Components of uncertainty in primary production model: the study of DEM, classification and location error

E. Livne*; T. Svoray*

*Department of Geography and Environmental Development, Ben-Gurion University of the Negev, Beer-Sheva, Israel

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Components of uncertainty in primary production model: the study of DEM, classification and location error

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Department of Geography and Environmental Development, Ben-Gurion University of the Negev, Beer-Sheva, Israel

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The use of geographic information system (GIS)-based ecological models is increasing and input datasets of these models are improving daily. Still, there is a notable gap in quantifying the uncertainty related to these models. Quantifying uncertainty in spatial ecology is indeed crucial because it may improve the support that GIS provides for decision support systems. This article aims to quantify uncertainty and error propagation in a dynamic GIS model that predicts ecosystem productivity in dry environments. This was done through the following operative objectives: (1) comparing the contribution to model uncertainty of topographic error with classification error; (2) testing whether the uncertainty contributed by the secondary topographic index (radiation layer) is greater than the uncertainty contributed by the primary topographic indices (aspect or slope); and (3) quantifying the contribution of the location error to model uncertainty. The research was applied in four steps: (1) spatial database design and collection of validation data; (2) standard error determination, based on statistical indices for simulation; (3) development of simulation codes to assess the uncertainty and error propagation of the environmental variables; and (4) determination of the hierarchy of uncertainty factors. The results show that the contribution of the DEM layer to the model uncertainty is substantial, as opposed to the negligible uncertainty contributed by the rock map. The error simulation results were found to be different among subregions and were dependent on slope gradient and error magnitude. Error propagation from the secondary topographic index (radiation layer) was occasionally found to contribute less to the model uncertainty than the primary topographic index (aspect). It was also found that location error correction has only a small positive effect on the model’s predictability. The reason is related to the limited ability to determine location error, because here the correction method was spatially uniform and based on visual interpretation. Future research can focus on the assessment of model behavior with different DEM spatial resolutions to find the best resolution for prediction. There is a need to analyze the effect of the model’s climatologic variables to better understand their uncertainty effect on the model’s temporal dimension. In addition, there is a need to develop a unique algorithm that will make an optimal assessment of spatial nonuniform correction of the location error.

Keywords: uncertainty; error propagation; DEM; classification; ecology; hydrology

1. Introduction

Ecologists are facing the continuing challenge of developing models for precise prediction of phenomena that change in both time and space (Saghfian et al. 2002). Recent developments in remote sensing technology and in the accuracy of digital elevation models (DEM)
offer an opportunity to combine these data sources in raster geographic information systems (GIS) for spatiotemporally explicit modeling of soil and vegetation dynamics (McBratney et al. 2003, Scull et al. 2003). The use of GIS for ecological modeling has become common, especially because of the need to assess the impact of accelerated land use and other environmental changes on the distribution of organisms (Guisan and Zimmermann 2000) and on ecosystem functioning. For example, aboveground net primary production (ANPP) is among the most important indicators of ecosystem capabilities, functioning, and resource utilization efficiency (Jobbagy et al. 2002, Cao et al. 2004). Consequently, many ecological studies require reliable quantification of ANPP (Shmida and Burgess 1988). Several GIS-based models have therefore been developed to predict ANPP variation in space and time (e.g., Svoray et al. 2004, 2008), but an accurate assessment of model predictive uncertainty and the source of such uncertainty still remains unsolved (Buttenfield 2000).

The need for further study uncertainty and error propagation in ecological models is reinforced by the unanimous agreement that complex reality cannot be transformed into a digital model without harming the accuracy of the phenomenon we want to represent (Dicks and Lo 1990, Brown et al. 1999, Zhang and Goodchild 2002, Fisher and Tate 2006). The inability to quantify the error in space and time significantly harms the reliability of spatial models and, thus, the resulting decision-making. As a result, it is essential to provide effective support for decision-making systems and, specifically, to determine the uncertainty in spatial model results (Fisher 2000, Crosetto and Tarantola 2001).

Studies of uncertainty analysis of environmental models have so far been mainly applied to study the effect of DEM error on model predictions (Crosetto and Tarantola 2001, Shortridge 2001, Van Niel et al. 2004). Others have studied the contribution of classified maps – mainly those of low spatial resolution (30 × 30 m²/cell) – on model predictions (Kyriakidis and Dungan 2001, Saha et al. 2005a, Svoray et al. 2008). This research has been carried out mostly using confusion matrices rather than error simulation (McGwire and Fisher 2001). Only a few studies have quantified location error effects (Arbia et al. 1998, Carmel et al. 2001) and even fewer studies (e.g., Canters et al. 2002) have applied uncertainty simulation analysis to compare the contribution of DEM error and classified maps error to the total uncertainty of model predictions.

In this article, we aim to estimate and compare the effect of a high-resolution DEM, orthophoto classification, and location errors in physiological units, on the predictive ability of a primary production model, at a spatial resolution of a few meters. More specifically, the following questions are investigated:

(a) Which of the two factors – DEM error or classification error – contribute more to increased uncertainty of the model predictions?

(b) Does location error contribute more to the uncertainty of model predictions than the thematic error (DEM or classification)?

(c) Does error propagation from the secondary topographic index (radiation layer) contribute more to the uncertainty of model predictions than the primary topographic indices (aspect/slope)?

2. Study site

The dataset used in this research covers an area of 25 km² at the Lehavim site (31°20' N, 34 45' E), located in the Northern Negev, Israel. The site is one of the worldwide Long-Term Ecological Research (LTER) stations. The climate is semiarid, with a mean rainfall of 270 mm.
per annum (Svoray et al. 2008). The terrain is hilly to the east (with slope gradient 5–15 degrees) and the topography becomes moderate (0–2 degrees) toward the western part. The vegetation in the site is characterized by scattered dwarf shrubs and patches of herbaceous vegetation, mostly annuals, interspersed between rocks and dwarf shrubs (Ungar et al. 1999). The dominant rock formations are Eocene limestone and chalk with patches of calcrete. The soils are brown lithosols combined with arid brown loess. The dwarf shrub community forms a steppe-like landscape with diffuse vegetation. The herbaceous vegetation appears shortly after the first rains and persists as green forage for 3–4 months. It is highly diverse, comprising mostly annual species that form 56% of the regional flora (Danin and Orshan 1990).

3. Methods

3.1. Model description

To study the effects of uncertainty and error propagation of topographic indices and classified remotely sensed data on the prediction of a GIS-based ecological model, we here used a well-established dynamic model that predicts the conditions for primary production of annual herbaceous vegetation in dry environments (Svoray et al. 2008). The model structure, validation, and sensitivity analysis are fully described by Svoray et al. (2008) and therefore we provide a short description of the main principles only. The model proposed by Svoray et al. is based on fuzzy algebra and uses membership functions for calculating conditions for germination and production, using high spatial resolution data of 2 × 2 m²/cell (the original version was applied to the data of 25 × 25 m²/cell). The model operates on daily resolution, using rainfall and temperature data. The environmental variables of the examined model include (1) a DEM layer with spatial resolution of 2 × 2 m²/cell; (2) its topographic indices (aspect, slope, solar radiation); and (3) an average rock outcrop layer that was created from classification of a 0.12 × 0.12 m²/pixel orthophoto, resampled to a resolution of 2 × 2 m²/cell.

Equation (1) is the joint membership function that represents the main function for simulating the conditions for production (µₚ) (predicted data), as was applied in the Svoray et al. model:

\[
\mu_{P_{ij}} = \sum_{t=1}^{r} \left( \lambda_{RD} \mu_{RD_{ij}} + \lambda_{RDE} \mu_{RDE_{ij}} + \lambda_{RAD} \mu_{RAD_{ij}} + \lambda_{EVP} \mu_{EVP_{ij}} + \lambda_{DEF} \mu_{DEF_{ij}} + \lambda_{RC} \mu_{RC_{ij}} + \lambda_{TMPP} \mu_{TMPP_{ij}} \right)
\]

(1)

where RD is the rainfall depth (mm), TMPP the temperature (°C), EVP the daily evaporation rate (mm), RAD the radiation flux (MJ/m²), DEF the soil moisture deficit (m), RC the rock cover (%), and RDE the soil moisture storage from the last day (mm). The weights λᵢ are of major importance, as their size determines the degree to which each MF (µ) contributes to the final set. The weights consequently represent a hierarchy of the variables’ contributions to the Joint Membership Function (JMF) (µₚ in day t and location ij) and, hence, each variable’s value in the final predictive model. The model was tested with a sensitivity analysis to determine its weights and it was found capable of explaining the variation of harvested biomass in the field, using regression analyses, with mean \( R^2 \) values of 0.76 (SD = 0.066; \( n = 15 \) years). The layers that contribute to the model’s predictive uncertainty are the radiation and the soil moisture deficit (calculated on the basis of the DEM), the rock outcrop
(classification map), and a layer of the physiographic units that was computed to create the basic units and described later.

The Svoray et al. (2008) model was chosen to study the effect of dataset error on the uncertainty of predictions of ecological models, because it uses two different kinds of physical databases (DEM and classification map) and therefore enables a two-way result comparison. This model is also well established against field data. In this article, the uncertainty analysis was applied to the model’s predictions of biomass production for the growing season of 2002–2003.

3.2. Uncertainty analysis

Model uncertainty and error propagation were studied here using Monte Carlo (MC) simulations, commonly used to explore the range of diversity in GIS error factors (e.g., Fisher 1998, Heuvelink 1998, Burrough and McDonnell 2000, Crosetto and Tarantola 2001, Karsenberg and De Jong 2005). MC was used here for three purposes: (1) error analysis of the DEM, (2) error analysis of the classification layers, and (3) error propagation within the model.

3.2.1. Error analysis of the DEM

The DEM error analysis was based on the traditional approach that includes using higher quality field data for validation (Hunter and Goodchild 1997, Wise 2000). After a field campaign, of 310 point measurements, measured $x$, $y$, and $z$ values, using a Total Station theodolite of a few centimeters accuracy, the standard deviation of error was calculated and used in the MC simulations (Van Niel et al. 2004). The MC simulation for DEM error analysis was applied based on procedures described in previous studies, such as Van Niel et al. (2004) and Oksanen and Sarjakoski (2005a). This was carried out in the following five steps:

Step 1: Based on 9–20 field measurements for every subsite that differed in the length and gradient of the slope, we determined a vertical standard error for the DEM cells.

Step 2: A random value from the error probability distribution function of each cell was selected.

Step 3: A spatial autocorrelation filter was activated on the ‘new’ DEM.

Step 4: Iterations of DEM and its topographic indices were generated. Steps 2–4 were repeated 150 times.

Step 5: Finally, we generated a mean error including DEM and topographic indices as the model’s variables.

For the analysis and to save computerization time, the study area was divided into three specific subsites with different error ranges of elevation. At these sites, we used validation plots (as part of the LTER project), representing the physical and environmental conditions of the study site (Table 1).

<table>
<thead>
<tr>
<th>Subsite</th>
<th>Relief type (slope gradient)</th>
<th>Slope length</th>
<th>Number of validation points</th>
<th>RMS error (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northern</td>
<td>Low</td>
<td>short</td>
<td>12</td>
<td>3.67</td>
</tr>
<tr>
<td>Southern</td>
<td>Low</td>
<td>stretchy</td>
<td>20</td>
<td>3.12</td>
</tr>
<tr>
<td>Eastern</td>
<td>High</td>
<td>stretchy</td>
<td>9</td>
<td>7.29</td>
</tr>
</tbody>
</table>

Table 1. Vertical standard error data of DEM in the three subsites.
The error analysis was applied based on the method of Oksanen and Sarjakoski (2005a). MC runs were applied using the ‘process convolution,’ for simulating 2D Gaussian random field process, to determine the spatial autocorrelation error, based on the Gaussian autocorrelation function:

\[ \rho(h) = \exp \left[ -3 \left( \frac{h^2}{r^2} \right) \right] \]

where \( \rho(h) \) is the correlation coefficient of the DEM error at the lag \( h \) and the specified range \( r \). The constant –3 was used to scale the Gaussian correlation function to a level of 0.05 at the lag of \( r \). This yields a symmetric matrix of autocorrelation coefficients; Oksanen and Sarjakoski (2005a) found that taking a square root of a squared matrix of Gaussian autocorrelation coefficients and then scaling the matrix properly yields a numerically correct weight kernel for filtering the uncorrelated Gaussian noise. We used the same range \( (r = 20 \text{ m}) \) of spatial autocorrelation as Oksanen and Sarjakoski (2005a) because \( r \) has to be smaller than the size of objects in the DEM, and this is a value that fits our data too. Semivariograms (Figure 1) were applied to validate 311 points (Figure 2), exhibiting a range of 143–178 m with a negligible nugget (0.09–0.32 m) and a sill of 90.55–329.68 m.

In addition, the total standard deviation error of the 310 validation points was 2.4 m, after the field campaign with high-quality GPS for location \((x,y)\) and theodolite for height \(z\). According to Oksanen and Sarjakoski (2001), error in the same order of size does not have much influence, if the range of spatial autocorrelation is 20–50 m. According to the extraction of the vertical standard error (Wechsler 1999), we executed 150 iterations of the

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Figure 1. Twelve semivariograms that were calculated to explore the optimal range between validation points in every square subzone of the study site.
DEM error analysis, separately for each of the three subsite DEMs. We proceeded with this process for error propagation analysis of the topographic indices, as we simulated 150 runs of those three errors, including DEMs in the ArcGIS modeler, to produce random error layers of slope, thematic aspect layer (Svoray et al. 2004), and radiation (Rich et al. 1994).

3.2.2. Error analysis of classification map

The classification error analysis was applied in this work based on the method of Canters et al. (2002) (see also, Fisher (1991)). Accordingly, after Maximum Likelihood Classification (MLC) (Franklin and Wilson 1991) was applied to map four classes of surface cover – rock outcrop, soil, herbs, and shrubs – we executed 200 MC simulation runs to explore the range of classification possibilities in every cell. The MC was applied using the same steps described in Section 3.2.1, whereas at Step 2, the random number was the factor
for changing the class condition in each cell and Step 3 was not needed, because the spatial autocorrelation error effects were controlled by the proximity relations between neighbors’ pixels and therefore not executed.

The simulation of possibilities for changes in classes within the cells were applied from the confusion matrix (CM), which was established from a validation database of 400 randomly distributed field points (100 for each class). The CM values were normalized to 0–1 value range. Then, by ‘If then...’ statements, we determined to which class a random number belonged depending on the CM possibilities. For example, if a cell of rock outcrop class could change to soil class by a chance factor of 0.07 and the random value of the simulation was 0.58, the cell class remained rock outcrop. Conversely, if a random value was 0.97, the cell could be changed only if at least one of its neighbors had changed too. The relation rules (from the CM) between the classes remained the same. This means, for example, that if, in the CM conditions, there is only a small possibility that soil be classified as shrub, this condition will remain the same even after we make it hypothetically possible to change classes. We used a hypothetical and much larger error than was actually observed (the possibilities of changing classes were doubled), because the observed error was relatively small and had a very limited effect.

3.3. Analysis of location error effect

Location error in the basic research units can cause a mixture of different explanatory variables and, therefore, is suspected of affecting predictive ability. Four physiographic units, along the slope catena, were mapped in the model of Svoray et al. (2008) as the basic research units: interfluve, shoulderslope, backslope, and footslope. These units were identified by the process-based terrain characterization model of Park et al. (2001) and the contour-based DEM of Hall and Cleeve (1990). We used visual interpretation for validating the location of the physiographic units but were not able to calculate the probability of all four physiographic unit locations on the slope, as it was impossible to visually interpret the shoulderslope and backslope. Three RMSE values, between observed and predicted cells, were calculated for the three subsites (northern site = 1.64 m, southern site = 4.32 m, and eastern site = 3.58 m), between equivalent topo-physiographic elements (interfluves or channels), which were identified in an ortho photo of 0.12 × 0.12 m²/pixel. These elements were used as validation cells for only two physiographic units (interfluve and footslope), at each point that was identified with incorrect location fitting. Evidently, the point’s number at every subsite was dissimilar (northern site = 9 points, southern site = 15 points, and eastern site = 10 points). The drawback of this method is a uniform spatial correction that works on the entire layer of physiographic units and causes a shift of the correctly located unit, too.

3.4. Statistical analysis

To test the difference among the errors contributed by the different database layers, we regressed the model predictions against biomass harvests measured in the field. The regression analysis was applied for the mean scores and the corresponding harvested biomass of the respective sampling plots (Svoray et al. 2008). High values of $R^2 (>0.65)$ indicate a good relationship between the predicted and observed values. The validation data were based on two harvest campaigns during the growing season, at every test site in a fenced plot. Five random repetitions were applied at every plot. With the assistance of the regression results, we can reach a better understanding of different databases’ (DEM or rock outcrop map) error contribution to the model’s predictive ability and can decide, after simulation, which error is
more influential. The same test was used to quantify the effects of location error (RMSE) against the two database layers.

The test of error propagation of topographic indices was based on a $z$-score test, as shown by Van Niel et al. (2004), using

$$Z_x = \frac{x - \mu_x}{\sigma_x}$$

where the original variable is used as the expected value ($Z_x$), $x$ is the mean error value of all iterations, $\mu_x$ is the mean of all iterations, and $\sigma_x$ is the standard deviation value for all iterations. With this statistical test, we checked whether the secondary topographic index (radiation) might have less error propagation than the primary topographic indices (aspect/slope) in the case of our study site.

### 4. Results

#### 4.1. DEM versus thematic maps

Table 2 shows coefficients of determination of the regression tests between predictions of five different versions of the model and the harvested biomass. The low-resolution model provided poorer correlation with the harvests than the model of higher resolution. But overall, the errors of the DEM, the classified rock data, and the location were found to affect the regression tests only to a minor degree. The DEM, however, was found to have a higher effect than the location and classification errors.

To better understand the difference between the effects of DEM and classification errors on model predictions, we analyzed the effect of a hypothetical vertical standard error in two subsites that had notable differences among their topographic characteristics. Table 3 shows that the change of classification error size in the two subsites results in only a slight increase in prediction error.

The DEM error effect was more substantial. Table 4 shows that in the eastern area, the contribution of error by simulation increased model predictive ability by 7%. In the southern and northern areas, however, the contribution of error by simulation reduced the predictive ability (by 8 and 5%, respectively). Therefore, predictive ability is reduced after adding the vertical standard error at places where the slope gradient is moderate. The total difference, however, is very small, as already shown in Table 2.

Table 5 shows that an increase in the DEM vertical standard error improves the model’s predictive ability in the two areas. The DEM was generated from 50 m distance points; therefore, on steep slopes, the error was larger as the outcome of weaker height prediction. As a result, the larger vertical standard error improved the possibility of a cell having more

<table>
<thead>
<tr>
<th>Model and database quality type</th>
<th>$R^2$ values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-resolution version of the model (25 × 25 m$^2$/cell)</td>
<td>0.73</td>
</tr>
<tr>
<td>High-resolution model (2 × 2 m$^2$/cell)</td>
<td>0.83</td>
</tr>
<tr>
<td>High-resolution model with error analysis on rock outcrop</td>
<td>0.83</td>
</tr>
<tr>
<td>High-resolution model with error analysis on DEM map layer</td>
<td>0.80</td>
</tr>
<tr>
<td>High-resolution model with error analysis of location error</td>
<td>0.84</td>
</tr>
</tbody>
</table>
realistic values. The improvement at the northern subsite is a bit higher, though, because of the small initial error, and therefore the predictive ability does not reach saturation, as in the eastern area. These results imply that moderate topographical zones increase the uncertainty contributed by the DEM (Svoray 2004). In addition, it is clearly shown that the classification standard error does not affect the predictive ability, as does the DEM vertical standard error in this model.

### 4.2. The effect of location error on model uncertainty

We tested the location error effect on the physiographic units layer, using confusion matrices and Kappa coefficients (Table 6). The results show that the location error of physiographic units, between the two aspects (north and south), is the main cause for low Kappa values (mainly at the eastern and southern subsites) and this is the result of the unified spatial correction limits, which cause a shifting of the entire layer and thus, of all the units, even if not necessary. In the northern area, the main factor for low Kappa value was the location error of physiographic units within the slope boundaries. Therefore, only in the northern area was there a small change (4%) in the predictive ability. Consequently, the total change was small, indicating that location error does not affect the model’s predictions as much as the DEM error.

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Table 3. Model prediction results by $R^2$ of four error (probability) range scenarios of rock outcrop map at hilly (east) and mild (north) topographic areas. Small error – half of real error, medium error – real, and large error – doubled real error.

<table>
<thead>
<tr>
<th>Subsite</th>
<th>No error</th>
<th>Small error</th>
<th>Medium error</th>
<th>Large error</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>North</td>
<td>0.91</td>
<td>0.90</td>
<td>0.90</td>
<td>0.89</td>
</tr>
<tr>
<td>Average</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 4. Summary of linear regression for testing the prediction ability at every subsite after adding DEM error effects by simulation.

<table>
<thead>
<tr>
<th>Relief type (slope gradient)</th>
<th>North</th>
<th>South</th>
<th>East</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS error (m)</td>
<td>3.67</td>
<td>3.12</td>
<td>7.29</td>
</tr>
<tr>
<td>Prediction ability by $R^2$</td>
<td>0.65</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>Prediction ability by $R^2$</td>
<td>0.59</td>
<td>0.74</td>
<td>0.87</td>
</tr>
<tr>
<td>Size of change in the models prediction ability</td>
<td>−0.05</td>
<td>−0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>Total average change</td>
<td>−0.02</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Model prediction results by $R^2$ of four vertical standard error scenarios of the DEM map at hilly (east) and mild (north) topographic areas.

<table>
<thead>
<tr>
<th>Subsite</th>
<th>Small error</th>
<th>Medium error</th>
<th>Large error</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>0.93</td>
<td>0.96</td>
<td>0.97</td>
</tr>
<tr>
<td>North</td>
<td>0.71</td>
<td>0.76</td>
<td>0.77</td>
</tr>
<tr>
<td>Average</td>
<td>0.82</td>
<td>0.86</td>
<td>0.87</td>
</tr>
</tbody>
</table>

---
4.3. Error propagation

The Z-score index was used to see whether error propagation within the DEM calculations of the primary topographic index (aspect) is higher than that of the secondary topographic index (radiation). The test was applied only to these two layers because they are more meaningful for the primary production process and, therefore, more dominant in the Svoray et al. model than the slope gradient. In addition, there is a mathematical limitation in calculating the Z-score for slope layers (Van Niel et al. 2004). The Z-score was computed for all the three subsites to test whether the size of error propagation is determined by the vertical standard error or by local topographic conditions. In this case, we used the third subsite (southern) for the scales because it is characterized by long slopes as at the eastern and very moderate slope angles as at the northern subsite.

Table 7 shows that at all sites, as expected, the lowest means and standard deviations belong to the propagation of DEM error for both topographic indices. In general, the Z-score values are low because of the high spatial resolution of the DEM. By focusing on the two topographic indices, we can see that, at the eastern and southern sites (hilly topography), the mean Z-scores are higher for the aspect layer and lower at the northern (mild topography). The standard deviation is very low at all sites, meaning that the propagated error distribution is steady. Consequently, we can understand that for cases of higher relief at our study site, the propagation of error from the aspect layer is more crucial than the radiation layer.

5. Discussion

Despite the importance of spatially explicit models in ecology, only a few studies have actually undertaken comprehensive research on error propagation and the uncertainty effect on the predictive capabilities of high-resolution spatial models. Most of the recent uncertainty and error propagation studies that were applied to ecological models use low-resolution data, for example, 30 × 30 m² spatial resolution of DEMs and Landsat.

Table 6. Summary of location error correction, Kappa test of the correction, and linear regression for testing the prediction ability at every subsite after adding location error.

<table>
<thead>
<tr>
<th></th>
<th>North</th>
<th>South</th>
<th>East</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>1.64</td>
<td>4.32</td>
<td>3.58</td>
</tr>
<tr>
<td>Kappa test</td>
<td>0.41</td>
<td>0.65</td>
<td>0.46</td>
</tr>
<tr>
<td>Prediction ability by $R^2$ of real model</td>
<td>0.65</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>Prediction ability by $R^2$ of model with location error</td>
<td>0.69</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>Size of change in the models prediction ability</td>
<td>0.04</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Total average change</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7. Comparison by Z-scores of error propagation analysis for DEM, aspect and radiation layers at three subsites.

<table>
<thead>
<tr>
<th>Subsite</th>
<th>DEM</th>
<th>Aspect</th>
<th>Radiation</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>0.000043</td>
<td>-0.000049</td>
<td>-0.000046</td>
</tr>
<tr>
<td></td>
<td>0.000628</td>
<td>0.001513</td>
<td>0.002466</td>
</tr>
<tr>
<td>North</td>
<td>0.000002</td>
<td>-0.000019</td>
<td>-0.000022</td>
</tr>
<tr>
<td></td>
<td>0.000573</td>
<td>0.001815</td>
<td>0.001503</td>
</tr>
<tr>
<td>South</td>
<td>0.000026</td>
<td>-0.000064</td>
<td>-0.000028</td>
</tr>
<tr>
<td></td>
<td>0.000525</td>
<td>0.003651</td>
<td>0.001586</td>
</tr>
</tbody>
</table>
TM (Kyriakidis and Dungan 2001, Van Niel et al. 2004). As a result, there is little understanding of the effect of uncertainty and error propagation on models’ results at the scale of a few meters – a scale that could be well compared to field measurements. Our results can provide the following answers regarding this issue.

5.1. DEM versus classification map

According to the first premise of our research, it was expected, based on previous studies, that classification error has a higher uncertainty effect on the model’s predictive ability than DEM error. We found that an increase of DEM spatial resolution had the largest positive effect on the predictive ability (by 10%). Contrary to our results, it was found in a crop yield study that, under spatial resolution of $30 \times 30$ m$^2$/pixel, predictive ability did not improve significantly with higher spatial resolution (Erskine et al. 2007). Because of the relatively high homogeneity in field crops, an improvement of spatial resolution was not found to be effective. Nevertheless, studies of open areas, like LTER Lehavim, show that improvement of physical variables has a large influence on model prediction, especially in mountainous and hilly environments, where the vegetation can be dispersed in a mosaic, with sharp transitions from one type to another (Zimmermann and Kienast 1999, Chaplot et al. 2000, Guisan and Zimmermann 2000, Thompson et al. 2001, Saha et al. 2005b).

Our results show that classification error of the orthophoto does not substantially affect model prediction. These results are contrary to the accepted view in the literature. According to previous studies, such as Lunetta et al. (1991) and Guisan and Zimmermann (2000), classification accuracy is one of the main limits of spatial ecological models. Moreover, a study that applied a comparison between the uncertainty effects of rock outcrop map and DEM on a physical morphometric model concluded that the rock outcrop map uncertainty has a larger effect on the model results than the DEM uncertainty effect (Canters et al. 2002).

We suggest two reasons for our opposite results: (1) the very high-resolution imagery source (an orthophoto with spatial resolution of $0.12 \times 0.12$ m$^2$/pixel), which probably decreased classification error substantially; and (2) the use of only two classes, as only the very distinctive rock outcrop class is required by the ecological model of Svoray et al. (2008).

Several studies have shown that in areas with highly patchy vegetation, as in semiarid zones, the spectral resolution is insufficient if classification is carried out on Landsat images with a spatial resolution of $30 \times 30$ m$^2$/pixel. The reason is a patchiness rate of several meters resolution and, as a result, the distinction is not applicable at such low resolution (Clark et al. 2001, Shoshany and Svoray 2002). In addition, the number of classes depends on the mapping aims (Foody 2002) and so affects the classification accuracy substantially. As a result, the chance of a rock outcrop class to change to another class is just 7% (very low), with a low effect on the overall accuracy.

The DEM vertical standard error was found to have only a small negative effect (3%) on model results. Canters et al. (2002) showed that DEM error only had a small effect on landscape classification, in contrast to the effect of rock outcrop map error and that was related to the homogenous terrain of their study site. But in the case of the Lehavim site, the terrain is very heterogenous. Other previous authors have found that DEM error relates to the degree of slope gradient (Hunter and Goodchild 1997, Fisher 1998) and that DEM error correlates with the topographic characteristic of the terrain (Kyriakidis et al. 1999, Carlisle 2005). As Table 4 shows, the results from the three areas in Lehavim clearly indicate a difference in the contribution of DEM uncertainty to the predictive ability of the model between the areas. The increase or decrease in uncertainty effect is related to the size of vertical standard error and topographic characteristics of the terrain in the specific area.
Holmes et al. (2000) showed that even when the total DEM error is quite small, examination of specific areas, based on accurate field data (e.g., DGPS), indicates that it is possible to find areas in the DEM that contribute larger error, whereas others contribute a smaller error (nonstationarity in space). Such nonstationarity may affect the predictions of physical models in different ways (Holmes et al. 2000). Oksanen and Sarjakoski (2005b) found that increasing DEM error caused an increase in topographic indices error. In addition, they showed that adding vertical error, combined with an autocorrelation model, can affect the propagation of DEM error in various ways, depending on the specific GIS application. Our results in Table 4 show that, in steep terrain, the measured error was larger and in fact, it increased model certainty (see below). On the contrary, for mild terrains with moderate-to-flat slopes, we measured an error smaller by half, but the effect on model predictive certainty was highly negative. Similarly, Florinsky (1998) showed that DEM errors in flat areas have large effect on topographic indices quality.

The results of the standard errors scenario effects (Table 5) explain these results. Although, in general, increasing standard errors improves prediction, in the eastern subsite, the large error allowed extraction of error effects at earlier stages of error size. However, in the northern subsite with a smaller error, the extraction of error effects improved prediction only when the size of error was similar to the original eastern error. We can explain these results by the fact that combining application of spatial autocorrelation and vertical error can improve predictive ability of ecological high-resolution models, only when the measured vertical error is sufficiently large. Otherwise, the predictive ability will be reduced, as Fisher (1998) and Oksanen and Sarjakoski (2005b) showed. Because the distribution of vertical error size at the Lehavim site was not similar, we conclude that the DEM error measured in the field has a negative effect on model prediction.

5.2. Location Error versus DEM and classification error

Based on the literature, we assumed that location error would have a more significant and negative effect on model predictive ability than the classification and location errors. Two previous studies had attempted to analyze the effect of location error, compared with classification error and they had found that location error had the greater influence (Arbia et al. 1998, Carmel et al. 2001). Another study showed that only if the location error is significant, will its correction have a positive effect on model predictions (Gabrosek and Cressie 2002). Here, the location error of the physiographic units’ layer was found to have a negligible effect (1–2% positive effect after correction) on predictive ability (Tables 2 and 6). We show that location error did apply to model results, but hardly had any effect on it, excluding that of the change of unit location between aspects.

Carmel (2005) developed a model to estimate the location error of classification objects in multilayer analysis, under the assumption that location error is not spatially unified. The determination of location error was based on the probability of the reasonable location of every class. As was found by Gabrosek and Cressie (2002), we found that a small location error does not affect model predictive ability. In addition, it confirms Carmel’s (2005) assertion that uniform spatial correction is restricted. We conclude that, in our study, changing unit location between aspects at the eastern and southern subsites neutralized the chance for correction process achievement and was the main cause for the minor effect of location error correction on predictive ability.
5.3. Error propagation of topographic indices

Regarding our third objective, we tried to determine whether the uncertainty, contributed by the secondary topographic index (radiation map), is greater than that contributed by the primary topographic indices (slope or aspect maps). As we expected, according to the mean and standard deviation values (Table 7), the lowest values relate to the DEM error propagates to its topographic indices at all three areas. The results show that, in all cases, the error propagation values is very low compared with the results of Van Niel et al. (2004), who analyzed the error propagation from DEM with a spatial resolution of $30 \times 30$ m$^2$/cell. The difference between our results and those of Van Niel et al. is reasonable, as found in the literature, improvement of DEM spatial resolution has a direct influence on the improvement of its topographic indices and their sensitivity (Guisan and Zimmermann 2000, Schmidt and Persson 2003, Erskine et al. 2007). In addition, we found that in some cases, as expected, the error propagation of the secondary topographic index is smaller than that of primary topographic index.

Dubayah and Rich (1995) analyzed a number of uncertainty and error types that relate to radiation maps and they then concluded that most of the uncertainty originates from error embedded in the source DEM, so that the largest error propagation should come from the radiation map. Van Niel et al. (2004) showed that despite the important part played by the primary topographic indices (aspect or slope) on the calculation of radiation map, the physical components, such as topographic height differences and degree of cloudiness, have a higher effect on the uncertainty size of that map.

According to Van Niel et al. (2004), there are three main factors that reduce the error propagation of the radiation map in relation to primary topographic indices: (1) a low topographic relief reduces the effect of shaded areas; (2) using a thematic slope map produces a generalization that reduces its error propagation (we used a four-factor thematic aspect map); and (3) cloudiness reduces even more the effects of primary topographic indices on the radiation map (Dubayah and Rich 1995, Wilson and Gallant 2000). Additional cause can be the method used to calculate slope and aspect that may affect the quality of the output indices (Skidmore 1989). Our results are in agreement with those of Van Niel et al. (2004), but we believe that the causes are different. We found (Table 7) that in hilly topography (eastern area), the error propagation from the radiation map is less. In fact, for the mild topographic relief area (northern), the aspect map contributed less error propagation than the DEM. Because we saw the same behavior at the southern and eastern areas, we conclude that the main factor for difference of error propagation in the topographic indices is the difference in topographic conditions between the eastern and northern areas. The higher height differences cause a greater influence of the thematic aspect map and, as a result, less error propagation by the radiation map, than we expected.

6. Conclusion

This study focuses on the contribution of two spatial datasets (DEM and orthophoto classification) to the uncertainty of a GIS-based model that predicts biomass production of annual herbaceous vegetation in dry environments. The results lead to the following conclusions:

1. Classification error in the orthophoto had a negligible effect on the model’s predictive ability because of the high-resolution source and the use of only two classes with sharp differences in brightness. The DEM error had large effect on
predictability in the moderate slopes. In areas of steep slopes, the error, although it is larger, has lower effect on predictability. We can further say that not only was the error found to be spatially nonuniform but also its effect on the model predictability was found spatially nonuniform.

(2) We found that location error hardly affected the model’s predictive capabilities. This is related to the difficulties encountered in determining the location error automatically and, as a result, it harmed the ability to determine the probable location of physiographic units on the slope. Mostly, it negatively affected the ability to determine the probable location of shoulder- and backslope, as they did not have corresponding topographic elements.

(3) In the comparison of error propagation from topographic indices by Z-score, we found that, as expected, in some cases, the aspect map (primary topographic index) can contribute more to the model’s uncertainty through error propagation than the radiation (secondary topographic index). These cases were found to be related to elevation differences and to the number of thematic classes of the aspect map. In areas with large elevation differences, the error propagation for the radiation map was less, because of large effect of the large slopes on the four factors thematic aspect map.

Future studies should focus on assessing the model’s behavior with several spatial resolutions, to determine the size of the most appropriate resolution for the best outcome. There is a need to assess the influence of climatic variables to understand the uncertainty contribution of the temporal dimension on the model outcome. It is essential to develop a unique algorithm that would enable a better assessment of location error, so it would not be spatially uniform.

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