

# The Influence of Physical Factors on Deforestation of Key Species and their Implication for Forest Management in the Dry Afromontane Forest of Desa'a, Northern Ethiopia

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**Abstract:** Deforestation has been practiced for millennia in Ethiopia. The power of GIS and remote sensing was combined with SPSS to investigate the effect of physical factors on the deforestation of key species. Landsat images of (1972 and 2013) were obtained and Imagine Subpixel classifier was used to detect species and estimate their respective area in the respective years. Logistic regression in SPSS was used to identify the deforestation deriving physical factors. Five percent of the total pixels (100,000 random points) were sampled and taken as permanent plots for change detection. Cover status were determined using the extract values to points function in Arcmap10 by overlaying these random points on the classified images. Elevation, aspect, altitude, and slope were derived from Aster DEM, and distance from settlement, roads were digitized from Topo map at scale of 50,000. For each random point response value was determined using the 1972 and 2013 classified images. The accuracy of the results of Subpixel classifications were assessed using 200 points, 100 for each species. This yielded 86% accuracy level with 5.5% and 8.5% commission and omissions respectively. All physical factors except aspect entered in SPSS for deforestation prediction were significant and have negative correlation coefficient indicating higher deforestation probability as the value of the physical factors decreases. The influence of slope seems to be constant with unit increment of its value. However, using the value of the coefficients; slope, distance from road, elevation, distance from deforested/forested edge, and distance from settlement area were found to influence the spatial distribution of deforestation in decreasing order. While creating ‘social fencing’ mentality is demanded, the current management system of this forest focuses on guarding and command posts along the main roads. Therefore, considering the influence of the physical characteristics of the area is very important for the effectiveness this management system.

**Keywords:** Desa'a, GIS, Imagine Subpixel classifier, SPSS, Logistic regression

## 1. Introduction

Forest resources in developing countries have been under tremendous pressure for a longer time resulting in loss of biomass and biodiversity, soil degradation and erosion [1]. In Tigray, forests are found fragmented and restricted in inaccessible and sacred areas such as churches. This is due to an alarming increment of population and therefore, need for larger areas for agricultural production, fuel wood collection and repetitive drought [2], [3], [4]. Desa'a forest being one of the two national prioritize forests found in Tigray, is constituted of different floral diversity dominated by *Juniperus procera* in the upper canopy followed by *Olea europaea* subsp. *cupsidata* which characterize that ecosystem [5], [4]. However, multiple references [3], [6], [7] have pointed out that these two key species are undergoing a dramatic retreat and degradation. For example, from all the species in the forest, it is *O. europaea* subsp. *cupsidata* followed by *J. procera* which is logged most [7] and among the diebacks recorded *O. europaea* subsp. *cupsidata* followed by *J. procera* takes the lion share [4]. Moreover, the degradation and dieback amount of these two species is different at different landscapes and along the altitude [4]. This indicates that physical factors that characterize the forest have an influence in the deforestation process of these two key species of the dry Afromontane forest of Desa'a. However, they are under studied and no document is found so far which can be very valuable in developing forest management plans. Therefore, this research project was done

with intention of identifying the main physical factors facilitating the eradication of the two key species in Desa'a forest. To achieve the objective set, different methods were utilized. To identify the deforested and non-deforested sites occupied by the two key species, a landsat image of two different years (1973 and 2013) were classified using a powerful add on software in ERDAS Imagine10, Subpixel classifier. After the occurrences of the two key species in the years selected is detected, 5% of the pixels (100,000 random points) were extracted and compared for deforestation status (Dependent variable). Similarly, these sites were characterized with the physical factors selected (independent variables). With these data, a binary logistic regression was used to analyse and measure the effect of the independent variables on deforestation of *O. europaea* subsp. *cupsidata* and *J. Procera*. Therefore this research is aimed at I) quantify the areal change of the two major species over 40 years and II) identify the major physical factors facilitating deforestation of the key species in Desa'a forest.

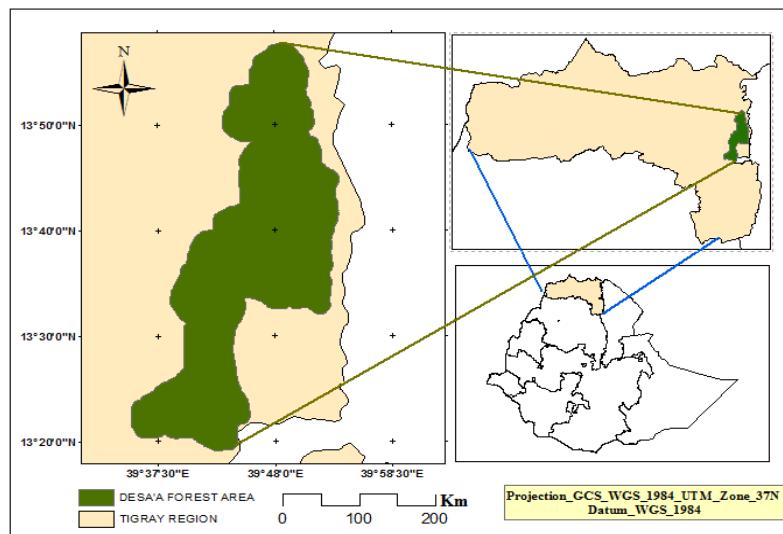
## 2. Methodology

### 2.1. Description of the Study Area

#### 2.1.1. Location

Desa'a forest represents heterogeneous landscapes accountable for the significant difference in biophysical setting of the study site. Geographically it is located between  $39^{\circ} 43' E$  and  $13^{\circ} 45' N$  having an area of 120,026ha [3] at

an altitude range of between 1500 and 2862 m.a.s.l. The forest area extends from Atsbi-wonbera Woreda of Tigray down to the Afar Regional State [3], [8].



**Figure 1:** Map of Desa'a forest, the study area

However, most of the forest area resides in the Tigray national state. In Tigray, the forest falls in three different *Weredas*, found in different administrative zones. The *weredas* are Saesie-tsada Emba, Atsibi which are in the eastern zone and Enderta in the southern zone of the state [3], [8].

The study site is selected merely for three reasons. Firstly, it possesses diverse landscape and biological habitat. Secondly, it represents nationally prioritized forests in Tigray region. Thirdly, since the forests extend in an easterly direction along and down the escarpment of the rift valley, it forms a climatic buffer zone between the cool highlands of Tigray and the hot lowlands of Afar [9] which makes it ecologically and socioeconomically very important in the region therefore, its conservation..

## 2.2. Landscape Characteristics

### 2.2.1. Landform

The topography of the study sites is varied and includes some flat and gentle slopes as well as steep escarpments. The altitude of the area ranges from 1,500 m.a.s.l. at the lower limit to 2,500 m.a.s.l. at the plateau [3].

### 2.2.2. Climate

The rainfall pattern is erratic within short rainy season but is regarded as marginal for tree growth. Since the forests extend in an easterly direction along and down the escarpment of the rift valley, they form a climatic buffer zone between the cool highlands of Tigray and the hot lowlands of Afar. According to [8], the annual average rainfall is between 406 and 692.5 mm. Data collected the mean minimum and maximum temperature for the area varies in the range of 7.5 °C to 19.3 °C and 22.6 °C to 33.4°C, respectively [3], [8].

### 2.2.3. Vegetation

Desa'a forest is exclusively located in the montane formation [5]. Most of the trees are found at the higher altitudes, and relatively undisturbed on the steep eastern slopes. The dominant tree species is *Juniperus procera* with some patches of *Olea europaea* subspp. *cupsidta*. At lower altitudes *Juniperus procera* tends to be replaced by acacia species, including *Acacia origena*, a species only found on the eastern escarpment of Ethiopia, Eritrea, and Yemen [9].

### 2.2.4. Soil

The soil is shallow in inclined surfaces and deep and fertile in the valley bottoms [9]. The dominant soil types in the study areas are Leptosols, Cambisols, Vertisols, Regosols and Arenosols [10].

## 2.3. Sampling Procedure

### 2.3.1. Ground control points (GCP)

In Subpixel classification method, as to the other traditional classifiers, GCPs are needed for two purposes, signature derivation and post classification verification [11]. The samples was confined to three categories according to their canopy cover level, 90-100% (for signature), 20-90 % (for valid detection) and 0-20% (for false detection of each species) [11], [12]. However, in this study, zero occurrences of target species was used in generating false detection AOI file. Therefore, for Ground control points the sample frame was all cover levels of *O. europaea* subspp. *cupsidta* and *J. procera* within Desa'a forest.

### 2.3.2. Sampling Units

Distance from (settlement, roads and priory deforested boundary), slope, aspect, elevation and altitude were the sample units that were measured for the logistic regression analysis of physical factors influence on deforestation process.

### 2.3.3. Sample size

For classification verification, geographically well distributed and adequate numbers of GCPs (100 for each species) were taken as proposed by [11], [12] of which half of them were from the ground to measure the omission level and half from the thematic map produced by the classification algorithm to measure the commission. What is different from the traditional classifier in this regard is; only three quality GCPs are required for signature derivation when similar phenological characteristics are displayed by the target species. Otherwise, three GCPs for each differently represented community of same species (for example, dark green *J. procera* and light green *J. procera*) are required to derive signature for each type to be combined later. However, similar procedures are employed in collecting GCPs for post classification verification as that of the traditional classifiers [12]. Whereas, for sampling the deforestation cases of the key species 5% of the pixels of a land sat image of the forest area (100,000 pixels) were sampled [13].

### 2.3.4. Data collection

For the analysis of significant factors of deforestation using the logistic regression different variables were selected based on literatures. Forest status (forested=1, deforested=0) was the dependent variable and six variables such as distance from road , settlements, an already deforested/forested boundary, slope, aspect and elevation and were evaluated. As it was described earlier, logistic regression suits well for success and failure types of data and therefore the response variables were set to a dichotomous data type(Forested/unchanged and deforested). Data on each variable were collected as follows:

a)**Distance from settlements and roads:** Topo map was used to digitize both roads and settlement areas within and at the periphery of the forest, the study area. Even though main and secondary roads may have different contribution to deforestation, they were treated equally in [14]. After digitizing both roads and settlements, a raster images were generated using Euclidian distance showing distance from each nearest roads and settlements separately. From these two raster data, distance values from each spatial random point to the nearest road and settlement were extracted to the generated 100,000 random points using the extract values to point tool of the spatial analyst tool set in Arcmap10 environment.

b)**Distance from forested /deforested edge:** The study area were first classified in to different LULC and then reclassified to forest and none forest dichotomous classes. These land use classes were vectorized for their boundary and a raster data showing distance radiating away from the boundary was generated using Euclidian distance tool in Arcmap10. Finally the distance to the 100,000 spatial random points from the nearest boundary was extracted to explore if deforestation varies with distance from already deforested areas.

c)**Slope:** One of the assumed deforestation factors was slope. Using the Aster digital elevation model of the study area, slope of the whole study areas were calculated using slope generator in the surface toolset of the spatial analyst in Arcmap10. Then, the slope values were extracted to the random points and exported to Excel to be used in SPSS to

see the relationship between slope and deforestation pattern.

d)**Elevation:** Elevation was simply extracted from the Aster DEM to each point of the 100,000 random points to inspect if the contribution of elevation to deforestation was significant or not.

e)**Aspect:** To explore if there was a difference in deforestation pattern along different directions, aspect raster was developed using surface (aspect) tool in spatial analyst manager of Arcmap10 toolbox set. In order to assess the effect of aspect on deforestation using logistic regression model in SPSS environment, aspect values were extracted to the 300,000 spatial random points after aspect values are reclassified in to whole number new values. Aspects named Flat, North, Northeast, East, Southeast, South, Southwest, and West were reclassified and coded as 1, 2, 3, 4, 5, 6, 7, and 8, respectively. These, the latter numerical codes, were the data extracted by the spatial random points specified above and exported to Excel for analysis in SPSS.

f)**Response (Forested/deforested):** Landsat images of Desa'a forest for the years 1972 and 2013 were classified using the Imagine Subpixel classifier in ERDAS Imagine10 in to eight cover classes. It resulted in species cover percentages of 20-30, 30-40, 40-50, 50-60, 60-70, 70-80, 80-90 and 90-100 named in the software as 1, 2, 3, 4, 5, 6, 7, and 8 respectively. These cover classes were extracted to the 100,000 random points from the two images (1972 and 2013). The resulting values of 2013 were subtracted from resulting values of 1972 (pixel to pixel comparison). If the difference is less than or equal to zero ( $\leq 0$ ), the pixel is assigned '1' (deforested or changed) and if the difference is greater than ( $> 0$ ), the pixel is assigned '0' denoting forested or unchanged.

## 2.4. Data Analysis

### 2.4.1. Image Analysis

#### 2.4.2. Pre-processing of satellite images

Before any classification system is undergone image pre-processing is a mandatory task [15]. Image pre-processing is needed because of different limitation of a raw image such as miss-registration of an image to a different location which requires orthorectification (assigning coordinate system and geo-referencing with ground truth points) and environmental problems such as cloud cover and haze which calls environmental correction [15]. For environmental problems such as cloud cover and haze environmental correction was processed. The Subpixel classifier performs environmental correction especially cloud removal as one component of the classification process.

### 2.4.3. Signature derivation and refinement

In the Subpixel classifier there are two types of signature derivation methods; manual and automated [11], [12], [16]. The manual signature derivation is implemented when signatures producing digitized area of interests (AOI) files are found to contain 100% of the matter of interest. Otherwise, the automated signature derivation is utilised. It must be noted that for more accurate image classification results, an area containing more than 90% of the object of interest should be used to generate training set AOI file [11],

[12]. Moreover, though optional, two additional AOI files are required to help the software refine the signature. An AOI file containing less than 90% of the material of interest (MOI) are used to dictate the process for the presence of the MOI and another set of AOI file with null presence of the MOI to dictate the software to discriminate reflectance from such objects in the process of signature derivation [11], [16], [17].

#### 2.4.4. Image classification

Subpixel classifier of the ERDS Imagine was used to classify images. The image classification procedure in Subpixel classifier is continuous process which includes pre-processing, environmental correction, mainly cloud removal, signature derivation, signature combination and finally matter of interest classification.

#### 2.4.5. Accuracy assessment

Among the core concerns in remote Sensing image classification is the accuracy of classified images to accurately represent the actualities on the ground. All the activities performed before image classification such as pre-processing (Georeferencing, environmental correction and sun angle correction among many are examples) are meant to improve the accuracy of image classification [15], [18]. Accuracy percentage is found to differ with the classifier algorithm used. Accuracy assessment determines the level of relationship between the commonly referred ‘data signature’ in the imagery and categories one made [19].

Therefore, to see how accurately the species were detected using Subpixel classifier of the ERDAS Imagine add on, post detection classification accuracy assessment was done for each species in a similar fashion by taking 100 ground control points for each species.

#### 2.4.6. Binary Logistic Analysis

Binary logistic regression model were used to identify the physical factors that determine deforestation. Logistic regression is used when there are continuous explanatory variables and dichotomous outcomes to look into the relationship between the dependent variable and the different independent variables [20]. It is well suited with odds rather than proportions. Odds are the ratio of the proportions for the two possible outcomes [21]. There are some assumptions in binary logistic regression though fewer than multiple and discriminant regression models [22]. The first assumption is the dependent variables or the outcomes should be dichotomous. Secondly, the outcomes are mutually exclusive (Independent to each other). The third assumption is that binary logistic regression needs large sample so as to be more accurate [22]. To ensure independency of the selected explanatory variable to each other (multi collinearity problem) different methods were employed. To check the multicollinearity problem of the continuous variables Tolerance and Variance Inflation Factors (VIF) were used. Tolerance is a measure of collinearity reported by most statistical programs such as SPSS; the variable’s tolerance is  $1-R^2$  [23]. A small tolerance value indicates that the variable under consideration is almost a perfect linear combination of the independent variables already in the equation and that it should not be added to the regression equation. Some suggest

that a tolerance value less than 0.1 should be investigated further [24]. If a low tolerance value is accompanied by large standard errors and non-significance, multi-collinearity may be an issue. The Variance Inflation Factor (VIF) measures the impact of collinearity among the variables in a regression model. The Variance Inflation Factor (VIF) is  $1/\text{Tolerance}$ , it is always greater than or equal to 1. There is no commonly agreed VIF cut value for determining presence of multicollinearity [22], [23]. However, Values of VIF that exceed 10 are often regarded as indicating multicollinearity, but in weaker models values above 2.5 may be a cause for concern [23], [24]. Variance Inflation Factors shows how the variance of an estimator is inflated by the presence of multicollinearity [23]. If  $R^2$  is the adjusted square of the multiple correlation coefficients that result when the explanatory variable is regressed against all other, VIF is computed as follow:

$$\text{VIF} = 1/(1-R^2),$$

Where, VIF = Variance Inflation Factor and  $R^2$  = adjusted R square

The fitness of the model was measured using the Chi square and Log likelihood tests and result was presented accordingly. The coefficient of the binary logistic regression was used to make inference about the direction of the relationship between each independent variable and the dependent (response) variables. Whereas, the  $X^2$  was used to see how strong the variables are in influencing deforestation as their value is increased by a unit value.

### 3. Result and Discussion

#### 3.1. Key Species cover Classification for 1972 and 2013

##### 3.1.1. Juniperus procera

The extracted values of *Juniperus procera* from a Subpixel classification resultant map (Table 1) indicates that *J. procera* covered more than 3000 ha in 1972, the reference year. Since then, this species has lost over 2000 ha covering only 1900 ha of the study area.

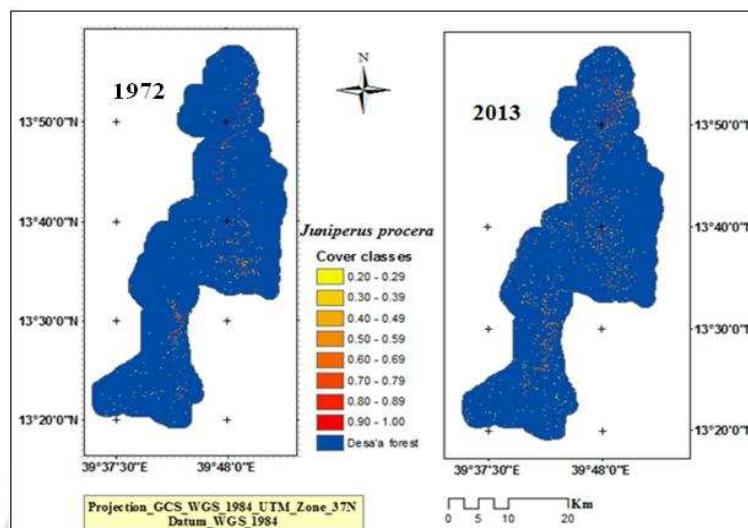
**Table 1: Juniperus procera areal extent in 1972 and 2013**

Class name	Area in ha		Change in ha
	1972	2013	
0.20 - 0.29	260	56	-204
0.30 - 0.39	528	157	-371
0.40 - 0.49	610	278	-332
0.50 - 0.59	632	388	-244
0.60 - 0.69	468	394	-74
0.70 - 0.79	296	294	-2
0.80 - 0.89	157	151	-6
0.90 - 1.00	136	137	1
Sum	3087	1855	-1232

Across the cover classes, more changes were observed in the lower and middle classes having 20 to 80 % of canopy cover. Generally, *J. procera* lost nearly 40% in 2013 of what had existed in 1972 which is an indicator of continued regeneration recruitment failure [3], [4]. The two key species were among the few disfavored species which were severely affected by this devastating fire hazard occurrence. Similar opinions and concern were obtained from focus group

discussion and the severity of the fire was well discussed by [3]. The theoretically protected species, *J. procera*, [8], is more affected and degraded in this study site in-term of area change. Similarly, [7] reported that this species is the second most logged following *O. europaea* subsp. *cupsidata* by the rural community where 1,840.440 tones are extracted yearly. Similar results are also documented from other parts of the country. Large amount of this species is being logged and degraded in Oromiya [25] against the law.

*Juniperus procera* together with *O. europaea* subsp. *cupsidata* are steadily declining with time. The net loss of *J. procera* between 1972 and 2013 was over 1200ha. There can be many reasons that could be attributed, however, being slow growing species and highly demanded by the community which encourages extraction of large amount of these species for household consumption and commercial purposes have contributed a lot. This brought imbalance between net increment and removal which degraded this species alarmingly [24], [7].



**Figure 2:** Map of *Juniperus procera* detections in 1972 and 2013

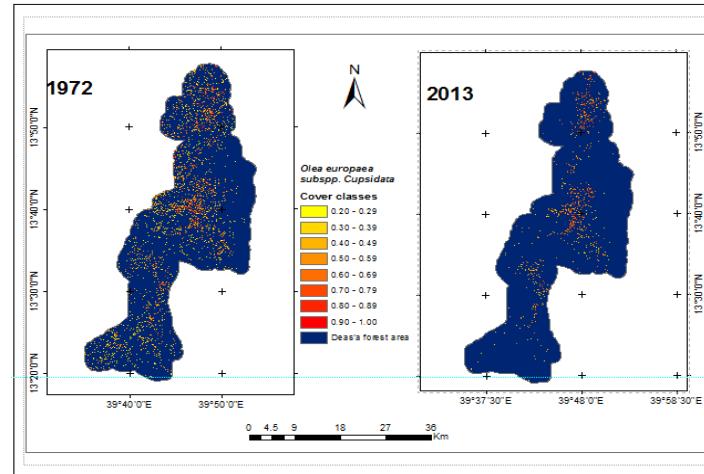
### 3.1.2 *Olea europaea* subsp. *cupsidata*

*Olea europaea* subsp. *cupsidata* is the dominant species in the dry afromontane forest of Desa'a forming the upper canopy strata next to *Juniperus procera*. *Olea europaea* subsp. *cupsidata* covered almost 3200 ha of Desa'a forest in 1972 few ha more than *J. procera*. In similar way to *J. procera*, *O. europaea* subsp. *cupsidata* was reduced to 2122 in 2013. This is more than 33% of the *O. europaea* subsp. *cupsidata* cover detected in 1972.

**Table 2:** comparison of *Olea europaea* subsp. *cupsidata* occurrences in 1972 and 2013

Class Name	Area in ha		Change
	1972	2013	
0.20 - 0.29	218	83	-135
0.30 - 0.39	297	220	-77
0.40 - 0.49	478	381	-97
0.50 - 0.59	542	459	-83
0.60 - 0.69	591	399	-192
0.70 - 0.79	462	254	-208
0.80 - 0.89	227	115	-112
0.90 - 1.00	370	210	-160
<b>Sum</b>	<b>3186</b>	<b>2122</b>	<b>-1064</b>

This might be explained by low regeneration of *O. europaea* subsp. *cupsidata* under exposed environment as documented in [10] and/or heavy browsing and clearance of this species more uniformly than *Juniperus procera* for the reason that different age classes are required by the society for different purposes than any other species. For example, young branches of *O. europaea* subsp. *cupsidata* are cut for tooth brush and sold in cities, others are cut for stick and farming tools. Older trees of this species are demanded for different uses ranging from construction and furniture purposes to energy sources [7]. *Olea europaea* subsp. *cupsidata* is the most used species for fuel wood followed by *Juniperus procera* and *Acacia etbaica* [7] and the most contributor to the total snag found within the study area[4]. Most probably, browsing and cutting of this species were higher in this period induced by severe drought, due to production failure of grasses, the primary feeds of livestock, owing to shortage of rain [3]. Complete distraction, replacement or branching off which left trees of *O. europaea* subsp. *cupsidata* naked were high in 2013. This might be attributed to increased higher dependency of the society on the forest entity.



**Figure 3:** Map of *Olea europaea* ssp. *cupsidata* occurrences in 1972 and 2013

### 3.2. Detection Accuracy Assessment

#### 3.2.1. *Juniperus procera*

To assess the omissions and commissions of *Juniperus procera*, a total of 100 GPS points were taken. Fifty points were collected from field and fifty points were picked from the classified image where continuous detections of the species were observed [11], [12]. The Fifty points were taken from the classified thematic map systematically(30 points from 80-100%, 10 points from 40-79% and 10 points from 20-39% cover classes) so as to include different cover classes. This has yielded an overall accuracy of 81 % with 8% and 11% commissions and omissions respectively. It was found that *Juniperus procera* was confused with *Cadia pupurea* especially with light green *Juniperus procera*. It is worth mentioning that the level of detection accuracy was improved by using the seed signature of both deep and light green *Juniperus procera* signatures which has improved the accuracy by 15%.

#### 3.2.2. *Olea europaea* subsp. *cupsidata*

For this particular species, the desired input for the automatic signature derivation (a pixel covered more than 90% of its area by *Olea europaea* subsp. *cupsidata*) was very difficult to find within the actual boundary of the study area, which literally may indicate the severity of degradation of this species. Fortunately, a church full of *Olea europaea* sub spp. *cupsidata* was found at the periphery of the study area (*Tabia Era*). To take the advantage of this AOI, the image was subset wider than the actual study area to include the church. Later, after the classification was made for the species

occurrences, the classified image was subset again by the actual shape file of the study area, Des'a forest.

Similar approach was repeated as to the *Juniperus procera* and an accuracy of 83% was achieved with 9% and 8% omissions and commissions respectively where confusions were recorded with young *Carissa edulis* species.

### 3.3. Physical factors influence on key species degradation

To evaluate the explanatory variables of deforestation logistic regression was run with six independent variables which were slope, elevation, aspect, distance from settlement, road and an already deforested edge and independent variable, the status of a forest area (Pixel). This was done using the detection of *Olea europaea* subsp. *cupsidata* and *Juniperus procera* in 1972 and 2013. With these limited variables, it was found that all variables were significant except aspect in predicting deforestation pattern in the model. The prediction accuracy of 99.98% at goodness of fit of 84000 was very high. The pseudo R-square was higher which was found to be 0.604. According to [28], a pseudo R-square greater than 0.2 shows relatively good fit of estimation or prediction. The coefficients in each independent variable were negative showing inverse relationship between each variables and deforestation distribution in the study area. The goodness of fit of the model was high at 95% confidence interval ( $p < 0.001$  for all significant variables except for distance from already deforested or forested boundary which was  $p = 0.011$ ).

**Table 3:** effect of physical variables on deforestation distribution in Des'a forest

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 <sup>a</sup>	Distance from Road	-.536	.049	121.095	1	.000*
	Slope	-8.586	1.083	62.889	1	.000*
	Elevation	-.063	.004	235.556	1	.000*
	Aspect	-.041	.048	.746	1	.388"
	Distance from Deforested edge	-.032	.002	259.528	1	.000*
	Distance from Settlement	-.005	.002	6.474	1	.011*
	Constant	44.544	4.437	100.803	1	.000*
						2.215E19

$\text{Exp}(\beta)$  = odds ratio (probability of success/probability of failure), SE= standard error of the estimate, \* =statistically significant at 0.05 level of significance, " = statistically non-significant at 0.05 level of significance, Sig=significance,  $\beta$  = regression coefficients which stand for the odds ratio of probability of success to the probability of failure and Wald statistics =  $\beta/(SE)^2$ , d.f. = degree of freedom

The  $\text{Exp}(B)$  which shows the change magnitude of the odds success due to a unit increment of the variable [29] was higher for the distance variables (distance from road, distance from deforested/forested edge and Distance from settlement) followed by aspect, elevation and slope. For instance, a unit increment in distance from road reduces the likelihood of a pixel being deforested by a factor of 1.71. The influence of slope seems to be constant with unit increment of its value. However, using the value of the coefficients; slope, distance from road, elevation, distance from deforested/forested edge, and distance from settlement area were found to influence the spatial distribution of deforestation in decreasing order. Similar results were reported from a number of studies where similar prediction accuracy, goodness of fit and dependent and independent variables relationship were achieved [28], [29], [33].

### 3.3. Implication for Forest Management

Des'a forest is situated between the hot lowlands of Afar and cool highlands of Tigray, buffering the two extreme climatic conditions, making it one of the sensitive biodiversity hotspots in the country [9], [30]. In addition to its rich flora and fauna diversity [3], [4], [9], it is also home to a large amount of carbon stock [7]. Beyond the climatic importance, the forest has immense economic and social benefits to the local community of Afar and Tigray and the regions at large [4], [7]. However, the forest is diminishing at an alarming rate [6] where as a result such forests can only be found in remote and inaccessible areas [31].

On the top of that, the quality of the forest in terms of productivity performance and species composition is dwindling [4], especially of the key, dominant species of the afromontane forest (*J. procera* and *O. europaea* subspp. *cupsidta*) [5] which are being replaced by light demanding succesional shrubs [3], [4], [7], [30]. This in time can alter the potential ecosystem services where the forest is being dominated by shrubs and all the social, economic and environmental services of the forest could be partially or completely lost. In this study the loss of the key species which are the ecosystem dictating species [32] was found to be highly affected by the on-going disturbance, resulting from socioeconomic factors, which was explained in terms of area coverage and altitude constriction [4]. This, after all, could potentially lead to environmental crisis, and socioeconomic disorder at the localities where there is high dependency on the forest (mainly on the key species) on daily basis.

Forest development success is a site quality dependent. Such factors that determine forest type and their growth performances are the topography, climatic conditions and human interferences. Physical factors mainly altitude, slope,

and aspect do influence the composition and type of forest groups in a landscape. For example, in Des'a, the dominant plant species is found to vary along the altitudinal gradient [4], [10].

In the same area, Des'a, human induced degradation of species is high where a lot of trees are cut for selling and farm tools [7]. Proximity to road showed significant effect in deforestation regime of the two key species including the feeder roads which are out of the sight of the guards which mainly focus on the main roads. Deforestation pattern is also dependent on the proximity to settlements which indicate the non-selective logging of these species for all purposes. Generally, the nearest plants of these key species to road, settlement, already deforested sites are more vulnerable to deforestation than those that are found far from these factors. This indicates how social factors strongly affect forest composition and further threaten selected species of high ecological importance.

Guarding and awareness creation are the main management practices in this forest reserve [3]. Therefore, the management practices in this forest should consider the point of entries for illegal cutting and community organization for effective administration of forest reserves. Therefore, until the 'social fencing' mentality is created, forest guarding, awareness creation, local level forest stewardship and other forest management practices should be introduced and strengthened. This will help to maintain the ecosystem services local communities were enjoying and save the forest from further fragmentation and extinction of these threatened key species.

### 4. Conclusion

Based on these results the depletion of the key species a continuous process where they have undergone a remarkable areal cover change. There is a loss of almost 2300ha between the 1972 and 2013 period. The degradation of these species was more severe in the period between 1972 and 2013 when almost 3000ha of *Olea europaea* subspp. *cupsidta* and *Juniperus procera* was degraded.

Particularly, *Juniperus procera* and *Olea europaea* subspp. *cupsidta* lost nearly 40% and 33% of their area in 2013 from what had existed in 1972 respectively. Moreover, the rate these species are disappearing, if conditions are kept similar, is very threatening. *Juniperus procera* and *Olea europaea* subspp. *cupsidta* are retreating at a rate of 32ha and 28ha per year respectively. This gives only 58 years to lose the ecosystem dominated by *Juniperus procera* and *Olea europaea* subspp. *cupsidta* together and 75 years to lose all *Juniperus procera* and *Olea europaea* subspp. *cupsidta*.

Among the factors facilitating their loss is a conducive environment for illegal cutting and transportation in addition to its location being situated and bounded in between different settlements. The existence of accessible road, both main and feeder roads, patches open areas, an already deforested areas, for landing, and altitude have played significant role in the deforestation process of these species.

Among these factors, settlement and road are noted to play more than the others in encouraging illegal cutting.

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