1 **Delineation of the forest-tundra ecotone using texture-based classification of**

2 **satellite imagery**

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Delineation of the forest-tundra ecotone using texture-based classification of satellite imagery

The transition zone between the boreal forest and Arctic tundra, the forest-tundra ecotone (FTE), is an area of high ecological and climatological significance. Despite its importance, a globally consistent high spatial resolution mapping is lacking. Accurate mapping of the FTE requires the use of satellite remote sensing data. Here we use the Landsat Vegetation Continuous Fields (VCF) product and reference point data to derive the location and characteristics of the FTE. An image texture-based supervised classification scheme is developed based on a study area in Central Eurasia to statistically exploit the spatial patterns of the transition zone. Texture statistics for the VCF image are derived from the grey-level co-occurrence matrix (GLCM) based on which the study area is classified into forest, tundra, and FTEs. Adaptive parameterisation is implemented to achieve optimal classification performance in the study area. This method is further applied to six additional study areas around the circumarctic region to test its adaptability. In all study areas, this method achieves better FTE delineation results than previously reported methods, showing better classification accuracies (average of 0.826) and more realistic and complete representation of the FTE as shown by visual examination. This shows the universal applicability of the method and its potential to be used to achieve more detailed and accurate circumarctic mapping of the FTE, which could serve as the basis of time series analysis of FTE positions, eventually contributing to a better understanding of the inter-relations between climate change and shifts in sub-arctic vegetation.

Keywords: forest-tundra ecotone; Landsat VCF; sub-arctic vegetation, texture analysis; image classification

1. Introduction

The forest-tundra ecotone (FTE), also interchangeably termed the taiga-tundra ecotone (TTE) or the 'arctic treeline,' is the transition zone from closed canopy forest to treeless tundra, featuring changes in tree cover and density, tree size and shape (Sveinbjörnsson, Hofgaard and Lloyd, 2002), with a variety of spatial patterns which challenge globally consistent high resolution mapping (ref.). As a circumarctic phenomenon, the FTE is the world's largest vegetation transition zone (Ranson, Montesano and Nelson, 2011), spanning more than 13400km in length and up to

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several hundred kilometres in width (Callaghan *et al.*, 2002). The configuration, composition and dynamics of the FTE vary greatly through time and across the circumarctic region according to local to regional abiotic and biotic drivers including disturbance history (Hofgaard, Harper and Golubeva, 2012; Timoney *et al.*, 2018).

Most current global vegetation models predict encroachment of boreal forest onto the treeless tundra in response to global warming (Larsen *et al.*, 2014). Recent Earth System Models (Settele *et al.*, 2014) show a general northward migration trend, with forest areas displacing between 11% and 50% of the tundra within 100 years (Larsen *et al.*, 2014). However, circumarctic and worldwide, forest advance in FTE areas since 1900 has been observed in only about half of sites studied (Harsch *et al.*, 2009) despite considerable climate change (Larsen *et al.*, 2014). Regional influences complicate the actual patterns of FTE movement (Callaghan, Werkman and Crawford, 2002; Rees *et al.*, 2002; Harsch *et al.*, 2009; Van Bogaert *et al.*, 2011; Hofgaard *et al.*, 2013; Larsen *et al.*, 2014). The FTE in different subarctic regions has been found to remain static or in dynamic equilibrium (Masek, 2001), show an increase in biomass or crown closure without moving (Payette, Fortin and Gamache, 2001), or be within a northward (Esper and Schweingruber, 2004; Gamache and Payette, 2005; Hofgaard *et al.*, 2013) or southward (Vlassova, 2002; Crawford, Jeffree and Rees, 2003; Montesano *et al.*, 2009) movement stage, with different displacement rates found for different species and different structures (Payette, Fortin and Gamache, 2001; Crawford, 2008; Hofgaard *et al.*, 2013). This diversity of FTE change modes and discrepancy between model predictions and empirical findings (Van Bogaert *et al.*, 2011; Hofgaard *et al.*, 2013; Timoney *et al.*, 2018; Rees et al. in prep.) emphasise the need for precise spatial mapping of the current circumarctic FTE.

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73   A clear characterisation of the circumarctic FTE and its temporal progression through

74   observation is lacking despite its high ecological significance (Harsch and Bader, 2011; Montesano

75   *et al.*, 2016). Because of the vastness and predominant remoteness of the transition zone, remote

76   sensing is the only feasible approach to retrieve its configuration (Rees *et al.*, 2002; Ranson,

77   Montesano and Nelson, 2011). Various remote sensing methods can be utilised for this purpose,

78   including spectral based methods using products from multispectral imagery, e.g. NDVI

79   (Normalised Difference Vegetation Index) and VCF (Vegetation Continuous Fields) products,

80   Synthetic Aperture Radar (SAR) data, or hyperspectral imagery through which spectral profiles

81   for different vegetation types can be established and monitored (Govender, Chetty and Bulcock,

82   2007; Hu and Li, 2007; Darvishzadeh, 2008; Im and Jensen, 2008; Li, Chen and Chen, 2010; Wu

83   and Peng, 2012, Walther et al, 2019). Traditionally, studies have defined the FTE according to

84   vegetation metrics including tree density and cover, tree height, biomass, tree growth form and

85   proportions of different vegetation types e.g. tree-to-tundra area ratio (Timoney *et al.*, 1992;

86   Callaghan *et al.*, 2002; Montesano *et al.*, 2014, 2016).

87   The spatial structure of the FTE can potentially be exploited as a tool through which the

88   FTE can be statistically separated from other landcover classes (forest and tundra). In remote

89   sensing imagery, the spatial arrangement of surface feature can potentially be recognised using

90   surface texture analysis. The inclusion of texture information into image classification and land

91   cover mapping have improved classification accuracies (Blom and Daily, 1982; Greenspan and

92   Goodman, 1993; Haack and Bechdol, 2000; Ferro and Warner, 2002; Coburn and Roberts, 2004;

93   Herold, Haack and Solomon, 2004; Otukei, Blaschke and Collins, 2012), and proven helpful in

94   vegetation analysis and mapping (Coburn and Roberts, 2004; Wood *et al.*, 2012). However, no

95   study has yet incorporated texture information into the derivation of FTE areas.

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96   The aim of this study is to provide an FTE delineation algorithm which incorporates texture

97   measures into a supervised classification scheme using Landsat VCF and reference point data. We

98   further aim to make the algorithm adaptable to be used in different regions through variable

99   parameterisation adjusted for optimal performance locally. For this purpose, we developed the

100   algorithm in a study area in Central Eurasia, and tested the method in additional study areas around

101   the circumarctic region.

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103   **2. Materials and methods**

104   *2.1. Study areas*

105   This study splits the circumarctic region into seven sub-regions following the scheme of

106   Montesano et al. (2009). Longitudinal limits of each region are: Eastern Canada (ECA): 55°W–

107   80°W; Central/Western Canada (CWCA): 80°W–130°W; Alaska (ALA): 130°W–170°W;

108   Eastern Eurasia (EEU): 180°E–110°E; Central Eurasia (CEU): 110°E–60°E; Western Eurasia

109   (WEU): 60°E–40°E; Scandinavia (SCA): 40°E–4°E (Figure 1). The algorithm development part

110   of this study focuses on a region in Central Eurasia (128.52 by 150.72 km, centring on 61.928E,

111   66.953N) which straddles the transition from forest to tundra, thus encompassing the regional FTE

112   (Figure 2). The region was chosen where a recent circumarctic FTE characterisation (Ranson,

113   Montesano and Nelson, 2011) overlap with the location of the northern limit of boreal forest as

114   shown by the Circumpolar Arctic Vegetation Map (CAVM), which is a circumarctic-scale

115   vegetation map based on Advanced Very High Resolution Radiometer (AVHRR) data (Walker *et*

116   *al.*, 2005). Six additional study areas of similar sizes to the Central Eurasia study area are chosen

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117   to test the applicability of the developed FTE delineation method, one in each of the other six sub-

118   regions (Figure 1).

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134   ***2.2. Data***

135   *2.2.1. Vegetation Continuous Fields*

136   The VCF is an estimate of the proportion of a pixel occupied by tree cover derived from

137   multi-spectral satellite remote sensing images (Hansen & DeFries 2004). Formally, the pixel value

138   is an estimate of the amount of skylight obstructed by tree canopies of at least 5m in height

139   (Montesano et al. 2009). Thus, a VCF image is a continuous (per-pixel) representation of

140   vegetation cover across space which depicts areas of heterogeneous landcover, such as the FTE,

141   better than traditional discrete classification schemes (Montesano *et al.*, 2009; DiMiceli *et al.*,

142   2011; Townsend *et al.*, 2011). The first VCF product is generated from Moderate Resolution

143   Imaging Spectroradiometer (MODIS) data at a spatial resolution of 250m, with yearly coverage

144   from 2000 to present (DiMiceli et al 2011). The 250m spatial resolution and relatively long

145   temporal coverage make such products potentially suitable for large-scale study of ecotone

146   dynamics (Stow *et al.*, 2004; Montesano *et al.*, 2009), and have been used by numerous studies to

147   map tree cover (Cross and Settle, 1991; Zhu and Evans, 1994; Mayaux and Lambin, 1997; Tottrup

148   *et al.*, 2007; Heiskanen and Kivinen, 2008). A global FTE product already exists at MODIS

149   resolution, i.e. the Ranson et al. (2011) FTE, which is based on image segmentation on MODIS

150   VCF data adjusted using Quickbird-derived tree cover estimates.

151   This study uses the Landsat VCF product as the primary data source, which is the MODIS

152   VCF product densified to 30 m resolution using Landsat images. It thus having improved

153   discriminatory power for small forest patches and increased ability to identify vegetation

154   transitions more accurately. It is currently the highest-resolution multi-temporal global dataset of

155   tree cover, and has been shown to have similar accuracies to MODIS VCF (Sexton *et al.*, 2013).

156   The most recent version of the dataset ,version 3 (Sexton *et al.*, 2013), is used in this study, which

157   covers four nominal epochs: 2000, 2005, 2010 and 2015, derived from MODIS VCF data in the

158   corresponding years. However, visual examination of Landsat VCF in our study area shows that

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159 the product suffers from artefacts that are cloud and shadow contamination and inconsistencies

160 among VCF values from different scenes, and the severity of these defects varies greatly between

161 epochs. This study uses the Landsat VCF dataset having the fewest apparent artefacts and thus the

162 best quality among the available epochs (the 2000 epoch for the Central Eurasia study area), which

163 is ensured through visual inspection (Figure 2(c)).

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2.2.2. Reference point data

179   Reference data points where the type of vegetation cover can be identified are needed for

180 training and validation purposes. For this, 100 randomly distributed points are generated for the

181 selected study region through the 'Create Random Points' function in the ArcMap 10.4 software.

182 The landcover class of the data points are determined through visual interpretation of vegetation

183 distribution in the area surrounding each point, thus taking into consideration local context. This

184 is achieved through the examination of high-resolution Google Earth coverage of the study area

185 (Sentinel-2 data, 10m spatial resolution). Thus, the points are divided into four landcover classes

186 (forest, two types of FTE and tundra, Figure 2(c)).

187   It is necessary to separate FTEs into two small-scale and large-scale ones (hereafter

188 referred to as FTE1 and FTE2, respectively) as they both represent a transition from forest to tundra,

189 but at considerably different spatial scales, thus having vastly different spatial texture features.

190 Therefore, they can confuse the classification scheme if regarded as a single class. This distinction

191 between two FTE classes is different than in the Ranson et al. (2011) study where the FTE is also

192 separated into class 1, which are image segments with mean VCF values between 5 and 20, and

193 class 2 which are those with mean VCF values of less than 5 but with standard deviation values of

194 larger than 5. The examination of spatial texture relies on focal analysis on a small area around

195 each VCF pixel, and the transition in FTE1 occurs in similar spatial scale to these focal areas. Thus,

196 FTE1 are mostly altitudinal FTEs, but also small-scale FTEs without significant elevational change.

197 On the other hand, FTE2 represents transition zones much larger in scale, and thus appear to be

198 pixels surrounded by windows composed of relatively uniform pixels having 'intermediate' VCF

199 values. These pixels correspond to large-scale latitudinal FTEs. Additional data points are

200 manually added for the FTE1 class which have very few data points randomly generated, while

201 still ensuring relatively even distribution of all data points. The final numbers of forest, FTE1,

202 FTE2 and tundra data points are 20, 22, 39, and 19, respectively. Additionally, three altitudinal

203 FTE data points (therefore FTE1 points) available from the published literature (Wilmking *et al.*,

204 2012) are included in the study (Figure 2(c)). Landsat VCF data and the reference point data are

205 then processed in subsequent steps (Figure 3) into an FTE map of the study area:

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214 *2.3. VCF thresholding*

215   To provide a baseline for performance assessment of the texture-based classifiers, we first

216 perform simple thresholding of the VCF data. The Ranson et al. (2011) study identified the FTE

217 as image segments with mean VCF percentages between 5 and 20, or those with mean VCF

218 percentages of less than 5 and standard deviation values larger than 5. This threshold pair envelops

219 the 'intermediate VCF values' that are considered to represent the core of the FTE (Ranson,

220 Montesano and Nelson, 2011). However, forests in various parts of the circumarctic region may

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221 have different ranges of VCF values because of differences in structure and composition.

222 Therefore, an experiment is conducted to find the pair of VCF thresholds with which reference

223 data points in different landcover classes could be best distinguished. Thus, the intermediate VCF

224 value envelope is derived programmatically to best fit the study area. According to this model, a

225 pixel is classified as forest if its VCF value is above some upper threshold and as tundra if it is

226 below some lower threshold. Pixels with VCF values in between are classified as FTE. All possible

227 combinations of two VCF thresholds from 1 to 100 are investigated, and the classification

228 accuracies and kappa coefficients (Cohen, 1960) are recorded. The threshold pair that gives the

229 best accuracies as measured by these two metrics is selected as the optimal threshold pair for FTE

230 characterisation in the study area. Preference is given to the threshold pair that gives the highest

231 kappa coefficients when the result judging from the two metrics differ, since the kappa coefficient

232 takes into account the possibility of agreement occurring by chance and is considered more robust

233 statistic than simple accuracy. This new threshold pair (hereafter referred to as the adaptive

234 threshold pair) is compared with the Ranson et al. (2011) 5-20 threshold pair to test their abilities

235 to correctly separate different landcover classes.

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237 **2.4. FTE delineation based on supervised classification utilising texture measures**

238 *2.4.1. Texture measures used in this study*

239 Common measures of texture include first-order statistics such as variance, and second-

240 order statistics calculated on the basis of the grey-level co-occurrence matrix (GLCM) (Ferro and

241 Warner, 2002). The calculation of GLCMs, as proposed by Haralick et al. (1973), has proved to

242 be one of the most powerful tools to extract information of spatial structure from remote sensing

243   images (Weszka, Dyer and Rosenfeld, 1976; Conners and Harlow, 1980). It is a tabulation of how

244   often different combinations of grey levels co-occur in an image or image section (Yang *et al.*,

245   2009), based on which numerous texture features can be derived to represent local spatial

246   variations at pixels of interest. In this study, a total of 11 GLCM-based texture measures (termed

247   primary texture measures, Table 1, Equations (1)-(11)) are analysed for their ability to distinguish

248   between different landcover classes. In addition, eight texture measures derived from the primary

249   GLCM-based textures are included in the analysis (termed secondary texture measures, Table 1,

250   Equations (12)-(19)). Thus, a total of 19 texture measures are used in this study.

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262   Please put Table 1 here.

263 Where:

264 $P_{i,j}$ is the *(i, j)*th entry in the GLCM; μ_x, μ_y, σ_x and σ_y are the means and standard deviations of p_x

265 and p_y; N_g is the number of distinct grey levels in the quantised image;

266 $\sum_i$ is $\sum_{i=1}^{N_g}$; $\sum_j$ is $\sum_{j=1}^{N_g}$;

267 $P_{x+y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_{i,j}$, ($i+j=k$; k=2,3,…,2N_g); $P_{x-y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_{i,j}$, (|$i-j$|=$k$; k=0,1,…,N_g-1);

268 $P_x(i) = \sum_{j=1}^{N_g} P_{i,j}$; $P_y(j) = \sum_{i=1}^{N_g} P_{i,j}$;

269 $\text{HXY} = -\sum_i \sum_j P_{i,j} \log P_{i,j}$; $\text{HXY1} = -\sum_i \sum_j P_{i,j} \log p_x(i)p_y(j)$;

270 $\text{HXY2} = -\sum_i \sum_j p_x(i)p_y(j) \log p_x(i)p_y(j)$; and HX and HY are entropies of p_x and p_y.

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2.4.2. Derivation of optimal window size

273 Our FTE characterisation method relies on texture analysis, which considers not only VCF

274 values of the selected points, but also the spatial configuration of the landscape within the

275 surrounding windows. The actual implementation of texture analysis needs to be adapted for

276 different regions because of the difference in the spatial configuration of FTE areas, requiring

277 different parameterisation in the texture analysis algorithm. An appropriate window size and a

278 suitable set of texture measures are key parameters in the texture analysis, and need to be

279 determined first. In this study, an optimal window size is determined before the derivation of

280 optimal textures. This is because the optimal window size is a distance at which textures from

281 different landcover classes can be properly separated. It is therefore a geographic phenomenon

282 independent of texture selection, and is only dependent on the scale at which the unique textures

283 of the FTE are identifiable. More importantly, differences in window size can directly influence

284 the separating power of the texture measures, i.e. texture measures perform differently when

285 applied with different window sizes (Ge *et al.*, 2006).

286   The determination of an appropriate window size for texture analysis is crucial for two

287 reasons. Firstly, texture measures are calculated within a window around each point, and the

288 window size must be appropriate so that it is smaller than the object, in our case the FTE, but big

289 enough to include the characteristic variability of the object (Hall-Beyer, 2017). Secondly, past

290 studies have shown increased class separability with the incorporation of texture in addition to

291 spectral information in image classification, and this benefit generally increases with larger

292 window sizes which reduce random error and thus produces more stable textures. However, larger

293 window sizes also lead to larger edge effects and introduce systematic errors. More importantly,

294 the window size needs to be compatible with the scale of texture resolvable by the remote sensing

295 product used. Instead of using arbitrary and fixed geometric windows regardless of study area, this

296 study produces data-driven geographic windows in a window size with which texture analysis is

297 able to produce maximum separability between different landcover classes.

298   Spatial statistical methods like the semivariogram can potentially be used to determine the

299 scales of spatial variability in the VCF image, and thus to estimate optimal window sizes in texture

300 analysis. However, in this study we utilise the information from the data points to specifically find

301 the scale at which the FTE classes can be optimally separated from other classes, thus yielding

302 more focused and meaningful spatial scale outcome. Specifically, the separability between data

303 points of different landcover classes is calculated for the Central Eurasia region using all the 19

304 GLCM-based texture measures. This process is repeated for window sizes from 3 to 91 pixels to

305 encompass the range of window sizes in which different landcover classes can be identified

306 through visual inspection. We adopt the Transformed Divergence as a statistical measure to assess

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307   the separability between landcover classes. Transformed Divergence and the Jeffries Matusita

308   Distance are both commonly used for this purpose (Davis *et al.*, 1978), and while they have been

309   found to have similar performances in assessing class separability (Gong, Marceau and Howarth,

310   1992), the Jeffries Matusita Distance is computationally less efficient (Jensen and Lulla, 1987).

311   Transformed Divergence (TD) is defined as follows: (Otukei, Blaschke and Collins, 2012),

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$$TD_{ij} = 2\left(1 - e^{\frac{-D_{ij}}{8}}\right) \tag{20}$$

314   where:

315    $D_{ij} = \frac{1}{2}\text{trace}\left((\mathbf{C}_i - \mathbf{C}_j)(\mathbf{C}_i^{-1} - \mathbf{C}_j^{-1})\right) + \frac{1}{2}\text{trace}\left((\mathbf{C}_i^{-1} - \mathbf{C}_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T\right)$ (21)

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317   The subscripts i,j represent signatures of the selected classes; $\mathbf{C}_i$ and $\mathbf{C}_j$ are covariance

318   matrices of i and j; μ_i and μ_j are mean vectors of i and j.

319   Transformed Divergence has a range of 0 to $2\sqrt{2}$, with higher values showing higher

320   separability. Usually, Transformed Divergence values of higher than 1.9 are deemed to represent

321   separable classes, while those between 1.7 and 1.9 represent good separation and those below 1.7

322   shows poor separation (Jensen 1996). Since the purpose of our study is to isolate FTE from other

323   landcover classes, transformed divergence values are only calculated between the FTE category

324   (both FTE1 and FTE2) and forest and tundra, thus resulting in calculated values for four landcover

325   class pairs (FTE1 – forest, FTE1 – tundra, FTE2 – tundra, and FTE2 – forest). The window size at

326   which maximum total separability is achieved in all the class pairs is chosen as the optimal window

327   size to be used in subsequent steps.

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This is an Accepted Manuscript of an article published by Taylor & Francis inInternational Journal of Remote Sensing on 09062020, available online: http://www.tandfonline.com/full/10.1080/01431161.2020.1734254 .

2.4.3. Derivation of suitable texture measures

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330   All 19 GLCM-based texture measures (Table 1) are calculated for all data points (Figure

331   2(c)) using the determined optimal window size (cf. above). The next task is the determination of

332   an optimal set of texture measures which can separate the FTE from other landcover classes in a

333   statistically robust way. This is conducted in a two-step process. In the first step, for each landcover

334   class, mean values of all 19 texture measures for all the data points are calculated. T-tests are then

335   performed to assess the separability between average texture values from data points in each

336   landcover class pair. Since the variance of the VCF values of the four landcover classes and

337   therefore that of the resulted texture measures may not be equal, two-sample F-tests are conducted

338   to determine the equality of variance, and subsequent t-tests are altered in accordance to the F test

339   results. If variances are determined to be unequal, Satterthwaite's approximation of the effective

340   degrees of freedom is used (Satterthwaite, 1946). A texture measure is retained only if it shows

341   the ability to separate either or both the FTE classes from other classes, i.e. reporting with statistical

342   significance that the texture measure averages of points in FTE classes are different from those in

343   both forest and tundra classes.

344   In the second step, the remaining texture measures filtered by the t-tests go through the

345   Spearman rank correlation test to determine their collinearity, and texture measures which

346   correlate strongly with others and hence provide minimal additional discriminating power are

347   excluded. This test is used because of its nonparametric properties and tolerance of extreme values,

348   and its ability to test for monotonic relationships that are not necessarily linear. Specifically, an 8-

349   pixel neighbourhood area (3 by 3) is constructed centred on each data point, and each remaining

350   texture measure is calculated for every pixel within this neighbourhood. Summary mean and

351   standard deviation values are calculated for the texture measures in these neighbourhoods.

352   Spearman rank correlation is then calculated for each pair of texture measures based on the mean

353   and standard deviation summaries for all data points, assessing their collinearity. The result are

354   Spearman rank matrices for the mean and standard deviation summaries of every texture pair.

355   For each texture measure, its Spearman rank correlation coefficients with all other texture

356   measures are averaged, and the five texture measures with the lowest averages of the mean

357   summaries are kept for further analysis. Then, the rest of the texture measures with at least one

358   mean summary that shows no significant correlation (p value > 0.01) with others are kept. Texture

359   measures filtered out by these two steps have relatively strong correlation with others and should

360   be eliminated from further analysis. However, exceptions can be made when the standard deviation

361   summaries are not strongly correlated, suggesting their ability to capture unique textural

362   heterogeneity (Wood *et al.*, 2012). Thus, five texture measures among those filtered out by the

363   two-step process having the smallest averaged standard deviation summaries are kept for further

364   analysis.

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366   *2.4.4. Supervised classification*

367   The selected texture measures from the previous step are calculated for the entire image

368   using the optimal window size. The resulting texture measures are then fed into the maximum

369   likelihood classification algorithm. Water body pixels (identified in the VCF product by the mask

370   value of 200) are ignored in the classification process. In order to convey the distinction between

371   VCF values for different landcover classes to the classification algorithm, thresholded VCF images

372   are created both using the 5-20 and adaptive threshold pairs, and then also fed into the classification

373   process. The classification is executed with randomly selected half of the data points as training

374   data, and the other half for validation, while ensuring that half of each landcover class are kept for

375   both training and validation. Due to the fragmented nature of the classification result, a

376   generalisation process involving image segmentation is performed to filter out FTE segments too

377   small in size in order to achieve a more desirable transition zone feature. After the classification

378   process, the FTE1 and FTE2 classes are merged into a single FTE landcover class. The final FTE

379   derivation results are compared to previously delineated FTEs qualitatively through visual

380   inspection and quantitatively through classification accuracy and kappa coefficient.

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382   *2.5. Application to additional study areas*

383   The above FTE delineation method developed in Central Eurasia is used on FTEs in the

384   other six study areas to test its applicability. To streamline the data retrieval process and enhance

385   the adaptability of our method, we explore the feasibility of vegetation data retrieval and

386   processing from the Google Earth Engine platform, hereafter referred to as GEE (Gorelick *et al.*,

387   2017). Landsat VCF data intersecting with the study areas of the best quality are downloaded, and

388   the derivation of optimal window sizes and texture measures are performed locally in MATLAB.

389   Texture image calculation using the derived parameters are performed in GEE, and the resulting

390   texture images are downloaded to be used in supervised classification in ArcMap. GEE currently

391   has 18 GLCM textures available, two of which are duplicates (inertia and contrast), thus making a

392   total of 17 usable texture measures. Autocorrelation (AUT) and inverse difference (IND) are not

393   available in GEE, and we replace them by similar-performing measures, i.e. correlation (COR)

394   and homogeneity (HOM), respectively (Haralick, Shanmugan and Dinstein, 1973). If either or both

395   of the latter two are also among the selected list of texture measures, no replacement of the former

396   two is given. The same supervised classification method as used in the Central Eurasia study area

397   is implemented to separate FTE with other landcover classes, in which training and validation data

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398   also come from randomly generated reference points in the study areas (Figure 10). This workflow

399   offloads the most time-consuming tasks (VCF data retrieval and texture image calculation) to

400   GEE's cloud-computation platform which saves a considerable amount of processing time. It also

401   ensures that the detailed statistical procedures developed in this study are followed through local

402   processing, which are much less time-consuming and not available in GEE.

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404 3. Results

405 *3.1. VCF thresholding*

406   The adaptive VCF threshold pair enveloping FTE pixels is determined to be 5 and 10 for

407   the Central Eurasia region using the method described above, as this threshold pair yields the

408   highest overall accuracy and kappa coefficient in separating forest, FTE and tundra data points

409   (Figure 4).

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422   The thresholding approach results in a pixelated thresholded image not desirable for the

423   delineation of a transition zone (Figure 5), but serves as a reference of the distribution of VCF

424   values within the study area. A more detailed look at a subset of the image (Figure 5 c-e) shows

425   that the thresholded image produced from the adaptive threshold pair gives a more realistic

426   representation of the forest areas corresponding to Google Earth visualization (Figure 5 d&e), and

427   the forest areas in the 5-20 thresholded image show heavy encroachment from FTE points which

428   produces very fragmented forest patches (Figure 5 c&e). This is presumably attributable to the

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429 adaptive threshold pair being derived directly using the VCF values of the data points, thus

430 reflecting a better distinction between different landcover classes. Therefore, the adaptive

431 threshold pair will be used to threshold the VCF image to be used in the supervised classification

432 process.

433 Please put Figure 5 here.

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453   *3.2. FTE delineation based on supervised classification utilising texture measurements*

454   *3.2.1. Selection of optimal window size and optimal textures measures*

455   Calculated Transformed Divergence of the class pairs (Figure 6) shows that the FTE1-

456   Forest and FTE2-Tundra class pairs have generally higher separability. Both the FTE1-Tundra and

457   FTE2-Forest class pairs reach a local maximum at the 15×15 window size, where the FTE1-Forest

458   and FTE2-Tundra class pairs are also maintaining high levels of separability. Thus, a window size

459   of 15×15 is deemed to be the optimal window size based on which the GLCMs and texture

460   measures will be calculated and incorporated into the classification.

461   Please put Figure 6 here.

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474   The selected window size is used to derive the optimal set of texture measures. The t-test

475   keeps 17 texture measures based on which a Spearman rank matrix is established. Mean summaries

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476   of most texture measures are highly correlated, while the Spearman rank correlation coefficients

477   calculated from standard deviation summaries have a wider spread. Based on the selection criteria

478   described above, seven texture measures are kept: cluster shade, correlation, difference variance,

479   homogeneity, information measure of correlation 2, inverse difference and maximum probability.

480   They have low collinearity with other texture measures or higher collinearity with others but

481   relatively low coefficients calculated from the standard deviation summaries.

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483   *3.2.2. Classification and segmentation results*

484   Texture images are constructed based on the final list of texture measures using the optimal

485   window size of 15×15, and are then fed into the classification process along with the thresholded

486   VCF image. The classification based on the 5-20 and 5-10 threshold pairs after merging the two

487   FTE classes (Figure 7) loses some of the fine details on the surface, which is expected from the

488   nature of the windowing approach in texture analysis.

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508   A more detailed qualitative comparison between and FTE areas derived using different

509   methods in a subset of the study area (Figure 8) shows that classification based on the adaptive

510   threshold pair yields a more realistic picture of FTE distribution comparatively when compared to

511   the Google Earth coverage of the study area.

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512 Please put Figure 8 here.

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521   Quantitative evaluation of the classification result is conducted using half of the data points

522   as validation (section 2.4.4). Quantitative assessment of the results (Table 2) shows that

523   classification based on the adaptive threshold pair yields higher accuracies than that based on the

524   5-20 threshold pair. Simple thresholding produces similar and higher accuracies than classification

525   based on the 5-20 threshold pair, but is outperformed by that based on the adaptive one, which

526   produces higher accuracy and kappa coefficient than all other methods. It is therefore the optimal

527 FTE delineation approach for our study area. Classification accuracy and kappa coefficient

528 calculated for the Ranson et al. (2011) FTE are based on two categories: FTE vs. non-FTE.

529 Please put Table 2 here.

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536 The supervised classification method based on calculated texture measures and the

537 adaptively thresholded VCF image, which produces the highest accuracies, is used to create the

538 final output of this study (Figure 9) – a map of FTE pixels (in green) in the study area.

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558   *3.3. Application to additional study areas*

559   The application of the above FTE delineation method to the additional six study areas is

560   conducted mainly locally in MATLAB and ArcMap, with GLCM texture images calculated in

561   GEE. On average, the application of GEE-based texture image calculation reduces the processing

562   time from approximately 2.5 hours to approximately 3 minutes per texture measure, greatly

563   expediting the analysis. FTEs derived using our classification method with these adaptive VCF

564   threshold pairs consistently produce the highest classification accuracy compared to other methods,

565   as can be seen from the comparison between Google Earth coverages of the study areas, Landsat

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566   VCF dataset and reference point data, the Ranson et al., (2011) FTE, and the FTE derived using

567   our method shown in Figure 10 and Table 3. FTE delineated using VCF thresholding also shows

568   higher accuracies when using the adaptive threshold pairs. Supervised classification using the 5-

569   20 threshold yields generally lower accuracies than VCF thresholding, except for the ALA and

570   CWCA study areas where they show similar or higher accuracies.

571   Please put Table 3 here.

572   Please put Figure 10 here.

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4. Discussion

The results suggest that the Landsat VCF product is a useful data source for FTE delineation which provides reasonable spatial resolution, and a texture-based classification method based on VCF values is able to reliably extract FTE information. For the Central Eurasia study area, the Landsat VCF product produces a more detailed depiction of the FTE area than the previous global FTE product (Ranson, Montesano and Nelson, 2011) derived from MODIS VCF, which is based on segmentation before thresholding with arbitrary limits of segment sizes. The MODIS-based FTE product creates large FTE patches that often include tundra areas that have been recognised as being within the same segments as the FTE pixels, see for example the FTE segment designated by letter 'A' in Figure 8.

Selecting the correct threshold pair is crucial for satisfactory performance of the texture-based classification method. FTE derived from classification based on the adaptive threshold pair produces smaller FTE patches than that based on the 5-20 one (Figure 7), which is also true for simple VCF thresholding (Figure 5), as expected. This corresponds to the forest areas in the study area producing VCF values of mostly around 10 to 20 due to relatively small biomass, thus making the 5-20 threshold pair unreliable. This hypothesis was partially validated by the typical tree heights of around 3-5 m in forests calculated from shadow length and capture time from the Google Earth coverage (e.g. Mathisen *et al.*, 2013). The inclusion of texture images into classification has resulted in improved classification accuracies, consistent with previous findings (e.g. Coburn and Roberts, 2004; Ferro and Warner, 2002; Otukei et al., 2012). Compared to other methods, classification based on the adaptive threshold pair yields a more realistic representation of FTE distribution when compared to the Google Earth coverage of the study area (Figure 8). This method also produces higher accuracy and kappa coefficient than all other methods. Simple thresholding

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610   produces similar and higher accuracies than classification based on the 5-20 threshold pair, further

611   confirming the importance of adaptive thresholding in the classification algorithm.

612   For the additional study areas, the optimal VCF threshold pairs, window sizes and texture

613   measures derived for different study areas vary considerably. The results show that FTE

614   delineation using texture-based classification based on adaptive VCF thresholding produces

615   consistently highest accuracies (Table 3), and again emphasises the need for adaptive

616   parameterisation in achieving optimal FTE delineation results. Qualitatively, our method produces

617   FTEs corresponding well with transition areas from forest to tundra shown in the Google Earth

618   coverages (Figure 10). Our method largely produces FTEs with similar placements to the Ranson

619   et al. (2011) FTE product, but with additional representation of small-scale FTEs and with more

620   spatial details for large-scale FTEs. They have more similar FTE placements for study areas where

621   large-scale FTEs are more spatially concentrated (WEU, EEU, ALA and CWCA). In other study

622   areas with more spread-out FTEs (as verified by visual examination of the Google Earth coverage

623   and also placement of VCF pixels with 'intermediate' VCF values), our method produces a more

624   complete representation of the transition zone. The MODIS-based FTE product misses part of the

625   FTE due to the limit in segment sizes and thus incomplete derivation of transition zones with

626   spread-out FTE pixels. Thus, our study provides a viable approach to delineating both large and

627   small-scale FTE areas across the circumarctic region.

628   The FTE delineation problem is highly scale-dependent. The MODIS VCF product

629   provides good spatial and temporal coverage for circumarctic FTE delineation, but FTE

630   recognition based on this product is limited by its 250m spatial resolution whereby local

631   transitional details can be overlooked. The Landsat VCF product also provides global coverage

632   but with finer spatial resolution, and our study proves that it can be used to derive large-scale FTE

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633 areas with the use of texture analysis. The Landsat resolution also enables the recognition of small-

634 scale FTEs not resolvable by the MODIS VCF product. It is therefore a more versatile tool for the

635 purpose of FTE delineation. With the even higher spatial resolution of the other satellite image

636 products, e.g. Sentinel-2 data (K. Fletcher, 2012), more spatial characteristics of FTEs can be

637 revealed, but the limited availability of usable cloud-free imagery limits its use in the effort at

638 deriving a universally adaptable method for circumarctic FTE delineation.

639 One important source of error in this study is the high dependence on the selection of

640 reference data points, which is based on inspection of high-resolution Google Earth coverage of

641 the study areas in addition to point data derived from previous work. The adaptive selection of

642 threshold pairs for dividing landcover classes based on VCF values, the calculation of optimal

643 window size and optimal set of texture measures are all dependent on correct classification of

644 reference data points. Data sources apart from locally generated random points are desirable to

645 improve confidence in the ground truth. Such data are available, for example, through the PPS

646 Arctic long-term monitoring network (http://ppsarctic.nina.no). Also, this study is built upon the

647 VCF products and thus affected by inaccuracies in these datasets including systematic errors as

648 well as the prevalent image artefacts (White, Shaw and Ramsey, 2005; Sexton *et al.*, 2013), which

649 is a major consideration in the selection of the epoch of the VCF dataset. Future application of our

650 method is likely limited by the availability of quality data in the areas of interest, which can

651 potentially be remedied by future improvements in Landsat VCF data quality, local image fusion

652 of Landsat scenes and MODIS VCF data, or the incorporation of higher-resolution datasets.

653 In this study, the maximum probability classifier is chosen in consideration of processing

654 time given the number and sizes of the study areas, an also because the emphasis of this study is

655 on the incorporation of image texture into the classification workflow. In future application of this

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656 method, more advanced classification techniques can be used to further improve on the

657 performance of the classification process. Finally, this study only looks into the horizontal spatial

658 arrangement of the landscape and does not include an analysis of the vertical dimension of the

659 FTE. FTE delineation can benefit from elevation information since the occurrence and placement

660 of altitudinal FTEs are associated with local topographic variation. Also, at a very high spatial

661 resolution, FTE delineation can benefit from tree height information e.g. from satellite LiDAR

662 products (Montesano et al., 2016b), as tree height variation is also an important component of

663 vegetation structural change through the FTE.

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4.1. Future tasks

666   This study provides an adaptable method for FTE delineation based on Landsat VCF which

667 can potentially be used in different parts of the circumarctic region. A future task would be to

668 create a circumarctic FTE map based on our method, a prerequisite of which is a reasonable

669 division scheme of the circumarctic region which recognises the ranges of VCF values of different

670 landcover classes in different regions. For example, the Montesano et al. (2009) division of the

671 circumarctic region can be used as a starting point, based on which sensitivity analyses can be

672 conducted to achieve geographically and ecologically meaningful sub-regions. Adaptive

673 thresholds can then be established for each sub-region. This circumarctic FTE product based on

674 different epochs of the Landsat VCF product (currently 2000, 2005, 2010 and 2015) can be used

675 to construct a times series of FTE change through the past two decades. The derivation of a

676 circumarctic product demands sufficient reference data points to be established whose landcover

677 classes can be determined and verified, either through field work or visual recognition based on

678 satellite imagery.

679   As previously noted, the location and spatial pattern of both latitudinal and altitudinal FTEs

680   vary greatly across the circumarctic region. These regional differences represent the effect of a

681   wide range of local influencing factors, the relative importance of which has great implications on

682   the ecotone's vulnerability to shift with climatic change. Therefore, it is necessary to move beyond

683   the task of FTE delineation and explore more detailed spatial patterns within the FTE areas. In this

684   study, texture information is only used to separate FTE areas from tundra and forest. However,

685   texture analysis is also potentially useful in the examination of the spatial configuration of FTEs

686   in different regions. Through observation, recent studies have confirmed a close link between

687   different FTE spatial patterns (FTE 'forms') and FTE movement in response to climate change

688   (Holtmeier, 2010; Harsch and Bader, 2011). Each FTE form is unique in the spatial arrangement

689   of vegetation which will be represented in their varying textures in remotely sensed images, which

690   can be exploited to identify and map different FTE forms, thus facilitating the identification of

691   FTEs that are the most vulnerable to shift with climate change. The analysis of these local

692   variations will rely on higher resolution datasets such as Sentinel-2 data, and the correspondence

693   between FTE forms and vulnerability can be validated by the incorporation of study sites where

694   historical records of FTE movements are available.

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696   **5. Conclusion**

697   This study introduces a texture-based classification approach to the FTE delineation

698   problem. The incorporation of texture measures is theoretically relevant in FTE delineation

699   because the FTE is a unique transition zone in which the mosaic distribution of forest and tundra

700   creates unique spatial patterns inexistent in either side of the ecotone. Compared to other

701   vegetation products, the reliable global coverage and reasonable spatial resolution provided by the

702   Landsat VCF is considered to be optimal for the purpose of FTE delineation. This study provides

703   a versatile delineation approach of multi-scale FTEs based on the Landsat VCF dataset, and

704   provide objective and adaptable approaches to every component of the texture-based FTE

705   delineation process through statistical determination of analysis parameters. It is based on

706   reference data points derived from expert knowledge and thus takes the specificities of the study

707   area into consideration, and also considers the spatial patterns surrounding the data points.

708   Compared to pixel-based thresholding and segmentation, our method provides a relatively natural

709   representation of a transitional area, utilising the information of VCF gradient while preserving

710   reasonable continuity of the interface, and is robust in handling small-scale variations. Quantitative

711   assessment also suggests that our method is able to provide more accurate FTE delineation results

712   than others. Our method can be potentially used to create a circumarctic map of the FTE based on

713   which a time series of circumarctic FTE change can be derived. This can potentially serve as a

714   more accurate baseline for future studies seeking to understand the interactions between arctic

715   vegetation and climatic change, and help models to explain and predict vegetation response to

716   global warming.

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References

Blom, R. and Daily, M. (1982) 'Radar image processing for rock-type discrimination', *IEEE Transactions on Geoscience and Remote Sensing*, (3), pp. 343–351. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4157309.

Van Bogaert, R. *et al.* (2011) 'A century of tree line changes in sub-Arctic Sweden shows local and regional variability and only a minor influence of 20th century climate warming', *Journal of Biogeography*, 38(5), pp. 907–921. doi: 10.1111/j.1365-2699.2010.02453.x.

Callaghan, T. V *et al.* (2002) 'The Dynamics of the Tundra-Taiga Boundary: An Overview and Suggested Coordinated and Integrated Approach to Research', *Ambio Special Report*, (12), pp. 3–5.

Callaghan, T. V, Werkman, B. R. and Crawford, R. M. M. (2002) 'The Tundra-Taiga Interface and Its Dynamics: Concepts and Applications', *Ambio Special Report*, (12), pp. 6–14. doi: 10.2307/25094570.

Coburn, C. a. and Roberts, a. C. B. (2004) 'A multiscale texture analysis procedure for improved forest stand classification', *International Journal of Remote Sensing*, 25(20), pp. 4287–4308. doi: 10.1080/0143116042000192367.

Cohen, J. (1960) 'A coefficient of agreement for nominal scales', *Educational and psychological measurement*. Sage Publications Sage CA: Thousand Oaks, CA, 20(1), pp. 37–46.

Conners, R. W. and Harlow, C. A. (1980) 'A theoretical comparison of texture algorithms', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-2(3), pp. 204–222. doi: 10.1109/TPAMI.1980.4767008.

Crawford, R. M. M. (2008) *Plants at the margin: ecological limits and climate change*. Cambridge University Press.

Crawford, R. M. M., Jeffree, C. E. and Rees, W. G. (2003) 'Paludification and Forest Retreat in Northern Oceanic Environments', *Annals of Botany*, 91(2), pp. 213–226. doi: 10.1093/aob/mcf185.

Cross, A. and Settle, J. (1991) 'Subpixel measurement of tropical forest cover using AVHRR

751   data', *International Journal of Remote Sensing*, 12(5), pp. 1119–1129. doi:

752   10.1080/01431169108929715.

753   Darvishzadeh, R. (2008) *Hyperspectral remote sensing of vegetation parameters using statistical*

754   *and physical models*, *GeoInformation Science*. Available at:

755   http://www.itc.nl/library/papers_2008/phd/roshanak.pdf.

756   Davis, S. M. *et al.* (1978) 'Remote sensing: the quantitative approach', *New York, McGraw-Hill*

757   *International Book Co., 1978. 405 p.*

758   DiMiceli, C. M. *et al.* (2011) *MODIS Vegetation Continuous Fields*, *Global Land Cover*

759   *Facility*. Available at: http://glcf.umd.edu/data/vcf/description.shtml.

760   Esper, J. and Schweingruber, F. H. (2004) 'Large-scale treeline changes recorded in Siberia',

761   *Geophysical Research Letters*, 31(6), p. L06202. doi: 10.1029/2003GL019178.

762   Ferro, C. J. S. and Warner, T. A. (2002) 'Scale and texture in digital image classification',

763   *Photogrammetric Engineering & Remote Sensing*, 68(1), pp. 51–63.

764   Gamache, I. and Payette, S. (2005) 'Latitudinal response of subarctic tree lines to recent climate

765   change in eastern Canada', *Journal of Biogeography*, 32, pp. 849–862. doi: 10.1111/j.1365-

766   2699.2004.01182.x.

767   Ge, S. *et al.* (2006) 'Texture analysis for mapping Tamarix parviflora using aerial photographs

768   along the Cache Creek, California', *Environmental Monitoring and Assessment*, 114(1–3), pp.

769   65–83. doi: 10.1007/s10661-006-1071-z.

770   Gong, P., Marceau, D. J. and Howarth, P. J. (1992) 'A comparison of spatial feature extraction

771   algorithms for land-use classification with SPOT HRV data', *Remote Sensing of Environment*,

772   40(2), pp. 137–151. doi: 10.1016/0034-4257(92)90011-8.

773   Gorelick, N. *et al.* (2017) 'Google Earth Engine: Planetary-scale geospatial analysis for

774   everyone', *Remote Sensing of Environment*. The Author(s), 202, pp. 18–27. doi:

775   10.1016/j.rse.2017.06.031.

776   Govender, M., Chetty, K. and Bulcock, H. (2007) 'A review of hyperspectral remote sensing and

777   its application in vegetation and water resource studies', *Water SA*, 33(2), pp. 145–151. doi:

778   10.4314/wsa.v33i2.49049.

779   Greenspan, H. and Goodman, R. M. (1993) 'Remote Sensing Image Analysis via a Texture

780   Classification Neural Network', *Advances in Neural Information Processing Systems 5*, pp. 425–

781   432. Available at: http://papers.nips.cc/paper/636-remote-sensing-image-analysis-via-a-texture-

782   classification-neural-network.pdf%5Cnfiles/3248/Greenspan ? Goodman - 1993 - Remote

783   Sensing Image Analysis via a Texture Classi.pdf%5Cnfiles/3249/636-remote-sensing-image-

784   analysis.

785   Haack, B. and Bechdol, M. (2000) 'Integrating multisensor data and RADAR texture measures

786   for land cover mapping', *Computers and Geosciences*, 26(4), pp. 411–421. doi: 10.1016/S0098-

787   3004(99)00121-1.

788   Hall-Beyer, M. (2017) 'Practical guidelines for choosing GLCM textures to use in landscape

789   classification tasks over a range of moderate spatial scales', *International Journal of Remote*

790   *Sensing*, 38(5), pp. 1312-1338. doi: 10.1080/01431161.2016.1278314.

791   Haralick, R., Shanmugan, K. and Dinstein, I. (1973) 'Textural features for image classification',

792   *IEEE Transactions on Systems, Man and Cybernetics*, pp. 610–621. doi:

793   10.1109/TSMC.1973.4309314.

794   Harsch, M. A. *et al.* (2009) 'Are treelines advancing? A global meta-analysis of treeline response

795   to climate warming', *Ecology Letters*, 12(10), pp. 1040–1049. doi: 10.1111/j.1461-

796   0248.2009.01355.x.

797   Harsch, M. A. and Bader, M. Y. (2011) 'Treeline form - a potential key to understanding treeline

798   dynamics', *Global Ecology and Biogeography*, 20(4), pp. 582–596. doi: 10.1111/j.1466-

799   8238.2010.00622.x.

800   Heiskanen, J. and Kivinen, S. (2008) 'Assessment of multispectral, -temporal and -angular

801   MODIS data for tree cover mapping in the tundra-taiga transition zone', *Remote Sensing of*

802   *Environment*, 112(5), pp. 2367–2380. doi: 10.1016/j.rse.2007.11.002.

803   Herold, N. D., Haack, B. N. and Solomon, E. (2004) 'An evaluation of radar texture for land

804   use/cover extraction in varied landscapes', *International Journal of Applied Earth Observation*

805   *and Geoinformation*, 5(2), pp. 113–128. doi: 10.1016/j.jag.2004.01.005.

806   Hofgaard, A. *et al.* (2013) 'Latitudinal forest advance in northernmost Norway since the early
807   20th century', *Journal of Biogeography*, 40(5), pp. 938–949. doi: 10.1111/jbi.12053.

808   Hofgaard, A., Harper, K. A. and Golubeva, E. (2012) 'The role of the circumarctic forest-tundra
809   ecotone for Arctic biodiversity', *Biodiversity*, 13(3–4), pp. 174–181. doi:
810   10.1080/14888386.2012.700560.

811   Holtmeier, K. (2010) 'Altitudinal and polar treelines in the northern hemisphere Causes and
812   response to climate change', *Polarforschung*, 79(September 2009), pp. 139–153.

813   Hu, B. and Li, Q. (2007) 'Vegetation classification using hyperspectral remote sensing and
814   singular spectrum analysis', in *Proc. SPIE*, p. 66960N. Available at:
815   http://dx.doi.org/10.1117/12.735278.

816   Im, J. and Jensen, J. R. (2008) 'Hyperspectral remote sensing of vegetation', *Geography*
817   *Compass*, 2(6), pp. 1943–1961. doi: 10.1111/j.1749-8198.2008.00182.x.

818   Jensen, J. R. and Lulla, K. (1987) 'Introductory digital image processing: a remote sensing
819   perspective'. Taylor & Francis.

820   K. Fletcher (2012) *Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational*
821   *Services*. Available at: https://sentinel.esa.int/web/sentinel/home.

822   Larsen, J. N. *et al.* (2014) 'Polar regions', in Barros, V. R. et al. (eds) *Climate Change 2014:*
823   *Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working*
824   *Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change*.
825   Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, pp. 1567–
826   1612.

827   Li, D., Chen, S. and Chen, X. (2010) 'Research on method for extracting vegetation information
828   based on hyperspectral remote sensing data', *Transactions of the Chinese Society of Agricultural*
829   *Engineering*. Editorial Office of Transactions of the Chinese Society of Agricultural
830   Engineering, 26(7), pp. 181–185.

831   Masek, J. (2001) 'Stability of boreal forest stands during recent climate change: evidence from
832   Landsat satellite imagery', *Journal of biogeography*, 28(8), pp. 967–976. doi: 10.1046/j.1365-
833   2699.2001.00612.x.

834   Mathisen, I. E. *et al.* (2013) 'Fifty years of tree line change in the Khibiny Mountains, Russia:

835   advantages of combined remote sensing and dendroecological approaches', *Applied Vegetation*

836   *Science*, 17(1), pp. 6–16. doi: 10.1111/avsc.12038.

837   Mayaux, P. and Lambin, E. F. (1997) 'Tropical forest area measured from global land-cover

838   classifications: Inverse calibration models based on spatial textures', *Remote Sensing of*

839   *Environment*, 59(96), pp. 29–43. doi: 10.1016/S0034-4257(96)00077-6.

840   Montesano, P. M. *et al.* (2009) 'MODIS tree cover validation for the circumpolar taiga–tundra

841   transition zone', *Remote Sensing of Environment*, 113(10), pp. 2130–2141. doi:

842   10.1016/j.rse.2009.05.021.

843   Montesano, P. M. *et al.* (2014) 'The uncertainty of plot-scale forest height estimates from

844   complementary spaceborne observations in the taiga-tundra ecotone', *Remote Sensing*, 6(10), pp.

845   10070–10088. doi: 10.3390/rs61010070.

846   Montesano, P. M. *et al.* (2016) 'Spaceborne potential for examining taiga-tundra ecotone form

847   and vulnerability', *Biogeosciences Discussions*, (January), pp. 1–36. doi: 10.5194/bg-2015-575.

848   Otukei, J. R., Blaschke, T. and Collins, M. (2012) 'A Decision Tree Approach for Identifying the

849   Optimum Window Size for Extracting Texture Features from TerraSAR-X Data', *GI Forum*

850   *2012: Geovizualisation, Society and Learning*, pp. 466–474.

851   Payette, S., Fortin, M.-J. and Gamache, I. (2001) 'The Subarctic Forest–Tundra: The Structure of

852   a Biome in a Changing Climate', *BioScience*. Oxford University Press, 51(9), pp. 709–718.

853   Ranson, K. J., Montesano, P. M. and Nelson, R. (2011) 'Object-based mapping of the

854   circumpolar taiga–tundra ecotone with MODIS tree cover', *Remote Sensing of Environment*.

855   Elsevier B.V., 115(12), pp. 3670–3680. doi: 10.1016/j.rse.2011.09.006.

856   Rees, G. *et al.* (2002) 'How Can the Dynamics of the Tundra-Taiga Boundary Be Remotely

857   Monitored?', *Ambio Special Report*. Springer on behalf of Royal Swedish Academy of Sciences,

858   (12), pp. 56–62. doi: 10.2307/25094576.

859   Satterthwaite, F. E. (1946) 'An approximate distribution of estimates of variance components',

860   *Biometrics bulletin*. JSTOR, 2(6), pp. 110–114.

861   Settele, J. *et al.* (2014) 'Terrestrial and inland water systems', in Field, C. B. et al. (eds) *Climate*

862   *Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects.*

863   *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel*

864   *of Climate Change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge

865   University Press, pp. 271–359.

866   Sexton, J. O. *et al.* (2013) 'Global, 30-m resolution continuous fields of tree cover: Landsat-

867   based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error',

868   *International Journal of Digital Earth*, 6(5), pp. 427–448. doi: 10.1080/17538947.2013.786146.

869   Stow, D. A. *et al.* (2004) 'Remote sensing of vegetation and land-cover change in Arctic Tundra

870   Ecosystems', *Remote Sensing of Environment*, 89, pp. 281–308. doi: 10.1016/j.rse.2003.10.018.

871   Sveinbjörnsson, B., Hofgaard, A. and Lloyd, A. (2002) 'Natural causes of the tundra-taiga

872   boundary.', *Ambio Special Report*, (12), pp. 23–29. doi: 10.2307/25094572.

873   Timoney, K. P. *et al.* (1992) 'The high subarctic forest-tundra of northwestern Canada: position,

874   width, and vegetation gradients in relation to climate', *Arctic*, 45(1), pp. 1–9.

875   Timoney, K. P. *et al.* (2018) 'Tree cover response to climate change in the forest-tundra of north-

876   central Canada : fire-driven decline , not northward advance', *Écoscience*. Taylor & Francis,

877   26(2), pp. 133–148. doi: 10.1080/11956860.2018.1532868.

878   Tottrup, C. *et al.* (2007) 'Mapping fractional forest cover across the highlands of mainland

879   Southeast Asia using MODIS data and regression tree modelling', *International Journal of*

880   *Remote Sensing*. Taylor & Francis, 28(1), pp. 23–46.

881   Townsend, J. *et al.* (2011) *User Guide for the MODIS Vegetation Continuous Fields product*

882   *Collection 5 version 1*.

883   Vlassova, T. K. (2002) 'Human impacts on the tundra-taiga zone dynamics: the case of the

884   Russian lesotundra', *Ambio Special Report*, (12), pp. 30–36. Available at:

885   http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&list

886   _uids=12374057.

887   Walker, D. a *et al.* (2005) 'The Circumpolar Arctic vegetation map', *Journal of Vegetation*

888   *Science*, (16), pp. 267–282. doi: 10.1658/1100-9233(2005)016[0267:TCAVM]2.0.CO;2.

889   Walther, C. et al. (2019) 'Modelling the Arctic taiga-tundra ecotone using ALOS PALSAR and

890   optical earth observation data', *Int J Appl Earth Obs Geoinformation*, (81), pp. 196-206. doi:

891   10.1016/j.jag.2019.05.008.

892   Weszka, J. S., Dyer, C. R. and Rosenfeld, A. (1976) 'Comparative Study of Texture Measures

893   for Terrain Classification.', *IEEE Transactions on Systems, Man and Cybernetics*, SMC-6(4), pp.

894   269–285. doi: 10.1109/TSMC.1976.5408777.

895   White, M. a., Shaw, J. D. and Ramsey, R. D. (2005) 'Accuracy assessment of the vegetation

896   continuous field tree cover product using 3954 ground plots in the south-western USA',

897   *International Journal of Remote Sensing*, 26(July 2014), pp. 2699–2704. doi:

898   10.1080/01431160500080626.

899   Wilmking, M. *et al.* (2012) 'Continuously missing outer rings in woody plants at their

900   distributional margins', *Dendrochronologia*. Elsevier GmbH., 30(3), pp. 213–222. doi:

901   10.1016/j.dendro.2011.10.001.

902   Wood, E. M. *et al.* (2012) 'Image texture as a remotely sensed measure of vegetation structure',

903   *Remote Sensing of Environment*. Elsevier Inc., 121, pp. 516–526. doi: 10.1016/j.rse.2012.01.003.

904   Wu, J. and Peng, D. (2012) 'Vegetation classification technology of hyperspectral remote

905   sensing based on spatial information', *Transactions of the Chinese Society of Agricultural

906   Engineering*. Editorial Office of Transactions of the Chinese Society of Agricultural

907   Engineering, 28(5), pp. 150–153.

908   Yang, W. *et al.* (2009) 'Supervised land-cover classification of TerraSAR-X imagery over urban

909   areas using extremely randomized clustering forests', *2009 Joint Urban Remote Sensing Event*,

910   pp. 1–6. doi: 10.1109/URS.2009.5137603.

911   Zhu, Z. and Evans, D. L. (1994) 'US forest types and predicted percent forest cover from

912   AVHRR data', *Photogrammetric engineering and remote sensing*, 60(5).

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designated by letter 'A' is an example of tundra areas being recognised as FTE in this product), and (d) Google Earth coverage over a subset of the study area whose location is shown by the red rectangle in the left-hand panel.

Figure 9. Final derived FTE area in the Central Eurasia study area.

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Figure 10. Application of the FTE delineation on additional study sites. (From left to right) Google Earth coverage; Landsat VCF and reference data points; Landsat VCF and the Ranson et al. (2011) FTE; classified image using our texture-based classification.

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938   **List of table captions**

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Table 1. GLCM-based texture measures used in this study.

940   Table 2. Classification accuracy and kappa coefficient of FTE delineation using VCF thresholding

941   and texture-based classification based on the 5-20 and 5-10 threshold pairs, and the Ranson et al.

942   (2011) FTE in the study area.

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944   Table 3. Parameterisation and classification accuracies of FTE delineation for the additional study

945   areas. Those for the Central Eurasia study area are also listed as reference.

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