Mapping invasive *Fallopia japonica* by combined spectral, spatial, and temporal analysis of digital orthophotos

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**Abstract**

Japanese knotweed (*Fallopia japonica*) is listed among 100 of the World’s worst invasive alien species and poses an increasing threat to ecosystems and agriculture in Northern America, Europe, and Oceania. This study proposes a remote sensing method to detect local occurrences of *F. japonica* from low-cost digital orthophotos taken in early spring and summer by concurrently exploring its temporal, spectral, and spatial characteristics. Temporal characteristics of the species are quantified by a band ratio calculated from the green and red spectral channels of both images. The normalized difference vegetation index was used to capture the high near-infrared (NIR) reflectance of *F. japonica* in summer while the characteristic texture of *F. japonica* is quantified by calculating gray level co-occurrence matrix (GLCM) measures. After establishing the optimum kernel size to quantify texture, the different input features (spectral, spatial, and texture) were stacked and used as input to the random forest (RF) classifier. The proposed method was tested for a built-up and semi-natural area in Slovenia.

The spectral, spatial, and temporal provided an equally important contribution for differentiating *F. japonica* from other land cover types. The combination of all signatures resulted in a producer accuracy of 90.3% and a user accuracy of 98.1% for *F. japonica* when validation was based on independent regions of interest. A producer accuracy of 61.4% was obtained for *F. japonica* when comparing the classification result with all occurrences of *F. japonica* identified during a field validation campaign. This is an encouraging result given the very small patches in which the species usually occur and the high degree of intermingling with other plants. All hot spots were identified and even likely infestations of *F. japonica* that had remained undiscovered during the field campaign were detected. The probability images resulting from the RF classifier can be used to reduce the relatively large number of false alarms and may assist in targeted eradication measures. Classification skill only slightly reduced when NIR information was not considered, which is an important recognition with regard to transferability of the method to the most basic type of digital color orthophotos. The possibility to use orthophotos, which at most municipalities are commonly available and easily accessible, facilitates an immediate implementation of the approach in situations where intervention is urgent.

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**1. Introduction**

Biological invasions by non-native species are recognized to pose significant losses in the economic value, biodiversity, and health of invaded systems (Hulme, 2007; Wittenberg and Cock, 2001). Alien species can act as vectors for new diseases, alter ecosystem processes, change biodiversity, disrupt cultural landscapes, reduce the value of land and water for human activities, and cause other socio-economic concerns (DAISIE, 2008). The spread of alien invasive species is not stopped at national boundaries, but can easily disperse to neighboring states. Therefore, several international initiatives were started to create an inventory of the current distribution of invasive species, to identify the factors involved, and to provide frameworks and directives for prevention and control (DAISIE, 2008; Hulme et al., 2008; ISSG/IUCN, 2009).

Among the “100 of the worst” invasive plant and animal species identified worldwide (DAISIE, 2008; ISSG/IUCN, 2009) is Japanese knotweed, *Fallopia japonica* (Houtt.) Ronse Decraene (*F. japonica*). Native to East Asia (Japan, North China, Taiwan, and Korea), *F. japonica* was introduced to Europe, North America, Australia, and New Zealand as a garden ornamental, to prevent soil erosion, and as a forage crop for grazing animals (Conolly, 1977). The species soon...
escaped from cultivation to establish itself at coastlands, ruderal and riparian zones, urban areas, roadsides, and wetlands (Conolly, 1977; Pyšek and Prach, 1993; Rouifed et al., 2011). *F. japonica* exhibits vigorous clonal growth and builds monospecific stands where it outcompetes native species and changes the soil parameters and ecosystem function. Moreover, prolific rhizome and shoot growth can damage foundations, walls, pavements, and drainage works, and cause flood hazards by increasing resistance to water flow and damaging flood prevention structures ( Aguilera et al., 2010; Collingham et al., 2000; DAISIE, 2008; Smith et al., 2007).

Due to the low decomposition rates of leaves and stalks standing biomass may accumulate and create a fire hazard (Seiger and Merchant, 1997). The spread of *F. japonica* in central Europe is mainly vegetative and evolves through the dissemination of rhizome or cane fragments via water courses, roads and railways, or through the transport of contaminated soil by humans (Conolly, 1977; Pyšek et al., 2003; Smith et al., 2007). The spreading rate of *F. japonica* is steadily increasing across Europe, which is also stimulated by elevated CO₂ and N deposition rates (Bradford et al., 2007; DAISIE, 2008). Once established, *F. japonica* is very difficult to eradicate. The whole procedure can take several treatments while removal efforts may have adverse impacts on the soil or other plants (Shaw and Seiger, 2002).

Maps depicting the spatial distribution and potential pathways of dissemination are an indispensable support for researchers and decision makers to react appropriately to the presence and threats of *F. japonica* infestations (Byers et al., 2002). Traditionally, mapping relies heavily on field-based inventories. The major drawback of field campaigns lies in the fact that during large area campaigns small stands may be easily overseen. For this reason, a detailed inventory of *F. japonica* has not yet been produced or has only been carried out at coarse scales (Jogan et al., 2001). Alternatively, remote sensing provides an opportunity for mapping and monitoring the occurrence and distribution of native and alien invasive species in a cost-effective, spatially contiguous, and timely manner (Aplin, 2005). The success of remote mapping of invasive species depends on a combination of factors, including the biophysical and biochemical properties of the invasive species relative to those of the indigenous ones, the spatial extent and pattern of dissemination, the measurement principle and spatial resolution of the employed remote sensing system, and the required degree of automation. Multi-spectral to low resolution optical remote sensing systems such as Landsat Thematic Mapper and NOAA/AVHRR have the advantage of providing historical data up to several decades facilitating time series analysis over large areas. For example, Peters et al. (1992) and Dewey et al. (1991) successfully identified rangeland infestations by various species from AVHRR data and Landsat TM while Frazier and Wang (2011) studied the suitability of Landsat TM time series to map riparian invasions of saltcedar in the US. Nevertheless, the spatial resolutions of these sensors are not sufficient to discern mixed community types or small areas of invasive species. Therefore, identification of an invasive impact can only be detected until the undesirable species has reached dominance and become widespread (Carson et al., 1995).

Alternatively, very high resolution data such as digital aerial photography and commercially available satellite imagery greatly improve the capability of detecting small scale infestations. For example, Laba et al. (2008) obtained high classification accuracies while mapping three wetland invasive plants from QuickBird imagery. Several authors showed that exploiting subtle spectral differences as contained in hyperspectral imagery contributes to improved mapping of native and non-native plants in various types of environments (Asner et al., 2008; Miao et al., 2011; Oldeland et al., 2010a; Underwood et al., 2003). A drawback of hyperspectral imagery is its generally reduced spatial resolution with respect to very high resolution multispectral imagery. Therefore, Walsh et al. (2008) integrated operationally available medium resolution hyperspectral Hyperion data with low spectral but very high spatial resolution QuickBird imagery for analyzing guava (*Psidium guajava*) infestations on the Galapagos Islands. Apart from increasing the spatial and spectral resolution of the employed imagery, scientists increasingly develop approaches for species differentiation that, supplementary to spectral reflectance, exploit other features, such as differences in temporal evolution (Oldeland et al., 2010b; Zhang et al., 2008). The recent widespread availability of very high resolution satellite data especially encourages the use of spatial texture in the images (Franklin et al., 2001; Wang et al., 2004). Tsai and Chou (2006) showed that for identifying invasive *Leucaena leucocephala* in Taiwan introducing co-occurrence texture measures significantly increased classification accuracy compared to using only pan-chromatic or multi-spectral QuickBird imagery.

The alarming dissemination rates of invasive *F. japonica* in many parts of the world call for a prompt inventory of the species based on (semi-)automated classification methods applied to very high resolution imagery. Due to its widespread (historical) availability and easy accessibility, ordinary aerial photos acquired in the framework of operational urban inventory campaigns constitute an obvious data source for this task. Nonetheless, such imagery may not be perfectly optimized for vegetation mapping purposes in terms of spectral coverage and resolution, radiometric accuracy, observation time/date, and level of image preprocessing. The usefulness of color infra-red (CIR) and visible-band (RGB) aerial photography was recently demonstrated by Jones et al. (2011) who mapped the occurrence of Japanese knotweed in a test area in Wales (UK) using an object-based classification approach. The objective of the study presented in this paper goes one step beyond the study of Jones et al. (2011) and explores, apart from the spectral information content, also spatial and temporal image characteristics for improved differentiation of *F. japonica* from other land cover types. Image classification is performed by applying the supervised random forest classifier to operationally collected bi-temporal aerial photography over a semi-urban area close to Ljubljana, Slovenia.

### 2. Study site and data

#### 2.1. Study site

The study area, which is known to be severely infected by *F. japonica* infestation, is situated in the southeastern part of the community of Ljubljana, central Slovenia (Fig. 1). The site is located at an altitude of approximately 280 m, receives an average annual precipitation of around 1400 mm, and has an annual mean temperature of 10.2 °C.¹ The study area includes urban land use as well as agricultural land (grasslands, crops) and forested areas (deciduous, coniferous, and mixed). The common presence of urban areas, water courses, riparian zones, roads, and railways makes the region vulnerable to the colonization and dissemination of *F. japonica*.

#### 2.2. Target description

*F. japonica* is a vigorously growing herbaceous perennial with annual tubular stems up to 4 m in height (Fig. 2). Its rhizome system penetrates 2–3 m deep into the soil and can extend 15–20 m laterally from a parent plant (Beerling et al., 1994). It forms dense, shading stands with only little light reaching the ground. During winter, the leaves die back to reveal orange/brown colored woody canes which may stay erect for several years (Fig. 2a). The plant

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2.4. Digital orthophotos

Bi-seasonal digital orthophotos were provided by the Municipality of Ljubljana and the Surveying and Mapping Authority of the Republic of Slovenia. The orthophotos were acquired with a Z/I DMC digital camera on 2006/04/08 (spring) and on 2006/07/11 (summer), respectively. Both images contain a blue, green, and a red channel, while the summer image additionally contains a near-infrared (NIR) channel. The images were projected into the Slovenian horizontal D48/GK coordinate system, based on Gauss Krüger projection and Bessel 1841 ellipsoid and were resampled to a spatial resolution of 0.5 m using bilinear convolution. The NIR channel has a reduced spatial resolution of 1 m. No radiometric calibration, anisotropy correction, and atmospheric correction had been performed prior to data delivery as such data enhancement operations are still not standard practice for most commercial aerial surveying companies. Because the required parameters for doing this (e.g., acquisition time, atmospheric composition) were not known, the data manipulations could not be performed in retrospect either. However, the purpose of this study is to develop a robust approach for operationally available digital orthophotos where in many instances preprocessing is far from optimal.

2.4. Ground truth mapping of F. japonica

In autumn 2007 the extent of F. japonica occurrence in the test area was mapped from a combination of field survey and visual aerial photograph interpretation. First, potential stands were identified from visual interpretation of the aerial photographs described in the previous section using a priori knowledge on color, texture, and known occurrences. The potential stands were visited and, if F. japonica was actually present in these areas, their final extent was delineated in the field using non-differential GPS measurements. In total, 10.4 ha of F. japonica were mapped in the test area, which equals approximately 0.5% of the total area covered by the imagery. Of the patches identified and mapped as F. japonica, the actual contribution of F. japonica to the total species composition ranged between 50 and 100% (average = 85%). All patches identified were located along the main river (Ljubljanica) in the central part of the image.

3. Methodology

3.1. Quantifying bi-temporal differences

For vegetation, spectral variations in the three visible bands of airborne digital cameras are primarily due to variations in plant chlorophyll a and b and leaf area index (LAI; Huete et al., 1997). Increased chlorophyll concentrations or LAI lead to enhanced absorption in the red and blue spectral domains while the green domain is less affected. While at the leaf level variations in chlorophyll concentrations can be invoked by different types of stress (e.g., water or nitrogen deficit) or natural plant development (e.g., growth, decay), chlorophyll status at the plant level for deciduous species is mostly dominated by seasonal trends of leaf growth and fall. This is seen in Figs. 2 and 3 which for F. japonica show the characteristic brown-red color of the stems that are exposed during winter in leaf-off situation (Figs. 2a and 3a). In contrast, the dense leaf canopy in summer completely covers the stems while high absorption in the red and blue bands leads to the bright green color clearly visible in the summer orthophoto (Figs. 2b and 3b). This characteristic seasonal spectral behavior in the visible spectral domain differs from annual vegetation species such as crops and
from perennial vegetation species such as meadows and coniferous trees.

To capture the characteristic seasonal spectral behavior in the visible wavelengths of *F. japonica*, we developed a band ratio based on the green and red channels of both image acquisition dates. Band ratios are widely employed in remote sensing to emphasize spectral features related to specific vegetation properties of interest, such as LAI, while suppressing variations induced by other vegetation elements and by external influences such as soil background reflectance and illumination effects (Baret et al., 1992; Dorigo et al., 2007). In addition to emphasizing phenological differences between the two image acquisition dates, the index concurrently seeks to minimize brightness differences between both acquisition dates induced by changing illumination and viewing properties and different camera calibrations (cf. Fig. 3). This compensates to a large extent the common lack of accurate camera calibration and atmospheric correction of digital orthophotos which would be required to allow for a reliable quantitative comparison between two observation dates. The bi-temporal band ratio (BTBR) is given by:

\[
\text{BTBR} = \frac{(R_{\text{off}}/R_{\text{on}}) - (G_{\text{off}}/G_{\text{on}})}{(R_{\text{off}}/R_{\text{on}}) + (G_{\text{off}}/G_{\text{on}})}
\]

where \(R\) and \(G\) stand for the digital number in the red and green spectral band, respectively, while the suffix indicates whether it concerns the image on which *F. japonica* is in leaf-off (off) or leaf-on (on) situation. The cross-quotient of leaf-off and leaf-on bands (i.e., \((R_{\text{off}}/R_{\text{on}})\) and \((G_{\text{off}}/G_{\text{on}})\)) was introduced to reduce index fluctuations caused by random noise in the images. BTBR values range between \(-0.5\) and \(0.5\) but are typically between \(-0.25\) and \(0.25\), with highest positive values for areas showing largest differences between red reflectance in leaf-off situation (spring) and green reflectance under leaf-on (summer) conditions.

### 3.2. Texture measures

Since the BTBR is only based on green and red reflectance, objects with a similar seasonal spectral behavior in these bands cannot be distinguished from *F. japonica* using this ratio. Fig. 4 shows some examples of land cover types for which separability based on spectral information alone is difficult. Apart from *F. japonica* these include a deciduous forest, an agricultural field that is bare in spring and covered with a green crop in summer, and a forest clearing area dominated principally by deciduous raspberry and blackberry bushes. However, Fig. 4 also shows that *F. japonica* patches often have a characteristic texture which is clearly distinctive from the other land cover types.

We characterized texture by means of the gray level co-occurrence matrix (GLCM; Haralick et al., 1973; Nixon and Aguado, 2002). The GLCM describes texture in a user-defined moving kernel and considers for this kernel the spatial co-occurrence of pixel gray levels. The GLCM operates by computing a matrix that is based on quantifying the difference in gray-scale values between pixels at a predefined distance, usually one pixel. This matrix is then used to compute a number of texture features to summarize and represent the structure of the matrix (Nixon and Aguado, 2002). These so-called Haralick features can be categorized into three groups containing highly correlated measures (Hall-Beyer, 2007): contrast measures (including contrast, dissimilarity, and homogeneity), orderliness measures (angular second moment and entropy), and statistics measures (mean, variance, and correlation). Several studies demonstrate improved classification accuracy when GLCM texture measures are considered in addition to spectral reflectance (Marceau et al., 1990; Tsai and Chou, 2006). For this study we used the GLCM implementation provided with the ENVI 4.4 software2 which calculates the eight standard Haralick measures mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment, and correlation. For a detailed description of the measures and the formula used to calculate them we refer to Nixon and Aguado (2002). Because correlations between the three visible bands were all very high (\(R^2 > 0.93\)) and including all bands would lead to a large data redundancy, we decided to perform the GLCM calculations only for the red channel, which of all bands showed the highest entropy. Co-occurrence measures were computed for both the spring and summer image.

Franklin et al. (2000) and Marceau et al. (1990) mention that the final result of texture analysis relies heavily on the size of the kernel. The ideal size of the kernel depends on a number of factors, including the spatial resolution of the image, the land cover types under consideration, and the scale of the different features. If the kernel is too small then it might not contain sufficient information to characterize the kernel’s texture. In contrast, if the kernel is too large it can overlap with other types of land cover, which is referred to as the edge effect (Puisant et al., 2005). In our study, we established the optimum kernel size in an iterative way, by evaluating the classification performance of GLCM measures based on increasingly large kernel sizes, as proposed by Murray et al. (2010).

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3.3. Quantifying vegetation vigour

In addition to the temporal and textural component we explored the diagnostic capability of the NIR reflectance in the summer image. NIR reflectance, which is particularly high for dense green vegetation (Dorigo et al., 2009; Huete, 1988) is expected to facilitate a better differentiation between the densely growing F. japonica and other land cover types having similar seasonal reflectance variations and texture signatures, such as less dense vegetation and non-vegetative surfaces. Vegetation vigor was quantified by computing the normalized difference vegetation index (NDVI; Rouse et al., 1973) which has been successfully employed in hundreds of studies.

3.4. Image classification

Not all occurrences of F. japonica exhibit all the typical growth characteristics shown in Fig. 3, nor are these characteristics always visible in the available imagery. For instance, sometimes patches are too small to reveal the characteristic texture signature, while in other cases F. japonica plants are overgrown by other vegetation species, or the patches are shaded by adjacent trees (cf. Fig. 3). This means that, if the different signatures are combined in a classification, for many F. japonica pixels not all characteristic signatures concurrently apply. Therefore, we decided to use the non-parametric random forest (RF) classifier (Breiman, 2001), which in recent years has proved to be highly successful in complex remote sensing applications with accuracies that are comparable to or even exceed state-of-the-art classifiers such as support vector machines (SVMs), neural networks, and boosting techniques (Benediktsson et al., 2007; Chan and Paelinckx, 2008; Gisnason et al., 2006; Pal, 2005; Rodriguez-Galiano et al., 2012; Sluiter and Pebesma, 2010). Unlike more traditional classifiers such as the maximum likelihood, RFs are non-parametric and therefore not affected by (potentially false) assumptions on the distribution of the input variable values.

The RF classifier is an ensemble classifier that combines multiple CART-like decision or classification trees (Breiman, 2001). Each tree is constructed from a random subset of the input variables (i.e. image bands). The number of variables per tree is a user-defined parameter. We used the default parameter which is the square root of the total number of variables. For each tree, 66.67% of the pixels in the training areas are randomly chosen to train the decision tree, which is not pruned. The remaining 33.33% of pixels is used to calculate an out-of-bag (OOB) error, which is used for cross-validation. This technique is also known as bagging, or bootstrap aggregation. Each decision tree, therefore, uses a random subset of training pixels and a random subset of input variables. This reduces the correlation between decision trees and reduces the overall computational complexity. The second user-defined parameter is the total number of trees in the forest, which generally ranges between 100 and 500. In this study, we used 200 trees after confirming the convergence of the OOB error around 150 trees (providing a trade-off between accuracy, robustness, and speed). After the ensemble of decision trees has been trained it is applied to the unclassified pixels. Given that each tree generates a class prediction, a probability for each class can be calculated from the ensemble, which results in a class probability image. From the probability images the final class label is based on a majority vote.

One of the key advantages of the RF classifier is that it calculates measures of variable importance for each individual class and for the classification as a whole. In this way it can be determined which of the spectral, textural, or temporal input bands contribute most to class separation. Variable importance plots are generated based on a random permutation of the input variables and the effect of the permutation is quantified for each variable by the change in the OOB error. Variables that are important for separating classes in the training data will show a significant change in the OOB error. Relative variable importance measures are scaled between 0 and 1.

Training and validation of the RF classifier were based on regions of interest (ROIs) that were digitized from the imagery. Apart from the F. japonica class, all major land-cover classes were selected, including “water”, “impermeable surfaces” (asphalt, roof surface), “perennial grassland (meadow/pasture), “coniferous forest”, “deciduous forest”, and a class containing agricultural fields that expose bare soil both in the spring and summer image. To test the approach in differentiating land cover types with a very similar seasonal spectral behavior in the orthophotos, we also included part of a forest “clearing area” underneath a power line, dominated principally by raspberry and blackberry bushes, and the agricultural class “bare soil in spring – green crop in summer”. All classes were verified with the Slovenian land cover map (Skumavec and Šabič, 2005) and by field observations. For each category 120 ROIs were randomly selected from the entire image in order to guarantee an accurate representation of the within-class variability. The polygons were selected in a way to minimize spatial

Fig. 4. Sample textures of land cover types with similar seasonal spectral behavior, both for spring (top row) and summer (bottom) digital orthophoto.
Table 1
Results of RF classification using all features (GLCM features calculated from a 43 × 43 processing kernel for spring and summer image, the BTBR and the NDVI; columns 2 and 3), all features except for NDVI (columns 4 and 5), and BTBR, NDVI, and 1 feature per GLCM categories for spring and summer image (for explanation see text; columns 6 and 7). In brackets the number of features used. PA: producer accuracy; UA: user accuracy. Accuracy computations were based on the validation ROIs.

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>All features (18)</th>
<th>All features except for NDVI (17)</th>
<th>BLR, NDVI, and selected texture features (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall accuracy (%)</td>
<td>95.4</td>
<td>94.4</td>
<td>93.6</td>
</tr>
<tr>
<td>Kappa coefficient</td>
<td>0.9480</td>
<td>0.9367</td>
<td>0.9281</td>
</tr>
<tr>
<td>PA (%)</td>
<td>UA (%)</td>
<td>PA (%)</td>
<td>UA (%)</td>
</tr>
<tr>
<td>F. japonica</td>
<td>90.3</td>
<td>98.1</td>
<td>90.9</td>
</tr>
<tr>
<td>Perennial grassland (meadow/pasture)</td>
<td>100.0</td>
<td>100.0</td>
<td>94.4</td>
</tr>
<tr>
<td>Coniferous forest</td>
<td>89.9</td>
<td>91.3</td>
<td>89.9</td>
</tr>
<tr>
<td>Deciduous forest</td>
<td>95.8</td>
<td>91.2</td>
<td>95.8</td>
</tr>
<tr>
<td>Bare soil in spring – green crop in summer</td>
<td>98.9</td>
<td>93.3</td>
<td>97.9</td>
</tr>
<tr>
<td>Bare soil (spring and summer)</td>
<td>90.6</td>
<td>95.7</td>
<td>91.5</td>
</tr>
<tr>
<td>Clearing area (raspberry, blackberry)</td>
<td>98.4</td>
<td>94.6</td>
<td>97.8</td>
</tr>
<tr>
<td>Water/river</td>
<td>99.7</td>
<td>98.7</td>
<td>97.0</td>
</tr>
<tr>
<td>Impervious (asphalt, roof)</td>
<td>94.3</td>
<td>90.7</td>
<td>94.0</td>
</tr>
</tbody>
</table>

autocorrelation between the ROIs as spatial autocorrelation of training and validation datasets is known to positively bias the evaluation of classification results (Friedl et al., 2000; Mannel et al., 2011). Thus, all polygons were taken from different fields and occurrences (patches) in the image. Only for the class “water” this was not possible, as there is only one obvious water course in the area. The plot size of each ROI was fixed at 7 × 7 pixels to account for registration errors between both dates (Rodriguez-Galiano et al., 2012). The ground reference dataset was randomly divided into 2/3 (80 polygons) and 1/3 (40 polygons) for training and validation, respectively. Rodriguez-Galiano et al. (2012) found that for a complex Mediterranean area the RF classification was robust for approximately 50 training samples or more, which shows that our number of 80 samples was conservatively chosen.

Image classification was performed at two successive stages. First, an iterative classification scheme was used to establish the optimum kernel size for calculating the GLCM texture measures. Starting with the minimum kernel size (i.e. 3 × 3 pixels) we calculated the eight GLCM measures for both the spring and summer image. For each observation date the stack of eight GLCM measures was used as input to the RF classifier. The classifier was trained using the training subset of ROIs while the result was evaluated against the validation subset using standard accuracy assessment statistics (Congalton and Green, 2009). This procedure was repeated for increasingly large symmetric kernel sizes until the kernel size leading to the smallest classification errors could be identified. In a second step, the GLCM measures resulting from the optimum kernel size were stacked with the BTBR and the NDVI image, and the ensemble of 18 signatures (i.e. eight GLCM measures spring, eight GLCM measures summer, BTBR, and NDVI) was fed into the RF classifier. Again, only the training ROIs were used to train the classifier. The final classification result was evaluated using the validation ROIs and the F. japonica polygons mapped during the field campaign (Section 2.4).

4. Results

4.1. Establishing the optimum GLCM window size

Fig. 5 shows the evolution of various quality indicator values of the iterative RF classification based on the eight GLCM bands. OOB errors are based on the training subset only, whereas accuracy descriptors and Kappa coefficient were calculated from the confusion matrix with the validation subsets (see Section 3.4). For both the spring and summer image classification accuracy is poor for the initial minimum kernel size of 3 × 3 pixels, i.e. accuracies and kappa are low and OOB errors are high. Up to a kernel size of approximately 40 pixels the classification performance steadily increases for both images and OOB errors practically drop to zero. For larger kernel sizes the various accuracy indicators show variable behavior. Whereas for the spring image overall accuracy and kappa still slightly increase, these measures start to reduce gradually for the summer image. For both images, the user and producer accuracy of F. japonica drop dramatically for larger kernel sizes. Based on this observation a GLCM kernel size of 43 × 43 pixels was assumed to be most appropriate for discriminating F. japonica from other land cover types based on texture and, therefore, selected for subsequent processing. Based on the ROI training and validation sets, overall accuracy obtained for the 43 × 43 pixels kernel amounted to 0.694 and 0.912, the kappa coefficient to 0.648 and 0.894, the user accuracy of the F. japonica class to 0.272 and 0.749, and producer accuracy of the F. japonica class to 0.602 and 0.633 for the spring and summer imagery, respectively.

4.2. Image classification

4.2.1. Evaluation based on validation ROIs

The eight GLCM features of the best performing kernel size (i.e. 43 × 43 pixels) for both the spring and summer digital orthophoto were stacked with the BTBR and the NDVI image. The resulting image stack of 18 bands was submitted to the RF classification. Overall accuracy is with 95.4% high while the kappa coefficient of 0.9480 indicates a low degree of chance agreement (Table 1). F. japonica has a producer and a user accuracy of 90.3% and 98.1%, respectively. Confusion between F. japonica and other classes can almost exclusively be attributed to the land cover classes “coniferous forest” and “clearing area” which show large similarities in either one or more of the information dimensions (i.e. spectral, temporal, or textural). Other evident sources of confusion are the two homogeneous surfaces that show little variation over time, i.e. “bare soil in spring and summer” and “impervious”.

4.2.2. Contribution of different data sources

The variable importance plots in Fig. 6 show the relative contribution of the 18 individual data sources for separating F. japonica from the other land cover classes and for the classification as whole. The plots reveal that all bands provide a considerable contribution to improving the classification result and that the textural, temporal, and NIR components play an equally important role and are therefore highly complementary.

To illustrate classification performance for imagery without a NIR channel, we repeated the classification for the same data stack
as above, but without NDVI. Results show that excluding the NDVI channel leads only to a small decrease of classification accuracy (Table 1).

The sharp jump in Fig. 6 between the most important three or four variables (for *F. japonica* and the overall classification, respectively) and the rest of the variables suggests a high degree of collinearity between the variables, in particular between various measures of texture (cf. Section 3.2). Therefore, the classification was repeated for a combination of BTBR, NDVI, and only one representative feature for each of the three texture categories contrast (homogeneity), orderliness (entropy), and statistics (mean) for both dates. Table 1 shows that overall accuracy based on this stack of eight features only slightly decreases with respect to the original input data stack of 18 features. Nevertheless, for the class *F. japonica* the decrease in performance is significant, both in terms of producer and user accuracy.

### 4.2.3. Comparison with *F. japonica* identified during field campaign

In the end we are primarily interested in the occurrence or absence of *F. japonica*, irrespective of the mutual confusion between the other classes. Therefore, after the final classification we assembled all classes but *F. japonica* into a single class named “other”. Thus, while the classification itself is based on nine classes, the results are now presented as a Boolean classification distinguishing between *F. japonica* and “other” (Table 2).

Based on the ground truth polygons, an overall accuracy of 93.8% was obtained. The ability of the algorithm to detect the occurrence

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**Fig. 5.** Accuracy and error assessment for GLCM classifications for different kernel sizes based on spring (left) and summer (right) digital orthophotos. Shown are the overall and *F. japonica* out-of-bag errors, the overall accuracy, the overall kappa coefficient, and the user and producer accuracies of *F. japonica*, computed for the independent validation ROIs. Errors and accuracies are provided as % divided by 100.

**Fig. 6.** Variable importance plots, expressed as mean decrease in accuracy when band is left out in classification, for *F. japonica* (left) and the ensemble of all classes (right). The GLCM measures included are contrast (CON), dissimilarity (DIS), homogeneity (HOM), angular second moment (SEC), entropy (ENT), mean (MEA), variance (VAR), and correlation (COR).
of *F. japonica* (producer accuracy) is satisfying with 61.4%. In total, 88.2 ha were mapped as *F. japonica*, which is about 8 times the spatial extent of the areas mapped as *F. japonica* during the ground mapping campaign. This relatively large number of pixels falsely classified as *F. japonica* results in a rather low kappa value. Fig. 7 shows the spatial distribution of the areas classified as *F. japonica*. Along the river shores, mapped and classified occurrences highly coincide. Nevertheless, also various occurrences of *F. japonica* outside the polygons identified during the ground mapping campaign can be observed.

5. Discussion

5.1. Image data requirements

The success of mapping *F. japonica* relies strongly on the properties of the available imagery, e.g., acquisition date, spatial resolution, and spectral coverage. As shown by the variable importance plots, having at the disposal at least an image taken at the leaf-off and one taken at the leaf-on stage of *F. japonica* appeared to be important for distinguishing the species from other vegetation types. A mono-temporal snap-shot would not be able either to reveal the typical reddish color of the canes (if the image is taken in summer) or the dense green canopy (if the image is taken in winter or spring). The potential of improved identification of *F. japonica* by using imagery from different seasons was also pointed out by Jones et al. (2011).

Very encouraging is the observation that performing the classification without NDVI only leads to an insignificant loss in classification accuracy. This guarantees a robust application of the method in situations where NIR reflectance is absent. A possible explanation for the only marginal additional discriminative power of NDVI is the fact that the seasonal behavior in the visible bands is already very discriminatory, as for vegetation a high negative correlation exists between the NIR and red bands (Dorigo, 2012). Nevertheless, we recommend including NIR whenever available as it consolidates the classification.

Since the occurrence of the *F. japonica* is a very local phenomenon and sometimes even concerns individual plants, the spatial resolution of the imagery should be very high. The 0.5 m resolution of the RGB channels of the digital orthophotos used in this study appeared to be able to detect very local occurrences but, maybe even more importantly, also capture the typical spatial pattern of individual bushes within the patches themselves which are regularly spaced at a distance of approximately three meters (Environment Agency, 2009). Aerial photography and several commercial very high resolution satellite sensors such as QuickBird, Worldview, IKONOS, and GeoEye provide imagery with a resolution that is able to capture this texture.

5.2. Texture

The characteristic texture of *F. japonica* appeared to be an important feature in differentiating the invasive species from other vegetation types with very similar seasonal spectral behavior. According to the RF variable importance plots, texture even appeared to be the most distinctive data source. Nevertheless, in order to quantify this characteristic pattern by calculating meaningful GLCMs, the patches should have a minimum spatial extent. This means that individual plants or small patches lack this spatial diagnostic feature, which may complicate remote sensing-based identification of the species in an early invasive stage. The effectiveness of GLCM measures in differentiating between *F. japonica* from other land cover types appeared to depend very strongly on the employed kernel size. The dependence on kernel size has

<table>
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<th>Table 2 Results of RF classification for <em>F. japonica</em> based on GLCM features calculated from a 43 × 43 processing kernel for spring and summer image, BTBR and NDVI. Accuracy computations were based on the field inventory of <em>F. japonica</em>.</th>
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<td>Overall accuracy (%)</td>
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<td>Kappa coefficient</td>
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<td>Producer accuracy <em>F. japonica</em> (%)</td>
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<td>User accuracy <em>F. japonica</em> (%)</td>
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<td>Producer accuracy “Other”</td>
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<td>User accuracy “Other”</td>
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<tr>
<td>Mapped area <em>F. japonica</em> (ha)</td>
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been recognized by several authors (Franklin et al., 2000; Marceau et al., 1990; Tsai and Chou, 2006) but so far no general method for establishing the optimum size has been proposed. The major reason for the low accuracy of the initial small window size has to be sought in the fact that calculated GLCM measures provided large within-class heterogeneity for each land cover type. Applying a larger kernel has a smoothing effect leading to more uniform GLCM feature values for the different land cover types and, thus, to more homogeneous and better separable characterizations of the land cover classes considered in the classification. Nevertheless, applying a larger kernel also leads to blurring effects between adjacent land cover types. Chen et al. (2004) found that the optimum window size depends on the structure of the considered area and the spatial resolution of the imagery. They concluded that in general a larger window size was needed at a finer spatial resolution than at a coarse resolution as land cover classes appear more heterogeneous in high resolution imagery. Depending on the test area and the resolution of the imagery they obtained a maximum accuracy for urban areas using a window size ranging from 40 m to 48 m. The kernel size obtained in our study (21.5 m; 43 pixels) lies between the one found by Chen et al. (2004) and the 1.8–3 m kernel sizes adopted by Tsai and Chou (2006).

To speed up processing time, one could consider summarizing highly correlated texture features into the three main categories contrast, statistics, and orderliness. Although this does not strongly affect overall classification accuracy, the identification of F. japonica is negatively affected by this choice.

5.3. Classification performance

In the study area not every occurrence of F. japonica is described by all typical spectral, spatial, and temporal image features of the species. Sources of “impure” F. japonica occurrences include edge effects contained in the GLCM measures, shadows casted by neighboring trees in one or more of the images, plants overgrown by or interfering with other vegetation species, and patches that are too small to display the typical texture pattern. For “impure” occurrences of F. japonica there is very likely a significant overlap with other land cover classes in the 18 dimensional feature space. As the ground truth polygons contained all identified occurrences of F. japonica, irrespective of their purity or visibility in the imagery, accuracy statistics obtained for these polygons were considerably lower than those obtained for the pure validation ROIs. Nevertheless, the producer accuracy of 61.4% obtained in this study is satisfying. Pixels within the ground truth polygons that were not classified as F. japonica (and thus leading to a reduced producer accuracy) could almost exclusively be traced back to the occurrence of trees overgrowing the F. japonica patches and cast shadows in the imagery. In contrast, the user accuracy is rather low, i.e. there are a large number of false positive alarms. However, it is expected that actual user accuracy is higher than the reported one, as some of the areas falsely classified as F. japonica are likely to be infested by F. japonica (Fig. 8a–c). If the invasive species is actually present in these areas should however be verified by additional field observations. In other areas identified as F. japonica the occurrence of the invasive species seems implausible (Fig. 8d–f). Potential misclassifications are mostly found in forested or bushy areas that show similar spatial, textural, and seasonal spectral properties (Fig. 8e and f). Misclassifications in urban areas (Fig. 8d) and at the transitions between different land cover types are partly due the absence of a clear class membership of the pixels.

The moderate classification result for ground-mapped F. japonica is also negatively affected by the small overall spatial extent of this class. Shortcomings in training set selection, in delineating F. japonica on the ground, and in the spatial collocation of field and image data lead to significant errors in the classification results. Finally, it should be recalled that the study is based on imagery that has not been corrected for atmospheric influences which has a considerable negative impact. Nevertheless, Foody (2008) warned for an over-pessimistic evaluation of classification accuracies obtained from error matrix calculations as results strongly depend, e.g., on the number and uniqueness of classes and the spatial resolution of the imagery, and because the utility of the results strongly depends on the application in hand. In addition, Jones et al. (2011) already
reported that users favor false positives over false negatives, i.e., in terms of management and control, an comprehensive approach delineating too many occurrences of *F. japonica* is of greater utility than an approach that disregards several occurrences.

The RF classifier classifies a pixel as *F. japonica* if the probability of belonging to the *F. japonica* class is higher than the probability of belonging to any of the other classes. From a practical perspective, the probability image of *F. japonica* can be used to further confine the areas that should receive highest priority in field visits to delineate and abolish *F. japonica* stands. Fig. 9 shows how the area initially classified as *F. japonica* can be reduced to some selected core areas with high occurrence probabilities. The figure clearly shows the high correspondence of areas with a probability of *F. japonica* >0.6 and the area mapped as *F. japonica* during the field validation campaign. It also shows that the probability image is very effective in filtering out “false alarms” like the ones occurring in the upper and lower part of the image.

6. Conclusion and outlook

In this study we presented a supervised classification approach based on random forests to detect occurrences of invasive *F. japonica*. Due to the rapid spread of the species, early detection is crucial. For this reason, we applied the method to readily available, low-cost digital orthophotos which in many countries are collected operationally on a regular basis for urban inventory tasks. The typical seasonal characteristics of *F. japonica* were captured in a bi-temporal band ratio based on the red and green bands of spring and summer imagery respectively. Typical texture of the species was captured in GLCM texture measures for each observation date while vegetation vigor was expressed through the NDVI.

The study showed that the temporal, spatial (texture), and spectral dimension all provide a positive contribution to the success of separating *F. japonica* from other land cover classes. Using bi-temporal imagery with only VIS information, i.e., neglecting the NIR band, only caused an insignificant loss in accuracy. This is an important recognition with regard to transferability of the method to the most widespread type of digital orthophotos which is based only on RGB channels. The overall satisfying result of this study is important knowledge in the light of the rapid action that is required in many areas, as many local authorities already have historic orthophotos at their disposal and updates for urban inventories are usually performed on a regular basis. Hence, mapping *F. japonica* form imagery that is collected in the framework of other purposes would only have a little impact on the budget of communities.

All core areas of *F. japonica* occurrences were identified with the method presented in this study. This means that the classification result is able to guide the responsible authorities to the right locations from where the actual extent can be well determined in the field. In addition, the probability images and visual inspection of the classification results help to distinguish those patches that should receive highest priority for eradication measures. Image classification should therefore be seen as a support and not as a substitute for field inventories. Integrating the classification results in a GIS-based expert system is expected to further increase the user accuracy, e.g., by weighing the classified occurrences according to their distance to potential paths or sources of dissemination such as railways, roads, streets, gardens, and waste dumps. Several authors already demonstrated the benefit of such hybrid approaches (Masocha and Skidmore, 2011; Wang et al., 2009). Our future research will focus on such an integrative approach and study the transferability of the method presented here to areas with different land cover composition.

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