All Ireland Roundwood Production Forecast 2021-2040 - Methodology

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The COFORD Wood Mobilisation and Forecasting Group is a working group of the COFORD Council. One of the groups aims was to update the forecasting system to ensure that the estimates being provided reflects the best available information and practice. The group is comprised of a range of experts and stakeholders from the forest sector, including Chairperson Patrick Murray (Murray Timber Group), Secretary Luke Heffernan (DAFM), Richard Walsh (DAFM), John Redmond (DAFM), Karl Coggins (DAFM), Owen Cooney (Irish Timber Growers Association), Michael Fairgrieve (DAERA FS), Liam Malone (Coillte), John Ryan (Murray Timber Group), Darragh Little (VEON), Geraldine O'Sullivan (Irish Farmers Association) and Francis McHugh (Teagasc).

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Disclaimer

While every effort has been made to ensure the information provided is accurate, the Department of Agriculture, Food and the Marine does not accept any responsibility or liability for errors of fact, omission, interpretation or opinion that may be present, nor for the consequences of any decisions based on this information.

Interpretation advice

Readers who intend using the forecast for planning or investment purposes are urged to thoroughly review the information provided. It may be advisable in certain cases to engage professional advice.

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Introduction

The first meeting of the COFORD Wood Mobilisation and Forecasting Group took place on the 5th December 2019 with stakeholders representing the forest and sawmilling sector. One of the key objectives of the Group was to update the *All Ireland Roundwood Production Forecast 2016 – 2035* to ensure that the forecast and the forecasting system reflects current practices and the best available information.

Roundwood production forecasts are essential for investment planning and the overall development of the forest and wood energy sector. They provide the information necessary to plan for wood mobilisation, realise the value of the forest estate and help shape the development of the forest sector. The Groups terms of reference identify three distinct action points in relation to forecasting:

- Review the existing methodology for estimating and presenting future roundwood availability.
- Update the All Ireland Roundwood Production Forecast 2016-2035 to cover the period 2021-2040.
- Provide the forest and wood energy sector with an accurate forecast of roundwood and wood fibre availability.

The *All Ireland Roundwood Production Forecast 2021-2040* is a compilation of two distinct spatial forecasts for the Republic of Ireland (i.e. Coillte and private sector) and tabular forecast data compiled for Northern Ireland forests. The eight tasks associated with completing the forecast are outlined in Table 1.

There are six distinct tasks associated with the completion of the Private Roundwood Production Forecast 2021-2040. The Department of Agriculture, Food and the Marine (DAFM) invited interested parties to submit tenders to provide technical services associated with the Roundwood Production Forecast 2021-2040. These services were divided into three distinct lots based on the tasks:

- Lot 1 - Defining the management inputs and dissemination of forecast outputs (Task 3 & 8)
- Lot 2 - Generating the forecast model and results (Task 5)
- Lot 3 - Remote Sensing (Task 4)

Data preparation was carried out by DAFM for the private sector forests in the Republic of Ireland (Task 1) and to assign ancillary spatial information to these forests (Task 2). The roundwood forecast from Coillte's forest estate was prepared internally by Coillte (Task 6). The forecast for Northern Ireland, both public and private, was prepared by the Forest Service division of the Department of Agriculture, Environment and Rural Affairs (Task 7). One final task (Task 8) was required to bring together the different components on the forecast to produce a consolidated All Ireland Roundwood Production Forecast.

In the following eight chapters the methodology used to complete the forecast is outlined.

Table 1. All Ireland Roundwood Production Forecast 2021-2040

Task List and Description	Responsible
1. Private Forest Cover Dataset for the Republic of Ireland	DAFM
1.1 Update information related to afforestation, reforestation and deforestation	
1.2 Update information on areas excised from the Coillte estate	
1.3 Document the methodology used to generate the forest cover dataset	
2. Ancillary spatial information	
2.1 Wind risk (i.e. A, B, C, D or E)	
2.2 Soil type (i.e. peat or mineral)	
2.3 Distance from public road network (i.e. 25m classes)	
2.4 Presence of forest road (i.e. Yes/No)	
2.5 Thinning status (i.e. Yes/No)	
2.6 Productivity of forest parcels (i.e. SS Yield Class)	
2.7 Classify forest parcels into one of three fertility categories	
2.8 Document the methodology used to generate the ancillary spatial information	
3. Management inputs	Silvalytics & H. Phillips
3.1 Determine rotation length and thinning practice	
3.2 Generate forecast model yield tables	
3.3 Deriving species productivity	
3.4 Development of thinning rules	
3.5 Assigning volume based forecast attrition percentages	
3.6 Assigning area based forecast reduction percentages	
3.7 Volume & fibre assortments	
3.8 Document the methodology used to generate the management inputs	
4. Remote Sensing	The ICON Group & Treemetrics
4.1 Identify areas with no tree cover present within forest parcels	
4.2 Detect and classify areas of unhealthy forest	
4.3 Document the remote sensing methodology used	
5. Generate forecast model and results	Silvalytics & H. Phillips
5.1 Defining the overall objective of the forecast model (Period 2021 to 2100)	
5.2 Build plans and models within the forecasting environment	
5.3 Development of a forecast model using the forest data, ancillary spatial data and management inputs	
5.4 Spatial optimisation and scheduling	
5.5 Evaluation of different scenarios for sensitivity analysis	
5.6 Smoothing supply output	
5.7 Output spatial and tabular data for final reporting and web-based forecast tool.	
5.8 Document the methodology used to generate the forecast model	
6. Coillte Forecast	Coillte
6.1 Output spatial and tabular data for final reporting and web-based forecast tool	
6.2 Document the methodology used to generate the forecast model	
7. Northern Ireland Forecast	Department of Agriculture, Environment and Rural Affairs (NI)
7.1 Output tabular data for final reporting	
7.2 Document the methodology used to generate the forecast model	
8. Forecast outputs	Silvalytics & H. Phillips
8.1 Liaise with Coillte and Northern Ireland Forest Service to supply forecast data	
8.2 Prepare forecast results document for the period 2021 to 2040, which will be an update to the previous publication "*All Ireland Roundwood Production Forecast 2016-2035*".	

Chapter 1. Private Forest Cover Dataset for the Republic of Ireland

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1.1 Update information related to changes in the private forest estate

The following sub-sections detail the tasks undertaken to prepare the private forest cover spatial data in the Republic of Ireland for the forecast.

1.1.1 Afforestation

DAFM regulates the licensing process for the afforestation of lands. As part of this process the spatial footprint of the areas afforested are recorded on DAFM's Integrated Forest Information System (IFORIS). Each year an extract of newly afforested areas is appended to the national private forest cover map. This dataset includes information on the composition of the land parcel area that has been afforested, such as planting year and tree species composition. A maximum of four tree species are specified for each forest parcel.

1.1.2 Clearfelling

All associated attributes of those areas which have been clearfelled are updated to ensure that the dataset is as accurate as possible. These clearfelled areas are identified in three ways:

1. Visual interpretation of the most recently available satellite imagery.
2. Assessment of those areas licensed for clearfell since June 2017. After this time the felling licencing system was integrated into IFORIS. Prior to this the licencing process was paper based.
3. Assessment using remote sensing techniques, which is described in greater detail in Chapter 4.

1.1.3 Deforestation

Those forest parcels that have been clearfelled and the land-use type has clearly changed to non-forest were excluded from the dataset.

1.2 Areas excised from the Coillte estate

Each year forest areas are excised from the Coillte forest estate for a variety of reasons (e.g. development of windfarms). Where these areas are retained as forest, the areas are then appended into the private forest cover dataset where appropriate.

1.3 Descriptive statistics on the private forest cover dataset

1.3.1 Land-use type

The private forest cover parcels included in the forecast dataset are classified by land-use type and land-use class (Table 2). Nearly 95% of the total private forest area is classified as having a land-use type of stocked forest, with 3.51% classified as temporarily unstocked forest and the remainder being forest open area (1.82%).

Table 2. Total private forest area by land-use type and land-use class

Land-use type	Land-use class	Area (ha)	%
Stocked Forest	Broadleaf High Forest	81,966	21.44
	Conifer High Forest	257,622	67.39
	Mixed High Forest	22,315	5.84
	Sub-total	**361,903**	**94.67**
Temporarily Unstocked Forest	Broadleaf High Forest	91	0.02
	Conifer High Forest	13,195	3.45
	Mixed High Forest	133	0.03
	Sub-total	**13,419**	**3.51**
Forest Open Area	Biodiversity area	2,998	0.78
	Building setback	13	0.00
	Road	261	0.07
	Right of way	8	0.00
	Setback	829	0.22
	Utility	2,836	0.74
	Sub-total	**6,946**	**1.82**
Total Forest Area		**382,269**	**100**

1.3.2 County level distribution

The spatial distribution of the total private forest area included in the forecast dataset is detailed in Table 3 by County.

Table 3. Total private forest area by county

County	Area (ha)	%
Carlow	2,886	0.8
Cavan	12,101	3.2
Clare	30,535	8.0
Cork	43,374	11.3
Donegal	21,696	5.7
Dublin	1,896	0.5
Galway	22,443	5.9
Kerry	37,321	9.8
Kildare	5,890	1.5
Kilkenny	11,846	3.1
Laois	9,635	2.5
Leitrim	15,017	3.9
Limerick	15,947	4.2
Longford	7,724	2.0
Louth	2,049	0.5
Mayo	24,585	6.4
Meath	7,096	1.9
Monaghan	3,691	1.0
Offaly	12,303	3.2
Roscommon	15,840	4.1
Sligo	10,907	2.9
Tipperary	23,612	6.2
Waterford	11,175	2.9
Westmeath	10,865	2.8
Wexford	8,295	2.2
Wicklow	13,539	3.5
Total	**382,269**	**100**

1.3.3 Ownership

The private forest area is classified into four distinct ownership cohorts (Table 4).

Table 4. Total private forest area by ownership

Owner	Description	Area (ha)	%
Private Grant Aided	Private afforested land which was or is in receipt of grant and/or premium over the period 1980 to present.	292,254	76.5
Private Grant Aided (Farm Partnership)	As above but area part of Coillte Farm Partnership Scheme.	12,675	3.3
Private Non-Grant Aided (PNGA)	Private forest land which was not established with grant aid since 1980. This category includes estate planting and natural succession land.	69,278	18.1
Private (formerly Coillte)	Forest land previously owned by Coillte.	8,061	2.1
Total		**382,269**	**100.0**

1.3.4 Species Composition

Information on the tree species composition of those stocked forest parcels within the forecast dataset is detailed in Table 5. Almost half (49%) of the area contained within the forecast dataset is comprised of Sitka spruce.

Table 5. Private stocked forest area by species

Species	Area (ha)	Species	Area (ha)
Additional Broadleaves	6,536	Lodgepole pine (North Coastal)	5,683
Alder	10,411	Lodgepole pine (South Coastal)	3,635
Ash	14,687	Monterey cypress	53
Beech	1,756	Monterey pine	16
Birch	2,489	Mature Pine/Spruce Mix (1998)	468
Broadleaf Mature Beech (1998)	1,288	Mixed Forest Mature (1998)	13,313
Broadleaf Mature Oak (1998)	3,745	Mixed Forest Young (1998)	937
Mature Other Broadleaves (1998)	36,680	Noble fir	122
Young Other Broadleaves (1998)	5,472	Norway maple	247
Cherry	189	Norway spruce	20,921
Conifer Mature Larch (1998)	83	Oak	4,737
Mature Other Conifer (1998)	1,159	Other Broadleaf	164
Conifer Mature Pine (1998)	571	Other Conifer	110
Conifer Mature Spruce (1998)	2,217	Other Forest	1,500
Corsican Pine	68	Pedunculate oak	6,396
Young Other Conifer (1998)	225	Poplar	25
Conifer Young Pine (1998)	378	Red oak	15
Conifer Young Spruce (1998)	2,635	Rowan	613
Downy birch	44	Silver birch	11
Douglas-fir	1,618	Spanish (Sweet) chestnut	93
European larch	981	Serbian spruce	155
Eucalyptus spp.	3	European silver fir	1
Grand fir	21	Sessile oak	318
Hawthorn	1	Scots pine	4,234
Hazel	24	Sitka spruce	176,377
Hybrid larch	2,034	Sycamore	5,402
Holly	2	Walnut	6
Japanese larch	15,316	Western hemlock	106
Lawson cypress	394	Willow	26
Lime	6	Western red cedar	151
Lodgepole pine	5,033	**Total**	**361,903**

*Those species names that are followed by the text (1998) are taken from the species classification work completed in the Forest Inventory and Planning System project completed in 1998.

Chapter 2. Ancillary Spatial Information for the Private Sector Forecast in the Republic of Ireland

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The purpose of this section is to describe the ancillary information that was added to the private forest cover dataset. These additional parameters were primarily used to develop thinning rules and assign an estimate of productivity to forest parcels.

2.1 Exposure

2.1.1 Wind zone

Using a preliminary wind zone map for Ireland (Miller, 1986), an adapted Wind Zonation was created for the Republic of Ireland (Figure 1). This map was based on exposure flag data from Northern Ireland, which was extrapolated across the whole of Ireland using published maps of physiography and regional variations in mean annual windspeed. These wind zones were a first approximation with the author recommending that additional exposure flag data was required to give an accurate wind zonation (adapted from Miller 1986). The private forest area is classified into the five distinct wind zones in Table 6.

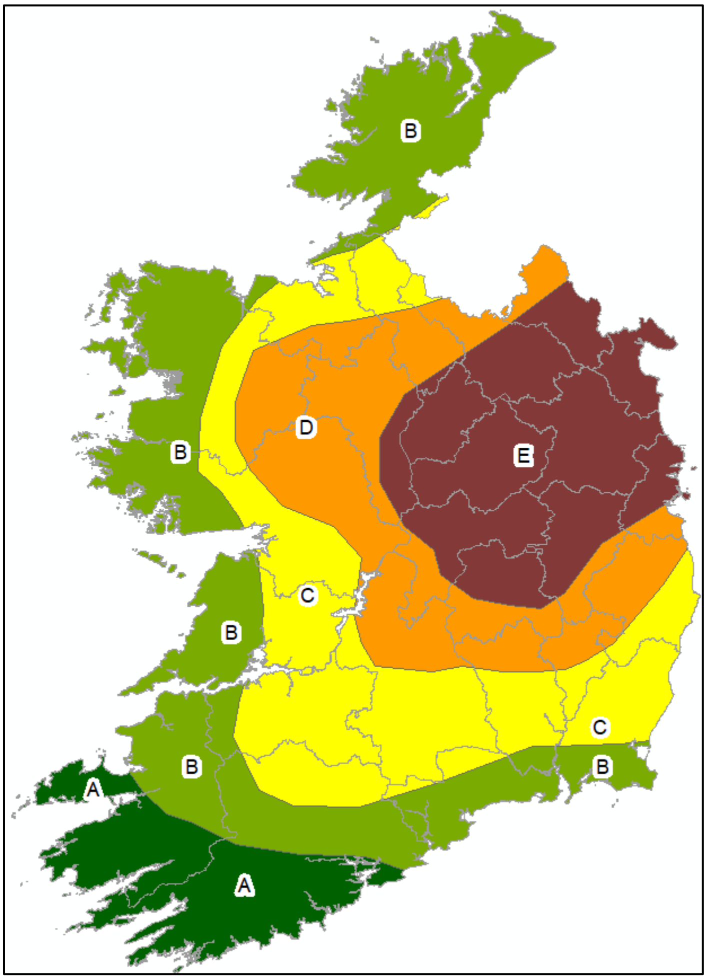


Figure 1. Distribution of wind zones

Table 6. Total private forest area by wind zones

Windzone	Area (ha)	%
A	39,185	10
B	109,848	29
C	91,148	24
D	83,367	22
E	58,721	15
Total	**382,269**	**100**

2.1.2 Wind speed

The Sustainable Energy Authority of Ireland (SEAI) created a wind atlas[1] detailing the wind speed (metres per second) at 20 m above ground level. Each forest parcel was assigned a wind speed, the results of which are summarised in Table 7.

Table 7. Total private forest area by wind speed

Windspeed at 20 m (m/s)	Area (ha)	%
2-2.9	618	0.2
3-3.9	26,692	7.0
4-4.9	121,326	31.7
5-5.9	181,016	47.4
6-6.9	44,036	11.5
7-7.9	7,279	1.9
8+	1,302	0.3
Total area	**382,269**	**100**

2.1.3 Comparison of wind zone and wind speed

To understand the relationship between wind zone and wind speed, Figure 2 presents the percentage of the private forest area within each wind zone classified by wind speed. As expected, there are a greater percentage of higher wind speeds in the more exposed sites. In the final forecast model wind speed was used, which is a change from earlier forecasts when wind zones were used.

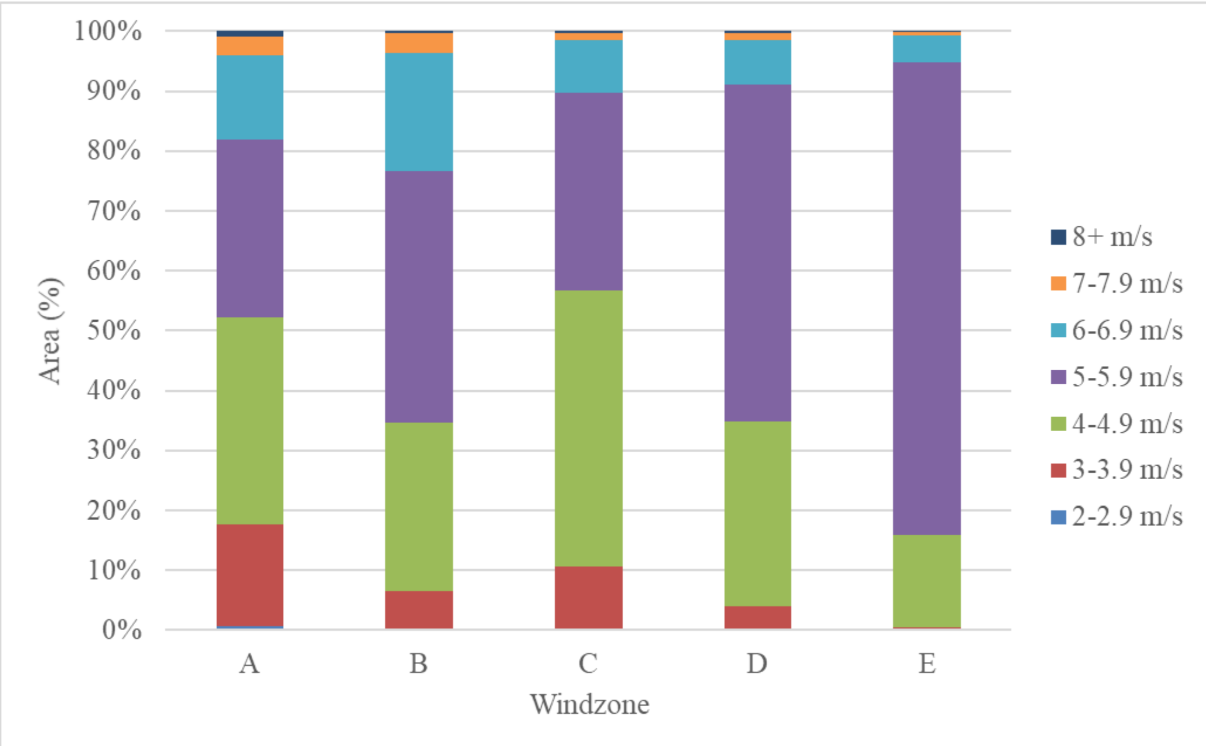


Figure 2. Private forest area within each wind zone classified by wind speed (m/s)

[1] https://www.seai.ie/technologies/seai-maps/wind-atlas-map/

2.2 Soil type

Using the Teagasc-EPA Soils and Subsoils map (Fealy *et al*. 2009), each parcel in the private sector dataset was assigned a soil type (Table 8). For the purpose of the modelling work, the soil types were reclassified into two distinct classes; mineral and peat.

Table 8. Total private forest area (ha) by soil type

Soil Class	Soil type	Area (ha)
Mineral	Aeolian	34
	Alluvium	16,300
	Acid Brown Earth & Brown Podzol	36,922
	Built land	528
	Estuarine	948
	Gley	96,615
	Grey Brown Podzol & Brown Earth (High Base)	13,410
	Lacustrine	2,243
	Rendzina	13,732
	Sand	106
Peat	Blanket peat	62,276
	Cutaway peat	61,772
	Fen peat	1,814
	Lithosol	28,022
	Marl	203
	Peaty gley	20,274
	Podzol (Peaty)	26,347
	Raised peat	2
	Scree	720
Total Area (ha)		**382,269**

2.3 Distance from public road network

The distance was calculated from the edge of each private sector forest parcel to the public road network (Table 9). Where a number of forest parcels are afforested at the one time by the same owner, each parcel have a common file reference number. All parcels associated with the file reference number were assigned the minimum distance value.

Table 9. Total private forest area (ha) distance from public road network

Distance to Road (m)	Fourth Class Road	Third Class Road	Regional	National Primary	National Secondary	Total
0-25	107,574	116,970	19,141	1,295	4,521	249,501
26-50	10,031	6,423	1,215	175	522	18,366
51-75	8,919	6,722	1,110	219	306	17,277
76-100	8,094	5,771	1,062	71	169	15,166
101-125	6,359	4,985	605	74	182	12,205
126-150	6,063	4,149	533	55	116	10,917
151-175	5,328	3,710	460	41	217	9,757
176-200	3,983	2,617	339	59	81	7,079
201-225	3,769	1,988	340	16	38	6,153
226-250	3,843	1,885	252	24	83	6,087
251-275	2,835	1,355	160	8	32	4,389
276-300	2,520	1,177	189	3	17	3,905
>300	14,298	5,882	1,015	26	246	21,467
Total	**183,615**	**163,634**	**26,423**	**2,066**	**6,531**	**382,269**

2.4 Forest roading status

During the review of the private forest cover dataset, the accessibility of forest parcels is assessed by using the most recently available satellite imagery. For each parcel, the presence or absence of a forest road is noted. Overall, one-third of the stocked forest area contains a forest road (Table 10).

Where a number of forest parcels are afforested at the one time by the same owner, each parcel has a common file reference number. A forest road may be only present in the parcel but nevertheless has the capacity to serve the adjacent parcels. Where this occurs, all parcels were classified as having a road present.

Table 10. Private stocked forest area (ha) by land-use class and forest roading status

Land-use Class	Roading Status (ha)		Total (ha)
	No	Yes	
Broadleaf High Forest (BHF)	61,109	20,857	81,966
Conifer High Forest (CHF)	165,765	91,858	257,622
Mixed High Forest (MHF)	13,237	9,078	22,315
Total	**240,111**	**121,792**	**361,903**

2.5 Thinning status

During the review of the private forest cover dataset, the thinning status of forest parcels is assessed using the most recently available satellite imagery. For each parcel, the presence or absence of a thinning intervention was recorded. Overall, 14% of the stocked forest area was classified as being thinned (Table 11).

Table 11. Private stocked forest area by land-use class and thin status

Land-use Class	Thin Status (ha)		Total (ha)
	No	Yes	
BHF	73,670	8,296	81,966
CHF	220,200	37,422	257,622
MHF	16,601	5,713	22,315
Total	**310,472**	**51,431**	**361,903**

2.6 Fertility classification

Through the examination of ornament on the six inch Ordnance Survey Ireland (OSi) map product (Figure 3), parcels of land were classified into four fertility classes (Table 12 and Figure 4) that reflect varying intensities of historic agricultural use. Over half of the area was classified as having fertility class A or B (Table 12). Those Counties on the western seaboard have a higher proportion of fertility class C due to the higher incidence of afforestation on unenclosed peats (Figure 5.).

Table 12. Private stocked forest area by fertility class.

Class	Description	Area (ha)	%
A	Fields & Ornamental Ground	141,423	39.1
B	Furze or whin	52,606	14.5
C	Rough Pasture, with or without outcropping rock	118,237	32.7
X	Woodland	49,637	13.7
	Total	**361,903**	**100**

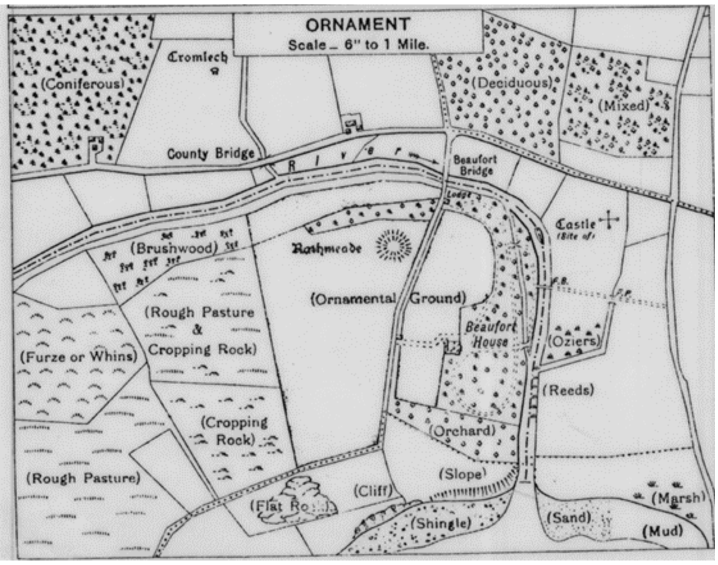
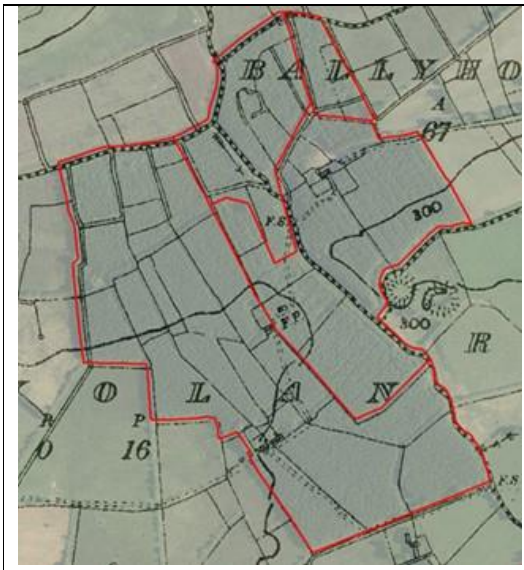


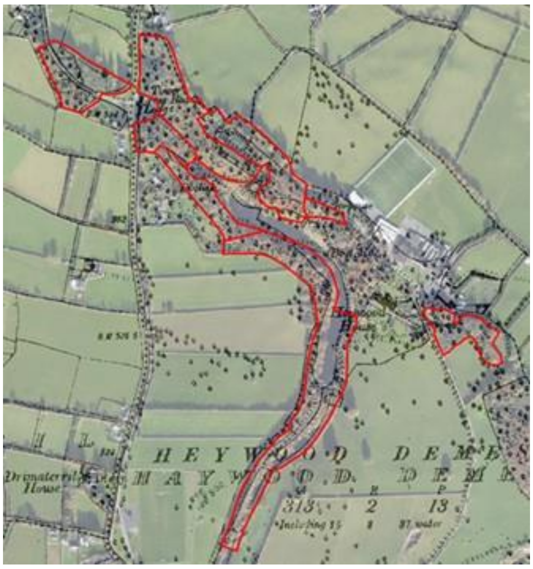
Figure 3. OSi six inch ordnance detail used to assign fertility classes



Class A

Class B

Class C



Class X

Figure 4. Fertility classification, detailing the six inch OSi detail and aerial photograph

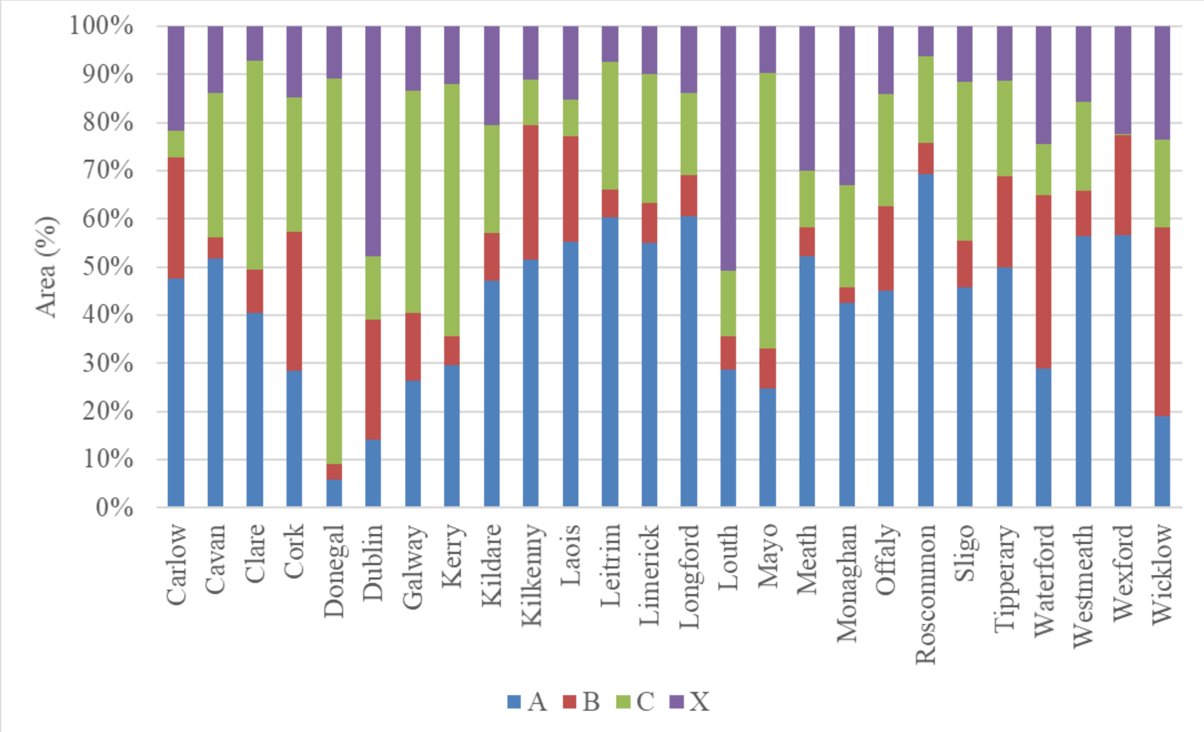


Figure 5. Percent of private stocked forest area by county and fertility class

2.7 Productivity

Each forest parcel in the private forest cover dataset was assigned a measure of productivity. A spatial model developed by Farrelly *et al*. (2011) was used to derive spatial predictions of productivity for Sitka spruce. Two yield class estimates were generated by Teagasc:

1. Yield Class estimate using a national model
2. Yield Class estimate using a local model that included fertility class

In Table 13 and Figure 6, details are provided on the estimated yield class for the private stocked forest area based on the national and local level models. The local model yield class values were used in the forecast.

Table 13. Productivity estimates for the private stocked forest area

Sitka spruce Yield Class (m^3 ha^{-1} yr^{-1})	National Model Area (ha)	Local Model Area (ha)
6	356	13
8	1,099	807
10	4,441	5,509
12	12,329	20,192
14	21,879	22,444
16	25,959	23,850
18	67,022	35,861
20	73,288	47,318
22	69,681	60,760
24	50,255	57,871
26	21,985	47,216
28	4,620	27,471
30	5,125	7,177
32	2,927	3,367
34	882	1,535
Weighted Average YC	**20.2**	**21.3**

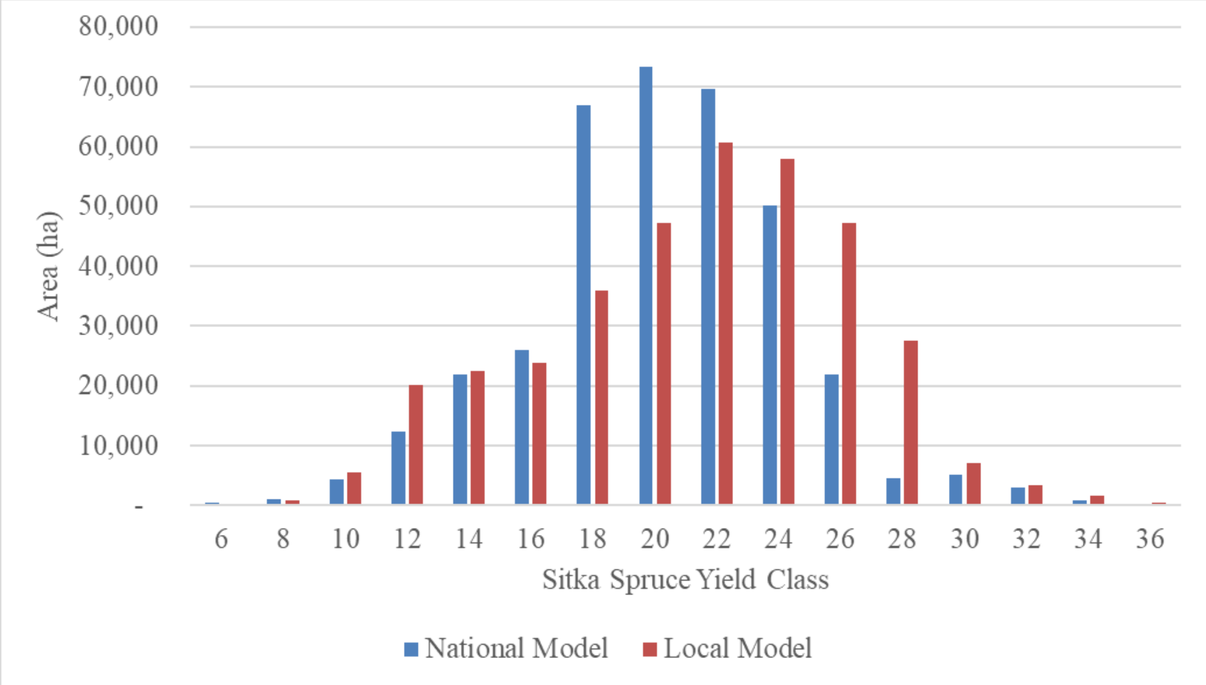


Figure 6. Comparison of national and local productivity estimates

2.8 Temporarily unstocked forest

In total, 13,419 ha were classified as temporarily unstocked forest (TUF). Clearfelling accounted for over 90% of this area (Table 14).

Table 14. Private stocked forest area by temporarily unstocked forest type

TUF Type	Area (ha)	%
Blown	64	0.48
Burn	1,204	8.97
Clearfell	9,863	73.50
Clearfell (Storm Darwin 2014)	2,288	17.05
Total	**13,419**	**100**

2.8.1 Clearfell Species

The area of species clearfelled in the private forest area is detailed in Table 15. Sitka spruce was the dominant species clearfelled followed by pine species.

Table 15. Species composition of clearfelled in the private stocked forest area

Species	Area (ha)	%
Sitka spruce	8,189	67.4
Conifer Mature Pine (1998)	1,342	11.0
Conifer Mature Spruce (1998)	462	3.8
Lodgepole Pine (South Coastal)	340	2.8
Norway spruce	274	2.3
Mixed Forest Mature (1998)	267	2.2
Mature Pine/Spruce Mix (1998)	244	2.0
Mature Other Conifer (1998)	188	1.5
Conifer Mature Pine (1998)	159	1.3
Conifer Young Pine (1998)	130	1.1
Japanese Larch	119	1.0
Other	438	3.6
Total	**12,151**	**100**

2.8.2 Clearfell year

Where forest parcels were identified as having being clearfelled, the year in which the felling took place was recorded. The clearfell year was estimated primarily from assessing the aerial photography available but data from the felling licences were also consulted (Table 16).

The year 2012 has a large area of clearfell which predominantly refers to the reassessment of the PNGA portion of the private forest estate. At this date, the clearfelled areas were visible in the satellite imagery but there was no earlier imagery to provide a more exact date of the felling event. No other supplementary information, such as felling licence, was available to ascertain a more accurate date for these older clearfell events.

Table 16. Private stocked forest clearfell Area by fell year

Fell Year	Area (ha)
Pre 2012	617
2012	1,872
2013	176
2014	2,346
2015	937
2016	900

Fell Year	Area (ha)
2017	1,471
2018	2,638
2019	1,082
2020	111
Total	**12,151**

2.8.3 Clearfell age of private grant aided Sitka spruce

The clearfell age has a large bearing on the timing that volume will be realised during a forecast period. To help inform future forecast assumptions the clearfell age of Sitka spruce already felled in the private (grant-aided) forests was assessed (Figure 7. and Table 17).

The overall average clearfell age was 27 years. Those areas impacted by Storm Darwin (2,063 ha) had an average fell age of 24 years and the remaining areas (5,041 ha) had an average fell age of 28 years.

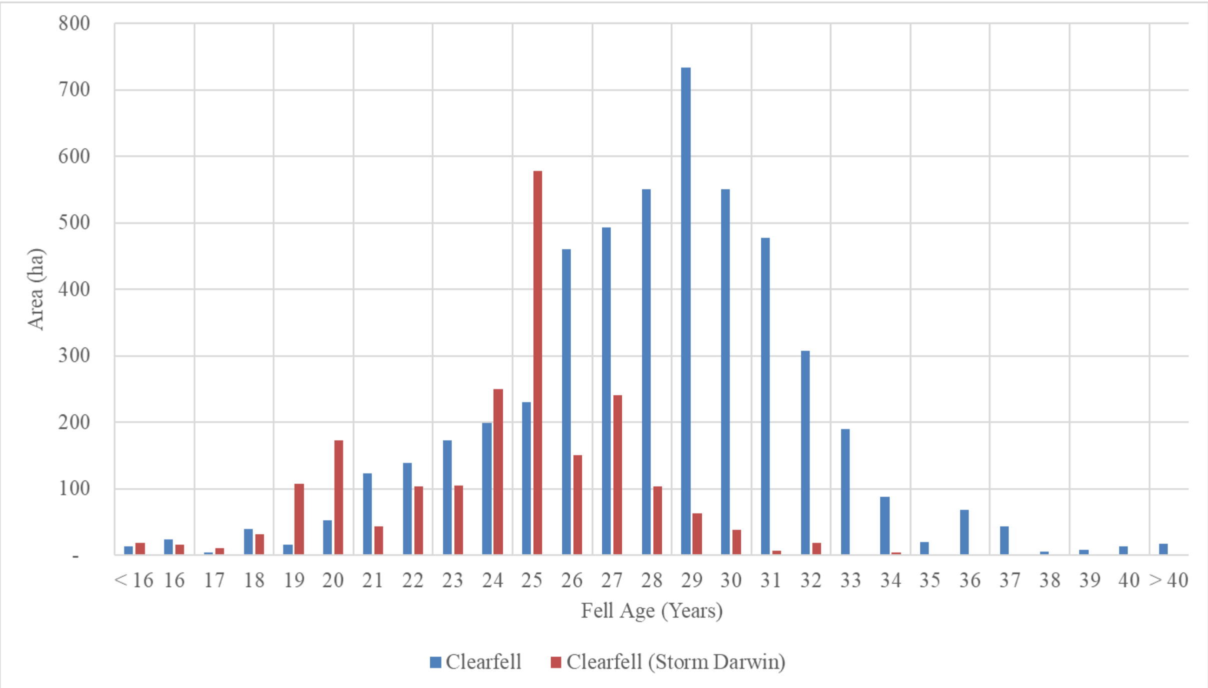


Figure 7. Clearfell age of private grant aided Sitka spruce

Table 17. Clearfell age of private grant aided Sitka spruce

Fell Age (years)	Clearfell Area (ha)	Clearfell -Storm Darwin Area (ha)	Total Area (ha)
< 20	98	184	282
20	53	173	226
21	123	43	166
22	139	103	242
23	173	105	278
24	199	249	448
25	230	579	809
26	460	150	611
27	494	240	734
28	550	103	653
29	733	63	796
30	550	38	588
31	477	6	484
32	307	19	326
33	190		190
34	87	4	92
35	20	1	20
36	68	1	70
37	44		44
38	6		6
39	8		8
40	14		14
> 40	17		17
Total	5,041	2,063	7,103

Chapter 3. Management Inputs for Private Sector Forecast in the Republic of Ireland

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3.1 Determine rotation length and thinning practice

3.1.1 Current practice

In line with previous All Ireland roundwood production forecasts and to ensure that the forecast reflects current practice, a survey questionnaire was designed and circulated to 21 potential respondents in the forestry sector comprising individuals, company-based forestry consultants and to Teagasc. Potential respondents were contacted by phone in advance of receiving the survey questionnaire.

A total of 17 completed returns were received representing a response rate of 81%. Completed returns were representative of all geographic regions in the country. Of the 17 returns, 15 completed all questions while two completed the majority of questions citing either lack of expertise or the questions as not being well framed.

Respondents' comments showed an increasing concern for windblow after thinning following on from storms over the past number of years. Proximity to markets was considered a major influence on the decision to thin while lack of markets, apart from firewood, was considered a deterrent to thinning broadleaves. There is the expectation that the Woodland Improvement grant will increase thinning in broadleaves. The accessibility of a forest has a large bearing on the decision to thin and the single consent system has increased costs. Felling licence delays are beginning to impact on the volume of thinnings. The proportion of conifers thinned depends to a very large extent on the licencing process for forest roads and felling. Owners are however willing and interested to thin when adequately informed.

Wind risk is a big influence in determining rotations (thinning and clearfell age) on ploughed and drumlin sites. Owners, even where the forest has a high value increment, prefer to have income today rather than wait for another four or five years until closer to financial maturity. This was reflected in the rotation ages across all yield classes in spruce forests. Clearfelling is not controlled by rotation type but by roundwood timber prices and the general perception is that if growing for 30 years then it must be ready for felling (Financial maturity in this instance is getting what is perceived to be a reasonable/good price offer and felling now).

3.1.1.1 Survey findings thinning conifers

Based on the survey, some 64% of conifer forests will on average be thinned – the median value is 70% (Table 18). This is in keeping with the two previous surveys where 65% to 70% was the estimate for the area of conifer thinning. Not surprisingly, the percentage thin area is higher for the east and south-east at 77% and less for the western seaboard and the north-west at circa 50% (where wind risk is deemed higher).

Thinning percentage is related to soil type, being highest for dry mineral soils (78%) and lowest for blanket and deep peats at less than 20%. The minimum yield class for thinning was given as 16 m^3 ha^{-1} yr^{-1} for Sitka spruce and 14 m^3 ha^{-1} yr^{-1} for Norway spruce. The previous forecast had a minimum of 16 m^3 ha^{-1} yr^{-1} for both species.

Table 18. Survey results for conifer thinning

1	**What % area of privately owned conifer plantations do you estimate will be thinned?**	**% Area**					
	Median	70%					
	Max	80%					
	Min	50%					
	Average	64%					
2	**What is your estimate of % thin?**	**East + SE**	**Midlands**	**South**	**West+SW**	**Northwest**	
	Median	80%	70%	70%	50%	45%	
	Max	90%	80%	80%	70%	80%	
	Min	65%	40%	50%	40%	25%	
	Average	77%	68%	68%	53%	50%	
3	**Will this vary with soil type?**	**Yes**	15	**No**	1		
3b	**If Yes, what % forests will be thinned on the following soil types?**	**Dry Mineral**	**Wet Mineral**	**Blanket Peat**	**Deep Peat**		
	Median	80%	65%	10%	3%		
	Max	100%	80%	50%	40%		
	Min	30%	50%	0%	0%		
	Average	75%	66%	19%	14%		
4	**Will the % thinning vary with Yield Class ? (Y/N)**	**Yes**	15	**No**	1		
4b	**What is your estimate of the minimum YC for thinning the following species?**	**Sitka spruce** m^3 ha^{-1} yr^{-1}	**Norway spruce** m^3 ha^{-1} yr^{-1}	**Larch** m^3 ha^{-1} yr^{-1}	**Pines** m^3 ha^{-1} yr^{-1}		
	Median	16	14	12	10		
	Max	18	18	18	20		
	Min	12	12	8	6		
	Average	16	15	12	11		
5	**Of the thin areas what % will receive the following number of thinnings?**	**One Thin**	**Two Thin**	**Three Thin**	**Four or more**		
	Median	30%	40%	20%	8%		
	Max	60%	80%	50%	10%		
	Min	10%	20%	10%	0%		
	Average	30%	43%	22%	6%		
6	**What is the normal thinning intensity?**	**Marginal**	7	**> Marginal**	2	**<Marginal**	7
7	**What is your estimate of the minimum viable area to undertake a thinning?**	**Area (ha)**					
	Median	5					
	Max	8					
	Min	2					
	Average	5.2					
8	**What is the average thin cycle in years?**	**≥ YC24 (years)**	**YC 22 - YC18 (years)**	**≤ YC16 (years)**			
	Median	3	4	5			
	Max	5	6	7			
	Min	3	3	4			
	Average	3.5	4.4	5.5			

Of the thinned forests, 43% will receive two thinnings with 30% being thinned only once and 22% thinned three times. This indicates a decrease in the number of thinnings in comparison to the previous survey where conifer forests were thinned on average three times. Respondents were split evenly between thinning to marginal thinning intensity and less than marginal thinning intensity with only two indicating a greater than marginal thinning intensity. This is broadly similar to the previous survey but would indicate a small reduction in thinning intensity.

The thinning cycle varied with yield class, where high yield class forests (≥ YC24) had a cycle of three years, four years for middle yield classes (YC 22 - YC18) and five years for lower yield classes (≤ YC16). The previous survey indicated four years across all yield classes. The average minimum area to undertake thinning was given as 5.2 ha with a median value of 5 ha. This compares with 4 ha in the previous survey.

3.1.1.2 Survey findings thinning broadleaves

Based on the survey, 53% of broadleaf forests will on average be thinned – the median value was 50%. Thinning percentage varied with soil type, being greater (70%) for dry mineral soil types.

Respondents indicated that only 22% of alder forests would be thinned, while over 60% of oak and ash forests would be thinned. There was a caveat expressed in relation to ash and the presence of ash dieback. The minimum yield class to undertake thinnings varied with tree species, being 8 m^3 ha^{-1} yr^{-1} for ash, alder and sycamore and 6 m^3 ha^{-1} yr^{-1} for oak and beech. This is broadly similar to the previous survey.

The thinning cycle averaged five years for soft broadleaves (e.g. ash and sycamore) and seven years for hard broadleaves (e.g. oak and beech). The minimum area to undertake thinning was on average 3.1 ha and this compares with 2.5 ha in the previous survey.

3.1.1.3 Survey findings rotation length conifers

Based on the survey 90% of conifers will continue to be managed under the clearfell silvicultural system, with 8% under some form of continuous cover forestry (CCF). Respondents indicated that the most common rotation type was financial (45%), with a rotation equivalent to a mean tree volume of 0.5 m^3 being second (18%). Very few forests would be felled at the age of maximum mean annual increment (MMAI), while only 22% of forests would be managed on a critical height basis of either 21 m or 23 m. The findings are again broadly similar to the previous survey.

For Sitka spruce, respondents indicated an average rotation age of 28 years for high yield class forests (≥ YC24), 32 years for average yield classes (YC 22 - YC18) and 36 years plus for lower yield classes (≤ YC16). These values are less than the true financial rotation which respondents had indicated was the most common rotation type. Similar findings were found for Norway spruce. The results however are broadly similar to the previous survey but would indicate a reduction of three to four years in rotation lengths.

The minimum area to undertake clear felling in conifers was on average 1.8 ha.

The survey included a question on clearfell product outturn. The results indicated an average outturn for Sitka spruce of 66% sawlog, 21% pallet, 10% pulp and 3% stake, although there was significant variation around these values. These averages are clearly less than one might expect for forests grown on a longer financial rotation and reflect owners' desire to harvest early rather than wait a number of years into the future for the forest to mature.

3.1.1.4 Survey findings rotation length broadleaves

Based on the survey some 43% of broadleaves will be managed under some form of CCF, 39% under the clearfell system, 17% under long term retention and 1% under coppice. This represents a major shift from the previous survey where the clearfell system was the most popular followed by CCF and then long-term retention. CCF implies some form of active forest management with harvesting interventions while long term retention reflects minimal if any management intervention.

Average rotation lengths for ash and sycamore at 54 years and 60 years respectively are greater than the age of MMAI and the same applies for oak while rotations for beech were broadly similar to the age of MMAI. The previous survey did not ask for rotation lengths but the main factor determining clearfell age was given as tree size and market price.

3.1.1.5 Changes to Remsoft forecast model

Changes to the Remsoft forecast model are specified for the age of first thinning (Table 19), thinning cycle (Table 20) and rotation age (Table 21. Fell ages). Further information on the implementation of these rules is given in Chapter 5.

Conifers: Based on the survey, it was decided to change the yield models for spruce forests to reflect (a) two rather than three thinnings, (b) thinning intensity of 85% of marginal and (c) thinning cycles of three to five years depending on yield class. To reflect the findings of the survey, rotation lengths for spruce forests were reduced across the range of yield classes by on average two to four years (Table 21). The survey findings did not indicate any requirement to change the thinning rules apart from the threshold area for thinning.

Broadleaves: Based on the survey, there was a need for broadleaf yield models to simulate the transition of even-aged broadleaf stands to CCF across the range of tree species. How this could be accomplished is not exactly clear as there are no appropriate models currently available. One approach could be to grow forests to 65% of their equivalent rotation age and thereafter remove an annual volume yield of a given average tree size. As there is no information on which forests will be managed under CCF, the difficulty arises as to how to assign this management regime to existing forests. The survey findings did not indicate any requirement to change the thinning rules apart from the threshold area for thinning.

To incorporate the CCF and the long-term retention of broadleaf forests into the forecast, each area of broadleaf was split between clearfell system (60%), CCF (30%) and long-term retention (10%), and managed accordingly.

Table 19. First thin age

Species	Description	Yield Class (m^3 ha^{-1} yr^{-1})													
		30	**28**	**26**	**24**	**22**	**20**	**18**	**16**	**14**	**12**	**10**	**8**	**6**	**4**
ALD	Alder										15	15	15		
ASH	Ash										15	15	15		
BE	Beech											25	25	30	
CP	Corsican pine						19	20	21	22	24	27			
DF	Douglas fir				16	17	17	18	19	21					
EL	European larch										18	20			
GF	Grand fir		16	17	18	19	20	21	22	23					
HL	Hybrid larch									14	15	17			
JL	Japanese larch									14	15	17			
LPN	Lodgepole pine (North Coastal)									20	22	25			
LPS	Lodgepole pine (South Coastal)								20	20	25	25			
NF	Noble fir					21	22	23	25	26					
NS	Norway spruce					21	22	23	25	26					
OAK	Oak												20	25	
OC	Other Conifers					21	22	23	25	26					
OHB	Other hard broadleaves											25	25	30	
OSB	Other soft broadleaves										15	15	15		
SP	Scots pine									22	24	27			
SS	Sitka spruce	15	16	17	18	19	20	21	22						
SYC	Sycamore										15	15	15		

*Grey shaded denotes no thinning. The OSB species category includes Birch (BIR).

Table 20. Number of thinnings and thinning cycle

Species	Cycle	Yield Class (m^3 ha^{-1} yr^{-1})													
		30	**28**	**26**	**24**	**22**	**20**	**18**	**16**	**14**	**12**	**10**	**8**	**6**	**4**
ALD	5										3	4	4		
ASH	5										4	4	5		
BE	5											11	12	13	
CP	5						4	4	4	4	4	5			
DF	5				4	4	4	4	5	5					
EL	5										4	5			
GF	4		2	2	2	2	2	2	2	2					
HL	5									5	5	5			
JL	5									5	5	5			
LPN	5									3	3	3			
LPS	4								3	3	3	3			
NF	4					3	3	3	3	3					
NS	4					2	2	2	2	2					
OAK	5												11	13	
OC	4					3	3	3	3	3					
OHB	5											11	12	13	
OSB	5										4	4	5		
SP	5									5	5	5			
SS	4	2	2	2	2	2	2	2	2						
SYC	5										4	4	5		

*Grey shaded denotes no thinning

Table 21. Fell ages

		Yield Class (m³ ha⁻¹ yr⁻¹)													
Species	**M'gmt**	**30**	**28**	**26**	**24**	**22**	**20**	**18**	**16**	**14**	**12**	**10**	**8**	**6**	**4**
ALD	No Thin										30	35	35	40	45
ALD	Thin										30	35	35	40	45
ASH	No Thin										30	35	40	45	50
ASH	Thin										30	35	40	45	50
BE	No Thin											80	85	95	105
BE	Thin											80	85	95	105
CP	No Thin						39	42	43	46	50	55	55	60	60
CP	Thin					37	39	42	43	46	50	55	55	60	60
DF	No Thin				32	34	35	36	39	43	48	53	57	60	
DF	Thin				32	34	35	36	39	43	48	53	57	60	
EL	No Thin										38	41	47	51	55
EL	Thin										40	45	52	56	60
GF	No Thin			27	28	30	31	32	35	37	40	42	45	50	60
GF	Thin			27	28	30	31	32	35	37	40	42	45	50	60
HL	No Thin									33	35	37	39	41	45
HL	Thin									39	40	42	44	46	50
JL	No Thin									33	35	37	39	41	45
JL	Thin									39	40	42	44	46	50
LPN	No Thin									35	35	39	42	54	
LPN	Thin									35	35	39	42	54	
LPS	No Thin								30	30	35	42	46	58	
LPS	Thin								30	30	35	42	46	58	
NF	No Thin					37	39	43	47	52	55	57	60	60	
NF	Thin					38	40	42	45	49	51	54	56	60	
NS	No Thin					35	36	38	40	44	49	50	55	60	
NS	Thin					35	36	38	40	44	49	50	55	60	
OAK	No Thin												80	90	100
OAK	Thin												80	90	100
OC	No Thin					35	36	38	40	44	49	50	55	60	
OC	Thin					35	36	38	40	44	49	50	55	60	
OHB	No Thin											80	85	95	105
OHB	Thin											80	85	95	105
OSB	No Thin										35	35	38	40	45
OSB	Thin										35	38	40	45	50
SP	No Thin									47	49	52	56	60	66
SP	Thin									47	49	52	56	60	66
SS	No Thin	26	27	28	30	31	32	35	37	40	42	45	50	60	
SS	Thin	26	27	28	30	31	32	35	37	40	42	45	50	60	
SYC	No Thin										40	45	50	55	60
SYC	Thin										40	45	50	55	60

*Text in red indicate change from previous forecast. Abbreviation includes Management (M'gmt)

3.2 Generate forecast model yield tables

3.2.1 Conifers

Volume yield tables for Sitka spruce were based on GROWFOR[2], using the Forestry Commission data at age of first thinning as a starting point. While GROWFOR can provide volume yield data for Norway spruce, it was decided to use the Forestry Commission (FC)

[2] http://www.coford.ie/toolsservices/growfor/

tables in line with the previous forecast. For Lodgepole pine south coastal, GROWFOR was used to derive volume yield tables using previously published models (Forest and Wildlife Service, 1975) as a starting point. For all other conifer species, the Forestry Commission yield tables were used (Edwards and Christie, 1981).

3.2.2 Broadleaves

Broadleaves presented a series of challenges in relation to volume yield models. There is limited data supporting the GROWFOR ash species model and no models are available for either no thin forests or forests managed under any form of CCF. Furthermore, the FC models are based on much higher initial stems per hectare.

FC models were used for thinned forests managed under a clearfell system. A series of no thin models were created using the FC models as a starting point with assumed mortality rates which were constructed to accommodate no thin forests. A general non-species specific model was constructed for forests managed using CCF, based on a combination of FC and ProSilva guidance (Sanchez, 2017).

3.2.3 Forest planning and inventory system (FIPS) categories

A full survey of all state and private forests was completed in 1996 under the Forest Service's Forest Planning and Inventory System – FIPS (Fogarty *et al*. 1999). It provided information on areas by tree species development category for all forests identified by remote sensing. Yield models were constructed for the BMB (broadleaf mature beech), BMK (broadleaf mature oak), BMO (broadleaf mature other) and MXM (mixed forest mature) to allow for a starting and closing growing stock over the forecast period. The percentage species and ages used for each category are shown in Table 22. Management regimes were assigned to each FIPS category and these were broadly similar to the previous forecast with some reduction in yields from the mature broadleaf categories.

Table 22. FIPS categories

Category	Description	First Species				Second Species				Third Species			
		1st	%	YC	Age	2nd	%	YC	Age	3rd	%	YC	Age
BMB	Mature Beech	BE	100	6	90								
BMK	Mature Oak	OAK	100	6	85								
BMO	Mature Other B'leaves	BIR	100	4	75								
BYB	Young Beech	BE	100	6	45								
BYK	Young Oak	OAK	100	6	45								
BYO	Young Other B'leaves	BIR	100	6	25								
CML	Mature Larch	EL	100	6	75								
CMO	Mature Other Conifers	DF	100	14	70								
CMP	Mature Pine	SP	100	8	75								
CMS	Mature Spruce	SS	100	18	52								
CYL	Young Larch	JL	100	8	28								
CYO	Young Other Conifers	DF	100	14	28								
CYP	Young Pine	SP	100	10	28								
CYS	Young Spruce	SS	100	18	28								
MPS	Mature Pine/Spruce Mix	NS	100	14	55								
MXM	Mixed Forest Mature	OAK	50	4	90	BIR	25	4	40	SP	25	8	85
MXY	Mixed Forest Young	OAK	50	4	40	BIR	25	4	23	SP	25	8	30
YPS	Young Pine/Spruce Mix	NS	100	14	28								

*Text in red indicates a change from previous forecast. Abbreviations include Broadleaves (B'leaves).

3.3 Deriving species productivity

3.3.1 Conifers

The estimate of productivity (i.e. local area yield class model) provided by Teagasc for Sitka spruce was used to determine the yield class for other conifer species. There were minor changes to the previous forecast and these are indicated in red in Table 23.

Table 23. Assigning productivity to conifer species

Species	Sitka spruce Yield Class (m^3 ha^{-1} yr^{-1})												
	6	8	10	12	14	16	18	20	22	24	26	28	30
CP	4	6	6	8	8	10	10	12	12	14	14	14	14
DF	6	8	10	10	12	14	16	18	18	20	22	24	24
EL	4	6	6	6	8	8	8	8	10	10	10	10	10
GF	6	6	8	10	12	14	16	18	20	22	24	26	28
HL	4	6	6	8	8	10	10	10	12	12	14	14	14
JL	4	6	6	8	8	10	10	10	12	12	14	14	14
LPN	6	8	8	10	10	12	12	12	12	14	14	14	14
LPS	6	8	8	10	10	12	12	14	14	16	16	16	16
NF	6	8	10	12	12	14	16	16	18	20	20	22	22
NS	6	8	10	10	12	14	16	18	20	20	22	24	24
OC	6	6	8	10	12	12	14	16	18	20	20	22	22
SP	4	6	8	8	10	10	12	12	12	14	14	14	14

*Text in red indicates a change from the previous forecast

3.3.2 Broadleaves

As with conifer species, the estimate of productivity (i.e. local area yield class model) provided by Teagasc for Sitka spruce was used to determine the yield class for the range of broadleaf species (Table 24). The yield class of ash was reduced compared with the previous forecast in order to simulate the impact of ash dieback disease on volume yield.

Table 24. Assigning productivity to broadleaved species

Species	Sitka spruce Yield Class (m^3 ha^{-1} yr^{-1})												
	6	8	10	12	14	16	18	20	22	24	26	28	30
ALD	4	4	4	6	6	6	8	8	8	8	10	10	10
ASH	4	4	4	4	4	4	6	6	6	6	6	6	6
BE	4	4	4	4	4	6	6	6	8	8	10	10	10
BIR	4	4	4	4	6	6	6	8	8	8	10	10	10
OAK	4	4	4	4	4	6	6	6	8	8	8	8	8
SYC	4	4	4	6	6	8	8	8	10	10	12	12	12
OSB	4	4	4	6	6	8	8	8	10	10	12	12	12
OHB	4	4	4	4	4	6	6	6	8	8	8	8	8

*Text in red indicates a change from the previous forecast.

3.4 Development of thinning rules

The decision to thin, leaving aside market considerations, involves a number of factors relating to the site and the forest itself. Important site factors include size (area), elevation, access (to road network), soil type and aspect. The main factors which influence the thinning decision are yield class, stocking, tree species, age (relevant to the recommended first thin age) and timber quality.

Rule 1- Thin Status: If the forest had previously been thinned, then it would continue to be thinned

Rule 2- Yield Class: Based on the findings from the survey each tree species was assigned a threshold yield class above which it was available for thinning

Rule 3- Access: If the forest was adjoined a public road or was within an economic roading distance from the public road, then it is available for thinning

Rule 4- Area: Based on the findings from the survey, minimum areas for thinning conifer and broadleaf species were set equal to 5.2 ha and 3.1 ha respectively

Rule 5- Stability: In earlier forecasts a combination of wind risk zone, soil type and elevation were used to determine whether a forest would be thinned which proved unwieldy. Therefore, wind speed was used to determine stability. At wind speeds of greater than 7 m/s, forests were deemed not suitable for thinning

Rule 6- Age: Where the forest age was within +/- four years of the standard age for thinning, then the forest was considered available for thinning. This represents a relaxation over the previous model where the criterion was +/- two years

3.5 Assigning volume based forecast attrition percentages

Attrition is the loss of productive capacity due to the incidence over time of creeping windblow and disease. The approach adopted in previous forecasts was to use a standard attrition factor of 5% across all tree species, yield classes and site types. This was considered as being too blunt and not reflective of the ranges in attrition that occur throughout the forest estate.

Three attrition rates were used representing low, medium and high incidences of attrition across the forest estate (Table 25). Wind speed was used to determine the attrition rate category. The attrition rate was applied as a percentage reduction to the final clearfell volume as with previous forecasts.

Table 25. Classification of attrition categories

Attrition Category	Windspeed (m/s)	Attrition Rate
Low	<5	2.0%
Medium	≥ 5 and ≤ 7	3.5%
High	>7	7%

3.6 Assigning forecast reduction percentages

3.6.1 Harvest volume reduction

To allow the forecast to estimate the roundwood volume at roadside post harvesting and potentially available to industry, harvest volumes were reduced to reflect losses occurring during harvesting (Table 26). The factors used were based on a previous analysis of losses undertaken by Coillte (Phillips, 2008).

Table 26. Harvest loss

Harvest Event	Harvest Loss
First Thin	12.5%
Second Thin	10.0%
Third and Subsequent Thin	8.0%
Clearfell	5.0%

3.6.2 Area reduction

In previous forecasts, broad percentage reductions ranging from 10% to 25% were applied to forests depending on the ownership category (Phillips *et al*., 2009). However, in this forecast remote sensing was used to calculate the productive area for each polygon based on the analysis of satellite imagery (Chapter 4). This was used as the value for net productive area. This represents a significant improvement on previous forecasts. Remote sensing however will not always provide a robust value for productive area when forests are young (e.g. there is no canopy closure). To reflect this, forests which were younger than their first thin age minus seven years had their productive area set to 85% where the remote sensing work had estimated a higher value.

3.7 Volume and fibre assortments

3.7.1 Assortment tables

Two assortment tables were used to provide the volume (overbark to tip) in the three standard assortments (7 cm–13 cm, 14 cm-19 cm and 20 cm+). Irish assortment tables (Jordan, 1992) were used for spruce and FC tables (Matthews and Mackie, 2006) were used for all other tree species. It is important to point out that neither of these assortment tables are recommended as being suitable for broadleaf forests with an average diameter greater than 20 cm. Consequently, broadleaf assortment volumes should be treated as indicative only.

3.7.2 Wood fibre

The current forecast provides an estimate of wood fibre availability in the Republic of Ireland (ROI). Unlike the previous forecast the wood fibre is based solely on the volumes forecasted from the forest estate.

Based on the roundwood forecast, there are three main sources of raw material for wood energy – small roundwood, wood residues from the processing sector and through the harvesting of lop and top (including branches and some harvest loss material) on suitable sites. Outside the scope of this report is the use of post-consumer recovered wood (PCRW). While information has been estimated on the potential contribution of harvest residues it is important to state that the harvesting of lop and top is currently at a low level estimated as circa 10,000 tonnes per annum[3] and has decreased since the previous forecast due to cost and suitable markets.

In compiling the estimate of potentially available material in the ROI, a number of assumptions were made of which the main ones were:

- Wood volumes comprise the private sector ROI and Coillte only
- The wood based panel volume demand[4] will be met through a combination of small roundwood and sawmill residues:
  - Assortment 7-13cm, 90% of Coillte volume goes to wood panels and 30% private sector volume goes to wood panels
  - Assortment 14-19cm, 20% of Coillte volume goes to wood panels, 20% private sector volume goes to wood panels
  - Wood residues from the sawmilling sector
- The volume of small roundwood from thinnings in the private sector will potentially be available for wood energy and for wood panels
- The volume of downgrade material from the larger size assortments in the private sector will be available for wood energy and wood panels. Downgrade comprises those logs ≥14 cm top diameter but due to physical constraints (e.g. crooked or high taper) they become available for wood energy or panel mill
- The volume of wood residues from the processing sector will be available for wood energy and wood panels. The wood residue data presented is the gross amount available from the sawmill sector, with no deductions made for residues retained by the sawmilling sector for their own use
- Harvesting residues of the order of 80 green tonnes per hectare will potentially be harvestable from the clearfell of spruce sites on mineral soils with a minimum yield class of 18 and a minimum harvest area of 4 ha. Harvest residues from thinnings are excluded. The tip to 7 cm volume is included in the estimate of harvest residues
- The total volume includes raw material which can be used for purposes other than energy e.g. animal bedding and stake production

Based on the qualifying assumptions above, the potential wood fibre available for energy and other uses was estimated.

[3] Personnel communication Des O'Toole (Commercial Biomass Manager, Coillte) and Tom Kent (Waterford Institute of Technology).

[4] An update of the analysis of forecast wood fibre demand in 2025 and 2030. Presentation by Eoin O'Driscoll (Drima Marketing) to Wood Mobilisation and Forecasting Steering Committee 12-02-2021.

Chapter 4. Integration of Remote Sensing into the Private Forest Sector Forecast for the Republic of Ireland

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The integration of remotely sensed information derived from satellite imagery into the roundwood forecast was completed to increase the accuracy of the forecast, particularly at regional level. There were two objectives:

1. Identify areas where no tree cover is present within forest parcels.
2. Identify unhealthy areas of spruce.

4.1 Pilot study

The work for this desktop study included the acquisition and preparation of the Sentinel data. All initial processing with regards to any Sentinel data was carried out prior to download, with additional processing being carried out afterwards. These additional steps varied depending on the imagery involved and are detailed in the corresponding sections below. All vector datasets that were provided and created were re-projected to Irish Transverse Mercator (EPSG:2157). A pilot study was undertaken first to define the methodological approach.

4.1.1 Materials and methodology - Sentinel-1 data

4.1.1.1 Time series analysis

The primary aim of the Sentinel-1 time series analysis was to assess for the presence or absence of tree cover within the forest dataset.

The Sentinel-1 mission is made up of two polar-orbiting satellites, operating day and night, performing C-band synthetic aperture radar (SAR) imaging, enabling them to acquire imagery regardless of the weather. Sentinel-1 works in a pre-programmed operation mode to avoid conflicts and to produce a consistent long-term data archive built for applications based on long time series (European Space Agency, 2020a).

Sentinel-1's SAR imagery was chosen for the time series analysis over Sentinel-2's optical imagery as it is capable of penetrating dense cloud cover, providing regular and uninterrupted imagery. For the purpose of the pilot study, multiple consecutive images were analysed to enhance the efficiency of the time series classification. Seven images were used to assess changes in the imagery over time. The temporal window used for the imagery was from April to May 2020 (Table 27).

Table 27. Sentinel-1 imagery used to identify areas with no tree cover present

Date	Sentinel-1 Image
02-04-2020	S1A_IW_GRDH_1SDV_20200402T064739_20200402T064804_031945_03B052_6E47
11-04-2020	S1B_IW_GRDH_1SDV_20200411T182202_20200411T182227_021100_028095_5600
14-04-2020	S1A_IW_GRDH_1SDV_20200414T064740_20200414T064805_032120_03B67E_8D77
23-04-2020	S1B_IW_GRDH_1SDV_20200423T182203_20200423T182228_021275_028619_14D1
26-04-2020	S1A_IW_GRDH_1SDV_20200426T064740_20200426T064805_032295_03BC9E_76A6
05-05-2020	S1B_IW_GRDH_1SDV_20200505T182203_20200505T182228_021450_028BA7_2625
08-05-2020	S1A_IW_GRDH_1SDV_20200508T064740_20200508T064805_032470_03C2A2_C348

4.1.1.2 Processing

Dual-polarized (VV and VH) high resolution Sentinel-1 A & B ground range data (GRD) was acquired for this study in the interferometric wide swath mode (IW GRD data). The GRD images have a pixel spacing of 10 m and a spatial resolution of approximately 20 m × 22 m (European Space Agency, 2021b). Sentinel-1 data were downloaded from Copernicus Open Access Hub (Scihub) and the pre-processing was undertaken locally using Sentinel Application Platform (SNAP). This pre-processing included a number of stages which include:

- Apply Orbit File - updates the orbit metadata with a replacement orbit file
- GRD Border Noise Removal - removes low-intensity noise and invalid data on scene edges
- Thermal Noise Removal - removes additive noise in sub-swaths to help reduce discontinuities between sub-swaths for scenes in multi-swath acquisition modes.
- Radiometric Calibration - computes backscatter intensity using sensor calibration parameters in the GRD metadata (calibrated to σ0)
- Terrain Correction (orthorectification) - converts data from a photograph to a map, by applying consistent scale across the image in consideration of terrain relief

The final output was geocoded and topographically normalized to gamma-naught VV and VH-polarized backscatter images at 10 m pixel spacing. The final file was exported to a GeoTiff file and this was used in the time series analysis. These steps were carried out for every Sentinel-1 image used in the pilot study.

The pre-processed Sentinel-1 images were imported and analysed using a knowledge-based image analysis. An algorithm was developed to form a hierarchical decision tree. The Sentinel-1 images were then clustered to create a thematic raster layer through RGB clustering functions. This RBG clustering function provides a simplistic classification algorithm that enables the compression of a three-band image into a single-band pseudo-colour image. This method also provides improved control over the parameters specified and those used to partition the pixels into similar classes. During the clustering process, the VH band is assigned as a red band, the VV band as a green band, and the VH/VV band as the blue band. This RGB image was processed to generate a clamped image for converting thematic class values into unique polygons, which then represent contiguous groups of the original class values. Within these clamped images, mean radar backscatter (dB) values of the VH and VV bands were generated, which were then used as input for the classification of land-uses.

4.1.1.3 Training Areas

The Area of Interest (AOI) (104,528 ha) for the pilot study was the Galty Mountains (Figure 8 and Figure 9). The vector data used was derived from a previously acquired dataset where Treemetrics[5] performed field surveys validating that the forest was predominantly Sitka spruce. Training areas were created in order to generate the time series analysis derived from the vector dataset of Sitka spruce found within the AOI. Once created, they were then cross-checked using

[5] Treemetrics are a software-based company located in Ireland that have developed innovative and dynamic technology to assess forest resources, which incorporates earth observation and field data.

historical imagery to ensure they were accurate. The land cover was split into six different classes which were used to create the Sentinel-1 time series (Table 28). Through the development of the various versions of the training areas, that were used during the time series classification and assessment of performance, these six classes were used to construct the versions. The final version was condensed down to two simple classes; Tree Cover and No-Tree Cover.

Table 28. Sentinel-1 Training Area including classes

S1 Training Area 1 (S1-TA1)		**S1 Training Area 2 (S1-TA2)**
Coniferous forest		Tree Cover
Broadleaved forest		No-Tree Cover
Grass		
Urban		
Arable		
Water		

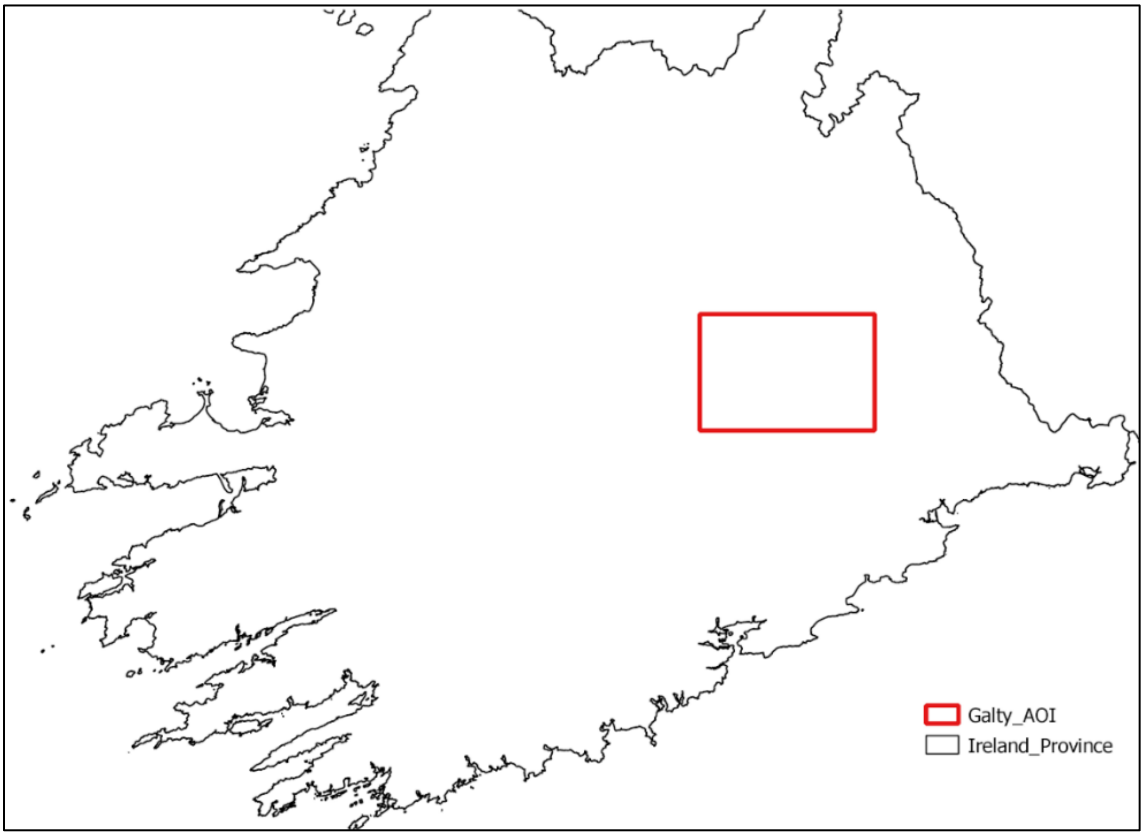


Figure 8. Location of the Galty Mountains AOI in which the Training Areas were created

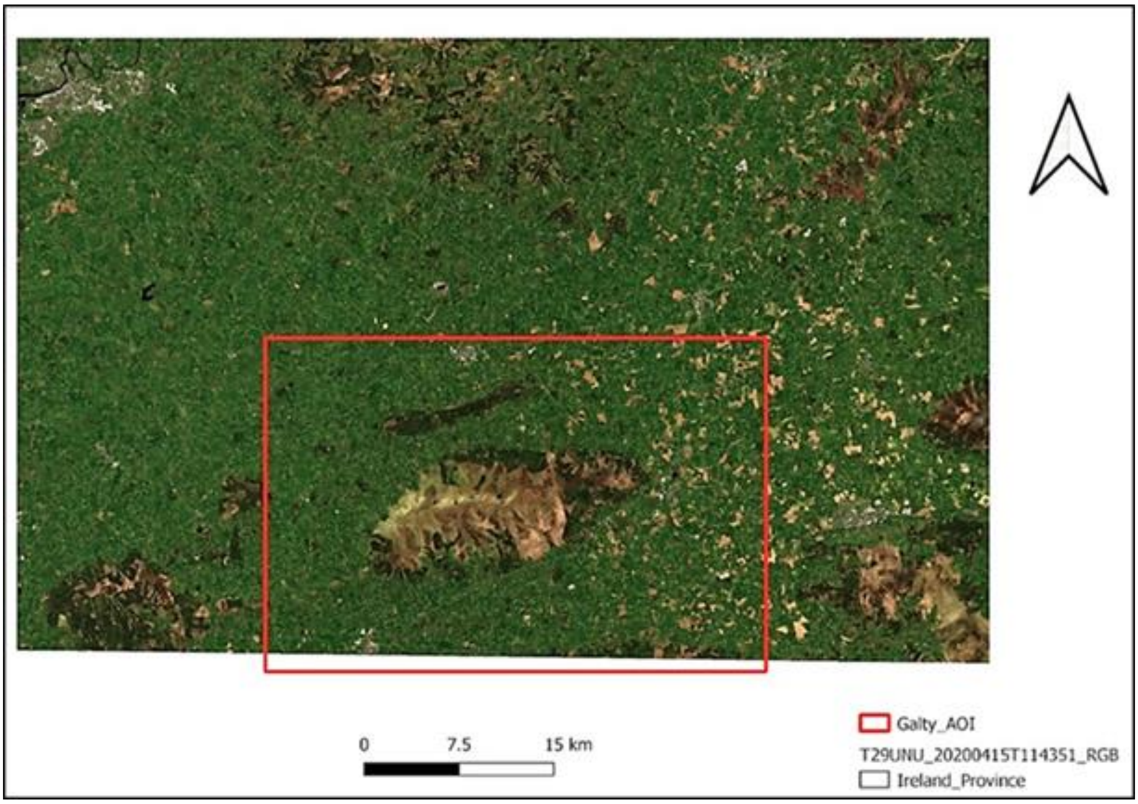


Figure 9. Galty mountains AOI against the Sentinel-1 imagery

4.1.1.4 Classification

A classification process was then undertaken using the specified training areas. The chosen classification was developed using a Machine Learning approach known as Random Forest. This is a supervised learning approach, and it can be used both for classification and regression. A 'forest' consists of several 'decision trees' (decisions to be made). The more 'decision trees' it has, the more robust a 'forest' is. Random Forest creates 'decision trees' on randomly selected data samples (within the training areas), it then gets a prediction from each 'tree' and identifies the best solution by means of deciphering which class is more predominant.

Random Forest provides a highly accurate and robust method due to the number of decision trees participating in the process. It does not suffer from a problem known as 'overfitting', which can occur when a model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data. This means that the noise in the training data is picked up and learned as a concept by the model (Brownlee, 2016). The model takes the average of all the predictions and this cancels out any bias. Furthermore, the model identifies the relative importance of features, which aids in selecting the most significant features to be used in the final classifier. The Random Forest approach was also used by Walshe et al. (2020) in their work on detecting nutrient deficiency in spruce forests using multispectral satellite imagery.

The aim of the Sentinel-1 time series was to produce a classification that could be examined, displaying the changes over time, in relation to the selected classes. To do this, multiple Sentinel-1 images were acquired and processed dating from 02/04/2020 to 08/05/2020.

To achieve best results, several versions of the classification were generated. With each new version, additional training areas were added, or erroneous ones were removed. This iterative process was carried out to achieve the best results during the classification stage. Three different training area datasets were used to test accuracy and strength of classes (Table 29).

Table 29. Sentinel-1 classification of Training Area (TA) versions

TA Versions	TA Dataset Included	TA Source	TA Description
V1	Training Area 1	Generated by Icon	Processed data from Sentinel-1
V2	Training Area 1	Generated by Icon & Treemetrics	Processed data from Sentinel-1 and coupled with vector data of validated Sitka spruce
V3	Training Area 2	Further refined Training Area generated by Icon & Treemetrics	Processed data from Sentinel-1 and coupled with vector data of validated Sitka spruce and refined the classes to Tree cover or no-tree cover

4.1.2 Materials and methodology - Sentinel-2 data

The Sentinel-2 data monitors variability in land surface conditions using wide swath, high resolution and multi-spectral imaging. It has a high revisit time which supports monitoring of changes to the Earth's surface (European Space Agency, 2020c). Sentinel-2 imagery was used for the purpose of differentiating between areas of healthy and unhealthy Sitka spruce, as the optical orientated sensors can differentiate between multiple categories. In order to avoid any potential errors, due to temporal variations, one completely cloud-free image was used during the pilot study (Table 30).

Table 30. Sentinel-2 image used in the pilot study

Date	S2 Image
15-04-2020	S2A_MSIL2A_20200415T114351_N0214_R123_T29UNU_20200415T142447

4.1.2.1 Processing

For Sentinel-2 imagery, several indices were generated to better determine the features of interest. These different indices included: The *Normalised Difference Vegetation Index (NDVI)* which is a measure of a plant's health based on how it reflects light at certain frequencies (some waves will be absorbed while others will be reflected). The *Transformed Normalised Difference Vegetation Index (TNDVI)* which is used to measure vegetation biomass. *The Ratio vegetation index (RVI)* which is used for green biomass estimations and monitoring of high-density vegetation coverage. This index is highly sensitive to vegetation and has a strong association with plant biomass. *The Normalised Difference Water Index (NDWI)*, which is used to measure the plant water content, helps indicate plants that may be under water stress. Lastly, the *Modified Chlorophyll Absorption Ratio Index (MCARI)* which is a measure of the depth of chlorophyll absorption and is very sensitive to variations in chlorophyll concentrations. The formulas of the vegetation indices used are detailed below in Table 31.

Table 31. Vegetation indices used in the classification

Index	**Formula**[6]
NDVI	(NIR - RED)/(NIR +RED)
TNDVI	√NIR−RED/NIR +RED+0.5
RVI	NIR/RED
NDWI	(GREEN-NIR)/(GREEN+NIR)
MCARI	((VNIR - RED)-0.2*(VNIR - GREEN))*(VNIR / RED)(GREEN-NIR)/(GREEN+NIR)

4.1.2.2 Training Areas

Like the Sentinel-1 Time series classification, training areas specific to the nature of the imagery being used were created. These training areas were derived from areas of Sitka spruce found within the AOI (Figure 10). For the Sentinel-2 image classification, ten classes were used to generate the Training Areas (Table 32).

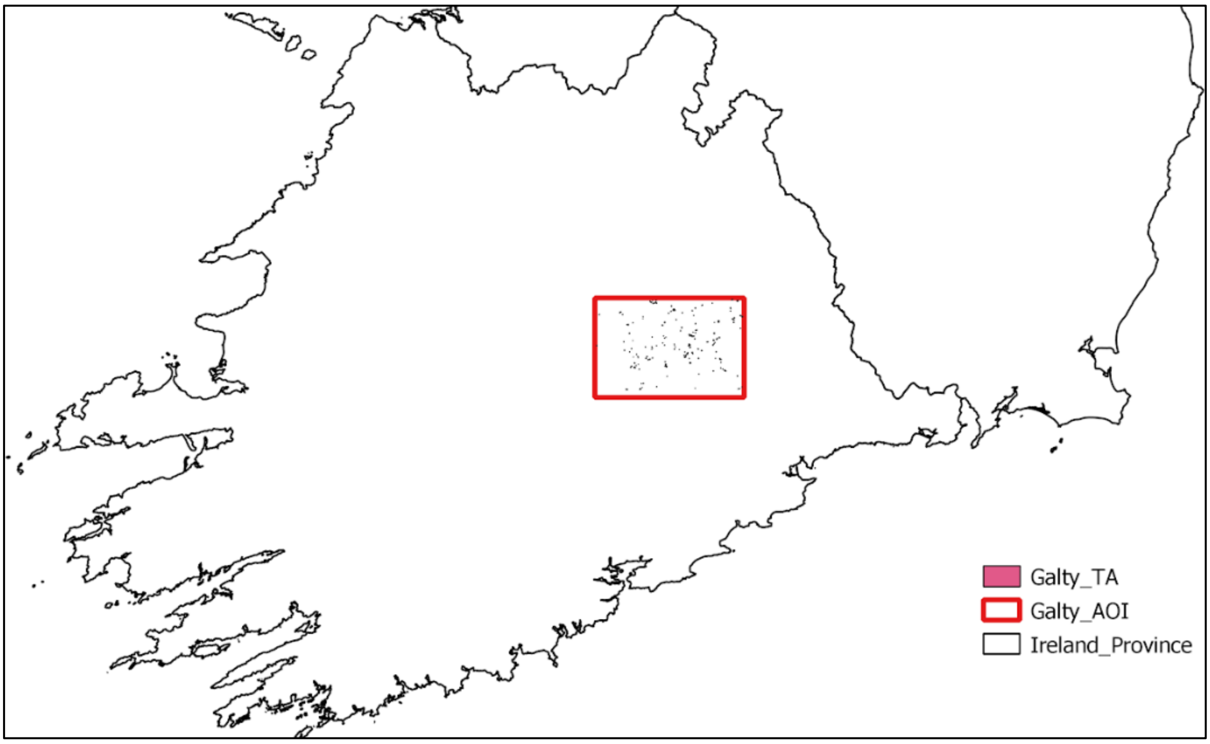


Figure 10. Displaying the Training Areas used for completion of the pilot study

[6] NIR – reflection in the near-infrared spectrum, RED - reflection in the red range of the spectrum, G - RED - reflection in the green range of the spectrum, VNIR - reflection in the visible near-infrared spectrum.

Table 32. Sentinel-2 Training Area including classes

S2 Training Area 1 (Ten Classes)	S2 Training Area 2 (Two Classes)
Forest - Healthy	Forest - Healthy
Forest - Unhealthy	Forest - Unhealthy
Larch	
Broadleaved forest	
Grass	
Arable	
Bracken	
Heather	
Urban	
Water	

4.1.2.3 Classification

For each of the two Training Areas (TA1 & TA2), three Training Area Versions (V1, V2, & V3) were used to test the accuracy and strength of the classification (Table 33).

Table 33. Classification of Training Area versions for Sentinel-2

Training Area (TA)	Version (V)	Source
S2 Training Area 1 (S2-TA1): Ten Classes	V1	Generated by Icon
	V2	Generated by Icon & Treemetrics
	V3	Further refined Training Area generated by Icon & Treemetrics
S2 Training Area 2 (S2-TA2): Two Classes	V1	Generated by Icon
	V2	Generated by Icon & Treemetrics
	V3	Further refined Training Area generated by Icon & Treemetrics

4.1.3 Pilot study results

For each classification created an Overall Accuracy (OA) Score was generated by comparing the classification's raster output with corresponding vector data. This was done for all the training areas used to generate the classification in order to assess individual class performance and provide an independent validation of the data generated.

Cohen's Kappa score is a statistic that is used to measure inter-rater reliability for categorical items. In general, it is thought to be more than a percent agreement calculation, such as OA scores, as it accounts for misclassification due to random chance (Laerd Statistics, 2018). The Kappa score ranges from 0 to 1, with 0 meaning that results of the classifications were most likely due to random chance, while 1 indicates that both data sets are in complete agreement (Table 34).

Table 34. Cohen's Kappa score (Landis and Koch, 1977)

Cohen's Kappa	Cohen's Kappa Percentage	Degree of Agreement
<0.20	<20%	Poor
0.21-0.40	21%-40%	Fair
0.41-0.60	41%-60%	Moderate
0.61-0.80	61%-80%	Good
0.81-1.00	81%-100%	Very good

4.1.3.1 Training area assessment

A breakdown of the number of polygons, which were used in both the TA and Validation areas for Sentinel-1 and Sentinel-2 are detailed in Table 35 and Table 36, respectively. The extent of the Validation Area vs. the Training Areas, which were derived solely from the AOI, is detailed in Figure 11 and Figure 12. From this validation data set, an overall accuracy (OA) and Kappa score were derived.

Table 35. Number of training and validation polygons used per class for Sentinel-1

Dataset Sentinel-1	Forest	Other	Total
Training (Polygons)	51	44	95
Validation (Polygons)	75	91	166

Table 36. Number of training and validation polygons used per class for Sentinel-2

Dataset Sentinel-2	Forest	Other	Total
Training (Polygons) -Multiple category	57	160	217
Training (Polygons)- Healthy/Unhealthy	51	33	84
Validation (Polygons)	95	220	315

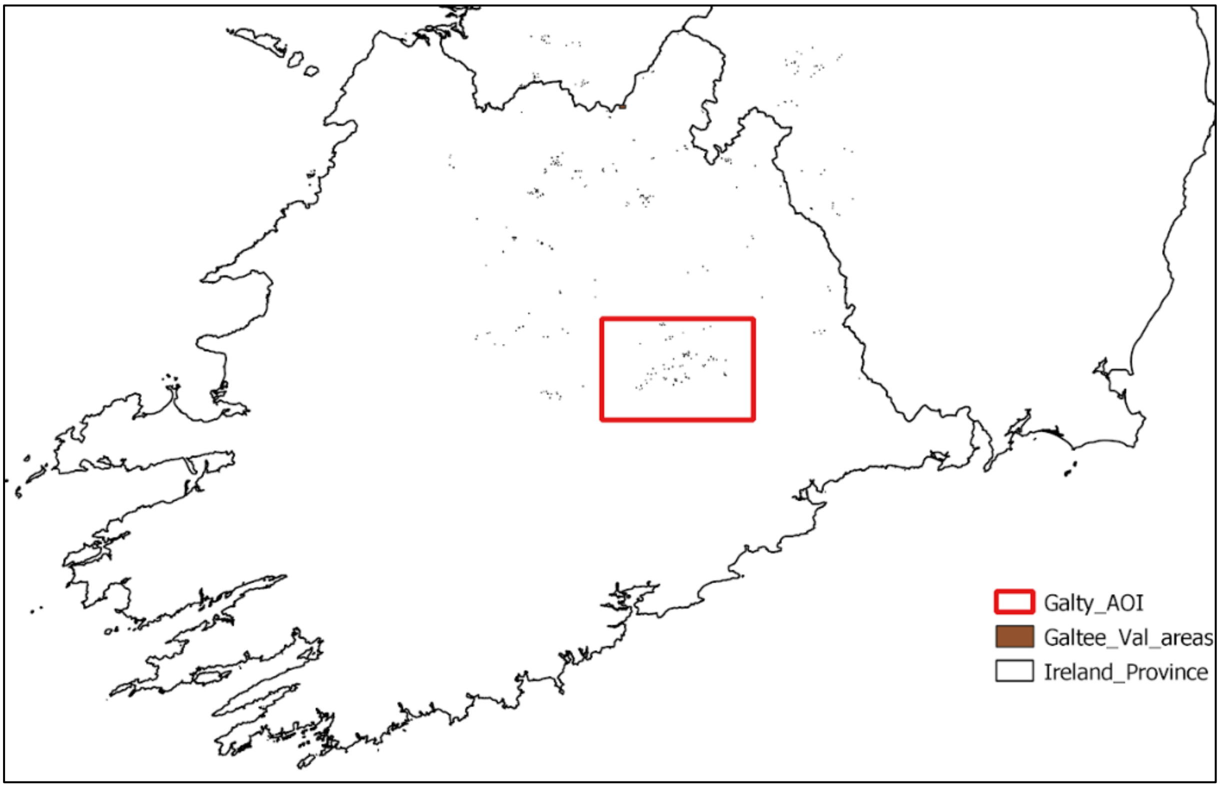


Figure 11. Training Area AOI vs. the extent of the validation areas used in the pilot study

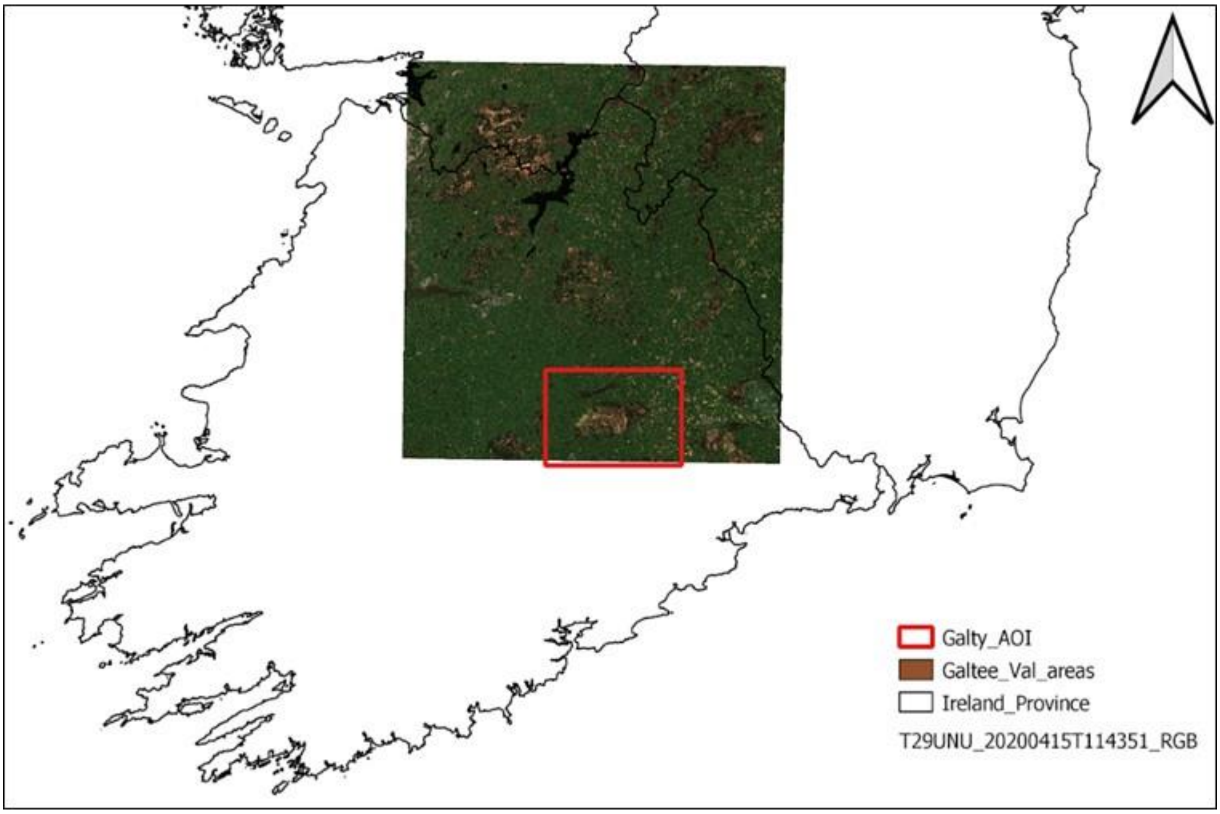


Figure 12. AOI of the Training Area vs. the extent of the validation areas used in the pilot study including the Sentinel-2 image as a layer

4.1.3.2 Sentinel-1 time series image classification results

As can be seen in Table 37, Training Area V3 (Tree Cover/No-Tree Cover Classes) had the highest level of accuracy. V1 and V2 included classes mentioned in Table 28 & Table 29, with variations of different training areas in each. The classification of Training Area V3 only includes Tree Cover/No-Tree Cover (Table 29) which reduced the chances of misclassification occurring, while also improving accuracy (Table 37).

Table 37. Sentinel-1 Overall Accuracy and Kappa score

Training Area Version	Overall Accuracy		Kappa	
	Score	%	Score	%
V1	0.376956	37.7%	0.286886	28.7%
V2	0.347156	34.7%	0.263957	26.4%
V3	0.967242	96.7%	0.934444	93.4%

A User, Producer, and Overall accuracies were calculated along with the Kappa index of agreement for the Sentinel-1 time-series (Table 38). The User accuracy represents the probability that a pixel classified into a given category actually represents that category on the ground. Whilst a Producer accuracy indicates how well the reference pixels of the ground cover type are classified.

Table 38. Accuracy and Kappa score for Sentinel-1 time series

Class	Tree Cover	No-Tree Cover	Total	User Accuracy
Tree Cover	1,178	4	1,782	99.77%
No-Tree Cover	2	1,394	1,396	99.86%
Total	**1,780**	**1,398**	**Overall Accuracy**	97%
Producer Accuracy	99.89%	99.71%	**Kappa Score**	93%

The boxplots below (Figure 13) display the distribution of the Green, Red and Short-wave Infrared Satellite imagery (SWIR) spectra for the Healthy (HE) training and validation areas, as well as the Unhealthy (UN) training and validation areas, using the Sentinel-2 imagery from the pilot study. There is an evident difference between the Healthy and the Unhealthy forests in all three spectra.

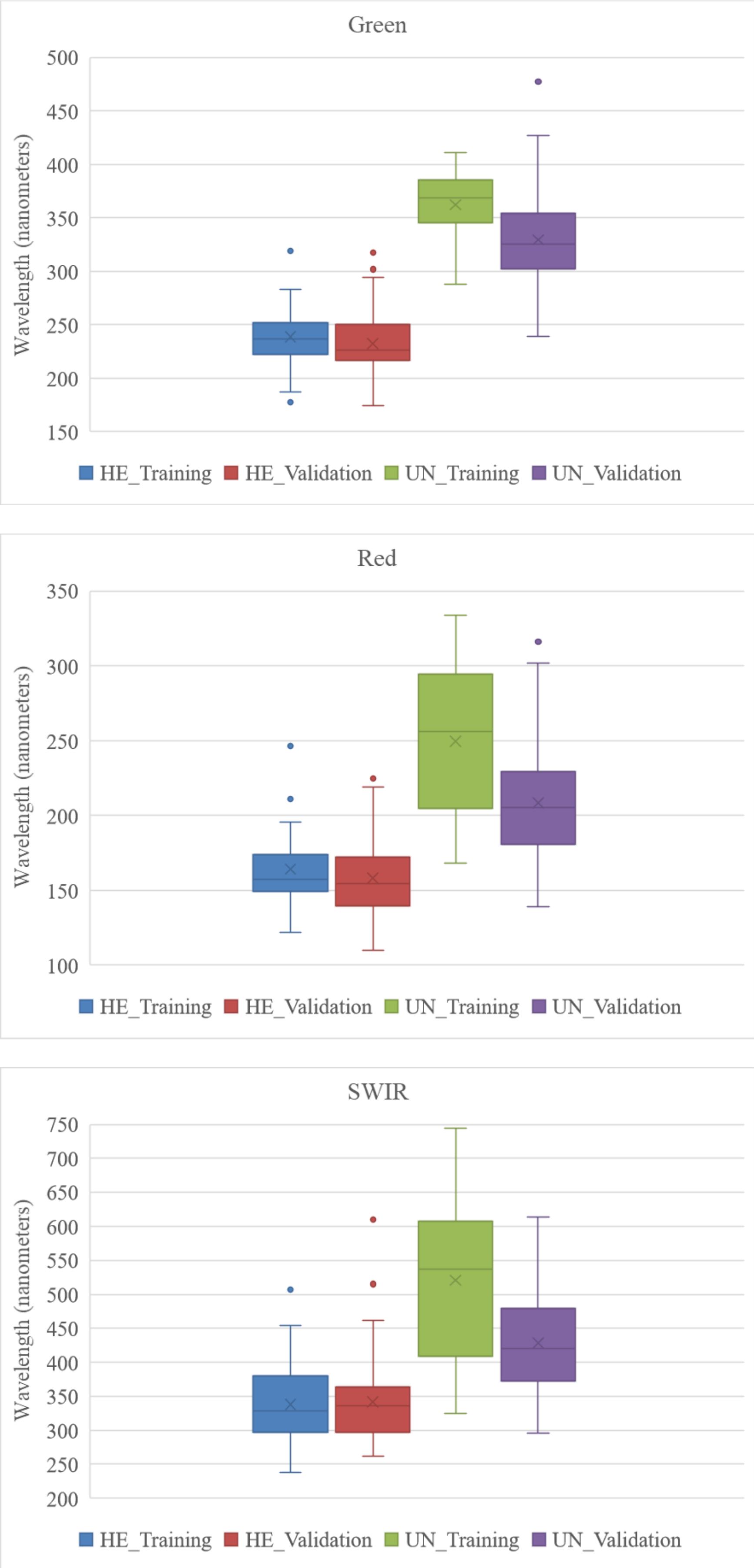


Figure 13. Boxplots displaying the distribution of the Green, Red and SWIR spectra for the Healthy and Unhealthy training and validation areas using Sentinel-2

4.1.3.3 Sentinel-2 image classification results

The overall accuracy (OA) scores for the Sentinel-2 TA1 Classification are presented in Figure 14. While particularly high OA scores were observed in all classifications, the best result was observed using S2-TA1 V2 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) having an OA score of 88.7%. This was closely followed by S2-TA1 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) having an OA score of 87.5%, and S2-TA1 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI) having an OA score of 86.8% (Figure 14).

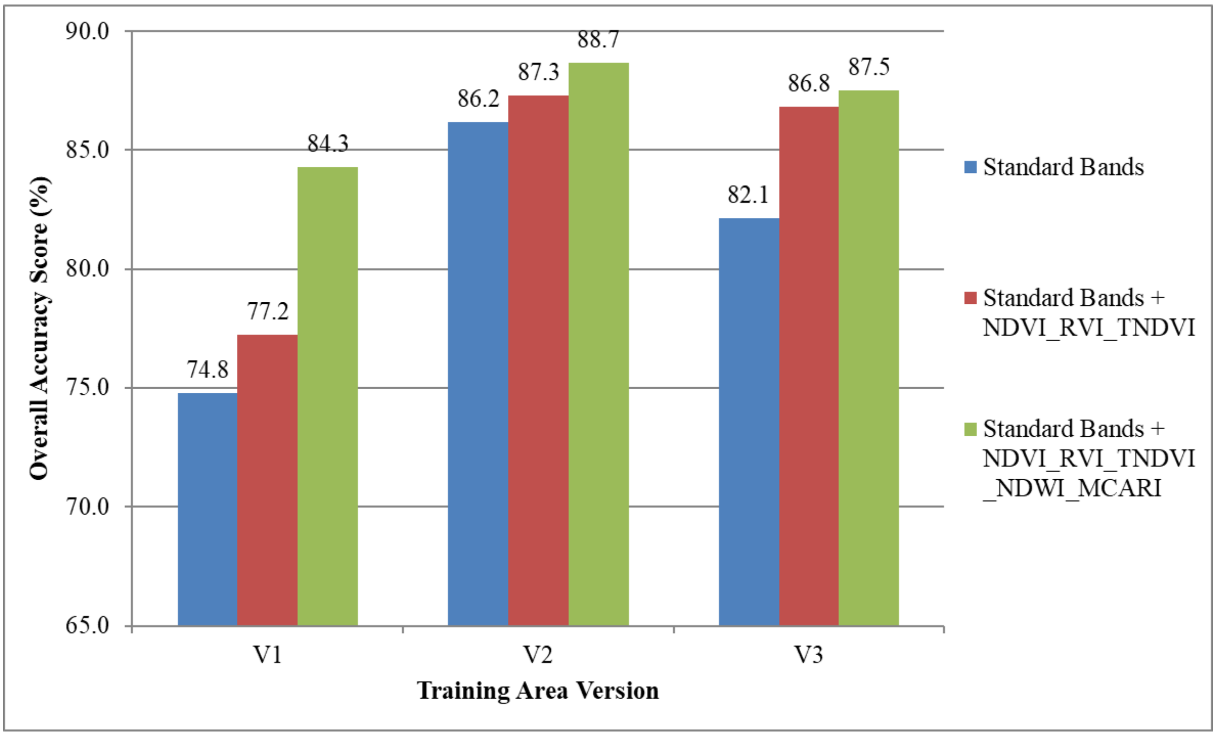


Figure 14. Overall accuracy in relation to various classes classification

Within the healthy and unhealthy forests (S2-TA2) classifications, Figure 15 presents the OA scores for each version and associated vegetation indices. Similar to the S2-TA1 OA scores, S2-TA2 presented relatively high OA scores in all versions and classifications. S2-TA2 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) had the greatest OA score of 88%. S2-TA2 V2 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) and S2-TA2 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI) resulted in 83.9% and 83.9% respectively (Figure 15).

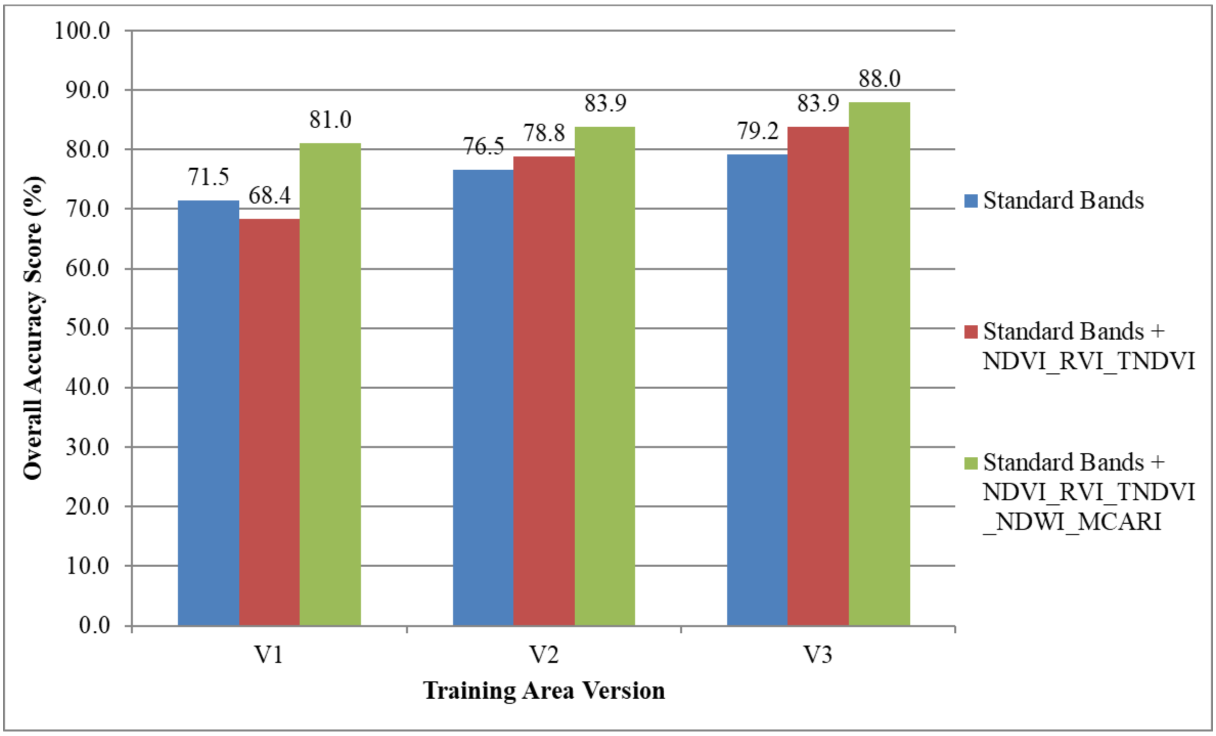


Figure 15. OA in relation to Healthy/Unhealthy classification

The Kappa scores for S2-TA1 are presented in Figure 16 for each version and associated vegetation indices. S2-TA1 V2 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) outperforms all other classifications with a Kappa score of 85.7%. It was closely followed by S2-TA1 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) and S2-TA1 V2 with multiple indices (Standard Bands + NDVI, RVI, TNDVI) having Kappa scores of 84.3% and 84% respectively.

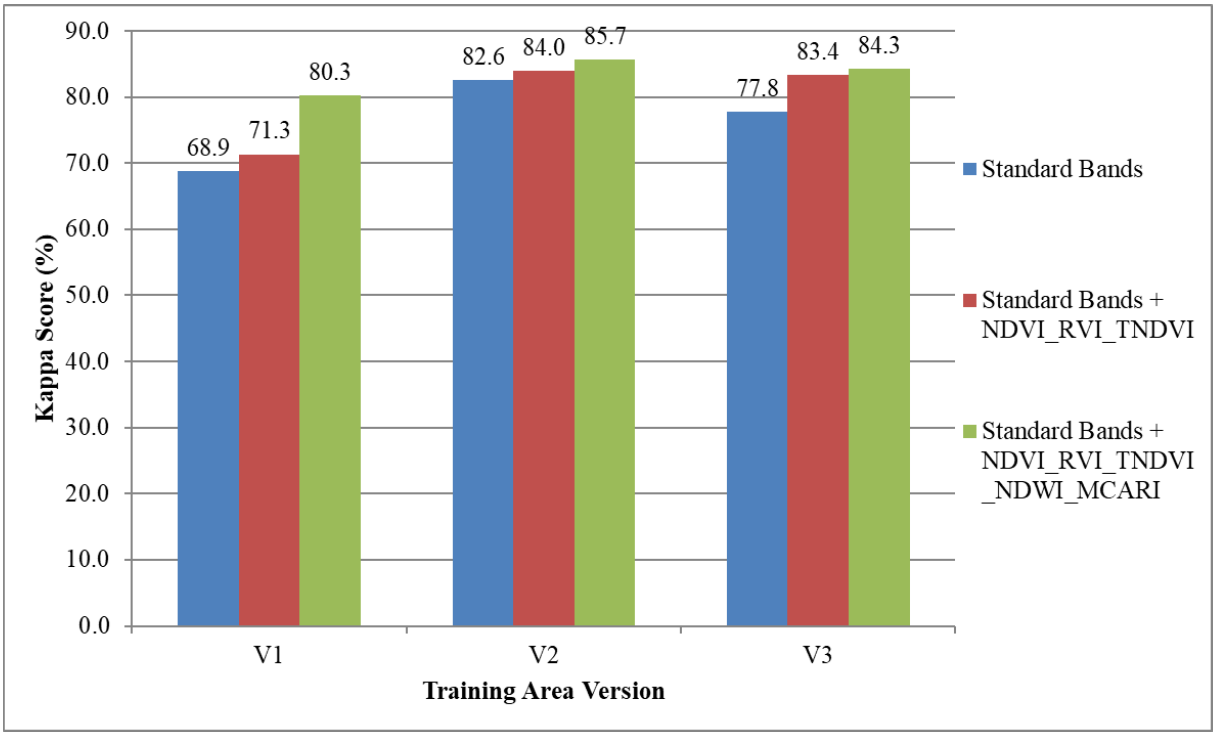


Figure 16. Kappa Score Various Classes classification

The Kappa scores for S2-TA2, in relation to the detection of healthy and unhealthy forests, are presented in Figure 17. S2-TA2 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) resulted in the highest Kappa score of 76.1%. S2-TA2 V2 with multiple indices (Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI) and S2-TA2 V3 with multiple indices (Standard Bands + NDVI, RVI, TNDVI) were found to have Kappa scores of 68.1% and 67.9%, respectively.

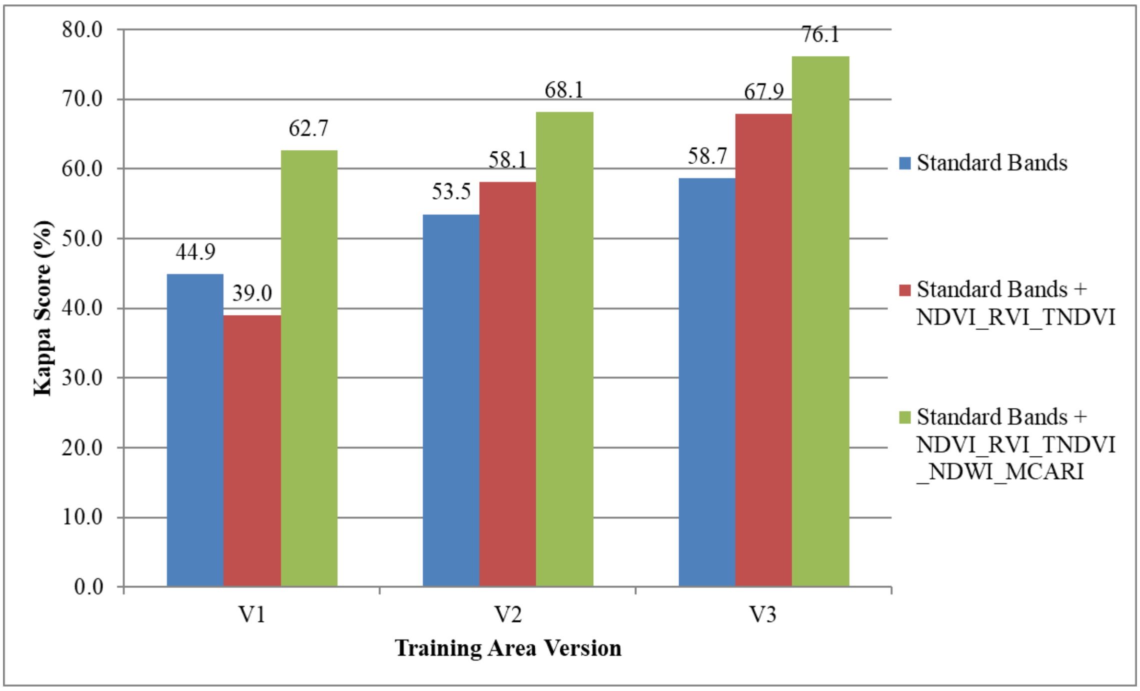


Figure 17. Kappa Score for Healthy/Unhealthy classification

Finally, the User, Producer, and Overall accuracies were calculated along with the Kappa score for Sentinel-2 TA1 (Table 39) and Sentinel-2 TA2 (Table 40).

Table 39. User, Producer, Overall Accuracy and Kappa score for various classes

Class	**Forest-Healthy**	**Forest-Unhealthy**	**Grass**	**Urban**	**Arable**	**Water**	**Larch**	**Bracken**	**Heather**	**Broadleaf**	**Total**	**Accuracy (%)**
Forest - Healthy	6,408	2,204	0	0	0	0	26	0	13	13	8,664	73.96%
Forest - Unhealthy	446	5,535	290	6	0	0	267	3	35	145	6,727	82.28%
Grass	0	6	2,079	0	5	0	3	1	0	5	2,099	99.05%
Urban	0	0	0	3,314	304	0	0	505	3	0	4,126	80.32%
Arable	0	0	63	46	2,027	0	0	217	0	2	2,355	86.07%
Water	0	0	0	0	0	15,777	0	0	0	0	15,777	100%
Larch	0	88	0	0	0	0	305	42	0	0	435	70.11%
Bracken	0	1	0	1	1	0	0	1,492	5	0	1,500	99.47%
Heather	0	5	0	0	0	0	0	36	721	5	767	94%
Broadleaf	2	62	4	2	0	0	42	0	0	770	882	87.30%
Other	0	0	0	0	0	42	0	0	0	0	0	0%
Total	**6,856**	**7,901**	**2,436**	**3,369**	**2,337**	**15,777**	**643**	**2,296**	**777**	**940**	**Overall Accuracy**	89%
Producer Accuracy	93.47%	70.06%	85.34%	98.37%	86.74%	100%	47.43%	64.98%	92.79%	81.91%	**Kappa Score**	87%

Table 40. Accuracy and Kappa score for Sentinel-2 Healthy and Unhealthy

Class	Forest- Unhealthy	Forest-Healthy	Total	User Accuracy
Forest -Unhealthy	1,958	1	1,959	99.94%
Forest -Healthy	3	1,794	1,797	99.83%
Total	**1,961**	**1,795**	**Overall Accuracy**	88%
Producer Accuracy	99.847%	99.94%	**Kappa Score**	76%

4.1.4 Pilot study discussion

As seen in the previous figures, both the incorporation of additional indices and the use of more detailed training area datasets can impact the accuracy of the final outputs. While the use of both standard bands and the addition of NDVI, RVI, and TNDVI consistently resulted in higher OA and Kappa scores, the addition of NDWI and MCARI showed the best results overall.

The addition of NDWI and MCARI also resulted in marginally increased processing times for imagery and generating the classification. It should be noted that this additional processing time was not an issue during the pilot study and, in turn, did not affect the delivery of the final results.

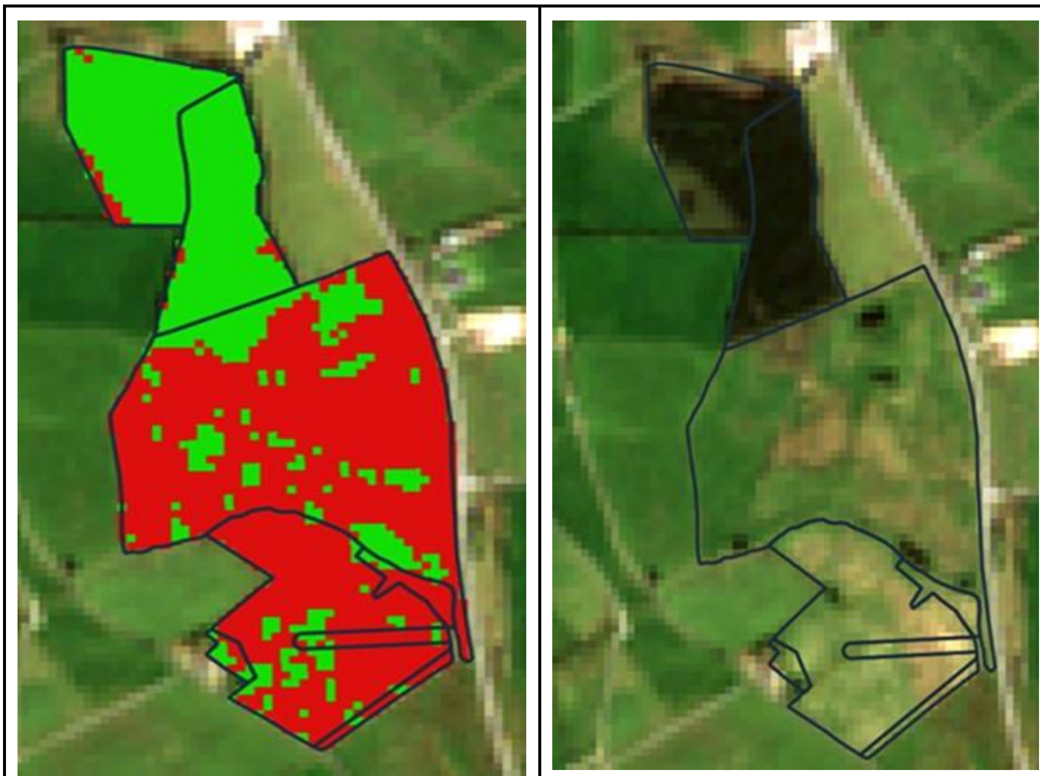
Based on the results of the Sentinel-2 classifications, it is clear that the use of multiple indices improves the classification. These improvements were present when looking at both multiple classes (S2-TA1) and healthy/unhealthy classes (S2-TA2).

The results of the Sentinel-1 time series analysis demonstrate that the imagery is capable of identifying the presence and absence of tree cover when trained to do so (Figure 18). In Figure 19-B the Sentinel-2 imagery with forest present is clearly visible to the north of the image. In Figure 19-A, the forest is classified by green displaying the presence of tree cover and red displaying the no-tree cover areas within the polygon.

Misclassification may occur as a result of the occurrence of pixel mixing due to Sentinel-1's 10 m resolution, or potentially due to the presence of extensive vegetative growth. However, this should not be an issue in areas recently felled due to the absence of vegetation in the one to two years following felling.

A	B

Figure 18. (A) Classification of Healthy and Unhealthy Sitka spruce (Green = healthy, Red = unhealthy), (B) Sentinel-2 imagery



A	B

Figure 19. (A) Classification of tree cover (Green = tree cover, Red = no-tree cover), (B) Sentinel-2 imagery

During the pilot study, the versatility of both the Sentinel-1 and Sentinel-2 datasets was demonstrated. Across the various classifications produced, a number of overlapping characteristics were observed. These included the identification of unhealthy forests between Sentinel-2 Multiple classes (S2-TA1) and healthy/unhealthy classes (S2-TA2), or the detection of areas with no-tree cover between the Sentinel-1 time series analysis (Tree Cover/No-Tree Cover class; S1-TA2) and the Sentinel-2 image classification (Figure 20).

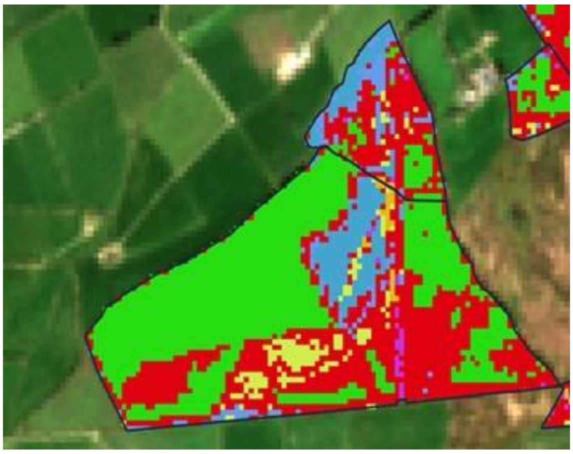
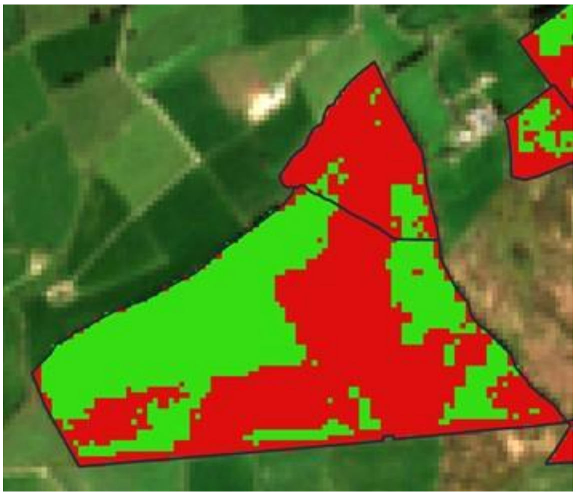
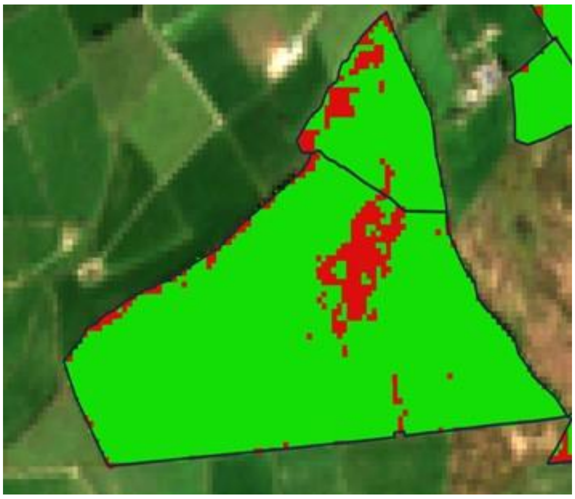
S2 RGB Composite	S2-TA1 Classification - Multiple category **Note:** Blue = Arable / Yellow = Larch
	
S2-TA2 Classification - Green = Healthy / Red = Unhealthy	S1-TA2 Time Series Classification – Green = Trees / Red = No Trees
	

Figure 20. Comparison of Sentinel-1 and Sentinel-2 classification results

4.2 Application of Methodology to Entire Study Area

Once the pilot study was complete, the results were examined and found to be satisfactory. As a result, the methodology outlined above was then used for the final study of the ROI. A final decision was made on the best classification to use based on the information derived from our confusion matrix. Three classifications were used for the whole study area (Table 41). Each classification choice was made based on the results of the Overall Accuracy score, as well as the Kappa Score. The Sentinel-1 (Two Classes) classification was applied to the wider study area (private forests in the ROI).

Table 41. Classifications selected from the results

Classification selected	Indices Included
Sentinel-2 Ten Classes	(Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI)
Sentinel-2 Two Classes	(Standard Bands + NDVI, RVI, TNDVI, NDWI, MCARI)
Sentinel-1 Two Classes	Not Relevant as analysis based on RGB composite

4.2.1 Sentinel-1 Processing

Sentinel-1 was chosen in order to create a time series analysis, as this imagery is not impeded by cloud cover. Therefore, it would be easier to detect changes over time. Imagery for the remainder of Ireland was then sourced. With Sentinel-1, three swaths (i.e. a path a satellite takes) were found to cover a large amount of Ireland (Figure 21). These three were used, as well as a further five swaths, in order to cover the whole of Ireland. Once these areas were chosen, seven images from April to June 2020 were chosen for each swath, and the pre-processing of the imagery was undertaken. Once completed the classification was produced. These classifications were then clipped to the private forest shapefiles and polygonised in order to produce the final results. Afterwards, a visual inspection of the classification was undertaken to ensure it was accurate (Figure 22). In a final processing step, a further examination was undertaken which involved calculating and displaying the percentage of trees and no trees within each polygon for validation purposes.

Figure 21. The Sentinel-1 imagery used for the Republic of Ireland

A	B

Figure 22. (A) Classification of Tree Cover (Green = trees, Red = No trees), (B) Sentinel-2 imagery

4.2.2 Sentinel-2 Processing

Two different classifications were applied for the Sentinel-2 imagery. One displaying healthy and unhealthy forest, and a second displaying the multiple category classification (i.e. ten classes). From the results above, it was decided that running both classifications would be beneficial to the project in producing the most accurate results. Once the classifications were chosen, 15 Sentinel-2 images were used. Although this may seem like a high number; more images were required in order to produce a cloud-free acquisition of the classification (Figure 23). Once the imagery was collected, it was pre-processed, and the classification was run for each of the 15 Sentinel-2 images. Following completion of the classification process, a visual inspection was undertaken for both the healthy/unhealthy and the multiple category classifications to ensure that the results being produced were accurate. On completion of this task, the classifications were then merged to create a full scene of Ireland and then clipped and polygonised to the private forest shapefile provided. As a final step for Sentinel-2, processing was undertaken to produce a table displaying the percentage of healthy and unhealthy trees within the polygons provided.

Figure 23. Extent of the Sentinel-2 imagery used in the final study

4.3 Results for Entire Study Area

The primary aim of the output of this project is to produce information from remote sensing techniques that will help improve the accuracy of the private sector roundwood forecast. The information on the private forest estate is provided in a forest cover GIS dataset with associated attribute information that describes the composition of each forest parcel. The two results of the remote sensing work which are most relevant to the forecast are:

1. The percentage of healthy and unhealthy trees within the forest parcels.
2. The percentage of no tree cover within the forest parcels.

The outputs of the remote sensing work produced results for the entire scene of the imagery used. However due to the composition of forest types within the parcels and the time of year that the imagery was acquired, it would not be appropriate to incorporate the results for all forest parcels. For example, broadleaf forests were not in leaf in the imagery used, therefore it would not be appropriate to apply results to these parcels. Using a range of variables associated with each parcel, a subset of parcels was identified for which it was appropriate to apply the remote sensing results (Table 42).

Table 42. Criteria to identify forest parcels using the remote sensing classification

Remote Sensing Product	LUT	LUC	Fertility	Species 1	Species 1 Canopy (%)	Species 1 Plant Year
Forests-Unhealthy	FOR	CHF	C	CMS	-	-
	FOR	CHF	C	CYS	-	-
	FOR	CHF	C	NS	>70	<2008
	FOR	CHF	C	SS	>70	<2008
No tree cover	FOR	CHF	-	-	-	<2008

Abbreviations include; LUT (Land Use Type); LUC (Land Use Cover); CHF (Conifer High Forest), FOR (Stocked Forest), C (Rough Pasture, with or without outcropping rock) SS (Sitka spruce), NS (Norway spruce), CMS (Conifer Mature Spruce), CYS (Conifer young spruce).

When the above criteria were applied to the forest cover dataset, the area of interest was 188,636 ha for the tree cover results and 60,056 ha for the unhealthy forests results.

Of the total area of the tree cover element (i.e. 188,636 ha) assessed, 91% (171,076 ha) was identified as having tree cover present (Figure 24). For the detection of unhealthy forest, the total area (60,056 ha) assessed, approximately half (33,292 ha) was identified as unhealthy (Figure 25).

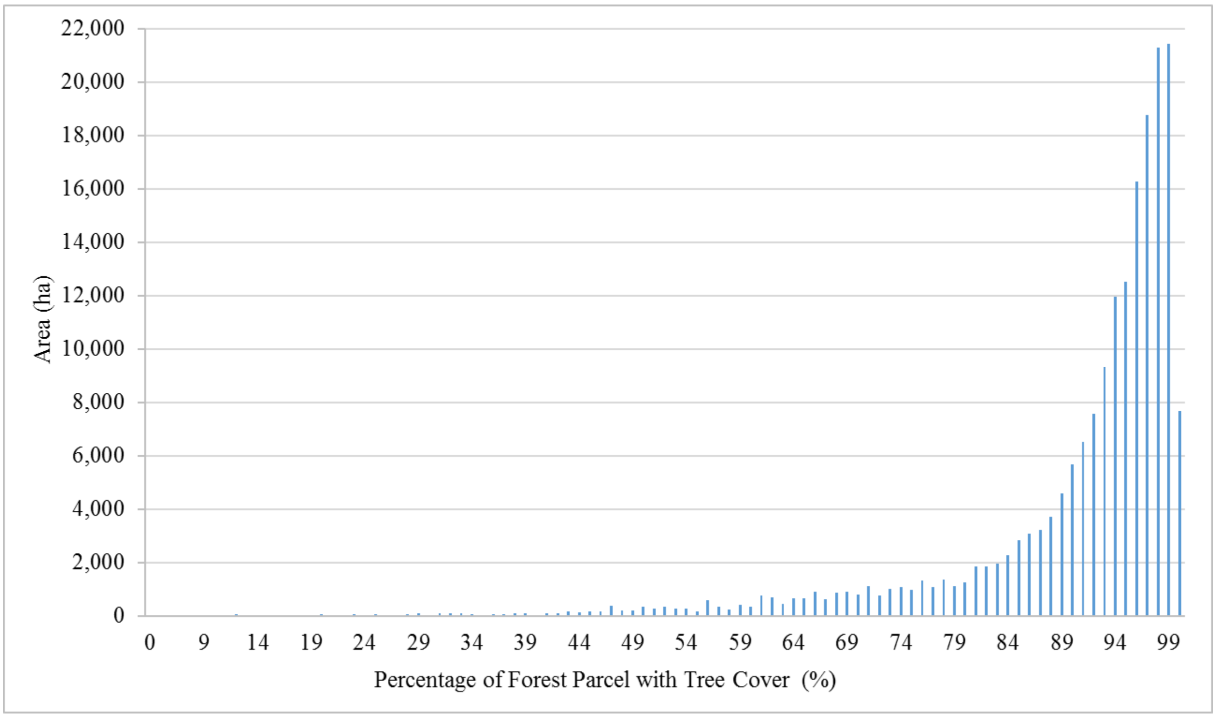


Figure 24. Percentage of relevant forest area with tree cover present

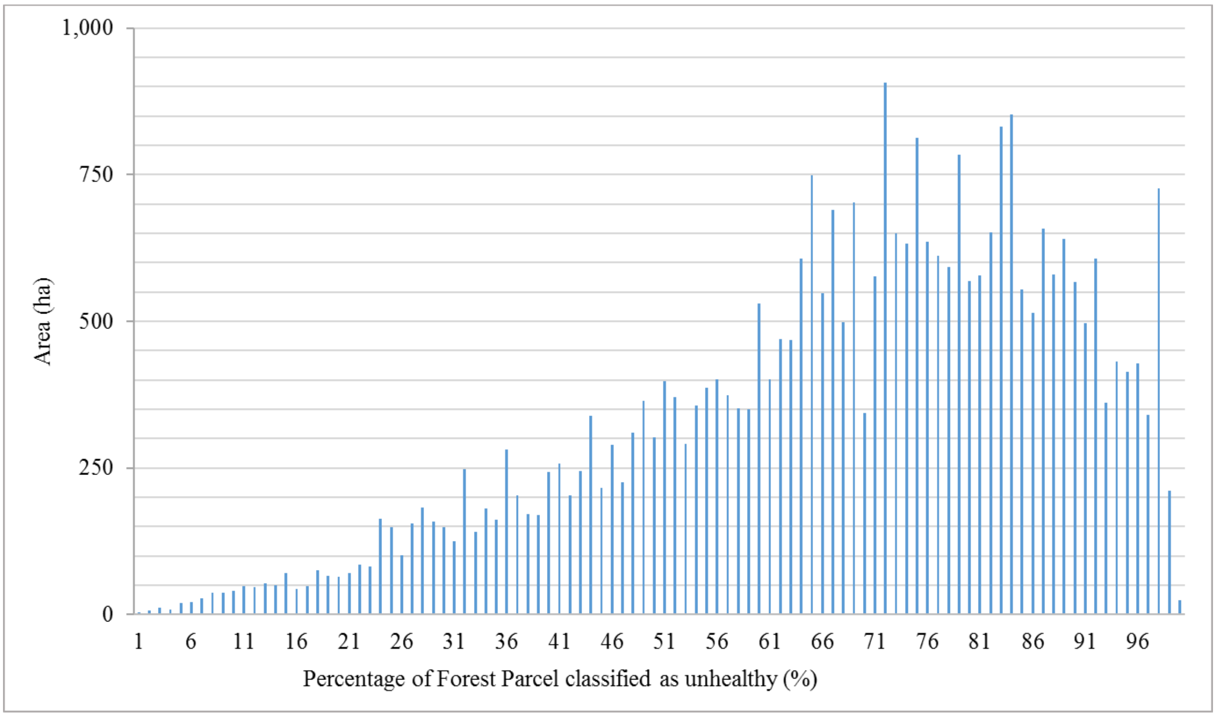


Figure 25. Area of unhealthy forests

4.4 Conclusion

The results demonstrate that unhealthy spruce, and areas with no tree cover can be identified and analysed using remote sensing techniques, specifically with Sentinel-1 and Sentinel-2, both of which are open-source satellite data.

The methodology used, and accurate results generated, indicate the capability of using remote sensing techniques for comprehensive analysis of trees and forestry. The volume of data required for this work is widely accessible to most users and can be analysed by utilising remote sensing techniques via open-source satellite imagery.

The use of a machine learning classification to learn and continuously report on the presence and lack of trees, as well as healthy and unhealthy trees, would be beneficial to the forestry industry. Higher-resolution imagery could be acquired intermittently to continue the validation of the results.

As with all machine learning processes, the results would become more accurate over time, providing a platform for an early detection tool for unhealthy forests in a range of tree species, therefore mitigating potential negative impacts on forest production and relying less on a field visit as the first point of detection. Wider uses of these technologies could lend themselves to detecting storm damage, windblow, pest or disease outbreaks or other forest damages soon after significant events.

Chapter 5. Generate forecast model and results for the Private Forest Sector in the Republic of Ireland

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5.1 Summary

A shapefile of private forest cover in the Republic of Ireland received from DAFM was imported and checked for any topological or logical errors. The records were then transformed into a format useable by the Woodstock software. The 2016 Forecast model was re-built using the updated yields and other settings as described in section Chapter 3. After a number of iterations, the accepted model was published for analysis in Microsoft Excel and exported for presentation in the DAFM Forecast web viewer.

5.2 Software

- Remsoft[7] Woodstock 2021.03 (64 bit)
- Remsoft Analyst for Excel 2021.03 (64 bit)
- Microsoft Excel
- Quantum GIS 3.12
- Postgres PostgreSQL 11.10 on Amazon Web Services (AWS) x86_64-pc-linux-gnu, compiled by GNU Compiler Collection (GCC) 4.8.3 20140911 (Red Hat 4.8.3-9), 64-bit
- Postgis 2.5.2
- PgAdmin 4.29

5.3 High level forecast objective

The overall forecast model objective was defined as:

"maximise volume production to tip, including residue bundling, over 80 years (2021-2100)"

5.4 Forecast Model Constraints

The high-level forecast model was subject to the following constraints:

- All areas available for thinning should be thinned
- The net realisable volume (NRV) cannot exceed the 2016 forecast value until 2036
- The NRV cannot decline over the forecast period 2021 – 2040
- Spruce sawlog (16 cm +) cannot decline over the forecast period 2021 – 2040
- Spruce sawlog and conifer pulpwood cannot exceed the estimated demand
- Areas flagged as blown must be felled within the first two years
- Areas that can be felled and which are flagged as over-mature must be felled within the first 20 years

[7] www.remsoft.com

- Annual clearfelled area in the category of Long-Term Retention (LTR) must not exceed 10% of the area in that category (equivalent to 402 ha)
- Annual thinning volume from areas flagged as not being available for clearfell (i.e. CCF) must not exceed 2 m^3 per hectare on average (equivalent to an annual volume of 25,161 m^3)
- All forest areas were limited to felling at their specified rotation age (+/- 2 years)

5.5 Forecast model

5.5.1 Data preparation

On receipt of the shapefile from DAFM, that combined the results of Chapter 1 and Chapter 2, a number of checks and updates were made:

- Check the topology of all received geometries
- Check that there are no duplicate geometries
- Set values of all species, TUF type data fields to upper case (for reliable query development)
- Set maximum Yield Class for all stocks and Teagasc Yield Class estimate to 30 if exceeding 30
- Check for illogical planting years and correct: two corrections made

5.5.2 Subset and transpose data

Steps included:

- Exclude areas owned by National Park and Wildlife Service or Coillte Farm Partners from the dataset. The latter were excluded as the data for these areas were received from Coillte
- Transpose the data to create a row in a stocks table for up to seven stocks per sub-compartment, where the species label is not null, and productive percent and the species percent are both greater than zero
- Create additional stocks for FIPS and CCF/LTR records according to the rules in Chapter 3

5.5.2.1 Handling of Age

The following rules are applied in the sequence set out below so that an age is assigned to each stand included in the forecast:

1. Setting Age
   - If planting year is 2020, set age to 1 (areas cannot have an age of 0 in Woodstock)
   - If species = ‘OF’, set age to 40 (Other Forest)
   - If rejecting the first two bullet points and where planting age is absent, set planting age to 50
2. Limit age to 100 for conifers and 150 for broadleaves
3. Finish by updating planting year to match age as calculated above

5.5.2.2 Net stock area

- Recalculate the canopy estimates for all stocks so that the total adds to exactly 100%. This avoids losing or gaining area due to rounding errors in previous steps, such as during the productive area estimation
- Where productive area has been estimated by the remote sensing work, use the productive area percentage estimate, otherwise use 85%
- Where the stock age is under 15 years, or age is less than the first thin minus 7 years and productive area has been estimated using remote sensing (see Chapter 4) at higher than 85%, then set the productive area to 85%. This is to prevent young stands having an exaggerated productive area percent estimate
- Combine productive area percent with stock canopy percent and polygon area to calculate net stock area accordingly

5.5.2.3 Yield class

The Sitka spruce yield class value assigned was the value estimated using the local model that considered fertility class, as described in Chapter 2. For all other species yield class was assigned using the yield class mappings detailed in Chapter 3 (Table 23 and Table 24). If the species does not match exactly then a substitute species is assigned using its mapped YC. The output of the remote sensing work in relation to the detection of unhealthy areas was not incorporated into the forecast model.

5.5.2.4 Conifer and broadleaf area

Calculated using a summary of the stocks in each plantation (i.e. polygons with the same contract ID), or per individual polygon where the contract ID is not known. This is required for elements of the ‘thin’ decision making.

5.5.2.5 Thinning

- Calculate the full thinning regime for every polygon, including the first thin age, thin cycle and the number of thinnings
- From the above, calculate the last thin age and create the thinning window (including delay of up to 4 years)
- Apply all the rules, as set out in Chapter 3, to flag each stock for thinning or not. Also check if the stock is already too old to begin thinning or is already older than the last thin age, if so set to no-thin

5.5.2.6 Brash Bundling

Apply the criteria in Chapter 3, including:

- Maximum straight-line distance to Edenderry Power of 60 km
- Minimum area (4 ha)
- Sitka spruce YC 18 plus

5.5.3 Treatment of temporary unstocked forest

At all times a certain proportion of the forest land will be devoid of trees, for example after forest fire, storms or clearfell. For the forecast, certain assumptions are made about how and when these areas are restocked, based on an estimate as to when they were cleared (Table 43).

Table 43. Treatment of temporary unstocked forest

<table>
<tr><th>Temporary Unstocked Forest Type</th><th>Description</th><th>Fell year</th><th>Age</th><th>YC</th><th>Productive area %</th><th>Assumptions</th></tr>
<tr><td colspan="7">Dealt with later in model using model transitions:</td></tr>
<tr><td>Blown</td><td>Windblown forest (63 ha).</td><td>N/A</td><td>As per existing p year</td><td>Restocked with same species and YC</td><td>As calculated (same for replacement)</td><td rowspan="2">Clearfell the first year of the forecast and replant in 2023 with SS (90%) and ADB (10%)</td></tr>
<tr><td>N/A</td><td>Ash felled during model run</td><td>N/A</td><td>As per fell year</td><td>SS 20 85%
OB 6 15%</td><td>As calculated (same for replacement)</td></tr>
<tr><td colspan="7">Dealt with during data preparation:</td></tr>
<tr><td rowspan="2">Forest fire</td><td rowspan="2">Forest area destroyed by fire (1,204 ha)</td><td>≤2017</td><td>2020 – (Fell yr + 2)</td><td>Based on local YC model as per other stands</td><td>85%</td><td rowspan="2">Primarily unenclosed ground; blanket peat. Replant in “Fell_Yr” + 2 with SS (50%) and LPS (50%).</td></tr>
<tr><td>>2017</td><td>1</td><td>Based on local yield model as per other stands</td><td>85%</td></tr>
<tr><td rowspan="2">Clearfell</td><td rowspan="2">Forest area clearfelled (9,881 ha)</td><td>≤2017</td><td>2020 – (Fell yr + 2)</td><td rowspan="2">Based on local YC model as per other stands</td><td>85%</td><td rowspan="2">Replant in “Fell_Yr” + 2 with SS (80%), LPS (10%) & ADB (10%).</td></tr>
<tr><td>>2017</td><td>1</td><td>85%</td></tr>
<tr><td rowspan="2">CF_SD</td><td rowspan="2">Forest area clearfelled following Storm Darwin in 2014 (2,288 ha)</td><td>≤2017</td><td>2020 – (Fell yr + 2)</td><td rowspan="2">Based on local YC model as per other stands</td><td>85%</td><td rowspan="2">Replant in “Fell_Yr” + 2 with SS (90%) and ADB (10%).</td></tr>
<tr><td>>2017</td><td>1</td><td>85%</td></tr>
</table>

5.6 Evaluation of different scenarios for sensitivity analysis

Once the draft model was built, numerous scenarios were run as part of the analysis stage. Using the Optimize section within Woodstock and the outputs of the previous forecast, the following scenarios were explored:

- Unconstrained demand
- Low, mid and high levels of demand for conifer pulp and spruce logs
- Using outputs from previous forecast as upper limits in production
- Using outputs from previous forecast as lower limits in production
- Placing upper limits on forecast of hardwoods

5.6.1 Smoothing supply output

Actual year-to-year production will not vary enormously, given the laws of supply and demand, and capacity bottlenecks such as limited flex in harvesting infrastructure. In all cases, production in 2020 was pinned to the actual production estimated for that year in the previous 2016 forecast. Various options for smoothing were considered:

- Non-declining NRV
- Setting maximum percentage changes in NRV
- Setting maximum step-wise changes from year to year in absolute terms (e.g. in m^3) in NRV

5.6.2 Selected scenario

The following constraints resulted in an acceptable profile of production:

- Non-declining output of NRV for the first 20 years of the forecast
- Non-declining output of Spruce 16 cm top diameter class volume for the first 20 years of the forecast
- Blown area (still stocked with forest) cleared in year 1
- Area that is already beyond the normal age of felling + 2 years must be cleared in the first 20 years (outside of LTR and other areas restricted from felling)
- Do not fall below 80% of the previous forecast NRV for the first 15 years
- Do not exceed 120% of previous forecast NRV for the first 15 years (Table 44):
    - Net spruce volume of TDC 16 cm+ for the first 20 years
    - Do not exceed the specified demand levels for net conifer volume of TDC 7-13 cm for the first 20 years

Table 44. Demand level constraints specified in the forecast model

Year	Sawmill million m^3	Wood Based Panels (WBP) million m^3
2021	3.38	1.81
2022	3.48	1.82
2023	3.59	1.84
2024	3.71	1.86
2025	3.83	1.88
2026	3.95	1.9
2027	4.07	1.92
2028	4.2	1.94
2029	4.33	1.96
2030	4.47	1.98
2031	4.61	2
2032	4.76	2.02
2033	4.91	2.04
2034	5.06	2.06
2035	5.22	2.08
2036	5.39	2.1
2037	5.56	2.12
2038	5.74	2.14
2039	5.92	2.16
2040	6.1	2.18

5.7 Attribute data for final reporting and web-based forecast tool

Standardised attribute data was assigned to the polygons from which the final forecast was produced (Table 45).

Table 45. Attribute data assigned to forecast polygons

Attribute	Description
REMSOFT_ID	Unique polygon identifier
OWNER	‘PRIVATE’
Harvest Type	‘FELL’ or ‘THIN’
Species Grouping	‘BROADLEAF’ ‘OTHER CONIFERS’ ‘LODGEPOLE PINE’ ‘SPRUCE’
Production year	2021 to 2040
Top Diameter Volume categories (NRV and Gross)	Tip to 7 cm
	7 cm to 13 cm
	14 cm to 19 cm
	20 cm+

Chapter 6. Coillte Forecast

For over 10 years Coillte has developed and refined its approach to the strategic and tactical planning of its forest resource using software produced by the Canadian firm *Remsoft*. Coillte adopts a ‘top down’ approach to forest planning, whereby Coillte’s strategy can guide the development of plans down to the level of each forest stand. The system uses mathematical optimisation to devise harvest schedules. The strategic forecast is based on the principle of maximising the value of the entire forest asset, subject to a range of management, environmental and other constraints. The harvest schedules are altered by the system for each of the 126,000 forest stands until the overall solution maximises value, subject to the constraints. An overview of the model structure is provided in (Figure 26).

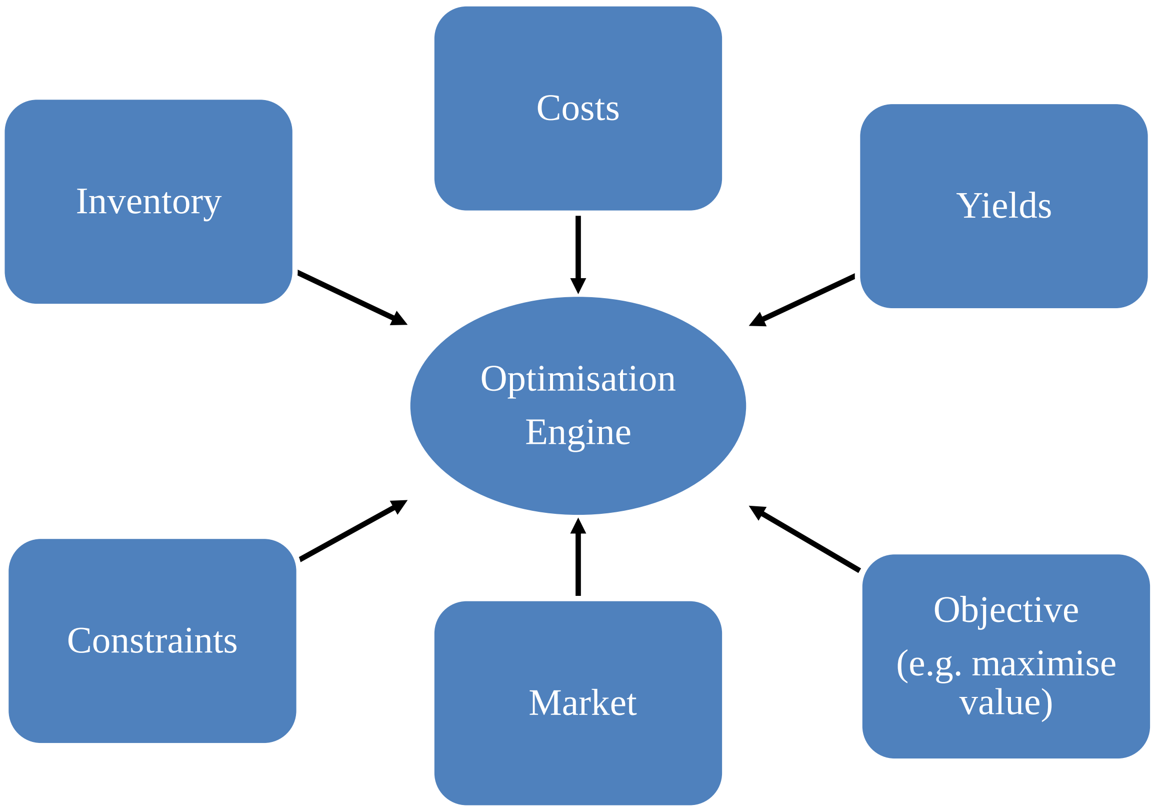

Figure 26. Inputs to the Coillte Remsoft Forecast Model

Constraints include sustainability in future volumes, year-on-year evenness of volume production, and constraints on felling in amenity and biodiversity areas. They are designed to provide for the long-term sustainability of the forest resource. They also simulate the effect of restrictions on felling design in terms of intensity, coupe size, ‘green-up’ and contiguity constraints. Adjustments to yield models are made to bring volume estimates and net harvest loss closer to those actually achieved.

The model can account for a number of economic, spatial and temporal factors in producing an optimal forecast, such as:

- Felling costs can vary considerably based on harvest type and tree size

- The positive impacts that thinning can bring, in terms of increased tree size, can be weighed against the higher wind throw risk that thinning may cause, on a site-by-site basis
- Total volumes of all products scheduled in any one year can be tracked and that haulage costs to, and capacities at, each potential customer are included in the analysis
- The increase in value which may accrue from retaining a stand for one extra year before clearfell can be weighed against the time value of money

While this forest management model provides improved accuracy, it also serves to highlight the influence of a wide number of factors on the actual harvesting outcome. The following factors have been shown to significantly influence the volume which is forecast:

- Patterns of conversion of roundwood into sawlog and non-sawlog
- Harvesting loss estimates
- Discount rate
- Roundwood prices
- Roundwood demand levels
- Costs (e.g. access, haul, harvest, restock)
- Constraints on felling (e.g. restrictions on the time of operations)

Excluded from the Coillte forecast are potential volumes from those forests which are deemed uneconomic or subject to certain management, physical access or environmental constraints. A separate forest management model was used to forecast broadleaf volumes.

Coillte has not published an updated forecast using a revised methodological approach for the years 2021–2035 but has provided inputs for the years 2036-2040. This is because Coillte are currently examining the implications on future timber supply of emerging environmental and other demands on the management of its estate.

Chapter 7. Northern Ireland Forecast

7.1 Private sector forecast

The private sector forecast is based on the most recent private woodlands data and includes information on planting year, forest/woodland type and individual polygon area.

Reference is also made to the updated NI Woodland Basemap[8]. The woodland basemap has been compiled using Geographic Information datasets provided by statutory and non-statutory bodies. The woodland register (version 1.0) was published by Department of Agriculture, Environment and Rural Development (DAERA) in April 2020. It replaces the draft woodland register and basemap published by DAERA in 2018.

The private sector dataset does not include owner objectives, or a productivity assessment, from which rotation or thinning cycles could be inferred. Therefore the forecast has been based on a number of assumptions. To estimate private sector softwood availability, management models were developed by DAERA Forest Service for conifer stands and conifer components in mixed woodlands. These models assume rotation lengths, thinning interventions and intensities, clearfell recoveries and re-establishment objectives. Top diameter volumes have been apportioned as per ‘Forestry Commission’ assortment tables (Matthews and Mackie, 2006).

This methodology has been used in the past three quinquennial forecast publications. It has borne reasonable comparison with reported annual private sector removals data, which was gathered by the Forest Service and published by Forest Research in Forestry Statistics[9].

7.2 Department of Agriculture, Environment and Rural Development (DAERA) Forest Service forecast

In Northern Ireland, production forecasting of softwood availability within the DAERA Forest Service estate is based on forest stand inventory measurement, combined with aspects of wider forest management planning requirements. This information, as well as informing softwood availability forecasts, is required to verify sustainable forest management and also to form the basis of forestry asset valuations for accounting purposes. The policy for sustainable forest management is delivered as a requirement under the Forestry Act (Northern Ireland) 2010.

As evidence of this, DAERA Forest Service sustainable forest management practices remain compliant with the UK Woodland Assurance Standard (UKWAS).They are confirmed through an independent audit accredited by the Forest Stewardship Council® (FSC®) (Licence code: FSC-C084232), and the Programme for Endorsement of Forest Certification (PEFC) (Licence code: PEFC/16-40-1924).

[8] https://www.daera-ni.gov.uk/publications/woodland-register

[9] https://www.forestresearch.gov.uk/tools-and-resources/statistics/statistics-by-topic/timber-statistics/

The 2021 DAERA Forest Service estate forecast is based on the most recent sub-compartment dataset, which incorporates recent inventory data and refreshed Yield Class values using the latest Forest Service planned felling dates and felling coupe geometries. Yield class values are derived using a kriging model[10], which includes an adjustment to generate a predicted value at felling age, based on historical data, indicating a reduction in yield class with increasing age. The forecast returns annual conifer volume availability averaged across 5-year age bands. The yield models used assume normal growth throughout rotations.

Targets for roundwood production figures will continue to be set annually in compliance with strategic objectives identified in, and met through, annual Business Plans. Strategic objectives and future timber marketing arrangements are subject to successive government policies, priorities and approvals.

[10] Kriging refers to a statistical technique used by Agri-Food and Biosciences Institute (AFBI) biometricians to allocate Yield Class values to all sub-compartments based on measured inventory values and spatially related criteria.

Chapter 8. Forecast Outputs

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8.1 Forecast data outputs

Following completion of the forecasting modelling work four separate forecasts were output:

1. Republic of Ireland
    a). Coillte
    b). Private Sector in the Republic of Ireland
2. Northern Ireland
    a). Department of Agriculture, Environment and Rural Affairs Forest Service
    b). Private Sector in Northern Ireland

The forecast variables generated by the four separate forecasts were harmonised to ensure that data from each forecast could be aggregated to an All Ireland level. Results information is presented in terms of:

- Production year (i.e. 2021-2040)
- Net realisable and gross volume
- Harvest area (ha)
- Species group (i.e. Spruce, Lodgepole pine, other conifers and broadleaves
- Harvest type (i.e. thinning or clearfell)
- Size assortment (i.e. top diameter classes Tip -7cm, 7-13cm, 14-19cm, 20cm+)

A report was produced summarising the All Ireland Forecast 2021 to 2040, which included detailed tabular and graphical outputs of the results. The report is available on the Coford website.

8.2 Web-based forecast tool for the Republic of Ireland

A GIS portal was developed by DAFM to accompany the forecast that generates user defined spatial forecasts for private and Coillte forests. The portal facilitates the dissemination of comprehensive volume forecast information on the national forest estate in an accessible, reproducible and transparent way.

Firstly, the user specifies the area of interest by selecting a distinct point and an associated search radius (Figure 27). A forecast report is then produced and the output of which may be altered by adding or removing variables (Figure 28).

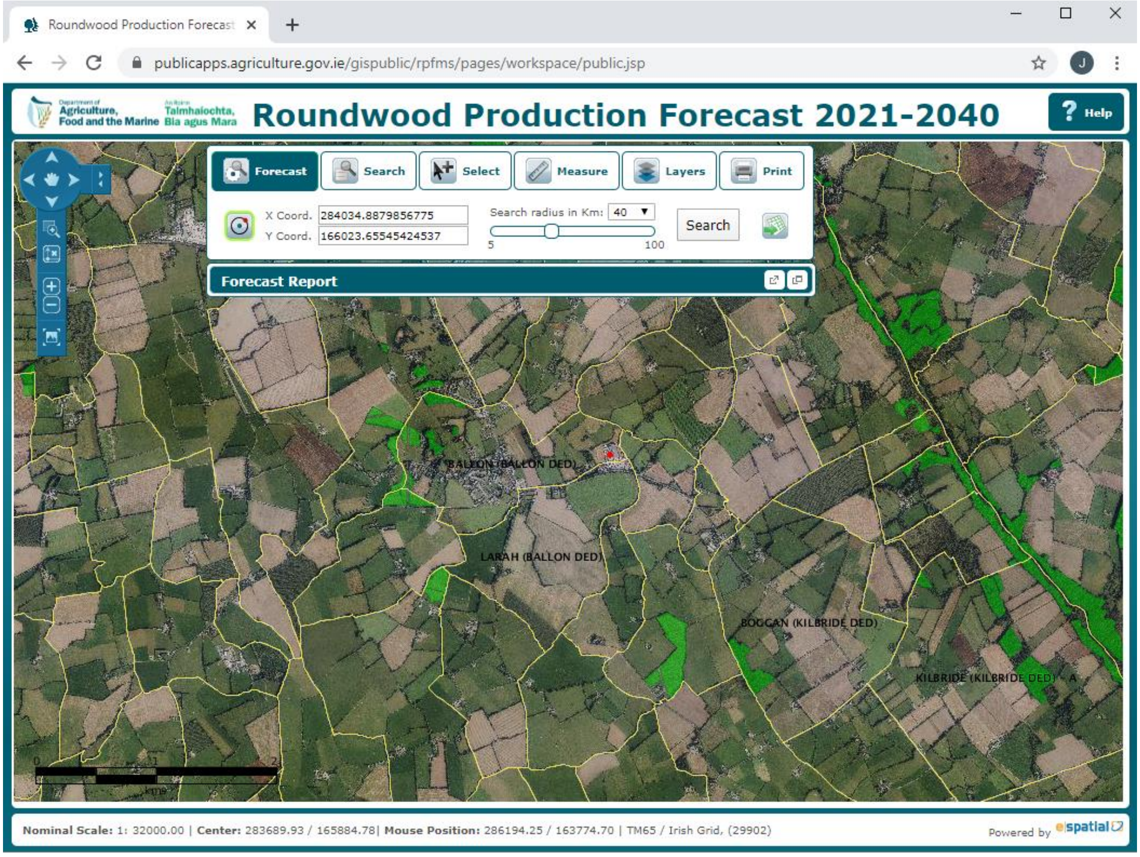

Figure 27. Defining the area of interest on web forecast tool

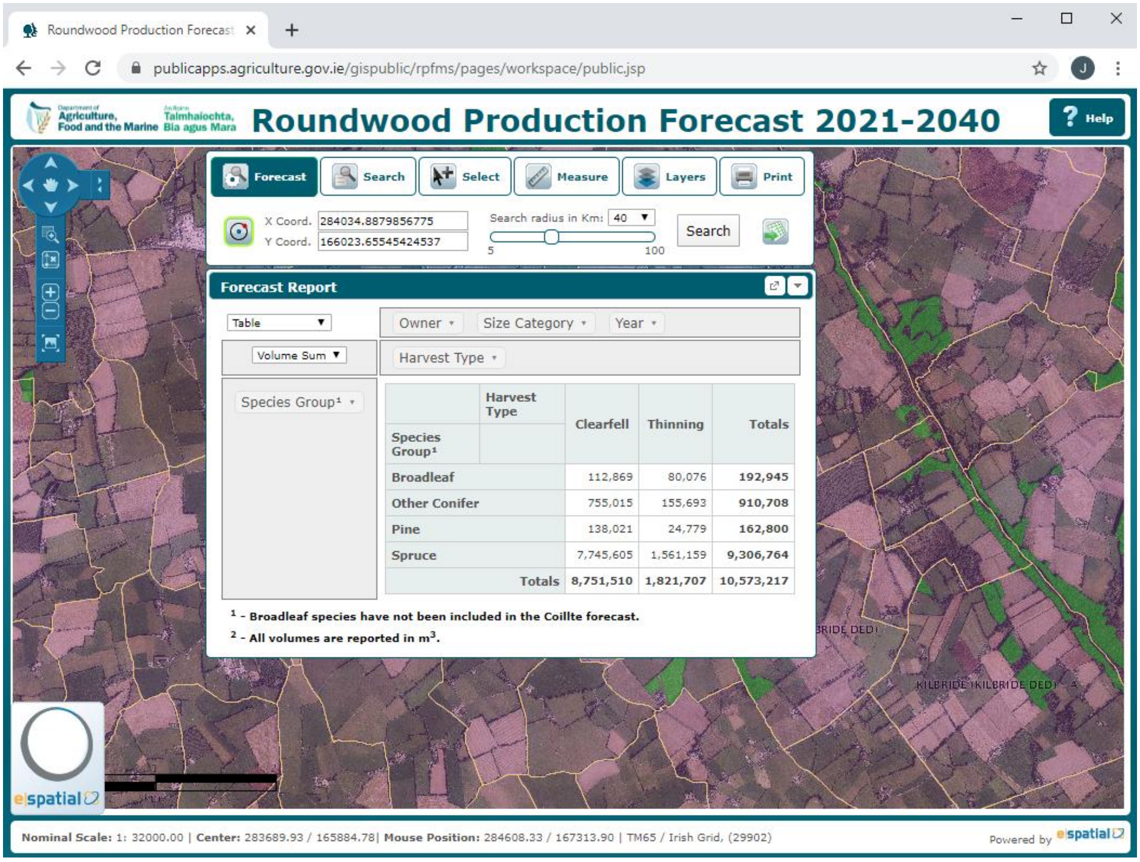

Figure 28. Results generation on web forecast tool

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