its validation is no considered very robust. F1 rates for class GRF, corresponding to 622 validation points, were higher by 3% on the rejected dataset compared to the accepted one.

GRF is one of the dominant agricultural classes for Greece, cultivated in numerous parcels (see also Table 3) and various regions of Greece. For this class as in the case of other over-represented classes like CTN, FLW, and CRL, the stricter ranges of the two rule sets were applied for most tiles, and as explained in section 3.1, it is very probable that correctly declared parcels are also rejected, for not having a very typical spectro-temporal behavior. As expected, these L1 classes presented smaller differences for the F1 rates between the accepted and rejected parcels. On the other hand, under-represented classes like MEL, GRH, BNS and RAP presented larger differences, even up to 32%.

L1	**# of Val. Points**	**F1 Cleaned LPIS**	**F1 Accepted Parcels**	**F1 Rejected Parcels**
OLG	925	94.64	97.46	93.11
VNY	131	88.44	92.11	71.8
CTR	74	91.67	92.31	90.74
POM	16	83.33	90.91	
STN	123	83.04	83.87	82.92
KWI	100	100	100	100
NUT	165	86.75	90.37	83.68
RIC	101	97.46	98.76	90.91
CRL	2902	94.35	95.23	93.47
CTN	2581	97.75	98	97.52
MAI	517	89.77	94.96	77.69
TBC	18	61.82	57.14	75
SUN	346	88.59	90.59	84.04
RAP	82	90.91	96.07	63.63
GRF	622	87.34	85.59	88.55
BNS	27	62.75	74.28	50
LEG	249	89.82	92.66	80
POT	61	64	74.36	
TOM	147	93.15	94.57	87.5
MEL	53	62.92	70.97	43.48
HRF	7	11.11	14.28	
HRP	43	53.66	65.62	
HRS	10	50	72.73	
GRH	10	63.63	66.67	57.14
FLW	325	50.42	51.7	49.84
Tot.	9635	78.35	82.49	69.27

Table 5. F1 rates for the cleaned, the accepted and the rejected parcels per L1 class aggregated for the entire country, along with the respective number of validation points per class.

3.3 Training Data for Crop Type Mapping

The developed methodology has been, also, implemented for the production of trustworthy training data for crop type classes in two studies, targeting joint land cover and crop type mapping. In particular in Karakizi et al., (2021) 18 crop types were mapped along with 17 general land cover classes over four study areas in Greece, presenting various environmental characteristics. For most study areas, average F1 scores for the classification using the Random Forest (RF) classifier and time series of less than 20% cloud coverage Sentinel-2 data exceeded the 80% rate.

Moreover, the proposed filtering methodology was recently exploited (Karakizi, 2022) for the production of reliable training data for all 25 L1 classes of the developed nomenclature. Under the context of this study, synthetic 5-day time series of spectrally and geometrically consistent Sentinel-2 data over the terrestrial Greece and nearby coastal regions, were employed towards mapping 17 general land cover classes and 25 crop type categories at national scale. The RF classifier was employed and the internal classification evaluation, documented average F1 rates for the 25 crop classes, over 81%. An external validation procedure on the map reported average user accuracy for the 25 crop classes at 79%, while major arable crops (e.g., CRL, MAI, RIC, GRF, CTN, TBC, SUN, RAP) which cover most of the agricultural land in Greece, resulted into an average user accuracy level above 87%.

4. CONCLUSIONS

This paper presented a pipeline for filtering LPIS data towards building trustworthy training datasets for crop type monitoring and mapping. The case study was Greece. The proposed methodology is based on geometric and spectral rules in order to filter outlier records and declaration errors. The application of the developed methodology resulted into a trustworthy national training set for 67 different crop sub-classes and 25 crop classes. The accepted polygons were validated using geospatial data from field visits. The quantitative evaluation confirmed that the application of the proposed methodology extracted a more reliable subset of the initial LPIS dataset, excluding most of the less trustworthy parcels. The efficiency of the proposed filtering methodology has been also demonstrated in two recent mapping studies that documented average F-scores values for crop types over 80%. Overall, the experimental results and their evaluation demonstrated the effectiveness of the proposed methodology and raised expectations for its integration in operational classification frameworks towards annual crop type mapping.

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