

# A REMOTE SENSING BASED FRAMEWORK FOR PREDICTING WATER QUALITY OF DIFFERENT SOURCE WATERS

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## Earth Observation for a Changing World

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### ABSTRACT:

In this paper, a satellite based remote sensing technique of acquiring water quality data is proposed. A review has been presented on retrieval of five major independent water quality variables (chlorophyll-a, Secchi disk depth, total phosphorus, turbidity and temperature) from the satellite data. A frame work has been developed for mapping water quality variables at landscape level using satellite and ground measured data with an intent to help classify source waters according to pollution levels in Alberta.

## 1. INTRODUCTION

Understanding the quality of source waters is important in deciding the level of treatment required for human consumption. Traditionally, the water quality indicators (that include physical, chemical, and biological properties) are determined by collecting samples from the sources of interest and analyzing them in a laboratory setup. Currently, in Alberta, there exists a number of sites, where water samples are collected during the months of May-September since 1984 (Swanson and Zurawell, 2006). Collecting water samples physically, while still desirable, is (i) labour intensive (ii) time consuming and (iii) cannot provide synchronous water quality data for large areas.

In order to address both spatial and temporal variability, remote sensing-based methods can be used in determining various water quality-related parameters (Alparslan et al. 2007, Cox et al. 1998, Kloiber et al. 2002a,b, Koponen et al. 2002, Lathrop and Lillesand 1986, Lillesand et al. 1983, Mancino et al. 2009, Östlund et al. 2001, Vignolo et al. 2006, Wang et al. 2006). These methods are having several benefits, which include (i) near continuous spatial coverage of satellite data over a complete geographic area of water body; (ii) capable of assessing water quality in remote areas; (iii) availability of satellite data in all seasons (iv) relatively low cost associated with satellite data and (v) efficient analysis. In this paper, our objectives are to (i) review existing remote sensing-based method in determining water quality variables; and (ii) develop a remote sensing-based framework to predict water quality of different sources across Alberta.

## 2. REVIEW

### 2.1 Major independent water quality variables

Twenty lakes of Alberta (as shown in Figure 1) were monitored for twenty water quality variables from 1984 to 2004 by Alberta Environment. In studies of Alberta lakes conducted by Alberta Environment only three major variables (i.e., chlorophyll-a, Secchi disk depth and total phosphorus) were considered to

classify lakes into four trophic states indicating low to very high productivity which were: (i) oligotrophic; (ii) mesotrophic; (iii) eutrophic; and (iv) hypereutrophic. In our framework we propose five major independent water quality variables instead of three that impact trophic status of surface water quality in Alberta. These water quality variables include chlorophyll-a, Secchi disk depth, total phosphorus, turbidity and temperature. The turbidity is associated with suspended particles in water like soil, sediments, sewage, and plankton due to which sunlight needed for photosynthesis gets blocked in water bodies and it affects nutrient growth and Secchi depth. We have considered turbidity as fourth variable of interest in our framework. The nutrient concentrations were also found to change with seasonal variations in Alberta lakes due to which we have proposed temperature as fifth variable in our framework.

### 2.2 Retrieval of water quality variables from satellite data

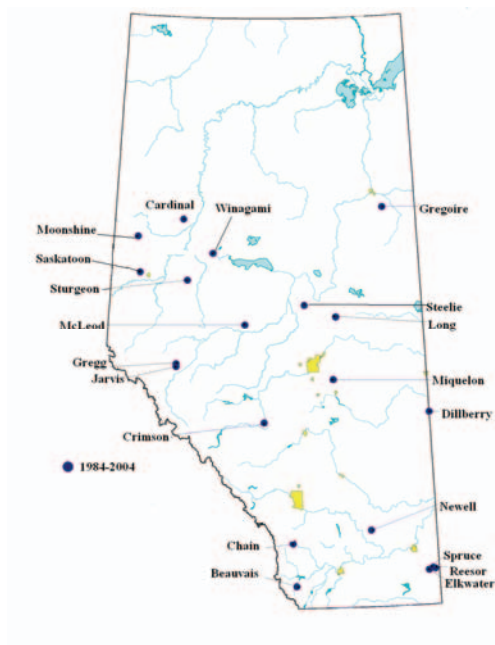
A review has been presented on remote sensing based techniques for retrieval of these variables from satellite data.

#### 2.2.1 Chlorophyll-a

Chlorophyll-a is a photosynthetic pigment in plants, algae and cyanobacteria. Since it acts as a link between nutrient (in particular to phosphorus) concentration and algal production it is considered a major indicator of trophic state in Alberta lakes. From literature, it is noted that the ratio between various visual spectral bands are used in quantifying chlorophyll-a. For example: (i) ratio between green (0.50-0.60  $\mu\text{m}$ ) and red (0.60-0.70  $\mu\text{m}$ ) or vice-versa were used by Hellweger et al. (2004) and Mancino et al. (2009); and (ii) ratio between blue (0.40-0.50  $\mu\text{m}$ ) and red or vice-versa were used by Han and Jordan (2005) and Mancino et al. (2009). In most of the instances, empirical relationships were developed between remote sensing-based indices and ground-based measurements of the water quality variables.

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**Figure 1: Alberta lakes for predicting water quality variables**

**2.2.2 Secchi disk depth**

Secchi disk depth is used to measure the transparency of water bodies. The ratios of visual spectral bands, e.g., (i) blue and green (Khorram et al. 1991); (ii) green and red (Wang et al. 2006); and (iii) individual band like red (Wang et al. 2006) were used to quantify Secchi disk depth in water bodies.

**2.2.3 Total phosphorus**

Total phosphorus is a measure of inorganic, organic and dissolved forms of phosphorus. Phosphates are plant nutrients and their increased quantity help plants and algae to grow quickly. Total phosphorus can be directly related to the biomass of phytoplankton (i.e. suspended algae and cyanobacteria, typically estimated by chlorophyll-a concentration) and indirectly related to water clarity or transparency, as estimated by Secchi depth (Swanson and Zurawell, 2006). MODIS bands, such as, green band (545 – 565nm), and integration of red (620-670nm) and green showed significant relationship with total phosphorus (Wu et al. 2009).

**2.2.4 Turbidity**

Turbidity is a measure of water clarity caused by the amount of particles suspended in water like soil, sediments, sewage, and plankton. It is considered as a variable in our framework due to its linkage with incoming sunlight which affects photosynthesis for growth of algae and plankton and it is also directly associated with Secchi depth. Literature showed that turbidity could be quantified using visual spectral bands: (i) green and red (Wang et al. 2006) and (ii) green (Khorram et al. 1991) and (iii) ratio of red and blue (Cox et al. 1998).

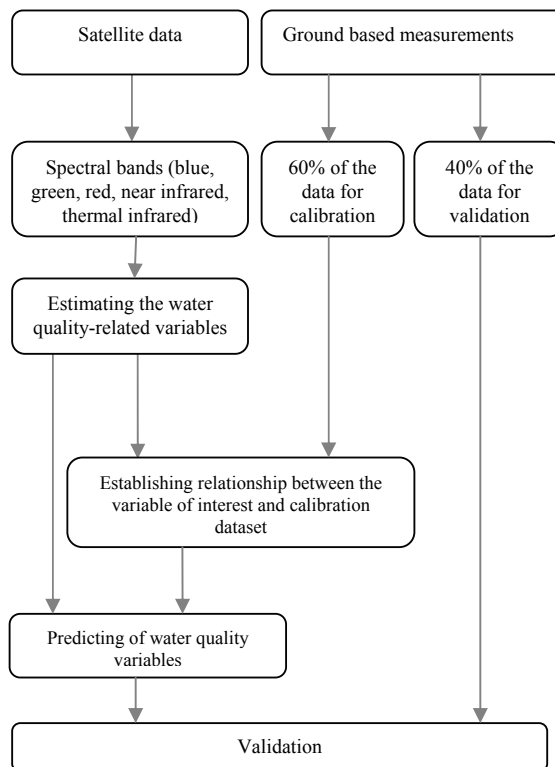
**2.2.5 Temperature**

Water temperature is an important variable which regulates physical, biological and chemical processes. It influences the

solubility, and thus availability, of various chemical constituents in water. Most importantly, temperature affects dissolved oxygen concentrations in water (oxygen solubility decreases with increasing water temperature) (Swanson and Zurawell, 2006). It is important to analyze temperature as there is an impact of season on water temperatures. Infrared thermal band (8.0-14.0 μm) measures the amount of infrared radiant flux (heat) emitted from surfaces. Literature indicated use of infrared thermal band for quantifying water temperature (Cox et al. 1998; Hassan et al. 2007).

**3. PROPOSED FRAMEWORK**

Figure 2 shows a schematic diagram of the proposed framework. The different components of proposed framework are summarized here:



**Figure 2: A remote sensing based framework for predicting water quality variables**

**3.1 Study Area**

Our proposed framework includes predicting water quality of all sources that supply drinking water to Alberta. The geographic area of Alberta is 661,185 km<sup>2</sup> (Statistics Canada, 2005) and it has a population of about 3.7 million (Demographic Quarterly, 2009).

**3.2 Ground based measurement**

The ground measurement water sampling data will be obtained from Alberta environment for sampling sites with geographic locations of all water sources. The water dataset will include concentrations of five selected water quality variables that include chlorophyll-a, Secchi depth, total phosphorus, turbidity and temperature. The water sampling

data for sampling sites as shown in Figure 1 has already been arranged and data for remaining water sources will be arranged.

### 3.3 Satellite data

The satellite-based spectral reflectance acquired by various spectral bands (blue: 0.40 - 0.50  $\mu\text{m}$ , green: 0.50 - 0.60  $\mu\text{m}$ , red: 0.60 - 0.70  $\mu\text{m}$ , near infrared: 0.70 - 0.90  $\mu\text{m}$  and thermal infrared: 8.0 – 14.05  $\mu\text{m}$ ) will be used to quantify water quality variables of interest. We found that Landsat TM/ETM+ data are widely used for water quality studies in inland waters (Alparslan et al. 2007, Baruah et al. 2002, Brivio et al. 2001, Cox et al. 1998, Dekker et al. 2001, Dekker et al. 2002, Fraser 1998, Giardino et al. 2001, Lathrop 1992, Lillesand et al. 1983, Lathrop and Lillesand 1986, Östlund et al. 2001, Mancino et al. 2009, Mayo et al. 1995, Vignolo et al. 2006, Wang et al. 2006).

TM data is provided by Landsat-5 which started its operation in 1984 and it is the oldest spacecraft of its type. According to a USGS manager, it was brought back from brink of "death" to life many times over last seven years. This satellite will be expired soon. Landsat-7 is operational but preference is given to data of landsat-5 because of complete coverage of data. Due to unpredictable nature of working of Landsat, we prefer to use MODIS satellite data. The Terra MODIS and Aqua MODIS view the entire earth's surface every 1 to 2 days and they acquire data in 36 spectral bands. The spatial resolution of MODIS ranges from 250 m to 1 km. The satellite images of Landsat data needs pre-processing in terms of atmospheric & geometric corrections. The digital values of landsat images are converted into radiance (unitless planetary reflectance) to eliminate the effects of high local variability on remote sensing observation values as done in previous studies (Wang et al., 2006, Mancino et al., 2009, Alparslan et al., 2007). The MODIS images are already pre-processed and can be used to quantify spectral reflectance of water quality variables. The high spatial resolution of Landsat TM/ETM+ is useful to study water quality studies but it has two limitations (i) long revisit cycle of 16 days and (ii) it will fail to provide satellite data in future as it has completed its life. The short revisit cycle (1-2 days) of MODIS makes it more beneficial for water quality studies but its use is not recommended for inland waters because of its low spatial resolution. To overcome this problem, we propose to use new spatial and temporal adaptive reflectance fusion model (STARFM) algorithm developed by Gao et al. 2007 to blend Landsat and MODIS surface reflectance which will give us surface reflectance product at ETM+ spatial resolution (30m). This will be a new approach to study water quality variables at landscape level in Alberta.

### 3.4 Estimation of water quality variables from satellite data

Upon enhancing the spatial resolution of the MODIS data into ~30 m like the Landsat data we will then estimate water quality variables. The ground measured data will be divided into two groups comprising of 60% and 40% of the data respectively. The satellite data will be used to quantify relationship of variables with bands or bands ratio using 60% of ground measured data. As a result, we will get models with most suitable bands or bands ratio to estimate each variable from satellite data. These models will be used to predict water quality variables at any location of surface water sources. The models will be validated using the remaining 40% ground measured data.

## CONCLUSIONS

A remote sensing based framework has been proposed for predicting water quality of different source waters by integrating satellite data and ground-based measurements. This proposed system which is still under development will help develop classes of source waters in Alberta. This will be immensely useful as to the best of our knowledge such a classification system does not exist. The success of this project will lead to similar models being developed in other jurisdictions in Canada and elsewhere in the world.

## REFERENCES

- Alparslan, E., Aydoğan, C., Tufekci, V., and Tufekci, H., 2007. Water quality assessment at Ömerli Dam using remote sensing techniques. *Environ. Monit. Assess.*, 135, pp. 391-398.
- Baban, S. J., 1993. Detecting water quality parameters in the Norfolk Broads, UK, using Landsat imagery. *Int. J. Remote Sens.*, 14, 1247-1267.
- Baruah, P.J., Tamura, M., Oki, K., and Nishimura, H., 2002. Neural network modeling of surface chlorophyll and sediment content in inland water from Landsat Thematic Mapper imagery using multivariate spectrometer data. In: Gilbert, G.D., Frouin, R.J. (Eds.), *Ocean Optics: Remote Sensing and Underwater Imagery. Proc. SPIE Int. Soc. Opt. Eng.* 4488, Seattle, pp. 205-212.
- Brivio, P.A., Giardino, C., and Zilioli, E., 2001. Determination of chlorophyll concentration changes in Lake Garda using an image-based radiative transfer code for Landsat TM images. *Int. J. Remote Sens.*, 22, 487-502.
- Chen, C., Tang, C., Pan, Z., Zhan, H., Larson, M., and Jonsson, L., 2007. Remotely sensed assessment of water quality levels in the Pearl River Estuary, China., *Mar. Pollut. Bull.*, 54, pp. 1267-1272.
- Cox, R.M., Forsythe, R.D.V and Olmsted, L.L., 1998. Assessing water quality in Catawba river reservoirs using landsat thematic mapper satellite data. *Lake Reservoir Manage.*, 14, pp. 405-416.
- Dekker, A.G., Vos, R.J., and Peters, S.W.M., 2001. Comparison of remote sensing data, model results and in situ data for total suspended matter (TSM) in the southern Frisian lakes. *Sci. Total Environ.*, 268, 197-214.
- Dekker, A.G., Vos, R.J., Peters, and S.W.M., 2002. Analytical algorithms for lake water TSM estimation for retrospective analysis of TM and SPOT sensor data. *Int. J. Remote Sens.*, 23, 15-35.
- Demographic Quarterlies, 2009. Quarterly Demographic Statistics (Alberta Population Reports). [http://www.finance.alberta.ca/aboutalberta/demographic\\_quarterlies.html](http://www.finance.alberta.ca/aboutalberta/demographic_quarterlies.html) (accessed 10 Apr. 2010).
- Dogan E, Sengorur B, Koklu R, 2009. Modeling biological oxygen demand of the Melen River in Turkey using an artificial neural network technique. *J. Environ. Manage.*, 90, 1229-1235.

- Fraser, R.N., 1998. Multispectral remote sensing of turbidity among Nebraska Sand Hills lakes. *Int. J. Remote Sens.*, 19, 3011–3016.
- Gao F., Masek J., Schwaller M., and Hall F., 2006. On the Blending of the Landsat and MODIS Surface Reflectance: Predicting Daily Landsat Surface Reflectance. *IEEE Trans Geosci. Remote Sens.*, 44, 2207–2218.
- Giardino, C., Pepe, M., Brivio, P.A., Ghezzi, P., and Zilioli, E., 2001. Detecting chlorophyll, Secchi disk depth and surface temperature in a sub-alpine lake using Landsat imagery. *Sci. Total Environ.*, 268, 19–29.
- Hassan, Q.K., Kamal, M.M., and Hossain, A. 1998. Implementation of algorithms of geocoding and SST estimation using AVHRR data in the EASI/PACE PCI Image Processing Software over Bay of Bengal. *J. NOAMI*, v. 15, no. 2, pp. 63–72.
- Hassan, Q.K., Bourque, C.P.-A., Meng, F.-R., and Cox, R.M. 2007. A wetness index using terrain-corrected surface temperature and normalized difference vegetation index: an evaluation of its use in a humid forest-dominated region of eastern Canada. *Sensors*, v. 7, pp. 2028–2048.
- Han, H., and Jordan, K.J., 2004. Estimating and mapping chlorophyll-a concentration in Pensacola Bay, Florida using Landsat ETM+ data. *Int. J. Remote Sens.*, 26, 5245 - 5254.
- Hellweger, F.L., Schlossera, P., Lalla, U., and Weissel, J.K., 2004. Use of satellite imagery for water quality studies in New York Harbor. *Estuar. Coast. Shelf Sci.*, 61, 437–448.
- Khorram, S., Cheshire, H., Geraci, A.L., and Rosa, G.L., 1991. Water quality mapping of Augusta Bay, Italy from Landsat-TM data. *Int. J. Remote Sensing.*, 12, 803–808.
- Kloiber, S.M., Brezonik, P.L., and Bauer, M.E., 2002a. A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sen. Environ.*, 82, 38–47.
- Kloiber, S.M., Brezonik, P.L., and Bauer, M.E., 2002b. Application of Landsat imagery to regional-scale assessments of lake clarity. *Water Res.*, 36, 4330–4340.
- Koponen, S., Pulliainen, J., Kallio, K., and Hallikainen, M., 2002. Lake water quality classification with airborne hyperspectral spectrometer and simulated MERIS data. *Remote Sen. Environ.*, 79, 51–59.
- Lathrop, R.G., 1992. Landsat Thematic Mapper monitoring of turbid inland water quality. *Photogramm. Eng. Remote Sens.*, 58, 465–470.
- Lathrop, R.P. and Lillesand, T.M., 1986. Use of Thematic Mapper data to assess water quality in Green Bay and Lake Michigan. *Photogramm. Eng. Remote Sens.*, 52, 671–680.
- Lillesand, T.M., Johnson, W.L., Deuell, R.L., Lindstrom, O.M., and Meisner, D.E., 1983. Use of Landsat data to predict the trophic state of Minnesota lakes. *Photogramm. Eng. Remote Sens.*, 49, 219–229.
- Mancino, G., Nolè A., Urbano V., Amato M., and Ferrara A., 2009. Assessing water quality by remote sensing in small lakes: the case study of Monticchio lakes in southern Italy. *iForest*, 2, pp. 154–161.
- Mayo, M., Gitelson, A., Yacobi, Y.Z., and ben-avraham, Z., 1995. Chlorophyll distribution in Lake Kinneret determined from Landsat Thematic Mapper data. *Int. J. Remote Sens.* 16, 175–182.
- Onderka and P. Pekarova, 2008. Retrieval of suspended particulate matter concentrations in the Danube River from Landsat ETM data, *Sci. Total Environ.* 397 (1–3) (2008), pp. 238–243.
- Östlund, C., Flink, P., Strombeck, N., Pierson, D., and Lindell, T., 2001. Mapping of the water quality of lake Erken, Sweden, from imaging spectrometry and landsat thematic mapper. *Sci. Total Environ.*, 268, pp. 139–154.
- Panda, U.M., Sundaray, K.S., Rath, P., Nayak, B.B., Bhatta, D., 2006. Application of factor and cluster analysis for characterization of river and estuarine water systems – A case study: Mahanadi River (India). *J. Hydrol.*, 331, 434– 445.
- Swanson, H., Zurawell, R., Steele Lake Water Quality Monitoring Report, 2006. Monitoring and Evaluation Branch, Environmental Assurance Division, Alberta Environment, Edmonton, Alberta.
- Statistics Canada, 2005. About Alberta. <http://www40.statcan.gc.ca/101/cst01/phys01-eng.htm?sdi=area> (accessed 10 Apr.2010).
- Vignolo, A, Pochettino, A., Ciceronea, D., 2006, Water quality assessment using remote sensing techniques: Medrano Creek, Argentina, *J. Environ. Manage.*, 81, pp. 429–433.
- Wang, F., Han, L., Kung, T., and Van Arsdale, R.B., 2006, Applications of Landsat-5 TM imagery in assessing and mapping water quality in Reelfoot Lake, Tennessee. *Int. J. Remote Sens.*, 27, pp. 5269–5283.
- Wu, M., Zhang, W., Wang, X., and Luo, D., 2009, Application of MODIS satellite data in monitoring water quality parameters of Chaohu Lake in China. *Environ Monit. Assess.*, 148, pp. 255–264.