MULTI-SOURCE DEM EVALUATION AND INTEGRATION AT THE ANTARCTICA TRANSANTARCTIC MOUNTAINS PROJECT

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ABSTRACT

Digital elevation models are essential tools in many glaciological studies and especially for mass balance studies, structural geology modeling and advance remote sensing and geophysical processing. However, due to the hostile climate and inaccessible environment of the Antarctic continent, there are insufficient elevation databases and their quality is poor. In this paper, we analysis the spatial distribution of error in the different DEMs that exists at the Antarctica Transantarctic Mountains. Based on this analysis, we investigate the various methods to combine elevation models with different properties (resolution, horizontal and vertical accuracy). There are five major data sets in the project area: The USGS 1:50000 maps which, covers the north west part of the project area and have 50 meter contour line interval; USGS 1:250000, taken from the Antarctic Digital Database, which, covers all our project area and have 200 meter contour line interval; satellite radar altimetry data derived from ERS-1 with 5 km resolution; airborne Radio-Echo Sounding profile data at the north east part of the project collected by Scott Polar Research Institute and field surveying control points collected by USGS.

Our final goal was to compile all those elevation models into one uniform grid elevation model with the highest accuracy and resolution that can be obtained. Many techniques and algorithm's exists for integrating database, some are based on interpolation methods in the boundary zone, other techniques perform simple data merging and apply various filtering functions to make the transition smoother. We review those procedures and compare their properties and apply some of them in our study. Last, we propose a method to combine the different DEM into one set using universal Kriging concept. In this process, we compute a covariance matrix for every data set individually and a cross covariance of the individual data set in the predication computation.

1 INTRODUCTION

1.1 The Tamara Project

The Tamara project is an international research aimed at integrating new aeromagnetic data, acquired by a cooperative U.S.-German field campaign, with satellite imagery, geological and structural mapping, and existing ground-based, airborne and marine geophysical data. With this comprehensive database we hope to answer outstanding questions about the evolution of the Transantarctic Mountains (TAM) - West Antarctic rift- in southern Victoria Land. The foundation of this database is a Digital elevation model (DEM) which is an essential tools in many glaciological studies and especially for magnetic and gravity modeling. It is important to use a data set which will have the best accuracy and with the highest resolution. However, due to the hostile climate and inaccessibility environment of the Antarctic continent, there are insufficient elevation databases and their quality is poor. Consequently, we need to apply methods to combine and integrate the different DEM's which were acquired from different sources with different spatial properties.

1.2 Review of data fusion methods

Many methods have been proposed for integrating multiple data sources. For a comprehensive review on data fusion we refer the interested reader to Abidy and Gonzales (1992). Here we mention only a few methods that are important for understanding the procedures described in this paper. Rapp (1984) examines various techniques; that can be used to combine satellite gravity field information with terrestrial gravimetry. He is using spherical harmonic expansions (Fourier analysis) to interpolate the data and weighted least squares to solve the augmented observation equations and to compute the combined interpolation function coefficients. Hahn and Samadzadegan (1999) transform the data using wavelet decomposition that yields a better local interpolation. (compared with spherical functions). The merging process of the two DTMs takes place on the same wavelet function scale by least squares fit. Honikel (1999) fuses digital elevation models derived from optical sensor (SPOT images) and SAR interferometry. She uses the correlation coefficient of each data, i.e. the coefficient generated by the automatic DEM program or image matching system for the optical sensor and the coefficient which was computed from the interferometry phase unwrapping process. The mathematical model for this method is given in (1) and represent a simplified approach to the least squares approach.

$$\hat{h}(x,y) = \frac{h_f(x,y)\rho_f^{\ 2} + h_{opt}(x,y)\rho_{opt}^{\ 2} + h_{sar}(x,y)\rho_{sar}^{\ 2}}{\rho_f^{\ 2} + \rho_{opt}^{\ 2} + \rho_{sar}^{\ 2}} \qquad (1)$$

Where:

$\hat{h}(x,y)$: resulting local height estimate.
$h(x,y)$: local height of the filtered (f) optical (opt) and SAR DEM.
ρ : Correlation coefficient derived for the appropriate data.

Liu (1999) uses a GIS approach for identification and exchange of data in regions, where the height measurement of one of the contributing sensors fails . We used a combined approach which incorporate Liu (1999) procedure for merging overlapping DEM's but also uses a least squares approach to fuse DEM's one into the other. Consequently we designed a two step process for the integration of data:

1. merging overlapping data sets to produce the primary DEM – in our case the 1:250k data from the ADD and 1:50k data from USGS.
2. fusion of the base DEM with more accurate elevation data in specific areas, to refine the primary DEM and produce a more accurate and with higher resolution DEM.

In the subsequent sections, we describe the data processing procedures; section 2 describe the different data sources and the evaluation methods used to estimate their accuracy; section 3 describes the merging technique; and section 4 describes a new statistical algorithm to blend two DEMs and improve elevation models on a smooth area.

2 DIGITAL ELEVATION MODELS ANALYSIS

2.1 Data sources

The main sources of DEM'S in the project area are (see also figure 1):

1. The Antarctic Digital Database, ADD – sheets ST 57-60 and ST53-56, which were created from the 1:250,000 USGS Antarctica Reconnaissance Series maps. These maps were mostly compiled from US Navy tricamera aerial photographs taken in the 60's. (ADD 1998). The digital contour line map has a 200m contour interval, providing a mean vertical accuracy of 100m (according to the USGS map standards the accuracy equals half of the contour interval). However, since those maps are part of the Antarctica Reconnaissance Series it may not comply with USGS standards and the accuracy of the data should be verified.

2. **The USGS 1:50K** digital data: which covers the north west part of the project area, and has a 50 meter contour line interval. Again we should examine the accuracy of those data sets.

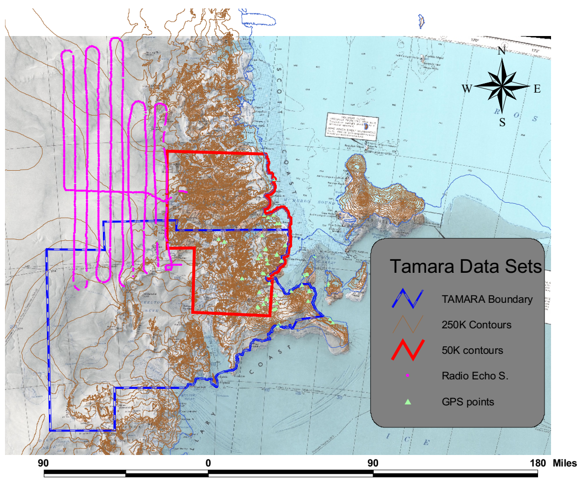

Figure 1: Tamara project, the different DEMs.

3. **Ice Altimetry data** - surface elevations of the Antarctic ice sheets derived from ERS-1 altimetry data, as processed by the Oceans and Ice branch of the Laboratory for Hydrospheric Physics of NASA/GSFC. The grid points have a nominal spacing of 5 km. The gridded elevations are derived from the data by a weighted fit of a bi-quadratic function (bi-linear where data distribution is poor) to the elevation data that fall within a certain radius of the grid location. This data was reported [Bamber 94] to have an error in the order of a few meters for elevations on slopes smaller then 0.65°. This error comprises of random errors, originates from the satellite retracking error, and bias, from the geographically correlated orbit error and uncertainties in the geoid. For regions with slope greater then 0.65° the elevation estimates are not reliable i.e. have very large error, due to large footprint of the radar altimeter.

4. **Airborne Radio-Echo sounding profiles** data at the north east part of the project area collected by Technical University of Denmark and Scott Polar Research institute, University of Cambridge, U.K using an airborne Radio- Echo Sounding equipment operating at 60 and 300 MHz [Drewry 1982]. The absolute accuracy of elevation is about 30m, However, the relative elevation accuracy is likely to be better than 10m; Data were collected on 10 subparallel lines 10-15km apart. Terrain clearance and ice thickness data measured at interval of 1.1 km.

5. **GPS and traverse surveying points**. Collected from many different sources and projects but mainly from USGS field campaigns. The accuracy of those points is a few centimeters, however due to the difficult climate conditions the Antarctic area have a paucity of control points.

2.2 Data analysis

It was important to evaluate the accuracy of our data and to get familiarity with the problematic areas. One way to estimate DEM is to compare with another independent and more accurate data. In our research, we use bilinear interpolator to compute the height of a given point from the DEM i.e. each point is computed from the closest four grid points. We did the following comparisons:

- USGS 1:250 DEM Vs. GPS points : 63 points, Mean difference: -158.49 m, Standard Deviation of difference: 122.65 m; Maximum: 182.89; Minimum: - 447.00. Those points were measured in the rough terrain area with rock outcrops of the Royal Society range and Mount Discovery in which the aerial photogrammetric methods are more accurate (in contrary to the flat uniformly white Antarctic Plateaus), On the one hand, lack of texture on the ice make Photogrammetric interpretation and measurement difficult on the other hand in on a very rough and mountainous topography small error in the horizontal position can cause big error in the vertical direction i.e. elevation measurement.
- USGS 1:50 DEM Vs. GPS points : 35 points; Mean: 53.30; Standard Deviation: 23.87. again in an area with rough Topography.
- Ice Altimetry data (ERS-1 data set) Vs USGS 1:250 DEM; General statistics in all our project area; 3590 points Mean: 180.10 m and Standard Deviation: 318.27 m. This very high error is due to the very rough area (rapid and big changes of height e.g. from 0 m to 3268 m across 35km) However ;In a flat area we get for 1463 points Mean: 71.25 m and Standard Deviation: 74.73 m; in an area with high slopes indeed the elevation estimate are not reliable e.g. 408 points Mean: 372.28 m Standard Deviation: 466.60 m.
- USGS 1:250K DEM Vs Airborne Radio-Echo sounding profiles : We have 1674 measured points; Mean: 20.11 m Standard Deviation: 77.97. Maximum error is: 570.00 Minimum error is: -305.00
- USGS 1:250 Vs USGS 1:50K; Statistical analyses of the difference grid gave us a Root Mean Square Error of 140m and expectation of 32m (i.e. 32m datum shift so the 250k data has a higher datum) Those result's were anticipated since the interpolation process introduce interpolation error and the Antarctica Reconnaissance Series accuracy's are worse then the USGS normal mapping standards.

3 MERGING THE 50K AND 250K USGS DATA

We used the original contour line coverage of the 1:50,000 and 1:250,000 USGS map and produce a grid from them. In the previous section we estimated the height errors of our data but we also need to check for irregular patterns in our data Consequently, we subtracted (overlay operation) the two data sets to get a difference grid. Close examination of this grid shows no significant trend or pattern which means that we can combine the two sets without any datum transformation. (see figure 2). After clipping the area of the 50k data from the 250k we choose to merge the two dataset using Arc/Info TOPOGRID command. The Topogrid command is based on Hutchinson (1996) interpolation method. The interpolation procedure has been designed to take advantage of the types of input data (in our case contour lines). This method uses an iterative finite difference interpolation technique. It is optimized to have the computational efficiency of 'local' interpolation methods such as inverse distance weighted interpolation, without losing the surface continuity of global interpolation methods such as kriging and splines. It is essentially a discretised thin plate spline technique, where the roughness penalty has been modified to allow the fitted DEM to follow abrupt changes in terrain, such as streams and ridges. In order to improve data continuity at sutures we could either filter our data at the merge line or give a data free zone for the interpolation. We choose the second option and thus we cut 1km from the 250k contours as a transition zone. With this transition zone the Topogrid interpolation was able to merge the two dataset and produce a seamless elevation grid at a resolution of 100 m (this grid resolution is a little high in the areas where we have only 1:250k data but we had to have a higher resolution grid for a SAR rectification process).

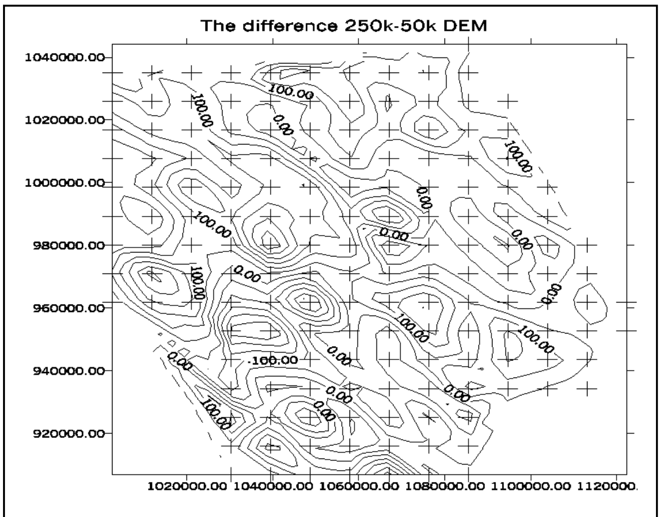

Figure 2: A difference grid between the USGS Antarctic DEM'S

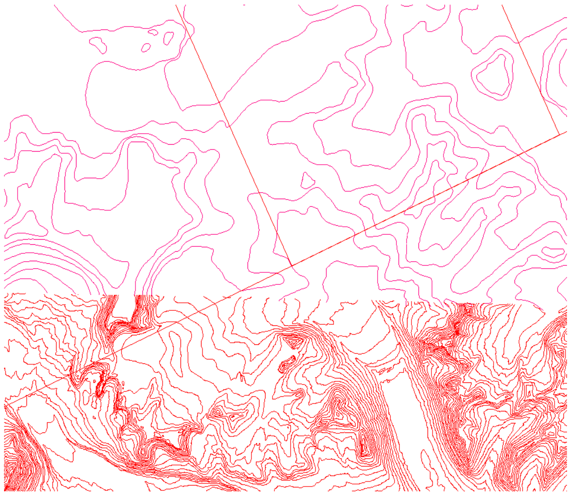

Figure 3A: 1:250k map and 1:50K before the merge process. The red line are SAR images frames.

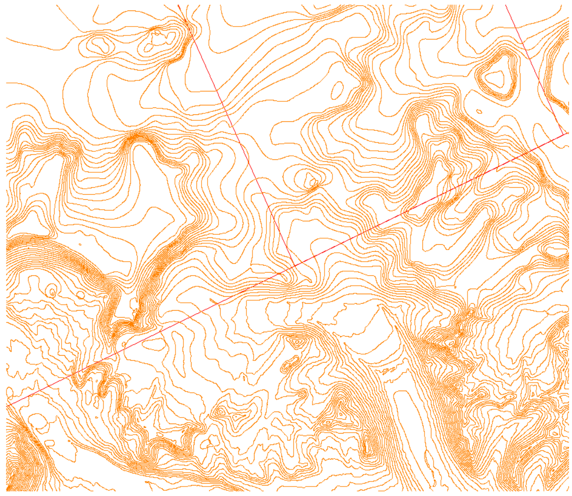

Figure 3B: The two map seamlessly combined. The red line are SAR images frames.

4 STATISTICAL ALGORITHEMS TO BLEND MULTI-SENSOR DEM'S

It was important to further improve our primary DEM to include also local DEM's that are more accurate i.e. Airborne Radio-Echo sounding profiles and the Ice Altimetry data in the flat areas. However, since the grid resolution of those DEM is small, we can not cut and replace the DEM as we did with the 1:50k DEM. Consequently, we propose to use a Least Squares Collocation (which is equivalent to simple Kriging with a trend) to statistically interpolate and blend the DEM's. We can use this statistical model since our area varies slowly (the Antarctica glacial plateaus). The basic mathematical model of our data is based on Least square collocation according to Moritz 1970. The measurement vector y (elevations) is equal to a random signal (on which we have statistical prior information) added to a linear trend vector A ξ and added to random vector of noise e (error) :

$$\begin{matrix} y = X + A\xi + e \\ X = e_0 \end{matrix} \qquad \begin{bmatrix} e \\ e_0 \end{bmatrix} \approx \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \sigma_0^2 \begin{bmatrix} p^{-1} & 0 \\ 0 & Q_0 \end{bmatrix} \right) \tag{2}$$

Where:
y is the observations at known points;
A ξ is a trend that we want to detect, we used in our project 2d polynomial to describe the trend and compute our design matrix A.
X a random signal that we want to detect with zero expectation and known variance.
e – noise
p is the weight matrix of the noise elements; Q_0 is Cofactor matrix of the random signal.
and the basic solutions of collocation are the estimated trend coefficients at a point:

$$\begin{matrix} \hat{\xi} = (A\bar{c}^{-1}A)^{-1} A^T \bar{c}^{-1} y \\ where \quad \bar{c} = (p^{-1} + Q_0) \end{matrix} \tag{3}$$

and the predicted random signal at a required point

$$\tilde{X}_P = Q_{0P}^T \bar{c}^{-1} (y - A\xi) \tag{4}$$

where Q_{0P} is the cofactor matrix computed between the required point and the other data points.
We need to combine two data sets and thus we will split the mathematical model of (2) into two equations as follows:

$$\begin{matrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \xi + \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} & \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} \approx (0, \sigma_0^2 \begin{bmatrix} p_1^{-1} & 0 \\ 0 & p_2^{-1} \end{bmatrix}) \\ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} e_{01} \\ e_{02} \end{bmatrix} & \begin{bmatrix} e_{01} \\ e_{02} \end{bmatrix} \approx (0, \sigma_0^2 \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix}) \end{matrix} \tag{5}$$

in model (5) we assume no correlation between our noise element of different data sets $C(e_1,e_2)=0$ the signal elements in contrast have correlation which should be computed. The derivation of this combined data set least square collection solution is done by plugging the appropriate matrices into equation (3) and (4) and using matrix arithmetic's especially the formula for the inverse of a 2*2 matrix, we will skip this derivation and present the solution: (a similar derivation can be found at Helmut & Hans (1978)

$$\hat{\xi} = \hat{\xi}_1 + \bar{p}_1^{-1} \bar{A}_2^T \bar{c}_{22}^{-1} (y_2 - c_{21} c_{11}^{-1} y_1 - \bar{A}_2 \hat{\xi}_1) \tag{6}$$

Where:

$$\bar{P}_1 = A_1^T c_{11}^{-1} A_1$$
$$\bar{A}_2 = A_2 - c_{21} c_{11}^{-1} A_1$$
$$\bar{c}_{22} = c_{22} - c_{21} c_{11}^{-1} c_{12} + \bar{A}_2 \bar{P}_1^{-1} \bar{A}_2^T$$

Accordingly in this sequential or stepwise formula we first compute the trend $\hat{\xi}_1$ due to the first data set and then we add the new data set effect. The sequential form for the random parameter is :

$$\tilde{X}_P = \tilde{X}_{P1} + (c_{p2} - c_{p1} c_{11}^{-1} c_{12} - c_{p1} c_{11}^{-1} A_1 \bar{P}_1^{-1} \bar{A}_2^T) \bar{c}_{22}^{-1} (y_2 - c_{21} c_{11}^{-1} y_1 - \bar{A}_2 \hat{\xi}_1) \tag{7}$$

As mentioned before, $\tilde{X}_{P1}; \hat{\xi}_1$ are the solution of the interpolation process done on the first data set, with the introduction of the second data set we uses formulas (6) and (7) to update our interpolation. Obviously, we can use this sequential process with as many data set as we need as long as we compute the appropriate covariance matrix for each data set and the covariance with all the others. We compute our covariance function from the data in an empirical way and using:

$$C\{x(s), x(s')\} = E\{[x(s) - E(x(s))][x(s') - E(x(s'))]\} =$$
$$C_x(s'-s) = C_X(h) \approx \frac{1}{(n-h)-1} \cdot \sum_{i=1}^{(n-h)} [x(s_i + h) \cdot x(s_i)] - \hat{\beta}^2 \tag{8}$$
$$Where \quad \hat{\beta} = \frac{1}{n} \cdot \sum_{i=1}^{n} x(s_i)$$

C is the covariance, β is the expectation, s and s' denotes the spatial position, h=s-s' is the displacement vector or lag. This is under the conditions of ergodicity and Isotropy, Cressie (1993) proves that variogram estimation is to be preferred over covariogram estimation. The main reasons for that are:

When our process is only a second order stationary (not intrinsically stationary) then both the variogram estimator and covariogram estimator are biased. However, the variogram bias is of smaller order.

If our data has trend contamination then it has "disastrous effect" on attempts to estimate the covariogram while on the variogram it has a "small upward shift".

Since we assume second order stationarity we can write the relationship $\gamma(h) = C(O) - C(h)$ (9)

Note that $C(0) = \sigma^2$, the variance of the random function and we can estimate the semivariogram by:

$$\gamma(h) = \frac{E\{[x(s) - x(s+h)]^2\}}{2} = \frac{\sum_{i=1}^{(n-h)} [x(s_i) - x(s_i + h)]^2}{2n} \tag{10}$$

Using (8) and (10) we computed the semivariogram in figure 3a. 3b. 3c.

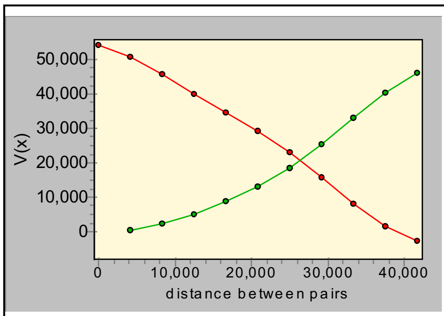

Figure 3a: Empirical Variogram (green - going up) and Covariogram (red - going down) of the USGS DEM.

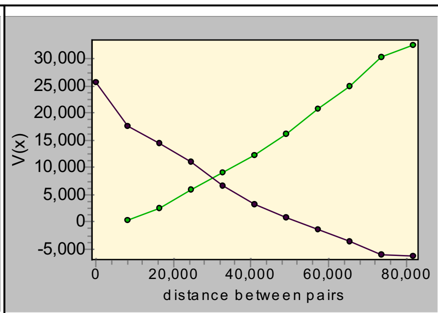

Figure 3b: Empirical Variogram (Black) and Covariogram (Blue) of the Radio Echo Sounding Data.

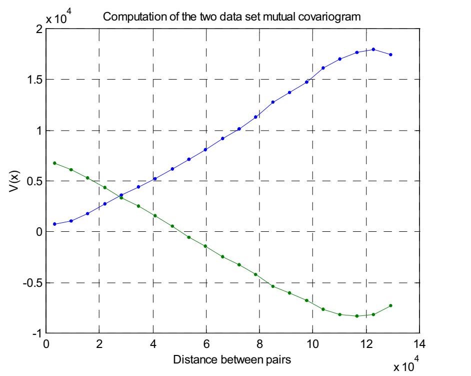

Figure 3c: Empirical mutual Variogram (blue) and mutual Covariogram (green) of the Radio Echo Sounding Data and USGS DEM

Following the generation of experimental semivariogram in the above figures; we used an interactive method to find the initial function and then used weighted least squares to fit the exact corresponding semivariogram functions. We should mention that to compute the sample semivariogram, we choose area in out data that have no visible trend (the selection was made using the contour line map). We were able to fit a Gaussian function to all the data sets that will also give us the required sill for equation (9) -C(0).

The USGS fitted Gaussian function has the following parameters: Nugget=g=366; Range=r= 50330; Sill=s= 90559.7; The Radio Echo Sounding Data fitted Gaussian Variance function has the parameters of: Nugget=g=130; Range=r= 61295; Sill=s= 35621 and the mutual data sets fitted Gaussian function has a Nugget=g= 500; Range=r= 88243; Sill=s= 20000. With those variogram models we followed the process of equation (6) and (7) to grid our data at 100 meter resolution and produce a grid with a better accuracy.

5 CONCLUSIONS AND FURTHER RESEARCH.

We have designed a complete schema to integrate DEM's acquired from different sources, and we demonstrated the execution of this process in an actual problematic case study area - The tranantarctic mountains in Antarctica. We divide the integration process into two separate classes of algorithms, namely; merging of overlapping data sets and fusion of one data set in the other. For the first technique, we suggest an interpolation zone of 1km, this means, that we smooth and decrease the effect of a 140 m variance over a distance 1KM (more then 10 times the variance is a good rule of thumb). For the fusion process, we propose to use a geostatistical interpolation - Least square collocation - it is not common to see statistical interpolations when using elevation models, those methods are being used extensively for potential fields, for geological analysis and spatial environmental examination. We decided to use those methods in our area since we assume a smooth behavior of the DEM over the ice topography of the Antarctic plateaus. More over, our interpolation algorithm is designed to work with small local subset or support which make it more suitable to deal with moderately varying data such as elevations model. The main advantage of the geostatistical mathematical scheme is that it fits a unique covariance/semivariogram model which encompass the measurement errors and the intrinsic data relationship in it, based on this analysis the algorithm interpolates the data. This is in contrast with other methods, which assume a certain data behavior in advance. Moreover, using geostatistics, we can get an estimate for our interpolation dispersion, The mathematical development of the sequential dispersion equation is long but follows the same line of arguments as the sequential least squares collocations. Further research is needed to evaluate the results of this model and compare it's performance with respect to other models.

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