The effect of spatial resolution on the accuracy of leaf area index estimation for a forest planted in the desert transition zone

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Abstract

An approach is presented for determining leaf area index (LAI) of a forest located at the desert fringe by using high spatial resolution imagery and by implementing values from a moderate spatial but high temporal resolution sensor. A 4-m spatial resolution multi-spectral IKONOS image was acquired under clear sky conditions on March 25, 2004. Normalized differences vegetation index (NDVI) and a linear mixture model were applied to calculate fractional vegetation cover (FVC). LAI was calculated using a non-linear relationship to FVC and then compared with ground truth measurements made in ten 1000 m2 plots using the tracing radiation and architecture of canopies (TRAC) canopy analyzer under bright and clear sky conditions during March and April, 2004. Calculated LAI, corrected with a measured clumping index, was highly correlated with measured LAI (\(R^2 = 0.79, p < 0.01\)). This approach was used to produce a 4-m resolution LAI map of the forest. The procedure was then applied to the MODIS 250-m resolution surface reflectance product, where MODIS LAI and VI products were used to calculate the extinction coefficient by inversion of the LAI-FVC relationship, and the extinction coefficient was then used to calculate LAI for moderate resolution. Histograms of resulting LAI distributions and descriptive statistics at the different spatial resolutions are compared. LAI spatial distribution at lower resolution was similar to that obtained at higher resolution and remained close to being normally distributed.

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1. Introduction

Forest stand description includes factors related to eco-physiological processes responsible for forest growth. One of those factors is the stand leaf area index (LAI), defined by Watson (1947) as the total one-sided area of leaf tissue per unit ground surface area (m²/m²). LAI is highly related to many processes (e.g. rain interception, evapotranspiration, photosynthesis, respiration, and leaf litterfall) and used as an input to various ecosystem models that produce detailed information about vegetation cover and condition (Jackson et al., 1983; Bonan, 1993). LAI can be estimated through different direct (contact) and/or optical indirect (non-contact) procedures (e.g. measurements of light transmission through canopies) that are well reported in the literature (e.g. Breda, 2003; Gower et al., 1999). Despite their extensive usage, these methods demand considerable amounts of labor and time, and yield information only for the close vicinity of the measured point. Therefore satellite remote sensing systems, which provide extensive spatial information for different forest phenomena, have been proposed as a good solution for measurement of forest parameters and statistics at different scales (Stoms, 1994; Bergen & Dobson, 1999; Ceccato et al., 2001; Santoro et al., 2002; Sims & Gamon, 2003). Consequently, remote assessment of LAI is of major interest (e.g. Andersen et al., 2002; Brown et al., 2000; Carlson & Ripley, 1997; Clevers, 1997; Colombo et al., 2003; Gong et al., 2003; Wang et al., 2004; Wang et al., 2005a,b).

Today LAI is supplied as an operational product of Moderate Resolution Imaging Spectroradiometer (MODIS) onboard EOS (Earth Observation System) Terra and Aqua satellites. This
product was developed primarily for global studies and consequently available only at 1-km resolution at 8-day intervals (Wang et al., 2004). However, that low spatial resolution data is of limited utility for local scales especially in arid and semi-arid forested areas that are mostly planted, non-timber, sparse, spread over small areas (no more than 3000–5000 ha) and usually accompanied by agricultural activity of local farmers. This high landscape heterogeneity can be completely dissolved in 1 km² pixels and consequently, it could be concluded that such areas are not well represented in readily available global data and require more detailed surface representation by high spatial resolution satellite images, such as IKONOS. This sensor provides a relatively new source of data for monitoring various environment processes represented by “pure” small pixels and can be used as a validation core for low and moderate resolution imagery (that was originally proposed for global studies), in which each pixel may be made up of many land-cover types (Colombo et al., 2003) and requires detailed validation for local implementation.

This validation problem is of interest and has been addressed in different studies. Most of it shows a successful application of LAI retrieved from low spatial resolution imagery (e.g. AVHRR, MODIS, or SPOT VEGETATION) as compared to radiative transfer based (Tian et al., 2002a,b), field-sampled data collected (Privette et al., 2002), or high spatial resolution IKONOS (Morisette et al., 2003) or ETM+ (Cohen et al., 2003) data. However, though the use of high-resolution sensor data is attractive, this data is still very expensive. Thus for effective monitoring of terrestrial ecosystems for a long period of time it is more convenient to use low cost high temporal resolution data.

As an opposite of other 44 MODIS products, surface reflectance data for red and near-infrared (NIR) bands is readily available to the scientific community at higher spatial resolution (250-m per pixel). This provides more detailed surface description and hence seems to be more promising to dry-land forestry studies. Consequently, our objective was to propose a method for small scale LAI monitoring based on frequently available MODIS data. We utilized operational MODIS products as sources of ancillary information for precise description of canopy architecture through the determination of canopy extinction coefficient, and finally compare the results to LAI assessed using high-resolution IKONOS data.

2. Study area

The study was conducted in Yatir forest (31°21′ N and 35°02′ E, 630 m AMSL; ~3000 ha area) located in the transition between arid and semi-arid climatic zones at the edge of the Negev and Judean deserts (Fig. 1). The mean annual precipitation (275–280 mm) usually occurs during ~30 days year⁻¹ between November and March and is characterized by large annual fluctuations and an uneven distribution of the events within the rainy season. The average total annual potential evapotranspiration is 1600 mm year⁻¹, yielding a

Fig. 1. Landsat-TM of central Israel. Note the location of the Yatir forest on the desert fringe, visible as the sharp contrast between bright tones (arid zone) and dark tones (semi-arid zone).
long-term aridity index (potential evapotranspiration/precipitation; Budyko, 1974) of ~5.7. Regions where aridity index is greater than unity are broadly classified as dry since the evaporative demand cannot be met by precipitation (Arora, 2002). Specifically, an aridity index between 5 and 12 is usually classified as arid (Ponce et al., 2000).

The hottest month in the Yatir region is July and the coldest is January. The average maximum and minimum temperatures are 32.3 °C and 6.9 °C, respectively (Schiller & Cohen, 1998). The forest was planted mostly during 1964–1969, is almost even-aged, and is close to being a monoculture dominated by Aleppo pine (Pinus halepensis Mill.). The trees grow on shallow Rendzina soil and lithosols (0.2–1 m deep) over chalk and limestone. The ground water table is deep (~300 m) and little and sparse understory vegetation develops during the rainy season and disappears shortly thereafter (Grunzweig et al., 2003).

3. Theory

3.1. Fractional vegetation cover

Reflectance spectra derived from satellite-based sensors usually constitute mixed signals of a number of endmembers such as vegetation, bare soil, and shadow (Richardson & Wiegand, 1977; Carpenter et al., 1999; Graetz & Gentle, 1982; Pax-Lemny et al., 2001; Strahler et al., 1986; Xiao & Moody, 2005). Assuming that the spectral signature of a given pixel is the linear, proportion-weighted combination of the endmember (a pure surface material or land-cover type that is assumed to have a unique spectral signature) spectra (Xiao & Moody, 2005) Spectral Mixture Analysis (SMA) has been used to estimate canopy proportions from multi-spectral satellite data at sub-pixel level (Roberts et al., 1998; Wu & Murray, 2003). Endmember signatures can be directly selected from the image (image endmembers), or extracted from field or laboratory spectra of known materials (reference endmembers; Ichoku & Karnieli, 1996).

A simplified SMA model is the two-endmember model (Wittich & Hansing, 1995) that assumes that a given pixel consists of only green vegetation and bare soil, and thus its spectral vegetation index (VI) value is the linear combination of contributions from these two components. Such a model consists of a single equation, which improves computational efficiency by simplifying the process of endmember selection. Consequently, surface reflectance measured by a satellite (ρ) can be taken as a weighted sum of canopy and background reflectance (ρc and ρb, respectively):

\[ ρ = ρ_c f_c + ρ_b (1−f_c) \]  

where \( f_c \) is fractional vegetation cover, which is a summation of crown areas as seen from above.

Fractional vegetation cover is an important element in models that attempt to account for the exchanges of carbon, water, and energy at the land surface (Nemani & Running, 1996; Ward & Robinson, 2000) since the change in vegetation pattern has a feedback influence on the local and regional climate by changing the patterns of evaporative water losses from the surface to the atmosphere. \( f_c \) is required for the parameterization of surface conditions and for modeling and land cover/land use change studies.

Rearranging (1) and representing the background and vegetation reflectance by the minimum and maximum values of the normalized difference vegetation index \((\text{NDVI}_{\text{min}} \text{and } \text{NDVI}_{\text{max}} \text{ respectively})\) yields (Tucker, 1979; Choudhury et al., 1988; Carlson & Arthur, 2000; Carlson & Ripley, 1997; Che & Price, 1992; Gutman & Ignatov, 1998; Price, 1987; Rouse et al., 1974):

\[ f_c = \frac{\text{NDVI−NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}}−\text{NDVI}_{\text{min}}} \]  

A common approach to the retrieval of maximum and minimum NDVI values is through time series analysis. However, leaf optical properties can vary during the year independently of LAI, e.g. from airborne dust cover common in deserts (Derimian et al., 2006; Ganor, 1994). It follows that parameters of Eq. (2) are site and time specific and therefore should be estimated locally, as discussed in Section 4.5.1.

3.2. Leaf area index

The fraction of incident light transmitted through a canopy (τ) is described by:

\[ τ = \exp(−k^6 \text{LAI}) \]  

where \( k \) is the extinction coefficient for the canopy and LAI is the leaf area index of randomly distributed leaves (effective leaf area index), which is for non-clumped canopies the same as the actual leaf area index (Chen et al., 1991). Note that for clumped canopies actual leaf area index is larger than effective leaf area index.

Assuming that the tree crowns are opaque and the only transmission is the transmission through the gaps in the canopy, Eq. (3) can be rewritten as (Kucharik et al., 1999)

\[ τ = 1−f_c \]  

where \( f_c \) is the same as in Eq. (1).

Consequently, for known values of \( f_c \) and \( k \), LAI could be calculated as (Norman et al., 1995):

\[ \text{LAI} = \frac{−\ln(1−f_c)}{k} \]  

where \( k \) accounts for clumpiness.

3.3. Extinction coefficient

The extinction coefficient is a measure of attenuation of radiation in the canopy. It is a function of wavelength, radiation type, and direction, as well as stand structure and canopy architecture (Jarvis & Laverenz, 1983; Jones, 1992). The extinction coefficient can be expressed as:

\[ k = \frac{G(θ, x)Ω}{\cos(θ)} \]
where $G(\theta)$ is the foliage projection coefficient (or “shape factor”) characterizing the foliage angular distribution (\textit{a}; Norman & Campbell, 1989), $\Omega$ is the clumping index and $\theta$ is the sensor viewing angle.

When no other data is available most applications assume that leaves are randomly distributed in the horizontal plane and symmetrically distributed around the azimuth (Coops et al., 2004), and thus the leaf angle distribution parameter (the ratio of the vertical to horizontal canopy elements) is unity and $G(\theta) = 0.5$. However, for more complex and clumped sparse canopies of conifer stands this assumption does not hold, since within such canopies the leaves are typically not uniformly distributed and non-randomness of the canopy makes the extinction coefficient highly variable (usually lower) (e.g. Cohen et al., 1995). Thus the random assumption is an idealization applicable only when information on canopy structure is unavailable, while it is preferable, especially for sparse and clumpy vegetation of arid regions, to determine $k$ experimentally.

Different models based on probability statistics have been used to estimate the extinction coefficients for homogeneous (e.g. Cowan, 1968; Miller, 1967; Monteith, 1969) and clumped (e.g. Nilson, 1971) canopies. Moreover, most available $k$ estimates have been obtained for specific sky conditions and canopy types (Cohen et al., 1997), which may make them inappropriate under other conditions than those prevalent during their derivation. For this reason we used readily available global data products determined by remote sensing (operationally produced MODIS LAI and NDVI 8-day composite products) combined with easily available \textit{in-situ} measurements as sources of information in order to invert Eq. (5) and solve for $k$ as follows:

\[
k_{\text{MODIS}} = \frac{-\ln(1 - f_c\text{MODIS})}{\text{LAI}_{\text{MODIS}}}
\]

where

\[
f_c\text{MODIS} = \frac{(\text{NDVI}_{\text{MODIS}} - \text{NDVI}_{\text{min}}^\text{meas})}{(\text{NDVI}_{\text{max}}^\text{MODIS} - \text{NDVI}_{\text{min}}^\text{meas})}
\]

and the subscript MODIS stands for data obtained from the MODIS platform for a given date, the superscript max indicates the maximum value of a specific scene and NDVI\textit{min} stands for the ratio computed from actual \textit{in-situ} measurements carried out with field spectroradiometer using data that correspond to visual gaps within the IKONOS scene (Section 4.5.1).

We use $k_{\text{random}}$, in conjunction with data obtained from the high-resolution platform (IKONOS) in order to obtain LAI at high spatial resolution, as follows:

\[
\text{LAI}_{\text{IKONOS}} = \frac{-\ln(1 - f_c\text{IKONOS})}{k_{\text{random}}}
\]

where

\[
f_c\text{IKONOS} = \frac{(\text{NDVI}_{\text{IKONOS}} - \text{NDVI}_{\text{min}}^\text{meas})}{(\text{NDVI}_{\text{max}}^\text{IKONOS} - \text{NDVI}_{\text{min}}^\text{meas})}
\]

with the sub and superscripts min and meas having the same meaning as above but obtained from the corresponding IKONOS images (Fig. 2).

4. Materials and methods

4.1. Sampling design

Ten plots (Fig. 3) of $\sim 1000 m^2$ (approximately $32 \times 32$ m; $8 \times 8$ IKONOS pixels; each, were chosen in order to collect ground truth data. Each plot was divided into seven parallel East–West oriented $\sim 32$ m long and $\sim 4.6$ m wide sub-plots. The total length of transects made along those sub-plots totaled approximately 200 m in length. This length matches the recommended lengths for the use of the TRAC LAI meter (i.e. 100 to 300 m; Leblanc et al., 2002).

The location of each plot perimeter was mapped in a field campaign using a differential Global Positioning System (GPS) with $\pm 2$ m accuracy. The resulting polygons were adopted into a GIS vector layer.

4.2. Canopy structure: ground truth measurements

LAI measurements were carried out with the tracing radiation and architecture of canopies (TRAC) photo-sensor device and software (Chen & Cihlar, 1995a,b; Chen et al., 1997). A transect was measured along the length of each of the seven sub-plots, and mean LAI was calculated for each plot. Transects were repeated three times a day for different solar zenith angles during March and April 2004.

TRAC design and operation are described in Chen and Cihlar (1995a,b), Chen et al. (1997), Eriksson et al. (2005), and Leblanc et al. (2002, 2005). The instrument was designed to overcome the bias resulting from the clumpy nature of discontinuous canopies (and particularly coniferous forests) that occurs at several scales, between plants within a stand, and between branches or shoots within plants, and has been found in various studies to be a major factor of LAI underestimation when using non-contact indirect methods (e.g. Chen et al., 1997; Cohen et al., 1995; Kucharik et al., 1997; Lang, 1986, 1987; Welles & Cohen, 1996).

Clumping can be dealt with by
introducing a clumpiness factor, $\Omega$ (Eq. (6)), which represents the ratio of effective leaf area index ($LAI_e$), estimated without taking into account clumpiness, to true LAI ($LAI_t$), i.e.:

$$LAI_t = \frac{LAI_e}{\Omega}$$

Clumping in the forest stand is related to stand density, which is usually expressed as the number of trees per unit area and is sometimes taken as a coefficient (Daniel et al., 1979). Density always expresses a relationship between the number of plants and their sizes (Zeide, 1995). Consequently, the clumping correction should be inversely proportional to stand density. However, measuring density by remote sensing is not easy and requires more rigorous analysis as even high-resolution space-born sensors have difficulty in detecting single trees in the stand. Therefore, a quantitative analysis of stand density was out of the scope of this study and $\Omega$ was determined independently from the distribution of gap sizes measured by TRAC (Chen & Cihlar, 1995a,b). We were not able to perform a destructive sampling in order to calibrate TRAC. A TRAC data was compared to LAI estimated from leaf litter. The latter was systematically collected at three of the ten sample plots between October 2001 and October 2002 (see Section 5.2.2 for details) assuming that leaves did not lose dry weight during the senescence thus leaf litter dry mass equals leaf dry mass (Grunzweig et al., 2003). These comparisons show negligible (less then 1.5%) differences between LAI computed from TRAC measurements ($1.33$ m$^2$ m$^{-2}$) and LAI estimated from leaf litter collection ($1.35$ m$^2$ m$^{-2}$) and we consequently will use the TRAC data in lieu of LAI ground truth.

4.3. Stand structure: direct measurements

In addition to LAI, standard tree biometrics including equivalent diameter at breast height (DBH), crown diameter (CD), and tree height (H) were measured using a caliper, a measuring tape and a clinometer, respectively, during a special field campaign in April–May 2004. The tree canopy was assumed to be circular, thus CD was converted to crown area (CA), which was aggregated per plot. The canopy cover (CC) of a plot was calculated as the ratio of the sum of crown area of all trees within a plot to plot area. Stem density was defined as the number of trees per plot (trees/pl). Field measured parameters and a comparison of the training plots are presented in Table 1.

4.4. Image data retrieval

4.4.1. High spatial resolution data

A 4-m spatial resolution multi-spectral IKONOS image was acquired on March 25, 2004. IKONOS is the first high-resolution commercial satellite that simultaneously captures 1-m panchromatic (black and white) and 4-m multi-spectral (color) digital imagery (blue, green, red, and near infrared). The panchromatic
Table 1
Characteristics of the ground truth plots

<table>
<thead>
<tr>
<th>Plot ID</th>
<th>LAI (m²/m²)</th>
<th>Density (trees/pl)</th>
<th>DBH (cm)</th>
<th>CD (m)</th>
<th>CA (m²)</th>
<th>HEIGHT (m)</th>
<th>CC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.47</td>
<td>23</td>
<td>19</td>
<td>5</td>
<td>19</td>
<td>10</td>
<td>44</td>
</tr>
<tr>
<td>2</td>
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<td>25</td>
<td>16</td>
<td>4</td>
<td>15</td>
<td>8</td>
<td>37</td>
</tr>
<tr>
<td>3</td>
<td>1.80</td>
<td>25</td>
<td>20</td>
<td>5</td>
<td>21</td>
<td>10</td>
<td>52</td>
</tr>
<tr>
<td>4</td>
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<td>30</td>
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<td>4</td>
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<td>8</td>
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</tr>
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<td>1.30</td>
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<td>4</td>
<td>13</td>
<td>8</td>
<td>50</td>
</tr>
</tbody>
</table>

and multi-spectral datasets are available separately or can be purchased as combined 1-m (or coarser) multi-spectral images. Onboard sensors can point both along and across the satellite track, providing a revisit frequency of 1–3 days.

This image was radiometrically and atmospherically corrected following Space IMAGING® specifications (http://www.spaceimaging.com/products/ikonos/spectral.htm) and 6S radiative transfer model (Vermote et al., 1997) respectively, and registered into the UTM projection by using Geographic Control Points.

4.4.2. Moderate and low spatial resolution data

MODIS provides high temporal resolution (every one to two days), radiometric sensitivity in 36 spectral bands ranging in wavelength from the visible (VIS) to the short-wave infrared (SWIR), and moderate to low spatial resolution (from 250 to 1000 m). The 44 standard MODIS products are available to the scientific community through the Earth Resources Observation System (EROS) Data Active Archive Center (DAAC), usually at 1000-m spatial resolution. Since MODIS was originally proposed for global studies (which explain its moderate/low spatial resolution) it requires detailed validation for local implementation.

Three standard MODIS products (Collection 4) were used:

- 1-km global data LAI product (MOD15A2) updated every 8 days in order to eliminate the contamination from cloud cover (Knyazikhin et al., 1999). This product’s algorithm uses vegetation maps built on the basis of six major biomes (cereal crops, shrubs, broad-leaf crops, savannas, broad-leaf forest and needle-leaf forest) to constrain the vegetation structural and optical parameter space (Fang & Liang, 2005). The main MODIS LAI algorithm is based on three-dimensional radiation transfer theory while LAI is retrieved by comparing the observed and modeled bidirectional reflectance factor (BRF). The latter utilizes a soil reflectance model (Jacquemoud et al., 1992) for each biome for varying sun-view geometry and canopy/soil patterns. Moreover, a backup algorithm based on a straightforward NDVI-LAI relationship is used when the main algorithm fails.
- 1-km global MODIS/Terra vegetation indices (VI) product (MOD13Q1). The VI product contains two indices, the NDVI and enhanced vegetation index (EVI) as well as VI quality information. The product is derived from daily MODIS red, near infrared, and blue surface reflectance data and is provided every 16 days as a plotted product in the Integerized Sinusoidal projection. The VI algorithm operates on a per-pixel basis and requires multiple observations (days) to generate a composite VI using a methodology with three separate components: maximum value composite (MVC), constraint-view angle–maximum value composite (CV-MVC) and bidirectional reflectance distribution function composite (BRDF-C).
- MODIS/Terra Surface Reflectance Daily L2G Global 250 m SIN Plot (MOD09GQK). This product is a two-band product computed from the MODIS Level 1B land red and near-infrared bands. The product is an estimate of the surface spectral reflectance for each band, as it would be measured at ground level if there were no atmospheric scattering or absorption.

The MODIS products were re-projected into a UTM projection in order to be compatible with IKONOS data.

4.5. Image data processing

4.5.1. Vegetation index

NDVImaxIKONOS was obtained from in-situ reflectance measurements carried above a surface composed primary of needle dry litter using a LICOR LI-1800 high spectral resolution field spectroradiometer in the range 400–1100 nm with spectral resolution of 2 nm. The LI-1800 was attached to a telescope with a field of view (FOV) of 15°, which was positioned above the surface at a height of about 80 cm. Measurements were repeated three times at each of five points randomly distributed over the forest and the average value was used in the analysis. Upwelling radiance from a white reference panel, measured twice at each sampling point (first and a last measurement) was used for calculating reflectance of each surface-target scan (Gitelson et al., 2002; Pereira et al., 2004). The sample points were selected from the IKONOS image as visually identifiable gaps within a canopy cover and located using a GPS.

NDVIminIKONOS was computed from IKONOS Red and near-Infrared reflectance of an area of 2 by 2 pixels (8 × 8 m each pixel?) with 100% coverage. The area was selected during the field reconnaissance, and subsequently located on the image using GPS.

4.5.2. Image classification

We performed a multi-spectral supervised classification of an IKONOS image using a supervised classification procedure of ERDAS Imagine software. As a result, each pixel of the image was ascribed to one of seven end members (agricultural fields, asphalt or non-asphalt roads, covered pixel or gaps, and deep or shallow water for a water reservoir at the North-Eastern part of the forest) according to their spectral characteristics. These characteristics and sequence endmember determinations were based on visual analysis of surface type. Canopy cover for training plots was calculated as a ratio of forested (Nf) and the total number of pixels that covers the specific plot (n):

$$CC = \frac{N_f \cdot 100}{n}$$ (12)
where $n$ is a sum of all (forested and non-forested ($N_{nf}$)) pixels in a sample plot ($n = N_f + N_{nf}$).

5. Results and discussion

5.1. LAI estimation for high spatial resolution (IKONOS) imagery

$f_{c,IKONOS}$ was calculated according to Eq. (10) using values of $0.13 \pm 0.04$ and $0.75 \pm 0.2$ ($\pm$ standard deviation) for $NDVI_{meas}^{\min}$ and $NDVI_{IKONOS}^{\max}$ respectively, determined by the procedures described above. This resulted in a map of the spatial distribution of $f_c$ at a 4 m resolution. $f_c$ ranged from approximately 40 to 70% over the forested area within the entire image and averaged $49 \pm 7\%$ for the ten training plots. These values were compatible with the average canopy cover calculated from measured canopy crown diameters of $48 \pm 9$. Eq. (5) was solved for LAI assuming a random angular distribution of leaf area. The resulting 4 m resolution LAI image was then overlapped with the 10 ground-measured plots’ vector layer and the mean LAI value for each plot was extracted using a Zonal Statistics procedure from the ERDAS Imagine software. The predicted variable, LAI$_{IKONOS}$ was highly correlated ($R^2 = 0.79$) to the ground truth LAI obtained using the TRAC. However, LAI was significantly ($p < 0.01$) underestimated by remote sensing, the differences being noticeable at high LAI values (Fig. 4a). This presumably results from canopy clumping, which is, as mentioned previously, a major cause of LAI underestimation by non-contact methods.

The clumping index was determined from the distribution of gap sizes measured by TRAC, which gave an average $\Omega$ value of $0.84 \pm 0.05$. This value can be interpreted as the large-scale clumpiness related to tree distribution in the forest; and (b) as a compensation for the error that results from the fact that the true extinction coefficient is not known. It would be useful to gain a better understanding of the relationship between clumpiness and density since stand density determination by remote sensing is likely to be easier than direct determination of the leaf angle distribution and the angle with which light transverses the canopy (required for calculating the extinction coefficient). Fig. 4b shows the remotely sensed LAI corrected for clumping, and features a similar level of correlation as the previous case ($R^2 = 0.79$) and a slope that is not significantly different from 1 (Student’s $t$-test for dependent variables). Thus, for high spatial resolution remote sensing (IKONOS), LAI computed from surface reflectance with Eq. (5) was significantly underestimated. However the introduction of the ground-based (TRAC) measured clumping factor resulted in values not significantly different from the ground truth (TRAC) measurements of LAI.

5.2. Validity of the MODIS LAI product

5.2.1. MODIS LAI data quality for our site

Since the empirical relationships between NDVI and LAI were applied in the current study (described in details in “Theory” section) it was important to be sure that such a relationship implemented by MODIS group backup algorithm (based on an empirical NDVI-LAI relationship) wasn’t utilized during the LAI product release. This was done through the appraisal of the MODIS LAI quality control layer. Such a layer, computed for 1 km$^2$ resolution, includes a status flag (SFC_QC) which can take one of five possible values: “0” and “1” refer to application of the main algorithm (RT) where “0” is the best possible result and “1” indicates that the RT method was used with saturation; “2” and “3” refer to high uncertainties in input reflectance data or biome misclassifications (“2” for failure due to geometrical problems and “3” for failure due to other problems) in which case the backup algorithm was used; and “4” indicates that both algorithms failed and therefore no data is supplied (Wang et al., 2004, 2005a,b). Analysis of the data quality statistics for the study site shows that more than 24% of the LAI data was marked as high quality (24 pixels), more than 66% was marked as sufficient results achieved by the RT algorithm (65 pixels), and only 9% was misclassified (9 pixels). Consequently, it was concluded that the MODIS group backup algorithm wasn’t used to produce the LAI product, thus and the assumption of independence between LAI and NDVI can hold over the research site and period.

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Fig. 4. A comparison between TRAC and remote sensing measured LAI before (a) and after (b) the correction for clumpiness. CV stands for coefficient of variation.
Table 2
Comparison of MODIS-derived LAI and values acquired from several LAI meters

<table>
<thead>
<tr>
<th></th>
<th>MODIS</th>
<th>LP-80</th>
<th>TRAC</th>
<th>SunLink</th>
<th>LAI-200</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAI (m²/m²)</td>
<td>1.7</td>
<td>1.69</td>
<td>1.33</td>
<td>1.56</td>
<td>1.49</td>
</tr>
<tr>
<td>Absolute differences with MODIS LAI pixel value (m²/m²)</td>
<td>0.01</td>
<td>0.37</td>
<td>0.14</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>Relative differences with MODIS LAI pixel value (%)</td>
<td>0.59</td>
<td>21.76</td>
<td>8.24</td>
<td>12.35</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>1.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

SunLink, SunScan and LP-80- are battery-operated linear sensors which measure PAR (Photosynthetically Active Radiation in the 400 to 700 nm waveband) transmittance by the canopy; the LAI-200 calculates LAI from radiation measurements made with a “fish-eye” optical sensor (148° field-of-view) that determines canopy light interception at 5 angles; TRAC described in details in sampling design section.

5.2.2. Inferring the validity of MODIS LAI product (comparison to ground-based measurements)

Due to its unique location the Yatir forest is a focal point for extensive dry-land research. Since 2000 the Weizmann Institute of Science has maintained a flux tower in the forest as part of the CarboEuroFlux program (http://www.carboeurope.org/). In the framework of this project, indirect measurements of LAI were conducted every 6 months from March 2001 until March 2004 in three plots of ~1000 m² each, located within the flux tower footprint area (1 km²). In March 2004 LAI was simultaneously measured by several devices (Table 2). These measured LAI values were averaged per device and over the plots, and compared with an extracted pixel value to evaluate the MODIS LAI product as an independent source of information that was necessary in order to apply Eq. (7) in the following steps (see Fig. 2 for details).

The MODIS LAI value was within the range of the values obtained by the different devices, and not significantly different from the mean (±12%), which led us to conclude that in our case the MODIS LAI product can be used without any correction factor.

5.3. LAI estimation for moderate spatial resolution imagery

The determination of LAI for moderate resolution, which involved the use of moderate and low resolution MODIS products, is described in a flowchart (Fig. 2) and in the following sections. Changing scale of surface reflectance and then applying the normal inversion for computing LAI would result in errors due to the exponential nature of the relationship between LAI and reflectance (e.g. Lang & Xiang, 1986). Therefore we chose not to downscale resolution of the LAI values directly (in the left branch of the flow chart). However, the extinction coefficient is linearly related to LAI and therefore when scale of the extinction coefficient is changed the mean LAI estimate should not change. Therefore, the 1 km resolution LAI and NDVI products were used to determine the extinction coefficient using Eq. (7) (Section 5.3.1). The extinction coefficient distribution map was then downscaled to 250 m resolution using ERDAS Imagine software (ERDAS, 1999) and was then used together with fractional vegetation cover (FVC), determined from an empirical relationship relating it to the 250 m reflectance product to determine LAI with Eq. (5) at moderate (250 m) spatial resolution (Section 5.3.3).

5.3.1. Fractional vegetation cover

Histograms of fractional vegetation cover assessed for 250-m resolution show trends identical to those observed at high resolution (see above). A comparison between trends presented for the whole study area (Fig. 5) shows a small shift at low resolution to higher FVC values. This pattern was also applied to the ten sampling plots and average FVC was 0.51±0.14 for 250-m as compared to 0.49±0.07 for 4-m resolution.

Measured and calculated FVC were compared by calculating the relative error (RE) per training plot, as well as the average relative value for all ten plots by the following equation:

\[
RE = \frac{|\text{simulation} - \text{observation}|}{\text{observation}}
\]  

Relative errors were calculated for high resolution as compared to ground measurements, as well as for moderate resolution compared to high resolution (Table 3). The average relative error was small both for CC vs. 4-m FVC (16%±12%) and for 4-m FVC vs. 250-m FVC (23%±21%). This accuracy was considered to be sufficient for further calculation. However, it should be noted that when the pixel resolution is coarser than a plot’s scale poor aggregate values result, and it is better to extract values for sub-pixel heterogeneity (Kustas et al., 2004). This statement is true for our set of data since the average relative error calculated for CC vs. 250-m FVC was found to be much higher (31%±35%) (not presented in Table 3).

5.3.2. Determination of the extinction coefficient

Following the procedure depicted by the left side of Fig. 2, Eq. (7) was solved for the extinction coefficient (k) using 1-km MODIS NDVI and LAI data. As was stated previously, our intent was to present a method to assess LAI at a scale that could be compared to other available remote sensing products adapted to environmental monitoring (e.g. ASTER, LandSat etc.). Consequently the spatial resolution of the image produced was downscaled by changing the pixel size from 1 km (too coarse for a 3000 ha forested area) to 250 m (close to high-resolution sensors).

Results showed relatively low variability over the forest with an average k of 0.45±0.11 (±STD), which is close to k for a random leaf angle distribution (0.5). The small (not significant) deviation from random may result from the clumpy nature of the forest and indicates that the use of a clumping correction may be
important, as noted above (Sections 4.2 and 5.1). A similar average value of $k$, 0.63±0.05, was determined in previous ground-based measurement campaigns referred to in Table 2 (unpublished results).

The uneven distribution of $k$ over the forest may result from different reasons such as variation in the soil depth, inhomogeneous age and species distribution in some of the stands, as well as management practices, which are dictated by specific objectives of the Israeli Forest Service (e.g. greening the landscape and recreation), and are different in different parts of the forest. However, since the distribution of $k$-values over the forest was not homogeneous, ranging from 0.01 to 0.66, (Fig. 6) and differed from the normal as indicated by the Shapiro–Wilk $W$ test (Shapiro & Wilk, 1965) with $W=0.9$ and $p=0.003$, it was decided to treat each pixel separately during the subsequent LAI assessment.

5.3.3. Leaf area index

After assessment of the FVC (Section 5.3.1) and extinction coefficient (Section 5.3.2) from the MODIS reflectance and LAI data we were able to calculate LAI for 250-m spatial resolution and to draw a map of its spatial distribution. This map, as well as the previously drawn 4-m spatial resolution LAI map is presented in Fig. 7. Similar patterns of LAI distribution are shown in both maps, i.e. higher values over the mature northern and western parts of the forest (2–2.5) and lower values towards the south and south-east (1–2). This trend is compatible with the age distribution over the forest that becomes younger from north-west (average tree age 36–37 years) to south-east (average trees age 20–23 years).

Unforested areas (“Bare soil” in the legend) in the high-resolution image were almost completely undetectable at coarser resolution and influence the patchiness of the picture by mixing with the surrounding vegetation and appearing as spots of low LAI (0.5–1).

As reported in previous studies (e.g. Tian et al., 2002a,b; Wang et al., 2004), a comparison of ground-based measurements from small areas to the moderate to coarse resolution products requires development of detailed and appropriate strategies in order to achieve a reasonable method for comparison. In our case, the linear correlation between the training plot LAI and that of matching pixels, which resulted in a high correlation coefficient at high resolution ($R^2=0.16$), was very low and non-significant at moderate resolution ($R^2=0.16$). This low correlation presumably resulted from the order of magnitude difference between pixel ($\sim 62,500$ m$^2$) and training plot (1000 m$^2$) size. The variation of LAI at different resolutions and, consequently, the validity of moderate spatial resolution data were investigated, as an alternative, through analysis of the frequency distribution of LAI values and its deviation from a Normal (Gaussian) distribution by calculating skewness and kurtosis (symmetry and “peakedness” measures of the distribution relative to a Normal distribution; Kustas et al., 2004).

Fig. 8 shows histograms of LAI distribution over the forest and statistics for both spatial resolutions and indicates similar trends regardless of the spatial resolution. The mean LAI was 11% higher for the higher than for the coarser resolution, i.e. 2.53 for 4-m and 2.25 for 250-m, and the coefficient of variation (CV) was high in both sets but lower for the coarser resolution, as expected (Kustas et al., 2004) since as spatial resolution

<table>
<thead>
<tr>
<th>Plot ID</th>
<th>CC</th>
<th>FVC 4-m*100</th>
<th>FVC 250-m*100</th>
<th>RE for CC vs. FVC 4-m</th>
<th>RE for FVC 250-m vs. 4-m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>44</td>
<td>44</td>
<td>43</td>
<td>0.01</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>37</td>
<td>47</td>
<td>79</td>
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</tr>
<tr>
<td>3</td>
<td>52</td>
<td>54</td>
<td>55</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>4</td>
<td>51</td>
<td>38</td>
<td>56</td>
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<td>0.45</td>
</tr>
<tr>
<td>5</td>
<td>41</td>
<td>49</td>
<td>60</td>
<td>0.19</td>
<td>0.22</td>
</tr>
<tr>
<td>6</td>
<td>67</td>
<td>41</td>
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<td>0.38</td>
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</tr>
<tr>
<td>7</td>
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<tr>
<td>8</td>
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<tr>
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<tr>
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<td>51</td>
<td>0.16</td>
<td>0.23</td>
</tr>
<tr>
<td>STD</td>
<td>9</td>
<td>7</td>
<td>14</td>
<td>0.12</td>
<td>0.21</td>
</tr>
</tbody>
</table>

RE stands for the relative error.

Fig. 6. The distribution of the extinction coefficient over the Yatir forest at 250-m spatial resolution. The broken vertical line indicates the forest average value.
Fig. 7. Leaf area index distribution over the Yatir forest for high (4-m) and moderate (250-m) spatial resolutions.
decreases one can expect the increase in homogeneity of the area covered by a larger pixel.

The results appear to indicate that a sufficient amount of the surface information would be retrievable by moderate spatial resolution (250-m per pixel) imagery. However, we assume that a further decrease in resolution is not desirable since coarser pixel sizes will combine the attributes of different surface elements within such a large area (e.g. 1000 m²) into a single reflectance value. So a significant amount of the surface information will be lost, and thus the possibility of detailed surface characterization (Fig. 7). This supported by the slight, almost negligible, divergency between the results presented in Fig. 8 may be considered as the beginning of the trend of recession from the normality with further decrease in spatial resolution as in combination with decrease in mean and CV indicates deletion of the differences between various surface elements.

6. Conclusions

Remote sensing of vegetation cover and its related variables and products is needed for understanding the impacts of land use and climate change in arid and semi-arid regions. In the current study we present a method to determine the LAI of a forest located at the desert fringe by analyzing results from a high spatial resolution sensor and applying the approach to moderate spatial but high temporal resolution imagery.

LAI values assessed remotely using high spatial resolution imagery were highly correlated with ground-based measurements made with the TRAC; however for successful LAI assessment the remote sensing data should be corrected with the clumping index, which has been shown to be the main source of LAI underestimation by indirect methods. For a better description of canopy patterns and as a compensation for non-random distribution of canopy elements, application to moderate spatial resolution (250-m) was performed through the calculation of the canopy extinction coefficient on a regional scale (pixel by pixel) using operationally produced MODIS LAI and VI products as ancillary sources of input data.

Histograms of resulting LAI distributions and descriptive statistics at the different spatial resolutions indicate that the overall distribution of LAI does not change dramatically with the decrease in resolution and remains close to being normally distributed. However, we suppose that one should be aware that the effect of spatial resolution on the precision of the results, as well as the implementation of global datasets (with moderate to low spatial resolution) to local studies (especially to heterogeneous semi-arid regions) should be considered carefully and site specific.

Although the results of this study suggest that LAI monitoring with available moderate (250-m) spatial resolution imagery dataset supplied by EOS at a high temporal frequency could be assessed with promising accuracy even for small scale applications, further investigation over a more heterogeneous areas (primarily in terms of species variability and age classes’ distribution) could be useful in supplementing the expensive high spatial resolution data on the one hand and in complementing the currently available MODIS product on the other hand.
References


