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Classifying fuel types combining photogrammetry with LiDAR data in Lazio region, Italy

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Greece - July 2018 FIRE KILLED 83 PEOPLE



The seaside town of Mati, east of Athens, was the hardest-hit community

Greece has "serious indications" that a fire that killed at least 83 people near Athens earlier this week was started deliberately, Citizen Protection Minister Nikos Toskas says.

The blaze broke out on Monday and hit coastal villages popular with tourists.

Some 60 people are still being treated in hospital, 11 in intensive care. Dozens more are missing.

Opposition politician Maria Spyraki accused the government of an "abject failure" to protect lives and property.

Ms Spyraki, spokeswoman for the conservative New Democracy, said the government ought to have warned residents via the media, deployed more firefighters, and evacuated people from Mati immediately.

Northern Spanish region of Galicia-October 2017



A forest fire on Sunday in Chandebrito, a village in the northern Spanish region of Galicia. Salvador Sus/European Pressphoro Agency

MADRID — At least 35 people have been killed and dozens more injured by wildfires in Portugal and northern Spain, as strong winds from a hurricane fanned hundreds of blazes sweeping across densely forested territory.

The authorities in Portugal declared a state of emergency in affected areas over the weekend, when about 500 fires were reported in the central and northern regions, and they raised the death toll to 31. About 4,000 firefighters were working to extinguish at least 65 blazes Monday morning.

Across the border in Spain, fires reached the outskirts of the port city of Vigo, forcing the temporary closing of a car factory. Television news reports and videos shared on social media showed residents forming human chains to pass water buckets in order to help put out flames.

The Spanish authorities said that more than 90 fires were burning in the

ITALY 2017 - 2018

LITP

10

Monte Serra (Pisa) September 2018

> Castel Fusano (Rome) July 2017

Naples (Vesuvio)

July 2017

Sardenia July 2017



- Approximately <u>30%</u> of land surface, <u>at a global scale</u> has experienced frequent intensive burning (Chuvieco E. et al., 2008).
- Extreme weather condition combined with high flammable fuel will continue to affect the European territory (European Commission, 2018).
- Wildfires destroyed 1 million hectares in MB (FAO, 2011).
- 7.855 total fires number in Italy which burned a total of 161.987 hectares (European Commission, 2018).



Prevention

Citizen education and awareness raising measurements

Directly or indirectly human actions cause more than 90% of worldwide fires; (Costafreda-Aumedes S. et al., 2017).

Forest fires causes in Italy (CFS, 2001)

Natural	Accidental	Voluntary	Arson (%)	Unknown
(%)	(%)	(%)		(%)
1	0.6	12.6	50.7	35.1
0.6	0.2	11.1	48.9	39.2
0.9	0.5	11.8	57.7	29.1
1.1	0.5	34.4	60.0	4.0
	Natural (%) 1 0.6 0.9 1.1	Natural Accidental (%) (%) 1 0.6 0.6 0.2 0.9 0.5 1.1 0.5	NaturalAccidentalVoluntary(%)(%)(%)10.612.60.60.211.10.90.511.81.10.534.4	NaturalAccidentalVoluntaryArson (%)(%)(%)(%)10.612.650.70.60.211.148.90.90.511.857.71.10.534.460.0



- Fuels are defined as all combustible organic material in forests and other vegetation types, including agricultural systems, such as grass, branches and wood, which create heat during the combustion process (TRG(A10.6)/GICM, FAO, 2005).
- A fuel model is a set of fuel parameters for each of the input required by fire behaviour model (e.g. loading, depth, heat content) that are quantified to represent expected fire behaviour and not actual fuel characteristics (Burgan & Rothermel 1984, Keane 2013).
- Fire models are equation that describes fire behaviour according to the characteristic of fuel type (Arroyo L.A., et al., 2008).

Background

What does exist at world level?

Albini, 1972; Anderson H. E., 1982; Scott and Burgan, 2005; FCCS, 2007, CFFRDS, etc. (Duka I. and Ioannilli M., 2016).

What does exist at the MB level?

Prometheus project, 1999;
FUELMAP project (JRC-ITT, 2011);
ArcFUEL LIFE project 2014.

What does exist for Italy?

Several studies to characterize fuel types have been developed for Italian territory (Lasaponara R. and Lanorte A., 2006; Salis M., 2007; Lanorte A. and Lasaponara R., 2008; Bovio G., Ascoli D., 2013; Salis M et al., 2013; Corona P, et al., 2014; Migliozzi A., Marotta A., 2014; Elia M. et al., 2015; etc.).



Weekness of the existing FTC studies in Italy

They are:

- focused on <u>small</u> study <u>areas;</u>
- based on <u>a lot of surveys</u> which required considerable time to collect fuel information <u>increasing costs</u> too;
- varying according data sources not publically available;
- impossibility to replicate them in other areas.

WHAT TO DO?

Study area/ Lazio Region (Italy)



1. Identify vegetation patterns using a double scale approach (regional and local).



Source: Duka I. and Ioannilli M. (2016). Fuel Type Classification in the Mediterranean Basin. Context: State of the Art and Future Research. International Journal of Environmental Science and Development. Vol. 7 (7), p. 546-552.

1. Identify vegetation patterns using a double scale approach (regional and local).



 1.279 different pattern categories derived as combination of: vegetation species, climate region, thermotype and ombrotype, forest structure and cover.

region lernotipo	Ombrotipo	
=		



2. Describe patterns in terms of surface fuel types



- 1. Indirect methods (capture photo from Google Street View).
- 2. Expert knowledge to recognize fire carrying Ft and literature.

2.1 Capture photos from Google Street View

- R5, the fifth generation of a series in house. It is made by a ring of eight <u>5-megapixel CMOS</u> cameras with custom lowflare lenses, plus a fish-eye lens on top to capture upper level of the buildings.
- R7, uses a <u>15 of the same sensors</u> and lenses of R5, but without fish-eye to get <u>high resolution images</u> over an increased field of view.
- 2017: uses eight of <u>20 megapixel cameras</u>. Includes two facing left and right to read street signs and business names.

2.1 Capture photos from Google Street View

- Patterns to be photographed are selected randomly considering location (Nord,South,West & East), altimetry (coast to inner land) and road accessibility.
- About 900 photos are captured from Google Street View (4 months).
- * 840 photos were selected from the 900 photos, georeferenced in a GIS environment (ArcMap 10.3) and described in terms of surface FT through expert knowledge

2.1 Capture photos from Google Street View

CRITERIA TO SELECT THE RIGHT PHOTO

- Side street vegetation must not cover fuel of the selected pattern to be photograph.
- Photos are captured nearest to the pattern and in front of it.
- Photos inserted from users on Google are considered.
- The captured photos belong to the four seasons.
- Some photos are taken from literature.
- Photos captured in private properties are excluded.

Photo not considered



Photo considered





1. Nonburnable

Described patterns

- Not described patterns
- Sampled patterns



2. Nearly pure grass and forb type (Grass)

6%

- 3. Shrub cover more than 50% on the site; grass sparse to non exist
- 4. Mixture of grass and shrubs
- 5. Timber undersory; Grass or shrubs mixed with litter from forest canopy
- 6. Tiber-Litter; Dead and down woody fuel (litter) beneath a forest canopy

Multiple

1. Nonburnable Fuel Type



2. Nearly pure grass and forb type (Grass)

3. Shrub cover more than 50% on the site; grass sparse to non exist

4. Mixture of grass and shrubs

5. Timber understory; Grass or shrubs mixed with litter from forest canopy

6. Timber-Litter; Dead and down woody fuel (litter) beneath a forest canopy

2.2 Sample data

15% of photos are processed to derive photogrammetrically plant measurements to assign fuel load.

Sampled vegetation patterns surface for each Fuel Type group.

2.3 Measuring plants

2.4 Assigning fuel load

FUEL LOAD	COMPACTNESS	HEIGHT (m)
Very low	Short, sparse	Grass <= 0,5
Low	Grass is more continuous, not short and some shrubs may be	
	present; in humid climate herbs are present too	Grass <= 0,5
Moderate	Continuous, tall, height greater than the above	0,5 < Grass <=2
High	Dense and continuous	Grass > 2
	Shrub fuel characteristics	
FUEL LOAD	COVER	HEIGHT (m)
Low	Very sparse shrubs	Shrubs <= 0,5
Moderate	Sparse to dense shrubs with foliage cover characteristics	0,5 < Shrubs <=2
High	Dense shrubs with moderate foliage cover characteristics	Shrubs > 2
Very heavy	Very dense shrubs with very dense foliage cover characteristics	Shrubs > 2 (Maquis)

Litter fuel evaluation characteristics (Bovio G., Ascoli D., 2013)

FUEL LOAD	COVER (%)	DEPTH (cm)
Light	Less than 30	Less than 2
Low	30-50	2-3
Moderate	50-70	4-7
High	>70	>10

2.4 LiDAR data verification

0.

The <u>average point spacing</u> <u>tends to be approximately</u> <u>0.7 m</u>, whereas the point density is approximately <u>2</u> <u>returns/sq.</u>

2.4 LiDAR data verification

Image: Image

- Organize strips
- Conversion LAZ to LAS
- ✤ Merge
- Remove duplicate points
- Clip
- Filter

2.4 LiDAR data verification

- in some cases 4th return points are classified as ground points;
- last return points are classified as 1.Unclassified category or in some cases also as vegetation category;
- there are many points classified as 1.Unassigned category including ground points;
- in some cases agriculture crops are classified as 2.Ground category.

Canopy Height surface

- Low Canopy Height: less than 0,5 m;
- ✤ Medium Canopy Height: from 0,5 m 2,00 m;
- ✤ High Canopy Height: more than 2,00.

2.4 LiDAR data verification

- ✤ Mean
- Majority
- Maximum
 - ✤ Median
- Minimum
- ✤ Minority
- ✤ Range
 - ✤ STD
- ✤ Variety
- ✤ Min_Max
- ✤ MeanSTD
- ✤ Min_Max_Mean

3. Artificial Neural Networks (ANN) to predict fuel types and measurements

Case 1: Grass and shrub measurements from Google photos without tree heights

Case 2: Grass and shrub measurements from Google photos and tree heights obtained from LiDAR data

VARIABLES

- Fuel type classes;
- The distance from the camera to the plant measured from Google photos (meter);
- Focal length of the camera (millimeter);
- Angular degree of the measurements obtained from Google photos (degree)
- Season: season of the captured photo on Google street view, obtained from Google photos;
- Years difference: it is obtain as a difference between LIDAR flight year and the captured photo on Google;
- Real height: Height of grass and shrub obtained from Google photo measurements (meter);
- Range, Mean and STD: Range, Mean (Height of grass, shrubs and trees) and standard deviation extract from LIDAR data (meter).

3. Artificial Neural Networks (ANN) to predict fuel types and measurements

- 1. PREDICT FUEL HEIGHTS
- Cascade Correlation (Fahlman and Lebiere) feed-forward architecture method (Alcázar et al. 2008).

RESULTS

- NET 6/ 6-5-1 direct connection network considering both LiDAR and Google photos.
- The r values (r > 0,8) in the training, testing and validation data suggest a high correlation between calculated and predicted heights
- The mean absolute error relatively low (Avg.Abs. = 0.28) suggest that the NET can be considered a good model to predict fuel height.
- The sensitivity analysis point out that: years differences (frequency of selection 0.88 and a low value in the sensitivity analysis 0.15); distance from the camera to the plant measured (frequency of selection 1 and a low value in the sensitivity analysis 0.37); and, Mean (frequency of selection 1 and a low value in the sensitivity analysis 0.42) are the variables that mostly influenced the model. Whereas the other variables shown a low frequency of selectin a 0 value in the sensitivity analysis.

3. Artificial Neural Networks (ANN) to predict fuel types and measurements

1. ASSESS FUEL TYPE CLASSIFICATION through CONFUSION MATRIX

Case 1: 118 observed data; 17 fuel types – 9 fuel types – 7 fuel types

RESULTS for 7 fuel types groups

- Classification models using only LiDAR data (Mean and Standard deviation of grass and shrubs) are not good models. Timber understory (TU) and timber litter (TL) are incorrectly classified cause of lack of tree measurements.
- Classification models using only photo measurements are better than classification model using only LIDAR data but not too good.
- Classification models using both photos and LiDAR (MEAN) measurements are better than the previous 2 models.

3. Artificial Neural Networks (ANN) to predict fuel types and measurements

1. ASSESS FUEL TYPE CLASSIFICATION through CONFUSION MATRIX

Case 2: 128 observed data; 7 fuel types

RESULTS for 7 fuel types groups

Classification models using both photos and LiDAR (MEAN) average measurements are good models with 71% of the data classified correctly.

pred	G1-3	G4	G5	GSH1-2	SH2-3-4-5	TL-TU1	TU2-3-4
G1-3	5	0	0	0	0	0	0
G4	3	5	1	0	0	2	0
G5	1	0	7	0	0	0	0
GSH1-2	2	7	1	10	2	1	0
SH2-3-4-5	1	0	1	3	15	0	2
TL-TU1	0	0	0	0	0	28	3
TU2-3-4	0	0	0	0	0	7	21
>							

IMPROVEMENTS

Organize in a geographic database all fuel information present in different studies in Italy in order to have an overall view and more structured and accessible information.

It is important to have the whole Italian territory covered from well processed LiDAR data and have free access on them.

Collect more photos for an area and obtain more measurements from them.

Use of other variables such as: climate to diversify fuel type classes and to predict fuel models classification

IMPORTANCE

Regional fuel maps are useful as inputs for:

- simulating carbon dynamics and smoke scenarios;
- biogeochemical cycles;
- describing fire hazards to support and prioritization of fire fighting resources (Keane R. E., Reeves M., 2012).

Intermediate- and fine-resolution digital fuel maps are important for:

- ✤ rating ecosystem
- ✤ health
- evaluating tactical fuel treatments
- computing fire hazard and risk
- aiding in environmental assessments and fire danger forecasting programs (Keane R. E., Reeves M., 2012).

Thank you!

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