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Mean and variance estimations with different pixel sizes: case study in a small water quality monitoring area in southern Finland

Saku Anttila* and Timo Kairesalo

*Department of Ecological and Environmental Science, University of Helsinki, Niemenkatu 73, FI-15140 Lahti, Finland (*corresponding author's e-mail: stanttil@mappi.helsinki.fi)*

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Spatial variation of water quality parameters produces inaccuracy in freshwater monitoring programs. Using spatially continuous measurements, such as remote sensing observations, this variation can be estimated. However, spaceborne remote sensing data that are usable for the operative monitoring of lake water quality suffer from coarse spatial resolution. Observations in small monitoring regimes are often restricted to only a few satellite image pixels that are not disturbed by the adjacent land areas. Consequently, it is often assumed that a medium- to coarse-resolution remote sensing does not contribute additional information for monitoring programs in these areas. The usability of pixel-type observations in a small monitoring area was assessed using a flow-through fluorometer in a moving boat. Nine spatially extensive data sets were collected from the Enonselkä basin of Vesijärvi in southern Finland during the summers of 2005–2007. The effect of spatial resolution on the observed mean and standard deviation of the chlorophyll-*a* concentration was studied. The Getis-Ord Gi* analysis and spatial interpolation were used to define surface areas of locations, where chlorophyll-*a* concentration varied from the mean concentration. Our results suggest that the mean value can be estimated with reasonable accuracy even with a single pixel observation. The information of the variation is, however, lost with the coarser resolution observations.

Introduction

Spatial distribution of lake water quality varies in time (e.g. Dekker *et al*. 2001, Hedger *et al*. 2001, Vos *et al*. 2003, Anttila *et al*. 2007), but at the same time stationary patterns in water quality are observed (e.g. George and Heaney 1978, Xu *et al*. 2000, Kallio *et al*. 2003, Wang and Liu 2004, Bracchini *et al*. 2005). These patterns can be explained by the sources of spatial variability. For example, systematic point sources of nutrients and suspended solids from rivers often create a stationary pattern in lake water quality (e.g. Vuorio *et al*. 2003). Diffuse sources, such as runoff from agricultural areas, also have a clear effect on the lake water quality (Ekholm and Mitikka 2006) and can have a similar effect on the spatial distribution of the water quality. Wind driven water movements together with the effect of bottom topography can also create localized patterns in lakes (George and Edwards 1976), though the effect of the wind might vary depending on its speed and direction (George and Heaney 1978). It is obvious that a sudden discharge event from drainage basin or strong wind can alter the spatial distribution and cause temporal variation in water quality. The sources of spatial variability, however, suggest that stationary patterns can be a typical property of water quality in lakes. Furthermore, these patterns are often located close to the shoreline, in e.g. river mouth areas or in shallow water where particles driven and resuspended by the wind are trapped (e.g. Schernewski *et al*. 2000).

Water quality monitoring programs typically include one or a few samples from the deepest parts of the lake (Heinonen *et al*. 2004) and spatial variation is not taken into account. The joint use of *in situ* and remote sensing measurements is suggested to enhance the accuracy of water quality monitoring (Pulliainen *et al*. 2001, Vos *et al*. 2003). This can be rationalized with the specific properties of both of these methods. Point source *in situ* measurements give information from the whole water column and especially, if automated stations are used, data can be collected with high temporal resolution. However, discrete point source water quality samples for spatially heterogeneous parameters are not representative for the whole monitoring area (e.g. Hedger *et al*. 2001, Dekker *et al*. 2001, Pulliainen *et al*. 2001, Kutser 2004) and, therefore, they cause a serious risk of under- or over-estimations (Kallio *et al*. 2003, Vos *et al*. 2003, Kutser 2004, Anttila *et al*. 2007, Laszlo *et al*. 2007). The clear advantage in remote sensing measurements is that they can provide extensive spatial coverage. The specific properties of the remote sensing data, however, restrict its usage in operative water quality monitoring. Firstly, the revisiting time of satellite above the same location must be frequent enough to get sufficient data. This temporal resolution is further reduced by clouds that hinder monitoring. Secondly, satellite instruments need to have suitable spectral channels to enable algorithm development. Finally, the spatial resolution of the remote sensing data must be high enough to allow observations without disturbance from adjacent land areas. Also, for sustainable monitoring, the price of the data should be low enough and unfortunately, this usually goes hand in hand with the spatial resolution. For the monitoring purposes, data are needed frequently and airborne or fine-resolution satellite remote sensing is often too expensive. Consequently, the satellite instruments that are currently most suitable in operative lake water quality monitoring, have a spatial resolution ranging from 250 meters to 1000 meters. When considering the benefits and drawbacks of *in situ* and remote sensing data, it can be argued that these methods can be used to complement each other in water quality monitoring. However, before different data sources are assimilated to achieve a maximum value estimate, the specific properties of each data source must be well known.

At present, the satellite instruments mostly used for operative lake water quality monitoring in Finland are MODIS instruments onboard Terra and Aqua NASA satellites (250–1000 meter spatial resolutions, 36 spectral channels and one-day revisiting time over Finland) and the MERIS instrument onboard Envisat satellite of the European Space Agency (300 m spatial resolutions, 15 spectral channels and one-day revisiting time over Finland). The spatial resolution restricts the usage of these instruments in small or fragmented monitoring areas. Basically, only pure-pixel observations without disturbance from land areas are applicable. Therefore, spatial resolution can limit remote sensing observation to only a few pixels in small monitoring areas. Consequently, information on the near-shore stationary patterns and also on the variation is greatly reduced (Harris and Smith 1977, Benson and MacKenzie 1995) and the advantage of extensive spatial coverage gained with remote sensing is partly lost. It can be questioned what is the additional information that remote sensing can give for the monitoring programs in small lakes. Pixel observations, however, typically cover a relatively large area of the monitoring regime and they have potentiality to give better mean-value estimations than e.g. discrete point source sampling. We studied the usability of remote sensing observations in small water quality monitoring areas. Study was divided into three sections: (1) to determine how the mean and variance in surface water chlorophyll-*a* concentration can be detected with varying spatial resolutions, (2) to detect areas where chlorophyll-*a* concentration tends to deviate from the mean concentration of the monitoring area, and (3) to define if these stationary patterns are detected with coarser spatial resolutions.

Methods

Study site, data sets and auxiliary data

Study site

Our study site, the Enonselkä basin of Vesijärvi, is located in southern Finland (25°37´24´´E, 61°0´30´´N). The surface area and the mean depth of the Enonselkä basin are 26 km^2 and 6.8 m. Respective values for the whole lake are 110 km^2 and 6 m (Fig. 1). During the summer months (June–August), the lake is thermally stratified and the water column is typically mixed in early September. In the early 1900s, Vesijärvi used to be a clear-water lake, but due to nutrient and organic matter loading from the domestic sewage of the city of Lahti, industry, agriculture and timber storage activities, it became severely eutrophicated in the 1960s–1970s (Kairesalo and Vakkilainen 2004). Despite the diversion of sewage waters that run into the lake, it still suffered from harmful blue-green algae blooms in the late 1980s. The reduction of external non-point nutrient loading together with large-scale and long-term (5 summers) biomanipulation (mass removal of cyprinid fish) clearly improved the ecological state of the lake in the 1990s (Sammalkorpi *et al*. 1995, Malinen and Peltonen 1996, Kairesalo *et al*. 1999). Nevertheless, water quality during the latest hot summers was strongly affected especially by internal nutrient loading from the sediments. According to Keto *et al*. (2005), *Bacillariophyceae* and *Cryptophyceae* dominated the algal groups during 1995–2003. In the past few years, however, the relative proportion of the *Cyanophyceae* group has again increased in the yearly average biomass of algae (*see* http://www.vesku.net/downloads/Vuosiraportti06.pdf). Currently, two parallel water quality monitoring programs are conducted at the lake — one by the regional environment authorities and the other by the University of Helsinki. Also three automated water-quality monitoring stations are installed in the Enonselkä basin.

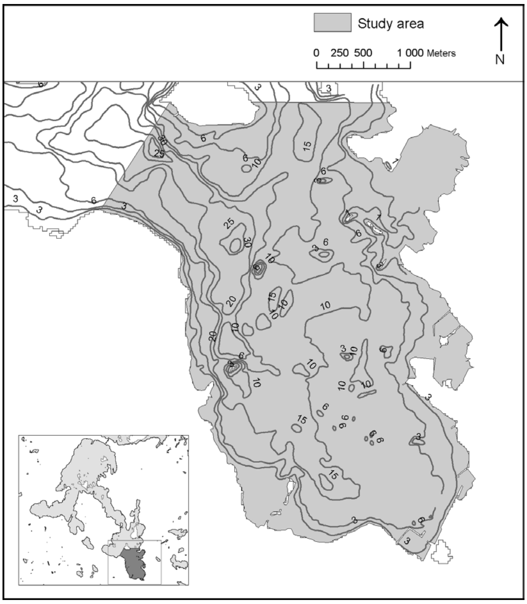

Fig. 1. Study area, Enonselkä basin of Vesijärvi.

Field surveys and data sets

Chlorophyll-*a* concentration was used as a parameter to describe the spatial distribution of water quality over the study area. It is included in most water quality monitoring programs and can also be estimated from the optical remote-sensing data. Measurements were conducted during nine field surveys in the summers of 2005–2007 at the Enonselkä basin of Vesijärvi. A flow-through system with the SCUFA II fluorometer (Turner Designs) in a moving boat was used to record chlorophyll-*a* fluorescence (excitation 460 nm – emission 685 nm) and turbidity (90° scatter) with 1 Hz frequency at the water depth of 0.4 m. The flow-through system included a submersible pump (Whale GP8815) attached to the front of the boat and a flow cap that was in turn attached to the fluorometer. Measurements were made with a constant speed of 9 and 11 km h^{-1}. A GPS receiver (Garmin 12CX) was used to record the time and location simultaneously with the measurements. In order to calibrate the fluorescence values to chlorophyll-*a* concentration, water samples were taken every 30 minutes from the output end of the flow-through system and tagged with the precise time. Chlorophyll-*a* concentrations of the water samples were analyzed after the field surveys in a laboratory according to the standard procedure (SFS 5772). Chlorophyll-*a* concentration was calculated from the temperature-corrected fluorescence values using the multiple regression technique with water sample chlorophyll *a* and turbidity as explaining variables (Scufa II Users Manual). All flow-through data sets were bound with the GPS locations using time as a relation parameter. The final step in data preprocessing included the averaging of the data from identical GPS-coordinates. This reduced the measurement interval for each data set to an average of one every 5 seconds. The lengths of transects, mean and standard deviations of measured chlorophyll-*a* concentrations, coefficients of variance and the correlation coefficients between water samples and fluorometer chlorophyll *a* of each data set are listed in Table 1.

Auxiliary data

A land mask is often used in remote sensing observations to ensure that the used reflectance values originate only from water areas and not from adjacent land. In this study, it was assumed that to get pure water pixel observations, the distance from the closest land area must be at least the same as the respective spatial resolution of the satellite instrument used. Therefore, the shoreline GIS-data of the Enonselkä basin was buffered to 10, 25, 100, 250, 300, 500 and 700 meter shoreline buffer zones (Fig. 2). These buffer zones were chosen partly according to the spatial resolutions of the suitable satellite instruments for the environmental monitoring (e.g. Landsat 7 ETM+, Terra/Aqua MODIS and Envisat MERIS). The shoreline buffer zone of 700 m was the coarsest one that could be fitted to the study site to get pure observations with above-mentioned restrictions. It must be noted that depending on the remote sensing application, the adjacency effect of land can reach much farther than the respective spatial resolution. Our aim, however, was to study how pixel type observations at different resolutions detect the mean and variance in a small monitoring area. Therefore, buffering with respective resolution was considered sufficient.

Table 1. Length of transects, mean ± SD of measured chlorophyll *a* concentrations (chl *a*), coefficients of variance (CV) and the correlation coefficients (r^2) between water samples and fluorometer measurements for all 9 data sets.

Date	Transect length (km)	Mean ± SD (CV) chl *a* conc. (μg l^{-1})	r^2
25 June 2005	18.5	8.97 ± 2.55 (28.4)	0.79
13 July 2005	20	3.54 ± 0.88 (24.97)	0.88
19 July 2005	22	3.68 ± 0.64 (17.35)	0.93
12 Aug. 2005	19.5	10.92 ± 2.04 (18.65)	0.89
6 Sep. 2005	21	9.63 ± 3.12 (32.43)	0.90
4 July 2006	25	3.92 ± 0.32 (8.18)	0.89
16 July 2006	25.5	3.15 ± 0.89 (28.43)	0.82
11 July 2007	26.5	13.18 ± 2.28 (17.27)	0.90
12 July 2007	23	10.8 ± 1.67 (15.51)	0.81

Statistical analysis

Resolution analysis

In order to simulate satellite observations with various spatial resolutions, chlorophyll-*a* measurement transects of each nine data set were first interpolated to grids with the 10-m resolution. Interpolation was conducted with geostatistical method called ordinary kriging (e.g. Johnston *et al*. 2001), where the spatial dependency occurring within a data set is modeled. This semivariogram model is used when values for the unmeasured locations are estimated. Assumption is that observations close to one another are more alike than those farther away. Geostatistics defines several semivariogram models for this purpose, all of which are functions of three parameters: nugget, sill and range. The *range* parameter defines the maximum distance where observations still correlate. The *nugget* parameter accounts for the sampling error. The *sill* parameter is equal to the semivariogram value at the distance of the *range* parameter. We used the VARIOWIN software (Pannatier 1996) to estimate the most suitable model and parameters for each data set. All interpolated chlorophyll-*a* grids with the 10-m resolution were then resampled also to 25, 100, 250, 300, 500 and 700 m spatial resolutions using the cubic convolution method (e.g. McCoy & Johnston 2001). Resultant square-like grids of differing resolutions were used to represent observations where only the averaging of small scale variation affects the variance estimations (Fig. 3). For the second data set, each resolution grid was extracted to respective shoreline buffer zones. The ARCGIS software (ESRI Inc.) was used in interpolation, resampling and extraction to shoreline buffer zones. For all the resultant resolution grids with and without extraction, absolute differences of the mean and standard deviation from the respective 10-m resolution values were calculated. Finally, these absolute differences from all nine field survey dates were averaged to present the effect of spatial resolution on the observed mean and standard deviation. These final steps were conducted using the Matlab-software (Mathworks Inc.).

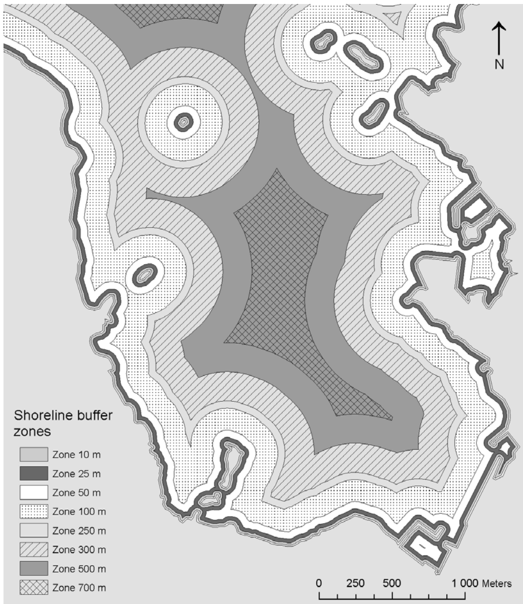

Fig. 2. Shoreline buffer zones at 10, 25, 100, 250, 300, 500 and 700 m distance from the shoreline GIS-data.

Getis-Ord Gi* analysis

The Getis-Ord Gi* analysis (Getis and Ord 1996) was used to find areas at the study site where chlorophyll-*a* concentration tends to vary from the mean concentration of the study area. In other words, it was used to find whether stationary patterns exist at the study site. The Getis-Ord Gi* method is a spatial analysis where a local weighted mean around each observation is separately compared with the mean of the whole data set. Result is a *Z*-score value for every observation. In the analysis, a local weighted mean for every measurement was first calculated using the measurement itself and measurements within 500-m distance from it. Weights for the measurements taken into the local mean were calculated using an inverse-distance squared method (e.g. Burrough and McDonnel 1998, Johnston *et al*. 2001). It gives the greatest weight for the observation that mean is calculated on and weights for the other observations decreases as a function of the squared distance from that. The *Z*-score value for each data point was then calculated as follows:

$$Z_n = \frac{\mu_{\mathrm{loc},n} - \mu}{\sigma}, \qquad (1)$$

where $\mu_{\mathrm{loc},n}$ is the local-weighted mean value calculated from the observation n, μ is the mean of the whole data set and σ is the respective standard deviation. Z scores higher than 1.95 mean that, in the vicinity of the measurement, it is 95% certain that chlorophyll-*a* concentration is higher than the mean concentration of the whole data set. Likewise, Z scores lower than –1.95 refer to lower concentrations in comparison with the study-site mean. A Z score was calculated for every chlorophyll-*a* measurement from all nine field surveys. *Z*-score transects were then interpolated to *Z*-score grids using an ordinary kriging method (e.g. Johnston *et al*. 2001) (Fig. 4). The spatial properties within each data set were taken into account by generating semivariogram parameters separately for each data set.

Z-score values in each grid were classified into two classes [0,1] indicating areas with no significant difference (Z scores between –1.95 and 1.95 were classified as 0) and areas with significantly lower or higher concentrations (Z scores lower than –1.95 or higher than 1.95 were classified as 1), respectively. Finally, a variability index grid (VarInd_{xy}) was derived by summing all classified *Z*-score grids and dividing this by the number of *Z*-score grids at each location:

$$\mathrm{VarInd}_{xy} = \frac{\sum_{n\,xy} Z_{xy}}{n_{xy}}, \qquad (2)$$

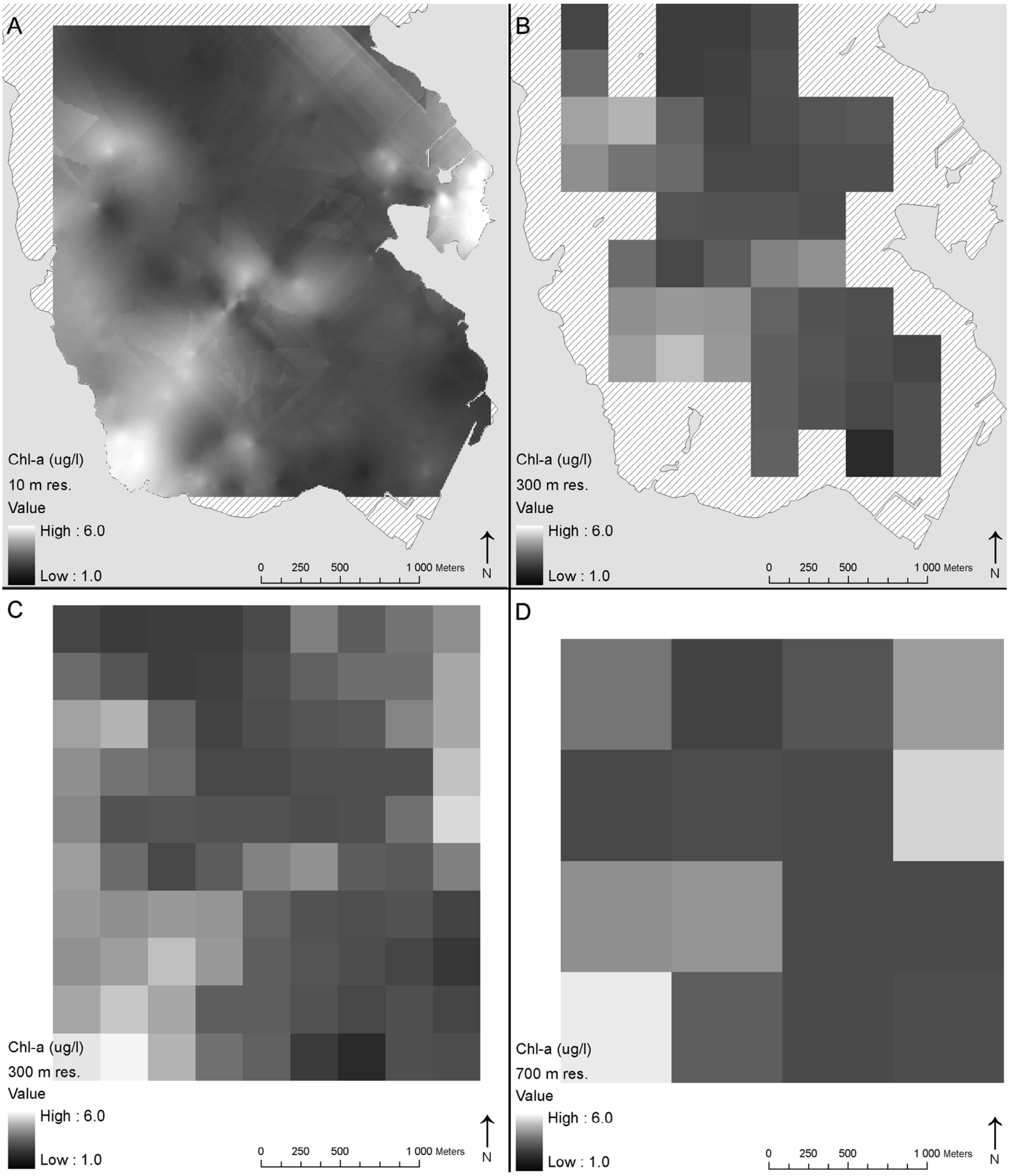

Fig. 3. Examples of chlorophyll *a* grids resampled and extracted to respective shoreline buffer zones at (**A**) 10 m and (**B**) 300 m resolutions, and examples of (**C**) 300 m and (**D**) 700 m chlorophyll-*a* grids without shoreline buffer zone extraction. Example grids are interpolated and resampled from 16 July 2007 chlorophyll-*a* measurements.

where Z_{xy} is the Z score and n_{xy} is the number of Z-score grids at the location x,y. In the variability index grid, areas where chlorophyll-*a* concentration tends to vary from the mean value gets higher values. In order to study whether areas with large variability can be observed with medium or coarse spatial resolutions, the variability index grid was extracted to shoreline buffer zones. Surface areas of different variability index classes inside each shoreline buffer zone were calculated. All calculations were carried out using the ARCGIS software.

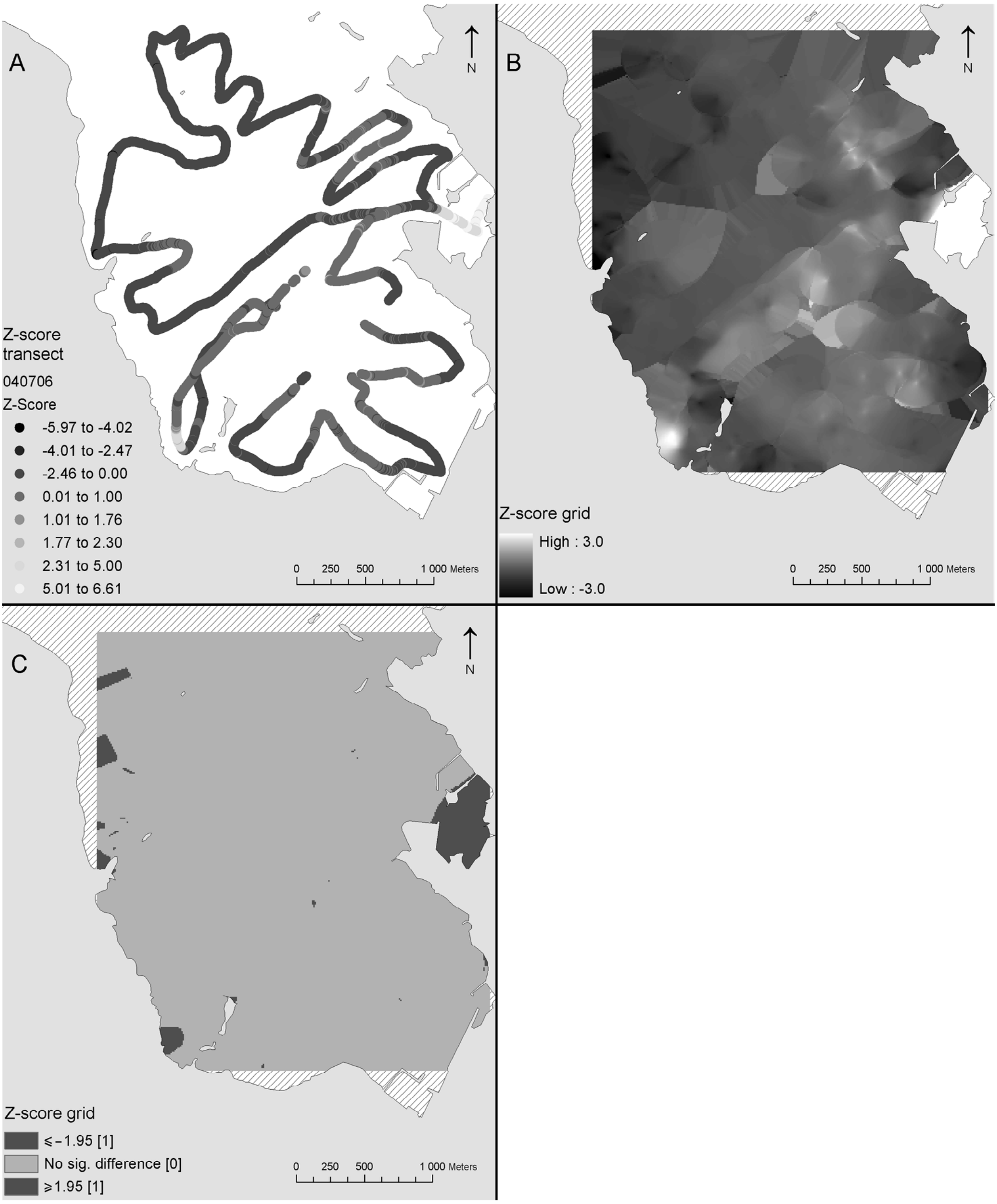

Fig. 4. Example of calculated *Z* scores (Getis-Ord Gi*) for (**A**) chlorophyll-*a* transect, (**B**) interpolated hot-spot grid, and (**C**) classified hot spot grid from 4 July 2006.

Results

Resolution analysis

It is obvious that as the spatial resolution decreases and pixels are restricted to respective shoreline buffer zones, the number of observations decreases radically (Table 2). Spatial resolution did not affect the mean estimation of chlorophyll-*a* concentration remarkably (Fig. 5A). Mean chlorophyll-*a* concentration was detected surprisingly well even with a single-pixel obser-

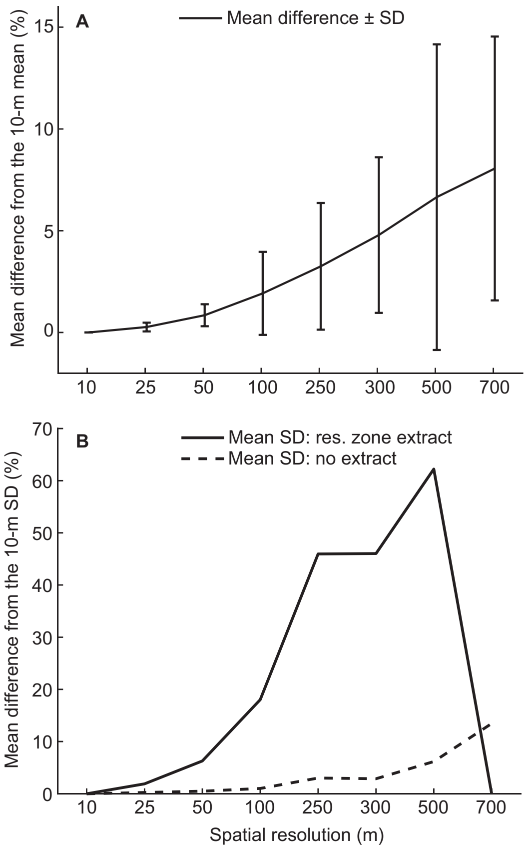

Fig. 5. (**A**) Averaged deviation of the mean from the mean value of 10-m resolution grid in different spatial resolutions with data set extracted to shoreline buffer zones, and (**B**) averaged deviation of the standard deviation value from the standard deviation of 10 meter resolution grid with different spatial resolutions.

vation. The average deviation from the mean was with one 700-m pixel observation only approximately 9%. Information on the observed variation of chlorophyll-*a* concentration varied radically on the resolution grids extracted to the shoreline buffer zones. With this data set, standard deviation started to differ significantly from the 10-m resolution grid already at 50-m resolution (Fig. 5B). At the 250-m pixel size, the detected standard deviation differed 46% from the 10-m standard deviation. Without the extraction, the effect of spatial resolution on the detected standard deviation was considerably smaller. This indicates that the majority of the variance estimation error with coarser resolutions is due to the fact that areas with higher variability cannot be observed. Whilst the effect of averaged small scale variation was less important at our study site.

Getis-Ord Gi* analysis

The Getis-Ord Gi* analysis revealed that chlorophyll-*a* concentration tend to vary in the semi-enclosed harbor area and in the shallow bay in the south-west part of the study site (Fig. 6). In the pelagic zone, chlorophyll-*a* concentration mostly remained close to the mean concentration. The detected surface areas of locations where chlorophyll-*a* concentrations tended to vary decayed together with the decreasing observation area (Fig. 7). According to the results, at the study site the areas with most variability cannot be observed with spatial resolutions coarser than 100 m. This is obviously the reason for the erroneous variance estimates with coarser resolutions. On the other hand, the relative surface area of locations with higher variability was not significant. Therefore, at our study site the mean value for the monitoring area can be estimated reasonably well even with a few-pixel observations.

Discussion

The usage of medium or coarse resolution (spatial resolution > 250 m) remote sensing observations in small and fragmented monitoring areas can be problematic. Currently, the technical

Table 2. Average number of observations in all nine data sets with and without extraction to shoreline buffer zones at respective spatial resolutions.

Resolution (m)	10	25	50	100	250	300	500	700
Average number of observations without extraction	78771	14234	3573	899	143	100	36	18
Average number of observations with extraction	66125	11591	2766	629	73	46	9	1

limitation related to the spatial resolution of the instruments is one of the main challenges when satellite images are used in water quality applications in small lakes (Kallio *et al*. 2003, Kutser 2004, Kallio *et al*. 2005, Arst *et al*. 2008). Interpreted remote sensing observation is basically a set of mean-value observations from the areas determined by the spatial resolution. Essentially, spatial resolution has a similar effect on parameter value estimations, as sample size has in conventional monitoring. Estimation is more accurate with an increasing number of estimations. Woodcock and Strahler (1987) concluded that the choice of an appropriate spatial resolution for a particular application depends strongly on the spatial structure of the scene or area studied. A lake is an environment under constant change, where several factors affect the scales of spatial distribution in water quality. Scales of variation depend on e.g. the wind, bottom topography, diffuse and point sources of nutrients and particulate matter, water currents, movements and feeding activities of fish shoals or zooplankton and different buoyancy properties of the phytoplankton (George and Heaney 1978, Jassby *et al*. 1997, Horppila *et al*. 1998, Hedger *et al*. 2001). Benson and MacKenzie (1995) addressed the fact that since most observed parameters are sensitive to spatial resolution, scaling issues should be taken into account when using satellite imagery. Furthermore, Aplin (2006) concluded that if features are scale-dependent, they can be represented differently at different spatial scales or resolutions. When medium or coarse, spatial resolution observations are used in small or fragmented monitoring areas at least two quations should be answered: (1) to which extent is the small scale spatial variation averaged? and (2) are there stationary patterns in water quality that cannot be observed due to the restrictions caused by spatial resolution? We found that the mean

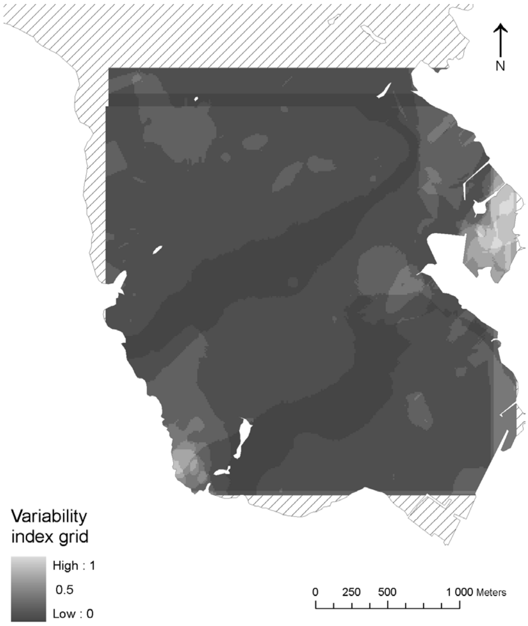

Fig. 6. Variability index grid over the study site based on 9 field survey measurements.

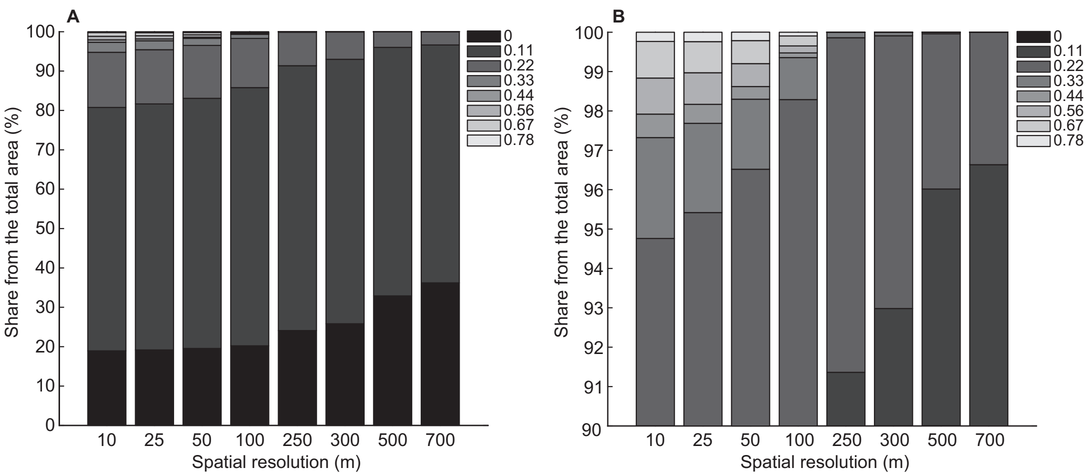

Fig. 7. (**A**) Shares of surface areas of different variability index classes in different spatial resolutions. (**B**) Variability index classes with greater variability.

value can observed reasonably well even with only one coarse resolution pixel observation. However, areas where water quality typically differed were located close to the shoreline and could not be observed with coarser resolutions. Therefore, information on the variance is lost with large pixel sizes. At our study site, small-scale variation is also averaged as the pixel size increases, but this had a minor effect on standard deviation estimates. It can be concluded that the spatial resolution of satellite instrument has an effect on how water quality is detected in lakes, but valuable information can be acquired even with very coarse-resolution observations.

Information on stationary patterns in water quality can help to understand whether sampling is representative in a monitoring regime. We found locations at our study site where chlorophyll-*a* concentration was constantly higher than the mean value for the entire monitoring area. These areas were not sampled in the monitoring programs conducted at the lake and, according to the results of this study, cannot be observed with the medium to coarse-resolution remote sensing data. At our study site, these areas did not significantly affect the mean-value estimations if the majority of the monitoring regime was sampled representatively with e.g. coarse-resolution satellite observations. However, conditions in these areas may indicate upcoming changes in water quality as they may also function as a source of nutrients and particulate matter. If these areas are neglected in the monitoring programs, information on the reasons behind the changes in water quality might be lost.

Spatial variation has been difficult to define with conventional monitoring methods and therefore, it has been neglected in many monitoring programs. It is suggested that the joint use of remote sensing and *in situ* observations increases accuracy of water quality monitoring (e.g. Pulliainen *et al*. 2001, Kallio *et al*. 2003, Vos *et al*. 2003). Lakes in Finland are typically small and fragmented. Therefore, the number of pure water remote sensing observations is strongly limited by adjacent land areas and, obviously, by the spatial resolution of the satellite instrument used. Results of this study indicate that to get full benefit from the extensive coverage of remote sensing in small monitoring areas, the spatial resolution of the instrument should enable detection of stationary patterns in water quality that are often located close to a shoreline. At our study site, this requires observations with less than 100-m spatial resolution that is not possible with the satellite instruments that are currently suitable for the operative water quality monitoring. Water quality monitoring can naturally be complemented with fine spatial resolution remote sensing observations, but in that case monitoring costs increase rapidly. High resolution remote sensing observations could rather be suitable for the calibration of the monitoring regime to specific spatial dynamics in water quality (Curran and Atkinson 1998, Hedger *et al*. 2001). This information could then be used in e.g. planning of the *in situ* sampling locations.

Aplin (2006) concluded that observations in multiple scales can increase the volume of information available to characterize and distinguish features. In our previous study carried out at the same study site (Anttila *et al*. 2007), we found that for a mean value estimation of reasonable accuracy, at least five samples from the study site are required. With remote sensing observations, smaller sample sizes, i.e. number of pixels, are adequate for the mean value estimation for the illuminated water column. The results of these studies also indicate that when using multiple methods in water quality monitoring, it should be considered for which scale and area each method is representative.

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