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Enhancing the Irish NFI Using k-Nearest Neighbors and a genetic algorithm

Daniel McInerney, Frank Barrett, Ronald E. McRoberts, and Erkki Tomppo

Abstract: This paper presents a nationwide application of k-Nearest Neighbors (k-NN) to estimate growing stock volume per hectare for the Irish national Forest Estate using optical satellite imagery and field inventory data from the second NFI. Two approaches are tested: an unweighted k-NN and an improved version, (ik-NN), that is optimised using a genetic algorithm. The performance of the models are assessed in terms of the Root Mean Square Error and prediction error. From the simulations, it was found that the optimal value of k was 3, and the smallest pixel level RMSE for growing stock was $126\text{ m}^3/\text{ha}$ when

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ik-NN was used. Comparisons with estimates from the NFI shows that the ik-NN technique can enhance the Irish NFI. These improvements include a total estimate of growing stock volume of 102 million m^3 with a confidence interval of $\pm 3\%$, which is smaller than the NFI reported confidence interval of $\pm 5\%$. In addition, while total county level estimates of growing volume estimated using ik-NN were consistent with those published from the NFI, their corresponding confidence intervals were much narrower, in the range of a 2- to 4-fold reduction in the width of the confidence interval.

Key words: Forest Inventory, Remote Sensing, k-NN, Nearest Neighbors, genetic algorithm.

1. Introduction

National forest statistics are primarily estimated from field-based National Forest Inventory (NFI) programmes that collect information on a range of forest related parameters [Lawrence et al., 2010]. However, they are typically based on a percentage sampling, with sample intensities commonly determined by forest area. These methods are employed since complete enumeration of all forests is not feasible due to costs and time. The sampling intensities employed in operational inventories are too coarse to provide accurate representations of the forest resources at local scales [Bottai et al., 2002, Tomppo et al., 2014]. Furthermore, there are specific limitations associated with large-scale field inventories as they cannot identify within stand variability, caused by differences in site productivity or active forest management operations, such as thinning or selective felling [Gjertsen, 2007]. Given that the intention of these inventories is to serve strategic purposes and national reporting, they are not designed to produce statistically robust estimates of forest resources at local scales despite the increasing need for such information.

Research carried out in Finland during the early 1990s sought to overcome this issue and to leverage multi-spectral satellite imagery, field inventory data and a variety of geospatial data in conjunction with a statistical estimator to produce small area estimates (several thousands of hectares) of forest parameters [Tomppo, 1991]. This research was primarily driven by the need to produce forest resource

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information for small administrative areas (i.e. municipalities) in a more cost-effective way than would be possible from the sole use of field inventory data. Since then, the approach has been routinely applied in Finland and Sweden to update forestry databases pertaining to national and regional forest inventories [Tomppo et al., 2008, Barrett et al., 2016]. McRoberts [2012] provides a comprehensive overview of where k-Nearest Neighbors (k-NN) has been applied in the context of forest inventory and identifies four principal areas where k-NN has been used that include: (1) imputation of missing forest inventory variables; (2) forest mapping; (3) small area estimation and, (4) probability and model-based inference. While k-NN remains the technique most widely applied in forestry, other variations of this non-parametric technique have also been used in a forestry context, such as Most Similar Neighbor (MSN) [Moeur and Stage, 1995], Gradient Nearest Neighbor (GNN) [Ohmann and Gregory, 2002], Random Forest algorithm [McInerney and Nieuwenhuis, 2009]. A detailed meta-analysis and literature review of these techniques is covered in Chirici et al. [2016].

The success of k-NN and the fact that it has been widely used to produce current estimates of forest resource information can be largely attributed to the following advantages. Firstly, k-NN is practical and statistically oriented in that it can simultaneously predict a wide range of forest variables [Makela et al., 2004]. Secondly, it is non-parametric and does not require any a priori information regarding the distribution of the data. Thirdly, it is cost-effective in that it can generate more detailed statistics for small areas and map products than can be achieved using field data alone. Fourthly, it is a versatile technique that can be used with different datasets and in different geographic locations [Chirici et al., 2016].

With a forest cover of slightly more than 10.5%, reference has often been made to Ireland being one of the least forested countries in Europe. At the beginning of the twentieth century, forest cover was less than 1.4%, but since the 1950s, Ireland's rate of afforestation has been one of the greatest in the EU and it is current government policy to increase national forest cover to 18% by 2046 [DAFM, 2014]. Planting of privately owned lands has been driven by EU and State grant payments [Zanchi

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et al., 2007]. Under such programmes, the area of privately- owned forests has increased from 81,958 ha in 1973 to 335,900 ha in 2012; over a four-fold increase. During the same period the state-owned forest area has also increased substantially from 242,056 ha to 395,760 ha [DAFM , 2018a]. The average size of private afforestation sites since 1980 to 2016 was 8.8 ha resulting in the development of a fragmented forest landscape, with patterns of spatial development related to existing agricultural activities, availability of grant aid, and environmental constraints precluding forest development [Gillmore, 1988]. These developments, coupled with the current structure of the Irish Forest Estate are almost unique and present challenges in terms of how the Forest Estate is measured and how robust estimates are produced using ik-NN, a variation of k-NN that is optimized using genetic algorithms (Sections 2.6-2.7).

There are many examples of where k-NN has been successfully implemented as part of an NFI programme, for instance in Minnesota [Franco-Lopez et al., 2001], Sweden [Reese et al., 2005] and Italy [Chirici et al., 2008], while additional examples are provided in [Chirici et al., 2016]. However, one common feature of many of the published examples of k-NN is that they have largely been carried out in countries characterised by vast areas of large percentage forest cover, consisting of a uniform forest structure in terms of age class distribution. In this study, we investigate the use of ik-NN to increase the accuracy and precision of Irish NFI estimates in a landscape dominated by forests at a juvenile development stage and characterised by a very sparse and fragmented forest cover, which are largely managed on short (35-45 year) rotations. In addition, there is no standard set of configuration parameters that can be applied to different forest environments and each implementation of k-NN requires optimization to local conditions, selection of different explanatory variables and estimation parameters (distance metric, value of k, selection of weights). Furthermore, this study provides an additional example to a small set of studies that have applied the k-NN approach but optimised it through the use of a genetic algorithm and coarse scale variables. Specific examples of this approach include the Finnish-NFI [Tomppo and Halme, 2004]; and for the prediction of categorical forest variables [Tomppo et al.,

2009]. The particular challenge in Ireland is the small forest percentage and scattered forest patches, which in turn implies that the coarse scale variables as explanatory variables play an even more important role. Furthermore, there are few operational examples of k-NN that have applied a detailed error estimation approach, which is also presented in this article.

The objective of this paper is to present an operational use of ik-NN, which is optimised using a genetic algorithm and coarse scale variables and a detailed error estimation technique. A related objective is to clearly describe an operational technique applied in a novel way to a unique national Forest Estate. The paper builds on previous studies carried out in Ireland [McInerney et al., 2005] and [McInerney and Nieuwenhuis, 2009]. However, the paper extends these studies as well as many others, by presenting a detailed description of the methods and data required to carry out this type of analysis on an operational scale across a large area.

2. Materials

2.1. Study Area

The analysis focuses on all of the forests in the Republic of Ireland including both public and privately owned stands, with specific reference to the country's counties (Figure 1). For the purposes of the processing and availability of satellite imagery, the country has been divided into three areas of interest (AOI) (Figure 2). The total forest area in 2013 has been estimated as 731,652 ha, which represents 10.5% of the total land area. The Irish Forest Estate consists largely of plantation forests managed on commercial rotations ranging in length from 35 to 45 years. The majority (more than 60%) of them are plantations consisting of either monocultures or mixtures of two coniferous species, with Sitka spruce (*Picea sitchensis* (Bong.) Carr.) and lodgepole pine (*Pinus contorta*) being the dominant species. The Forest Estate is very young, with two-thirds of the forests less than 20 years of age. Approximately 31% of this juvenile stage forest is held in private ownership, which is spatially fragmented with the average size private plantation being 8.8 ha [DAFM , 2018a]. Despite these characteristics there is a

substantial quantity of growing stock present in older broadleaf forests and increasingly a more diverse range of species is being planted by Irish forest owners [Forest Service , 2013b].

A small portion of the Forest Estate has been excluded from the analysis due to a lack of satellite imagery or cloud cover; the corresponding areas are 6,234 ha and 9,256 ha respectively, which represents 2.1% of the total Forest Estate. While these areas are not processed, it is considered that their overall contribution to the estimates are minimal given that more than 60% of this area is less than 20 years of age.

2.2. Applying best practice in the use of plot based NFI data and Earth observation data

Based on questionnaire responses from NFIs representing 65% of global forest area, Barrett et al. [2016] provided specific guidelines and identified best practice for countries initiating, expanding or revising the use of remotely sensed data in their NFIs, including the following recommendations:

1. In some instances, it may be required to remove non-applicable field plot data caused by differences between the date of field data collection and the acquisition of satellite imagery. Plot level disturbances caused by biotic or abiotic factors between the two dates can cause large error in estimates and map products. Plots with these issues should be either removed or up-dated.
2. Adequate handling of positional error in regard to georectified imagery is of critical importance and appropriate post-processing of GPS data should be carried out to reduce these errors.
3. Range of variation in both response and remotely sensed variables in the sample or reference data should cover ranges in the same variable in the entire inventory area of interest.
4. Prediction for map units simultaneously and in a consistent manner using a multivariate method such as the k-NN technique.
5. From a technical perspective, the input data must provide the required accuracy for estimates using the selected analytical methods.

131 6. Uncertainty in forest attribute maps and map-assisted estimates should be estimated using statis-
132 tically rigorous methods.

133 7. Map-based estimates should be adjusted to compensate for prediction errors (typically by com-
134 paring map predictions and ground data for a probability sample using techniques such as the
135 model-assisted, generalized regression estimator).

136 These recommendations for best practice were applied in the use of NFI plot data, satellite imagery,
137 auxiliary geospatial data, model diagnostics, a genetic algorithm and the ik-NN method as discussed
138 further below.

139 2.3. National Forest Inventory Data

140 Field inventory data from the 2nd NFI were used as a reference dataset in the k-NN estimation. The
141 NFI is based on a sample of all forests using a 2x2 km systematic sampling design across the entire
142 country with the inventory designed for a five year rotation. It consists of 1,747 permanent sample
143 plots located on forest lands [Forest Service , 2013a]. The field data were collected between 2010 and
144 2012. The plot design is a concentric circle with a maximum radius of 12.62 m centred on the plot
145 coordinate encompassing a total area of 500 m^2 . The plot centres are located using a differential GPS,
146 which also used real-time RINEX correction of the signals. It was estimated that the average location
147 error was less than 5 metres. In situations where there was insufficient GPS signal, laser range finders
148 are used to navigate from known GPS coordinates to the plot centre. A total of 105 timber and non-
149 timber variables is assessed on each plot. The primary focus of our analysis is on plot-level estimates
150 of growing stock volume per hectare ($m^3 ha^{-1}$).

151 For the purposes of this study, estimates were only produced for stocked forests. As a results,
152 NFI plots that were temporarily unstocked (i.e. clearfelled) were relabelled as non-forest plots and
153 not used as part of the analysis. This was done to ensure that estimates were only produced for areas
154 that were stocked with forests; clearfelled and temporarily unstocked forest lands are still considered

155 forest from a land-use perspective, but they will clearly be identified as non-forest from a landcover
156 or remote sensing context. Furthermore, field inventory plots that had a volume more than 50 m^3 , but
157 a Normalised Difference Vegetation Index (NDVI - an indicator of green vegetation) less than 0.25
158 were considered anomalies and were removed from the reference dataset. This represented a total of
159 22 plots and was likely caused by a clearfell intervention during the intervening period between the
160 field inventory survey and the acquisition of the satellite data. The spatial distribution of the NFI plots
161 is presented in Figure 1.

162 Insert Figure 1

163 Estimates of growing stock volume per hectare and basal area per hectare were estimated using
164 the Irish Single Tree Volume Models that were developed in conjunction with the NFI [Forest Service
165 , 2013a]. Uncertainty relating to the allometric model predictions is acknowledged but has not been
166 actively considered as part of this study as they are deemed negligible relative to the effects of sampling
167 variability, which has been demonstrated in similar types of studies [McRoberts and Westfall, 2014].
168 However, there is a growing amount of literature on this topic of attempting to quantify this difference
169 [Breidenbach et al., 2014] but it is considered out of scope for this paper. Figure 3 presents the scatter
170 graphs of growing stock volume per hectare, basal area per hectare and mean plot height for both public
171 and private plots. In addition, boxplot figures of volume and basal area per hectare are presented and
172 they show that the respective means for the public Forest Estate are greater than for the private estate,
173 which is expected as the publicly owned Forest Estate is older.

174 Insert Figure 3

175 2.4. Satellite Imagery

176 Optical satellite imagery from SPOT-4 and Indian Resource Satellite (IRS LISS 3) acquired as part
177 of the IMAGE2012 programme was used as the source of the explanatory variables in this analysis.
178 The images were all acquired during the spring/summer of 2011 or 2012, which corresponded with the

179 acquisition of the NFI field data. Each satellite image scene covered a specific part of the country and
180 therefore the images were processed separately. In the case of the IRS data acquired in the western half
181 of the country, three scenes from the same path were acquired on the day and were mosaiced together
182 and treated as one scene. Therefore, only NFI plots located within a scene were used for the ik-NN
183 analysis on that scene. Table 1 outlines the specific properties of each satellite sensor with respect to
184 its spectral bands and spatial resolution.

185 The paper refers to three distinct Areas of Interest, which correspond to the three separate image
186 datasets:

- 187 1. AOI West 3 IRS scenes from the same path and acquired on the 29th April 2011
- 188 2. AOI South 1 SPOT scene acquired on the 20th June 2012
- 189 3. AOI East 2 IRS scenes acquired on the 27th May 2012

190 A mask of cloud and cloud shadow was manually digitised to remove cloud affected forest areas
191 from the analysis, the cumulative area of the cloud mask affecting forest land was 9256 ha.

192 In addition to the spectral bands, band ratios were calculated as explanatory variables. IRS LISS-III
193 and SPOT-4 both have four spectral bands as outlined in Table 1. Practical tests have shown that the
194 use of the band ratios, in addition to the original bands, assists in distinguishing among forest types
195 and tree species. Band ratios are similar to vegetation indices and for the purposes of this study, the
196 following set of band ratios was calculated: $2/1, 3/1, 4/1, 3/2, 4/2 \& 4/3$.

197 **2.5. Auxillary Data**

198 A number of auxillary datasets were also generated and used as explanatory variables for the
199 weighted k-NN estimation. Details regarding these datasets are outlined below:

- 200 • Digital Terrain Model (DTM) with a spatial resolution of 50 m from which the slope, aspect and

angle were calculated. This DTM was produced by the Ordnance Survey Ireland (OSi) using photogrammetry and their stereo-ortho photography campaigns from 2004.

- The Irish Forest Services National forest map from 2012 was used as a forest mask as part of this analysis. This vector-based dataset was estimated from a combination of an automated classification of satellite imagery and the on-screen interpretation of Landsat TM imagery (1993 - 1997), panchromatic orthophotos (1995), and the Ordnance survey topographic maps. Forest boundaries were digitised using orthophotos (to within 2 m accuracy), and where appropriate the boundaries observed on the Ordnance Survey topographic maps (map series referred to as the OSi 25 inch series). This national forest map has since been updated for newly planted areas on an annual basis using digital orthophotograph available to the Irish Forest Service. The resulting inventory database includes all forest areas of more than 0.2 ha with a classification accuracy of 88% for the forest species and age classes comprising the database [Gallagher , 2000, DAFM , 2018b].

- An indicative soils map of Ireland was produced and published in 2006 at a working scale of 1:150,000 by the Spatial Analysis Unit (SAU) within Teagasc as part of the Subsoils, Land Cover, Habitat and Indicative Soil Mapping/Modelling Project funded initially by the Irish Forest Service and subsequently by the Department of Environment, Heritage and Local Government. [Fealy, 2009]

- Accumulated temperature across the country [Black et al., 2010]. Baseline and future climate data for Ireland have been calculated from simulations of future climate scenarios (IPCC - A2 and B1 scenarios). The simulations are from a regional climate model (RCM) developed by the Rossby Centre in Sweden [McGrath, 2005]. The data have been calculated using a dynamic downscaling method, published by the Community Climate Change Consortium for Ireland (C4I), and validated using back-casting techniques [McGrath, 2005]. The simulated daily mean temperatures, daily total rainfall, and daily total evaporation have been compiled into mean monthly values while the accumulated temperature grid at 1 km resolution as used in this study was calculated for the growing

season March to October inclusive [Ray, 2002].

- Coarse scale variables of growing stock volume per hectare were generated for the three main forest type groups, which included conifer dominated forests, broadleaf dominated forests and mixed forests. The datasets were generated by interpolating the NFI field plot estimates of growing stock using Inverse Distance Weighting and kernel filtering. Due to the sparseness of the field plots, the coarse scale variables represent the variation of growing stock at the scale of tens or hundreds of kilometres. These coarse scale variables assist in directing the search of the nearest neighbors in the ik-NN estimation.

- Administrative county boundaries for which forest variable estimates were made.

Examples of the coarse scale variables are included in Figure 5.

Insert Figure 5.

The above auxillary datasets were combined in a common file based on the Easting and Northing grid coordinates of the NFI plot location as well as the pixel information from associated bands of the IRS and SPOT satellite images.

Using `pktools`, a collection of computer based utilities written in C++ for image processing [McInerney and Kempeneers, 2015], an ASCII file containing the Easting and Northing coordinates of the field inventory plots was created by extracting the pixel values for all NFI plots from the feature variables (satellite imagery and auxillary spatial data layers) and formatted to the required specifications for ik-NN estimation. Weighted mean pixel values were extracted based on a 3×3 window of pixels around the target pixel to reduce uncertainty relating to the location of the field plots.

2.6. Model Diagnostics

McRoberts [2009] detailed diagnostic tools for evaluating and enhancing nearest neighbours prediction for continuous, univariate response variables. One specific diagnostic that is used prior to k-NN

estimation is that the reference dataset adequately covers the distribution of the target dataset. This test ensures that the estimation process will not extrapolate predictions for all target variables. Figure 6 presents the density distributions for the reference and target datasets. This diagnostic test demonstrates that the distribution of the satellite image bands for the reference plots fully covers the range of values in the target dataset and would therefore not extrapolate variable predictions.

Insert Figure 6.

2.7. Explanatory variable weight determination using a genetic algorithm

Genetic Algorithms (GAs) are iterative search algorithms that are based on the principles of evolutionary processes to solve optimisation problems. In the context of ik-NN, GAs begin with the random selection of a set of values for the selection of weights for the explanatory variables. The search uses genetic operators, such as inheritance, selection, mutation and crossover to ultimately find the values that optimise the search criterion [Tomppo and Halme, 2004, Tomppo et al., 2009, McRoberts et al., 2016]. Three simulations were constructed in order to identify the optimal selection of weights for the explanatory bands and to evaluate the effectiveness of the coarse scale variables (CV). These included:

- Zero CV (0 CV): spectral bands, band ratios but no additional coarse scale variables used;
- One CV (1 CV): spectral bands, band ratios used with 1 additional coarse scale variable used (in this case DTM);
- Five CV (5 CV): spectral bands, band ratio used in conjunction with 5 additional coarse scale variables, which included DTM, Accumulated temperature and interpolated growing stock volume for conifer, broadleaf and mixed forest dominated stands.

The genetic algorithm was parameterised to run 16 times as this was considered sufficient to estimate the appropriate weights and Figure 7 presents the impact on the RMSE for growing stock volume

per hectare for the three constructed simulations. The graph demonstrates that the smallest RMSE is achieved after 12 iterations for the model (5CV), which uses the spectral bands, band ratios and five coarse scale variables. It is also noteworthy that this model shows a decrease in RMSE of approximately $5m^3/ha$ after the third iteration compared to the two other simulations.

Insert Figure 7

2.8. ik-NN method

k-NN is a supervised learning technique that uses a reference dataset consisting of sample population units that contain observations of both response and feature variables. The feature variables are auxiliary variables, which in this case are multi-spectral satellite image bands and auxiliary spatial layers. Within this study, two k-NN approaches are used for the purposes of comparison, namely an unweighted, k-NN method and the ik-NN technique. The unweighted k-NN approach only used the satellite image bands and the corresponding band ratios as explanatory variables and applied equal weights to each.

The ik-NN technique was developed in Finland and is underpinned by a genetic algorithm, which is used to find optimal weights for explanatory variables. These weights correspond to the diagonal values for a weighted Euclidean distance matrix. ik-NN extends the conventional k-NN technique, which has been employed in the Finnish Multi Source NFI to combine field plot data, satellite images and digital map data since 1990 [Tomppo, 1991], and its improved version since early 2000 [Tomppo and Halme, 2004, Tomppo et al., 2014].

The core of the ik-NN estimation method is the new weights (Eq. 3) for each field plot by spatially discrete computation units, e.g., by municipalities [Tomppo, 1996]. The weights are computed for each field sample plot $i \in F$, where F is the set of field plots on forestry land. These plot weights are sums of the weights that are computed for the field plots over all satellite image pixels on the forest land mask of the computation unit. The plot weights corresponding to a single pixel (Eq. 1), in turn, are

296 computed by a non-parametric k-NN estimation method [Tomppo, 1991, Tomppo et al., 2008]. The
 297 method utilises the distance metric d , defined in the feature space of the satellite image data and coarse
 298 scale forest variables.

299 Following Tomppo et al. [2008, 2014], let us denote the k nearest feasible field plots by $i_1(p), \dots, i_k(p)$.
 300 The weight $w_{i,p}$ of field plot i to pixel p is defined as

$$w_{i,p} = \frac{1}{d_{p_i,p}^t} \bigg/ \sum_{j \in \{i_1(p), \dots, i_k(p)\}} \frac{1}{d_{p_j,p}^t}, \quad \text{if and only if } i \in \{i_1(p), \dots, i_k(p)\} \quad (1)$$

$$= 0 \quad \text{otherwise.}$$

301 The distance weighting power t is a real number, usually $t \in [0, 2]$. Leave-one-out cross-validation
 302 tests were carried out using the field plot data and explanatory variables in order to find the values of
 303 t and k that minimize the leave-one-out RMSEs. A small quantity, greater to zero, is added to d when
 304 $d = 0$ and $i \in \{i_1(p), \dots, i_k(p)\}$. The distance metric d employed was

$$d_{p_j,p}^2 = \sum_{l=1}^{n_f} \omega_{l,f}^2 (f_{l,p_j} - f_{l,p})^2 + \sum_{l=1}^{n_g} \omega_{l,g}^2 (g_{l,p_j} - g_{l,p})^2 \quad (2)$$

305 where $f_{l,p}$ is the l th normalised intensity value of the spectral band image variable, normalising
 306 done on the basis of digital elevation model, $f_{l,p_j} = f_{l,p_j}^0 / \cos^r(\alpha)$, with α the angle between sun
 307 illumination and terrain normal, r the user given power for the cosine correction, $g_{l,p}$ the large area
 308 prediction of the l th applied forest variable, n_f the number of image variables (or features), n_g the
 309 number of coarse scale forest variables and ω_f and ω_g the weight vectors for image features and coarse
 310 scale forest variables respectively.

311 The values of the elements of the weight vectors ω_f and ω_g are computed by means of a genetic
 312 algorithm [Tomppo and Halme, 2004]. Further details on this methodology are provided in Tomppo
 313 and Halme [2004].

314 The first phase of the improved version of k-NN (ik-NN), is to run the optimization algorithm by
315 strata. The estimation after that is similar to the basic k-NN estimation.

316 For computing forest parameter estimates for computation units, sums of field plot weights to
317 pixels, $w_{i,p}$ are calculated by computation units, and by map stratum h over the pixels belonging to the
318 unit u . The weight of the plot i in map stratum h to computation unit u is denoted

$$c_{i,h,u} = a \sum_{p \in u_h} w_{i,p} \quad (3)$$

319 where u_h is the set of the pixels in the map stratum h , a is the pixel size. Ratio estimators with
320 these plot weights, that is with inclusion probabilities, are used for parameter estimation.

321 Predictions of some forest variables are expressed in the form of a digital map during the procedure
322 [Tomppo, 1991, 1996]. A pixel-level prediction of variable Y for pixel p on forest land is defined as

323

$$\tilde{y}_p = \sum_{i \in I_h} w_{i,p} y_i, \quad (4)$$

324 where y_i is the value of the forest variable Y on plot i , I_h the set of the field plots belonging to
325 map stratum h , and F the set of the plots i belonging to forest land. The mode or median value can be
326 used instead of the weighted average for categorical variables. Mode has turned out to work better than
327 median in the practical tests [Tomppo et al., 2009].

328 The Euclidean distance metric is widely used in many k-NN applications, but a distance metric
329 that is based on the weighted sum of spectral components and coarse-scale variables was developed
330 by Tomppo and Halme [2004]. This distance metric underpins the ik-NN methodology and also uses a
331 genetic algorithm for the optimisation of the feature variable weights. In the current work, we focus on
332 the basal area and growing stock volume estimates.

To compensate for systematic model prediction errors, we used model assisted estimators for the final estimates [Sarndal et al. , 1992, Baffetta et al., 2009]. For the totals, calculated with the inclusion probabilities (eq. 6), 'the correction term', C , is

$$C = \hat{A} \times \frac{1}{n} \sum_i^n \epsilon_i \quad (5)$$

where $\epsilon_i, i = 1, \dots, n$, are the prediction errors in the reference dataset set of a size of n , obtained, e.g., using leave-one-out cross validation and $\hat{A}$ is the estimate for the area in question, e.g., for forest area. The estimates of the means are corrected in similar manner, that is, just leaving out the estimate $\hat{A}$ in (Eq. 5).

A model-assisted estimator was used to calculate the confidence intervals of the k-NN and ik-NN estimates. The estimates are corrected using the estimated bias resulting from the systematic prediction error by comparing the reference data (field inventory plots) and the map data (k-NN and ik-NN estimates). The model assisted general regression estimators provided by [Sarndal et al. , 1992] are as follows:

$$\hat{\mu} = \frac{1}{N} \sum_{i=1}^N \hat{y}_i - \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (6)$$

and

$$\hat{Var}(\hat{\mu}) = \frac{1}{n(n-1)} \sum_{i=1}^n (\hat{y}_i - y_i)^2 \quad (7)$$

3. Results

3.1. Model Prediction Errors

The root mean square error (RMSE) for growing stock volume and the associated prediction error (mean deviations) are presented in Figure 8 for values of k from 1 to 10 from ik-NN using the optimal

run of the genetic algorithm heuristic search (blue lines) and the unweighted k-NN (red lines). This graph demonstrates that the optimised ik-NN yields lower RMSEs across all values of k in the three AOIs when compared to the unweighted k-NN. It also shows that $k=3$ provides the smallest pixel level RMSE for volume predictions, or represented the value of k at which the RMSEs levelled off. These values were (126-, 128- and 148- m^3/ha for AOIs West, South and East respectively) (Figure 8). Practical tests showed that the effect of the value of k on the regional level estimates played a smaller role than on the pixel level predictions. For consistency and due to the fact that some of our estimation regions were fairly small with a relatively small number of sample plots, we selected the smallest feasible value of k , that is 3. As a result, this value is used for the estimation process for the entire study area. The RMSEs expressed as a percentage of the mean of the NFI field plots are 55%, 42% and 60% for each of the respective AOIs.

Insert Figure 8

The estimation process was used to estimate the parameters across the entire study area excluding areas that were covered by cloud. The estimates were corrected based on the prediction error using Equation 5 as defined previously. The map and corresponding table of estimates by county are provided in Figure 9 and Table 2. The map is an indicative presentation of the distribution of growing stock volume across the national Forest Estate. The table of estimates by county include those from NFI, k-NN and ik-NN. At a national level, the NFI estimated that the total growing stock for the Forest Estate was 97 million m^3 ($\pm 4.4\%$), whereas the growing stock estimated using ik-NN is 102 million m^3 ($\pm 3\%$), which is within the upper confidence interval of the NFI estimate. The total estimate of gross standing volume calculated using k-NN was 126 million m^3 ($\pm 4\%$), which is considerably larger than the NFI and ik-NN estimates. These estimates are the cumulative total and therefore correspond to all tree species within the Forest Estate. At county level, the county with the largest forest area, county Cork has a total growing stock of 12 million $m^3 \pm 12\%$ as estimated from the NFI, while ik-NN estimated that the total growing stock was 11.8 million $m^3 \pm 6\%$. County Louth, in the north east of the

country, has the smallest forest area and correspondingly the smallest total volume in both the NFI and ik-NN estimates with the largest associated confidence interval, 100% and 76% for the NFI and ik-NN respectively. Despite this anomaly in county Louth, which is due to the small forest cover (and small number of NFI plots, six in total), the estimates from ik-NN are consistent with the NFI estimates, but with typically a narrower confidence interval. Whereas the county level estimates produced using the unweighted k-NN are all larger than either the NFI or ik-NN despite having similar confidence intervals.

Insert Figure 9 and Table 2

4. Discussion

This paper has presented a study to use ik-NN estimation optimised with a genetic algorithm to estimate growing stock volume per hectare for the Irish Forest Estate and compared the results to the Irish NFI results [Forest Service , 2013b] . The research builds on the initial pilot projects that were carried out in counties Clare and Wicklow using data from the first NFI [McInerney and Nieuwenhuis, 2009] and provides a robust approach to process the entire national Forest Estate using optical satellite imagery. There are multiple reasons that make ik-NN estimation an appropriate technique that can be easily integrated into forest inventories. Firstly, it is cost effective and produces spatially explicit estimates that could not be obtained when field data are used alone. Secondly, it uses a synthetic estimator, which utilises data outside of the area of interest. Thirdly, it is non-parametric and statistically oriented, meaning that there are no assumptions made regarding the underlying distribution of the data and the estimation process preserves the natural dependence between the forest variables.

In terms of comparisons to other studies, the meta-analysis carried out by Chirici et al. [2016] provides a good benchmark of the most important k-NN applications carried out on operationally around the world. In terms of the selection of k , the majority more than 60% of the k-NN applications used a value of k of less than or equal to five. This demonstrates that the selection of a value of three

used in the study is consistent with the majority of applications. In terms of the reported values of relative RMSE, it was found that almost 70% of the studies reported a relative RMSE of between 20-40%, which is lower than that reported in this analysis. However, if we consider the RMSEs obtained in studies focussing on temperate oceanic forests and/or those based on medium resolution satellite data (e.g. SPOT), the median relative RMSEs were 38% and 44% respectively. These figures are therefore consistent with the findings and results from this study.

More specifically, a study carried out in Japan to estimate stand volume using multi-spectral satellite data achieved relative RMSEs between 58% and 60% [Tanaka et al., 2015]. These findings are broadly similar to the relative RMSEs achieved in this study across the three AOIs (between 42% and 59%). Furthermore, Fazakas et al. [1999] achieved relative RMSEs of 66.6% in Sweden to estimate wood volume using satellite imagery. However, as in many studies dealing with k-NN applications, there is no detailed error assessment, as presented in this study which uses a model-assisted approach to calculate the associated confidence intervals of the estimates.

It is important to note that while the integration of Earth observation data into field inventory campaigns can contribute positively to the improvements in estimating forest parameters there will continue to be a requirement for field surveys for the purposes of creating or maintaining auxiliary reference layers (e.g. the forest mask maintained by the Irish Forest Service as part of their forestry vector database) as well as generating the coarse scale variables used as part of the ik-NN analysis. It is also necessary to note that the products generated from this approach can be used for indicative forest management at local scales, but there is too much uncertainty of the estimates at individual stand-level. The ik-NN method applied in this study reduces the prediction errors and standard errors for standing volume when compared to the NFI results (Table 2). Consequently, techniques, such as ik-NN and map products are intermediate products that allow for the production of confidence intervals.

One of the distinct benefits of this approach is that NFI data can be combined with pre-existing and largely free or low-cost satellite imagery to extend the applications and use of the NFI data. As a result

it can produce information that has the potential to inform policy, and act as an aid to sustainable forest management by providing data on the national resource that is timely, spatially complete, verifiable, and can be used for retrospective analysis. From an operational perspective, it is regarded that the NFI provides Estate-level estimates pertaining to the Ireland's forests, but that it is not designed, nor applicable at regional level. Consequently, the data products generated using ik-NN can be used to assist in the development of national and regional forest policies. From an operational planning perspective, many of the current models rely on either out-of-date forest inventory data and/or are based on assumptions regarding forest growth and developments. As a result, the data products generated using ik-NN provide an independent data source that can be used to validate and complement existing timber supply forecasts. This will enable national forest authorities to ascertain whether the assumptions underlying the forecast have been implemented correctly and whether they are biased.

With the advent of sensors such as Landsat-8 and Sentinel-2 there are more opportunities to avail of multi-temporal cloud-free observations of the Forest Estate, which can be combined with NFI data for these types of applications and which will allow for ik-NN analyses to be re-run at shorter time intervals in order to update map products and statistics.

Barrett et al. [2016] provided specific guidelines and identified best practice for countries initiating, expanding or revising the use of remotely sensed data in their NFIs. With the exception of adjustments to map based estimates for prediction errors, this study can be viewed as best practice in the use of plot based NFI data and Earth observation data. Future work will attempt to specifically focus on time-series analysis of ik-NN estimates with a view to quantifying changes in regional timber volume stocks.

5. Conclusions

Four primary conclusions can be drawn from this study:

- 448 1. The ik-NN method can add value to Irish NFI field plot data by using Earth observation data to
449 enhance estimates for the most meaningful and commonly reported forest resource parameters
450 and provides more accurate estimates than a simple, unweighted k-NN method.
 - 451 2. The precision of the ik-NN estimates are increased when the field data are combined with remote
452 sensing data and a model-assisted estimator.
 - 453 3. The ik-NN method developed by Tomppo and Halme [2004] is flexible, and when adapted to
454 local conditions, is suited to the specific Irish Forest Estate.
 - 455 4. The operational use of Earth observation data with Irish NFI field plot data can promote more ef-
456 ficient use of limited financial resources and increase the accuracy and precision of Forest Estate
457 estimates at geographic scales beyond what was originally intended. This is becoming increas-
458 ingly relevant with the widespread availability of free, multi-spectral satellite imagery, such as
459 Landsat-8 OLI and Sentinel-2. Furthermore, the derived products from this type of analysis are
460 needed for the preparation of up-to-date timber supply forecasts and regional management plans
461 as they provide robust information concerning the spatial distribution of timber volume.
- 462 Vegetation height data, such as those provided by airborne laser scanning (ALS), are being used
463 more and more as auxiliary variables for parameter estimation in operational forest inventories, but the
464 main obstacle associated within its operational use on a wall-to-wall basis is the cost and availability
465 of the data. For this reason, and given the relatively small cost and wider availability of multi-spectral
466 satellite imagery, methodologies that employ these latter data sources will remain more attractive for
467 bodies charged with carrying out NFIs at least in the short term. Furthermore, while frequent and
468 extensive cloud cover has historically been a barrier to national scale remote sensing surveys using
469 optical sensors in Ireland, multiple or dual constellation optical sensors satellite such as RapidEye and
470 Sentinel 2 [McInerney et al., 2016] can now potentially provide the required image data to facilitate
471 ik-NN parameter estimation in a flexible, timely and reliable way.

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600 **Tables**

Table 1. Spectral bands, Ground Sampling Distance (GSD) and swath of satellite sensors

Data source	Spectral bands	GSD	Swath
IRS-P6 LISS-3	4 spectral bands		141 km
	band 1 (Green) (0.52 – 0.59 μm)	23.5m	
	band 2 (Red) (0.62 – 0.68 μm)	23.5m	
	band 3 (NIR) (0.77 – 0.86 μm)	23.5m	
	band 4 (mid-IR)(1.55 – 1.70 μm)	23.5m	
SPOT-4	4 spectral bands		60 km
	band 1 (Green)(0.5 – 0.59 μm)	20m	
	band 2 (Red)(0.61 – 0.68 μm)	20m	
	band 3 (NIR) (0.78 – 0.89 μm)	20m	
	band 4 (SWIR)(1.58 – 1.75 μm)	20m	

Table 2. Gross standing volume by county estimated from NFI and *ik*-NN estimation including forest area, 95% Confidence Intervals

County	Total Forest (000s ha)	NFI Total volume 000s m ³ (95% CI)	<i>ik</i> -NN Total Volume 000s m ³ (95% CI)	<i>k</i> -NN Total Volume 000s m ³ (95% CI)
Carlow	8,400	1,272 (± 47%)	1,273 (± 33%)	1,936 (± 23%)
Cavan	16,830	1,931 (± 41%)	2,011 (± 15%)	1,548 (± 22%)
Clare	53,290	7,071 (± 17%)	6,981 (± 10%)	9,911 (± 9%)
Cork	83,620	12,513 (± 12%)	11,790 (± 6%)	15,135 (± 7%)
Donegal	55,380	6,202 (± 21%)	8,584 (± 6%)	8,888 (± 7%)
Dublin	5,220	1,197 (± 52%)	809 (± 20%)	1,216 (± 20%)
Galway	59,410	8,003 (± 13%)	8,793 (± 5%)	9,654 (± 6%)
Kerry	53,180	6,921 (± 22%)	8,296 (± 6%)	10,955 (± 8%)
Kildare	10,400	1,393 (± 35%)	1,045 (± 21%)	1,684 (± 18%)
Kilkenny	19,010	3,209 (± 24%)	3,365 (± 15%)	4,134 (± 12%)
Laois	25,260	4,632 (± 21%)	4,875 (± 17%)	6,024 (± 11%)
Leitrim	26,500	3,071 (± 26%)	3,577 (± 5%)	3,723 (± 7%)
Limerick	26,340	3,295 (± 25%)	3,253 (± 8%)	4,293 (± 8%)
Longford	8,360	1,059 (± 33%)	1,438 (± 9%)	1,199 (± 17%)
Louth	2,420	455 (± 100%)	12 (± 76%)	186 (± 25%)
Mayo	51,730	5,583 (± 17%)	5,949 (± 7%)	5,483 (± 14%)
Meath	12,490	1,566 (± 40%)	1,399 (± 17%)	1,867 (± 17%)
Monaghan	5,600	482 (± 44%)	537 (± 14%)	982 (± 16%)
Offaly	24,520	2,486 (± 28%)	2,354 (± 14%)	3,665 (± 13%)
Roscommon	25,880	4,060 (± 27%)	4,555 (± 11%)	5,590 (± 10%)
Sligo	20,590	3,108 (± 27%)	4,036 (± 7%)	4,179 (± 10%)
Tipperary	47,850	5,865 (± 17%)	6,125 (± 8%)	6,507 (± 9%)
Waterford	26,550	3,267 (± 24%)	3,266 (± 15%)	4,566 (± 12%)
Westmeath	13,180	1,084 (± 41%)	890 (± 11%)	1,634 (± 15%)
Wexford	13,840	1,705 (± 26%)	1,799 (± 14%)	2,816 (± 13%)
Wicklow	35,860	6,037 (± 24%)	5,665 (± 8%)	8,391 (± 8%)
Total	731,710	97,476 (± 5%)	102,677 (± 3%)	126,166 (± 4%)

601 **Figures**

Fig. 1. Spatial distribution of the NFI field plots overlaid on the Digital Terrain Model.

Fig. 2. Map detailing the extents of the three AOIs analysed as part of this research. In addition, areas unprocessed due to lack of satellite data are also mapped.

Fig. 3. NFI-2 scatterplots of basal area by volume and mean height on plot by volume. Boxplot distributions of growing stock volume per hectare and basal area per hectare by ownership

Fig. 4. Extent of satellite image scenes used for the nationwide *ik*-NN estimation: IRS LISS-III (AOIs: West & South) & SPOT-4 (AOI: East). Areas in white within the Irish land boundary are excluded from the analysis as no imagery were readily available for these areas)

(a) Coarse Scale Variable - Conifer Forest volume (b) Coarse Scale Variable - Broadleaf Forest volume

(c) Coarse Scale Variable - Mixed Forest volume (d) Coarse Scale Variable - Accumulated Temperature

Day Degrees

Fig. 5. Summary of Coarse Scale Variables used during by the genetic algorithm for the optimisation of explanatory variable weights

Fig. 6. Density distribution of the reference data (dashed line) and the target dataset (solid line) for the four bands from the LISS-III data. Note that the Density (y-axis) and the x-axis is the Digital Numbers of the satellite image bands.

Fig. 7. Three Models used in the genetic algorithm (0 CV: Zero Coarse Scale Variables, 1 CV: 1 Coarse Scale Variable; 5CV: 5 Coarse Scale Variables)

Fig. 8. Plots of RMSE and bias for unweighted k-NN (red) and ik-NN (blue) from the optimal run of the genetic algorithm for k=1:10. (AOI West: Solid line; AOI South: Long dash; AOI East: short dash)

Fig. 9. Nationwide map of growing stock volume per hectare at national scale estimated using ik-NN and genetic algorithm with county boundaries included. The inset map shows a subset of the Slieve Blooms forest, located in Laois.