

Modeling of the McMurray Formation using MPS Tied to Tidal Range

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Multiple point statistics (MPS) are used to generate categorical models for deposition environments that cannot be effectively described by two-point statistical modeling techniques. Many developments have been made in the field of MPS to model domains that require non-stationary training images, or that require multiple training images. This work develops a method that uses multiple stationary training images to generate a non-stationary model. The images are combined using a linear weighting scheme to obtain MPS in zones of transition from one training image to another. Transitions can be continuous in the case of a gradual change in geometry or proportions, or they can be abrupt in the case of an unconformity. The method is demonstrated using a set of training images that reflect some of the deposition found in the McMurray formation. Images describe an estuarine environment ranging from inner fluvial to outer marine. Models were generated using an adapted version of SNESIM with promising results.

Introduction

It is well known that the geology of the McMurray formation is very complex, consisting of a variety of depositional environments or different successions of the same environment (Carrigy, 1959; Ranger and Gingras, 2003). The deposit varies from fluvial to marine from base to top respectively, with different stages of deposition occurring gradationally and with varying degrees of overlap. The formation is often divided into three different units termed upper, middle and lower (Carrigy, 1959; Stewart and MacCallum, 1978; Flach, 1984; Ranger and Gingras, 2003); however, other research (Hein et al, 2000; Hein and Dolby, 2001) suggests that only two units are possible because the upper and middle cannot be segregated regionally. In either case, the different units are not necessarily separated by crisp boundaries, and within each unit there is a mixture of gradational and abrupt variations in the magnitude, orientation, and incidence of depositional features. See Hassanpour (2009) for more background information on the McMurray formation geology.

The complex, non-stationary geology of the McMurray formation make it challenging to model using traditional geostatistical techniques such as sequential indicator simulation (Deutsch and Journel, 1998; Deutsch, 2002). Multiple point statistics (MPS) techniques are more capable of reproducing some of the complex features that are observed in outcrops of the McMurray formation, or that are predicted to exist in the subsurface (Strebelle, 2002). The use of MPS for tidal, estuarine and fluvial geology is explored by some authors (Strebelle and Zhang, 2004; Feyen and Caers, 2005; Strebelle and Levy, 2008); however, most of the examples therein are two dimensional binary categorical systems. Direct application of the MPS approach to build realistic models of the McMurray formation specifically has not been published.

An important and difficult task involved with MPS is choosing a training image (TI) (Boisvert et al, 2007; Pyrcz et al, 2008). Because of the gradational features and variation of geology, it is difficult to assign a single representative TI to derive the statistics required for building models. Such features may also cloud the available measures available to aid in the TI selection process. For example, choosing a single estuarine image with a specific channel width for the middle McMurray unit may be challenging if channel width varies aurally and with depth due to changes in energy and sediment load over time. Some research has been done to overcome the limitation of TI's with stationary feature dimensions and orientations (Chugunova and Hu, 2008; Straubhaar and Renard, 2011). Auxiliary variables are used to index non-stationary features of an image and an exhaustive map of the auxiliary variables in the domain to be modeled is used to guide the simulation.

As with any modeling technique, there are a few challenges involved with MPS modeling using a single TI and auxiliary variables. Obtaining a single TI that covers the range of architectures that may be present in a reservoir, and that contain enough repetition of those architectures to be statistically meaningful, is a non-trivial task. A second challenge is then having the ability to index the image to an auxiliary variable. For example, consider an estuarine TI and an auxiliary variable that is the degree of channel amalgamation. Deducing such a quantity from an image of facies is not straightforward;

however, it is straightforward to generate a set of stationary estuarine TI's, each having a different degree of amalgamation. To overcome the single TI and non-stationarity limitations, this work proposes the simultaneous use of multiple TI's to account for the geological complexity encountered in the McMurray formation.

Background

In this work, the McMurray formation is considered as an estuarine depositional environment varying from inner estuary or fluvial to outer estuary or delta front and covering the range of environments occurring in-between. A description of the different types of estuaries, tide-dominated and wave-dominated, and the structure of each is described by Dalrymple et al (1992). A typical depositional model of a tide-dominated estuarine environment taken from Dalrymple et al (1992) is shown in Figure 1 and a similar one from Ranger and Gingras (2003) in Figure 2. The three structures common to estuaries as tidal range varies from outer to inner estuarine are shown and include the marine dominated outer estuary, meandering channel middle estuary, and river dominated fluvial inner estuary. Literature suggests that the upper McMurray unit is a shoreface or open marine depositional environment; the middle unit is an estuarine environment with outer to middle tidal ranges; and that the lower unit is an inner estuarine fluvial environment (Flach and Mossop, 1985; Smith, 1987; Wightman and Pemberton, 1997; Ranger and Gingras, 2003).

To use tidal range as a parameter for geostatistical modeling, it must be possible to construct conditional models of a tidal range variable. Two methods that can be used to determine tidal range from the types of data obtained for reservoir modeling are described here. Tidal range could be deduced from the types of facies observed in core samples and their local proportions. Whether they are river-, tide- or wave-dominated facies would be an indicator of their tidal position in an estuary. Idealistic models of the facies distributions in wave- and tide-dominated estuaries are given by Galloway and Hobday (1983) and Dalrymple et al (1992) and of fluvial-dominated deltas by Galloway and Hobday (1983). The representation of the middle McMurray unit shown in Figure 2 given by Ranger and Gingras (1992) indicates the middle unit covers the full range of an estuary from outer to inner. Cross stratified sands with tidal indicators may originate from an outer estuary setting, while sand- and mud-dominated inclined heterolithic stratification (IHS) and the occurrence of interclast breccias and bioturbated muddy contacts may originate from a middle estuary with meandering channels (Ranger and Gingras, 2003). The presence of facies from crevasse splays, rooted or bioturbated and coal containing layers along with inclined heterolithic stratification (IHS) and breccias may indicate a tidal fluvial setting

The second approach to determine tidal position is based on ichnology, which is the study of fossil traces left by organisms (Ranger and Gingras, 2003). A variety of fossil traces can be observed in core samples taken during reservoir exploration. Traces provide indications of the species of organism present and in turn, they provide evidence of the environmental conditions at the time the trace was left. For example, certain organisms cannot tolerate fresh water conditions; therefore, their presence is an indicator of tidal ranges associated with salt water such as shoreface or tidal flats. Others can only tolerate fresh water and indicate inner estuarine conditions beyond the maximum tolerable salt concentration for such organisms. A variety of fossils that are visible in core samples and their association with different facies and depositional conditions is given by Ranger and Gingras (2003).

For MPS modeling, a significant enough change in tidal position would require different TI's. It is only reasonable to consider depositional environments for which it is possible to obtain TI's for. TI's are either generated numerically via process mimicking (event based) techniques or object based modeling, or they are generated by digitizing analogues, for example from present day estuaries or outcrops. A review of literature pertaining to TI generation using numerical methods is given by Maharaja (2007). Recent developments in event based modeling are discussed by Pycrz et al (2012). An example using a digitized satellite image as a TI can be found in Straubhaar and Renard (2011). Tools exist to generate TI's that cover the majority of depositional settings suspected to exist in the McMurray formation. For example, the marked point process images in Pycrz et al (2008) could be used to represent arrays of tidal bars in an outer estuarine delta and the fluvial images from an inner estuary. Estuarine TI generation described by Hassanpour and Deutsch (2010) would apply to the middle tidal range environment.

Methodology

The proposed approach to model the complex geology encountered in deposits such as the McMurray formation is to use multiple TI's in conjunction with a range model that defines the TI's to apply to different areas of a model. With this approach, it is also possible to use multiple TI's to calculate the conditional probabilities required for indicator simulation in the case of a gradational change from one depositional environment into another, or to account for gradual changes of other parameters such as depositional energy within the same environment. Probably the most similar idea to this is the concept of search tree partitioning described by Boucher (2009), where a complex TI is partitioned into different regions based on pattern similarity. For simulation, a model that defines which partition to use in different areas of a model must be defined. A model of tidal position as discussed previously could be used for example. A similar approach that uses multiple TI's is described by Wu et al (2008). The modeling space is divided into a set of distinct regions, each one is modeled using a different TI.

Each of these similar techniques contains qualities that are necessary to account for the variability in geology observed in the McMurray formation: the search tree partitioning approach is able to handle geological settings that change gradationally, since the complex TI's that it is intended for may contain such features; the use of multiple training images to build a single model allows for abrupt changes from one geological setting to another and can account for features such as unconformities or other erosional contacts. The approach developed in this work mixes multiple training images for modeling transition zones and abrupt discontinuities. Generating models with abrupt discontinuities with multiple TI's is straightforward: a different TI is used in the different regions. The primary challenge is being able to create the transition zones, possible without having a specific TI of them.

In the approach developed here, a range model is used to index a set of TI's that represent the depositional environments present in a region to be modeled. Each TI is assigned a specific range value. For example, if range varies from 0 to 1 as we transition from marine to fluvial, range values of 0.1, 0.5 and 0.9 could be assigned to outer, middle and inner estuary TI's respectively. A range model containing values from 0 to 1 then identifies the TI's to use for any spatial position. Where the range model contains values equal to the TI range index, only a single TI is used and where the values are in between, at most two TI's are mixed. In the present approach, only a maximum of two TI's are mixed as it is highly unlikely that three or more depositional environments would be transitioning into one another at a given location. Considering the same example, a range of 0.3 would involve mixing the outer and middle estuarine TIs. The essential components of the workflow are as follows:

1. Determine the number of TI's and important features of each and assign range indexes.
2. Construct a range model based on available conditioning data.
3. MPS simulation: for each position along a random path:
 - a. Select TI's based on the range model value.
 - b. Search for nearby conditioning data and previously simulated nodes.
 - c. Compute conditional probabilities from each image.
 - d. Combine the probabilities.
 - e. Simulate a category.

An algorithm such as SNESIM (Strebelle, 2002) could be used to compute conditional probabilities, possibly with other complexities like trend models. When the range value in 3.a. matches an images range index, only one TI is used and the approach is fundamentally identical to MPS with a single TI. This allows both abrupt and transitioning zones in the same modeling space (Figure 3). For combining probabilities in step 3.d., a linear weighting of the conditional probabilities from each TI is used. Weights, w_i and w_j , are calculated using Equation (1), where $r(\mathbf{u})$ is the range value at spatial location \mathbf{u} , r_i is the range value of TI i and r_j is the range value of TI j with $r_i < r(\mathbf{u}) < r_j$.

$$w_i = \frac{r(\mathbf{u}) - r_i}{r_j - r_i} \quad (1)$$

$$w_j = 1 - w_i$$

Other weighting schemes could be considered to control the development of a transition zone as long as the weights sum to one. Merged probabilities are then computed using Equation (2), where $P_i(Z(\mathbf{u}) = k)$ is the probability that a random function $Z(\mathbf{u})$ is equal to category k based on TI i (likewise for TI j) and \hat{P} is the combined probability.

$$\hat{P}(Z(u) = k) = w_i \cdot P_i(Z(u) = k) + w_j \cdot P_j(Z(\mathbf{u}) = k) \quad (2)$$

This calculation is done for all categories that $Z(\mathbf{u})$ can retain. Merging probabilities in this fashion introduces two main limitations on the characteristics of the TI's that will be mixed in transition zones:

1. TI's must contain at least some of the same categories so that it is possible to determine their probability based on spatial patterns that do not necessarily contain all possible categories. If two TI's contain completely different categories, then there is no information on the spatial relationships between categories from different TIs.
2. There must be some similarity between images to ensure a smooth transition. A pair of TI's to be mixed should have common MPS, that is, there should be some spatial patterns of categories that are common to the images. As similarity between images increases, the smoothness of the transition will increase. If similarity is too low, transition zones are likely to be erratic. Similarity can be assessed by comparing the search trees of different TI's and is discussed later.

In the case of two TI's with no categories that are the same, a program such as SNESIM will perform in a known manner. At some point during construction of a realization, the search for nearby conditioning data and previously simulated grid cells may return a pattern containing categories from the different TIs. For purposes of discussion, let categories 0 and 1 originate from TI 1 and categories 2 and 3 from TI 2. When computing the conditional probabilities from the search tree for each TI, conditioning data that do not exist in the tree will result in zero patterns being recovered from the tree. All data having categories 2 and 3 will be pruned during the computation of probabilities from TI 1. Estimates of the probabilities of categories 0 and 1 are obtained from TI 1 and of 2 and 3 are obtained from TI 2 based on the different subsets of conditioning data that contain these categories. When they are combined using Equation (2), we end up with a PDF involving all 4 categories without any knowledge of how they exist together spatially. Resulting realizations will contain random combinations of the four categories in transition zones.

Pruning conditioning data from the search so that enough patterns are found in a search tree to estimate reliable probabilities is typically done by removing the data that is furthest away. Based on stationary two point statistics, this is a natural choice since data further away are deemed less correlated to a location being estimated. In the case of two TI's with different categories, pruning would occur until the closest point having a category not present in the associated search tree was removed. Instead, the approach was changed so that categories that are not present are removed from the pattern of conditioning data prior to computing the conditional probabilities. This results in fewer data being pruned to obtain a pattern with enough support to obtain a confident evaluation of the probabilities.

For the second limitation where TI's must have some similarity to ensure a reasonable transition, a measure of similarity between two TI's is defined by Equation (3), where i and j are adjacent TI's that will be mixed, N_i is the total number of patterns in TI i (likewise for j) and $N_{i \in j}$ is the number of patterns from TI i that exist in TI j (likewise for $N_{j \in i}$):

$$S_{ij} = \frac{N_{i \in j} + N_{j \in i}}{N_i + N_j} \quad (3)$$

This measure is very similar to comparing the multiple point histograms of two TI's described by Boisvert et al (2007). The more similar two TI's are the more patterns they will share and the similarity will

approach 1. If TI's are identical, $S_{ij} = 1$ and if they do not share any common features, $S_{ij} = 0$. Similarity depends on the geometry of the patterns used for comparison; therefore, it depends on the geometry of the search template used to construct search trees or pattern lists for MPS modeling. In a program such as SNESIM, a user-defined template is provided along with the number of multiple grids to use during simulation. The template is scaled for each multi-grid level, so similarity depends on multi-grid parameters. Coarser or high-level multi-grids compare more widespread disjoint patterns whereas low-level grids compare tighter more compact patterns. Similarity also depends on the proportions of categories within each TI. Two TI's that have a particularly high proportion of a common category will tend to have a higher similarity even if the geometry of other lower proportion categories is not similar. In these cases, similarity is calculated conditional to each category in Equation (4).

$$S_{ijk} = \frac{N_{ik \in jk} + N_{jk \in ik}}{N_{ik} + N_{jk}}, k = 1, \dots, n \quad (4)$$

In Equations (3) and (4), computing the total number of patterns within a TI is accomplished by traversing the search trees built in SNESIM while evaluating the cumulative sum of the number of patterns (replicates) stored in the tree. In the conditional case, only the number of replicates for the specified category is considered in the summation. To compute the number of patterns of one TI that exist in another TI, the search trees from both TI's are traversed in parallel: for $N_{i \in j}$, categories from TI i in each node of its search tree are used to traverse the search tree of TI j and vice versa for $N_{j \in i}$.

It is not clear the value of similarity that will guarantee a transition zone that coincides with a user's intentions. Some calibration of TI's and associated range values will be necessary. If transition zones are not displaying the desired smoothness for example, either the two TI's involved in the transition zone are not similar enough, or an additional TI at the midpoint of the associated range values is required to improve the transition. This concept is demonstrated using simple TI's of ellipses with 3:1 anisotropy and an orientation that varies with range (Figure 4). Range values of 0.1, 0.5 and 0.9 were assigned to TI's 1, 2 and 3 respectively and the associated azimuths were 90, 60 and 30 degrees. A realization using TI 1 and 3 only is shown with a realization using all three TI's in Figure 5. Similarity and conditional similarity between the TI's for both cases is summaries in Table 1. Since there is less correspondence between the 90 and 30 degree images than the 90 and 60 degree and 60 and 30 degree images, the transition is more abrupt.

Table 1: Similarity between TI's for the ellipse example. First number is similarity, second number is conditional to category 0 (background) and third is conditional to category 1 (ellipses).

Multi-Grid Level	$S_{13}, \%$	$S_{12}, \%$	$S_{23}, \%$
5 (coarse)	38, 40, 31	40, 44, 33	41, 44, 36
4	31, 35, 23	40, 44, 31	41, 44, 34
3	46, 53, 29	56, 63, 40	58, 65, 42
2	61, 72, 37	71, 80, 50	72, 81, 52
1 (fine)	78, 86, 60	85, 90, 72	85, 90, 73

Program

Parameters and code were added to the SNESIM program originally written by Strebelle (2002) to perform MPS modeling with multiple TI's and a range model. Parameters are given in Table 2, with new parameters starting on Line 20 where the specified number of TI's to use is defined. Multi-grids, files and search parameters are repeated in blocks for each TI on lines 22 – 27 and 28 – 33. The file and grid definition for the range model are specified on lines 34 – 38 and the range values assigned to each TI in the same order they were input on Line 39.

Similarity and conditional similarity between adjacent TI's is computed by the program and output for each multi-grid level used. When the number of multi-grids is the same for each TI the computation is done for all levels; however, if a different number of multi-grids is used for each TI, the

pattern template is scaled differently and similarity can only be computed for the lower levels that coincide. The input range model does not have to be defined on the same grid as the simulation grid, in which case it is re-sampled from one to the other. Multiple realizations of a range model are also possible to account for uncertainty in this variable.

Table 2: Parameters for SNESIM

Line	Parameter	
1	START OF PARAMETERS:	
2	data.dat	- file with original data
3	1 2 3 4	- columns for x, y, z, variable
4	2	- number of categories
5	0 1	- category codes
6	0.7 0.3	- (target) global pdf
7	0	- use (target) vertical proportions (0=no, 1=yes)
8	vertprop.dat	- file with target vertical proportions
9	0 0.5	- target pdf repro. (0=no, 1=yes), parameter
10	snesim.out	- file for simulation output
11	1	- number of realizations to generate
12	256 0.5 1.0	- nx,xmn,xsiz
13	128 0.5 1.0	- ny,ymn,ysiz
14	1 0.5 1.0	- nz,zmn,zsiz
15	89069	- random number seed
16	template.dat	- file for primary data template
17	48	- max number of conditioning primary data
18	12	- max number of data per octant (0=not used)
19	10	- min number of data events
20	2	- number of training images
21	0.5 0.5	- weights for training images
22	5 5	- number of multi-grids, number with search trees for TI 1
23	trainim1.out	- file for TI 1
24	200 200 1	- TI 1 dimensions: nxtr, nytr, nztr
25	1	- column for variable of TI 1
26	20.0 20.0 5.0	- search radii (hmax,hmin,vert) for TI 1
27	0.0 0.0 0.0	- angles for search ellipsoid of TI 1
28	5 5	- number of multi-grids, number with search trees for TI 2
29	trainim2.out	- file for TI 2
30	200 200 1	- TI 2 dimensions: nxtr, nytr, nztr
31	1	- column for variable of TI 2
32	20.0 20.0 5.0	- maximum search radii (hmax,hmin,vert) for TI 2
33	0.0 0.0 0.0	- angles for search ellipsoid of TI 2
34	range.out	- file with TI range model
35	1	- column with range variable
36	256 0.5 1.0	- nx,xmn,xsiz
37	128 0.5 1.0	- ny,ymn,ysiz
38	1 0.5 1.0	- nz,zmn,zsiz
39	0.1 0.9	- range values of input TIs

Example

The methodology is demonstrated using a synthetic tide-dominated estuarine environment that ranges from the fluvial inner estuary to marine outer estuary and drains from West to East. The corresponding tidal range varied from 0 for inner to 1 for outer estuary. Training images were acquired from two sources: 1 – the library of images from Pycrc et al (2008) for fluvial and sand bar images; 2 – generated using programs from Hassanpour and Deutsch (2010). A total of six TI's were selected and are described as follows (Figure 6):

1. Fluvial inner estuarine TI consisting of generally straight channels, medium sized crevasse splays and levees.
2. Fluvial inner estuarine TI with meandering channels, small crevasse splays and levees.
3. Middle estuarine TI with highly meandering channels and point bars with IHS.
4. Middle estuarine TI with generally straight channels and less prominent point bars with a small fraction of IHS.

5. Outer estuarine sand bar TI consisting of small bars generally elongated in the east-west orientation.
6. Outer estuarine sand bar TI with large bars elongated in the east-west direction.

Five facies were used to describe the architectural elements in each TI. Flood plain (code 0); Channel (code 1) that is associated with fluvial channels in TI 1 and 2, meandering channels in TI 3 and 4, and bifurcated channels in TI 5 and 6; Point bar (code 2) that is associated with levees in TI 1 and 2, IHS point bars in TI 3 and 4, and sand bars in TI 5 and 6; crevasse splay (code 3) that is only in TI 1 and 2; and shale (code 4) that takes the form of mud drapes in TI 3 and 4 only. Facies proportions and tidal ranges assigned to each image are summarized in Table 3. As the tidal range varies from inner to outer, the proportion of flood plain facies decreases; channel facies generally increases; point bar facies increases, and crevasse splay and shale are only present in the inner and middle zones respectively.

Table 3: Facies proportions and tidal range for each TI.

TI No.	Range	Facies proportions for code:				
		0	1	2	3	4
1	0.0	0.365	0.452	0.114	0.069	0.000
2	0.3	0.220	0.500	0.165	0.116	0.000
3	0.5	0.407	0.359	0.187	0.000	0.047
4	0.7	0.259	0.526	0.207	0.000	0.008
5	0.9	0.000	0.843	0.157	0.000	0.000
6	1.0	0.000	0.571	0.429	0.000	0.000

Each TI was specified on a 100 by 100 grid of 16 by 16 m cells. The estuarine model was built on a 400 by 100 cell grid with the same cell size. A tidal range model that varies linearly from West to East was used and a 120 node template was used for search tree construction. The tidal range model and a single realization are shown in Figure 7. The influence of each TI can be observed in the realization.

Conclusion

An approach was developed to utilize multiple TI's in order to construct geologically complex models that are difficult to describe with a single TI. Available tools for building TI's make it possible to create them for specific depositional environments that are reasonably stationary, but not necessarily for creating non-stationary TIs. By evaluating two TI's that have different MPS and that have some similarity, it is possible to generate transition zones that retain MPS from both TI's using a weighting scheme. Implementation of the weighting scheme allows modelers to generate realizations with continuous or abrupt transition zones using a TI range model. Challenges for the method are primarily implementation based. Finding or creating a complete set of TI's for an application can be tedious and setting up and calibrating the parameters for the obtaining visually realistic results was time consuming. More work is necessary for evaluating similarity between TI's as the process was excessive for larger images and for understanding the link between similarity and expectations for transition zones.

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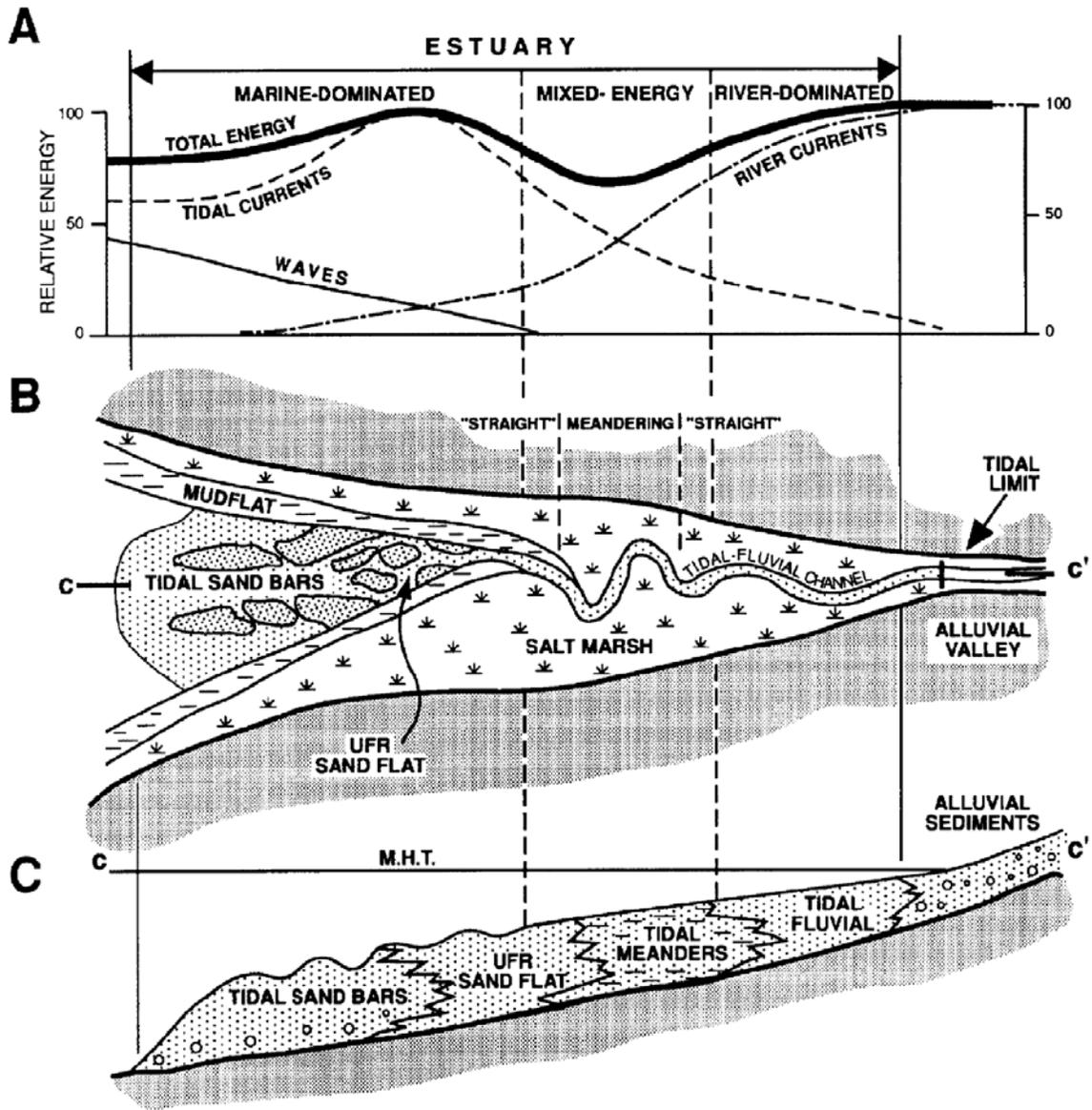


Figure 1: Schematic of a tide dominated estuary taken from Dalrymple et al (1992) showing A distribution of energy, B morphological elements, and C sedimentary facies.

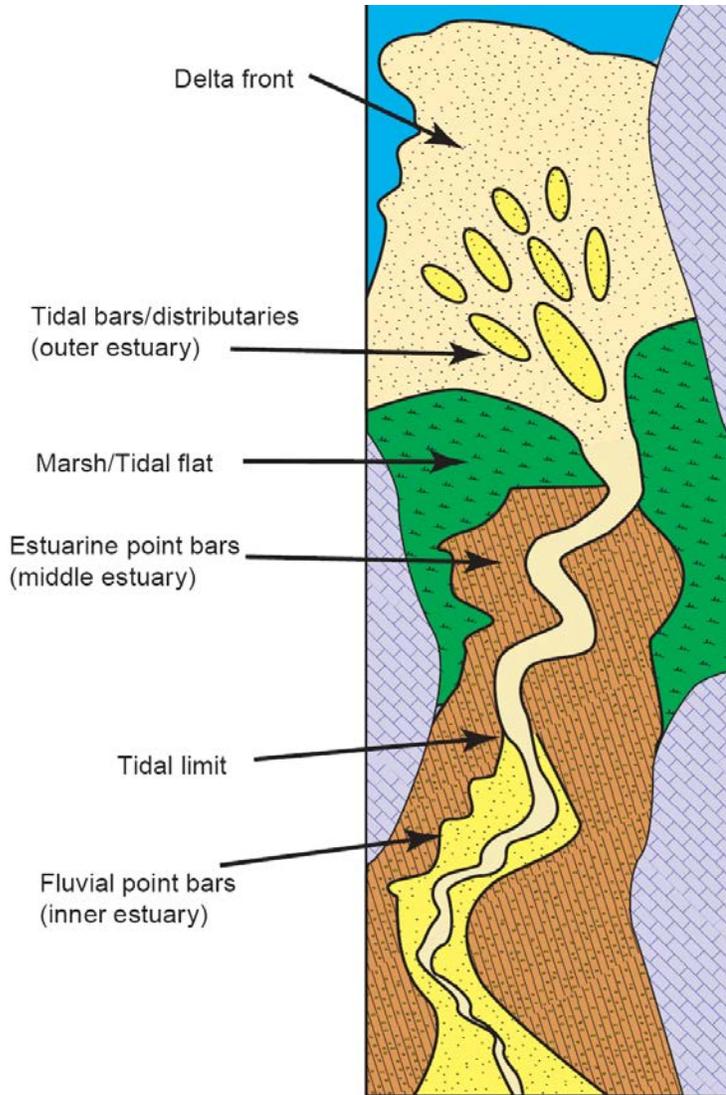


Figure 2: Schematic of a tide-dominated estuary from Ranger and Gingras (2003) representing the middle McMurray unit and associated facies.

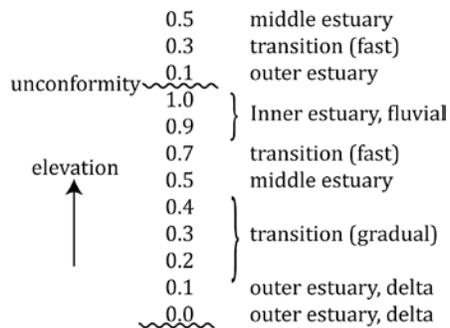


Figure 3: Example range model representing two estuarine successions showing gradual, fast, and abrupt transitions. Range varies from 0 to 1 as tidal position varies from outer to inner estuary.

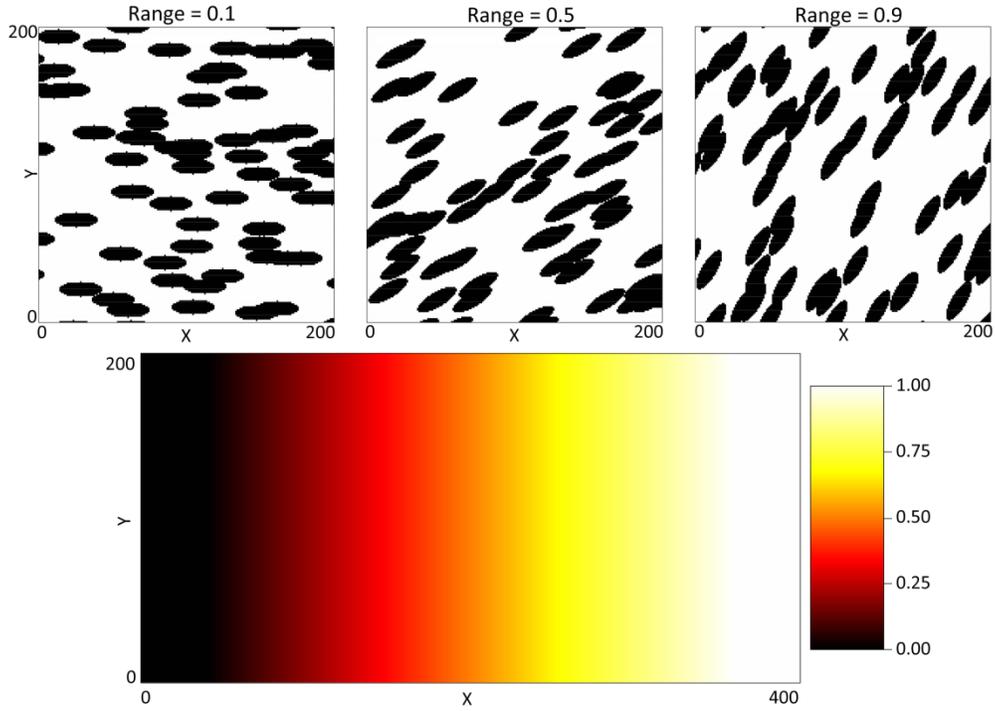


Figure 4: Ellipse TI's (top) and range model (bottom). Major and minor ellipse radii are 15 and 5 units respectively.

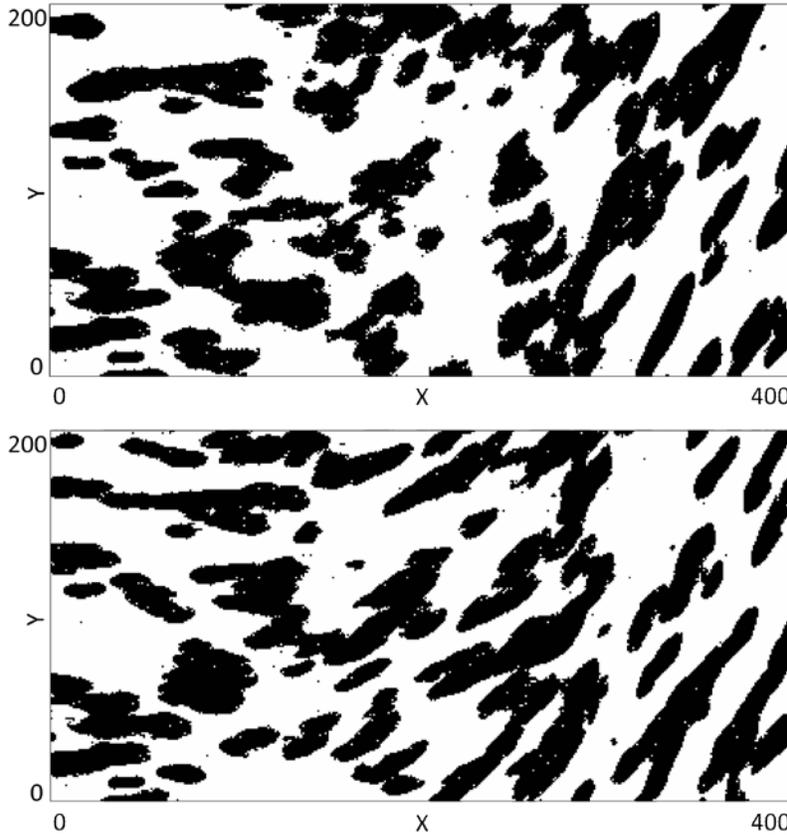


Figure 5: Realization using ellipse TI 1 and 3 (top) and using ellipse TI 1, 2 and 3 (bottom).

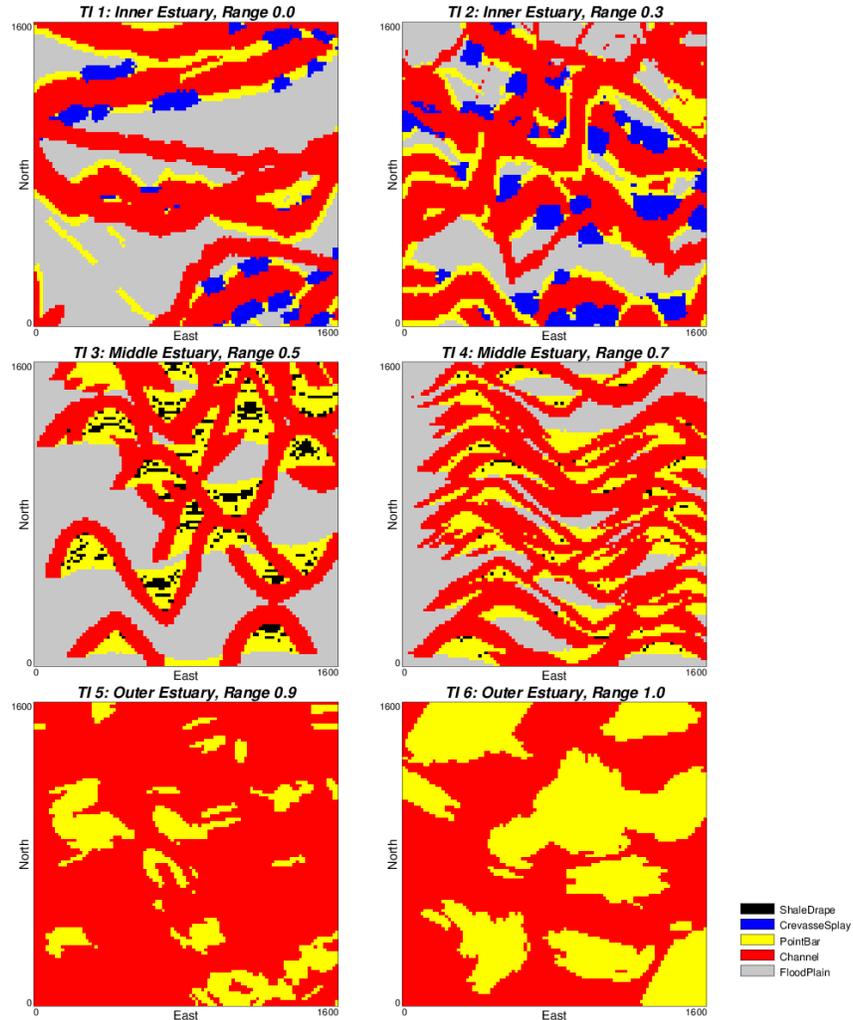


Figure 6: TI's used in the example ranging from inner estuarine fluvial (upper left) to outer estuarine sand bar (lower right).

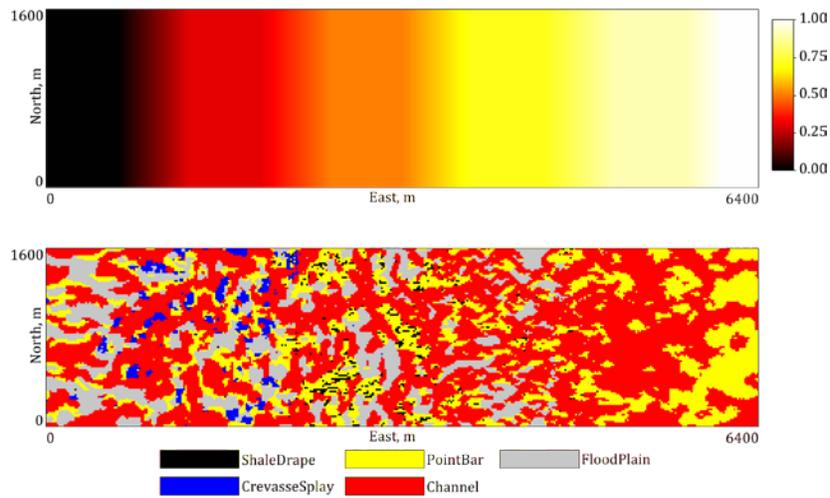


Figure 7: Tidal range model (top) and a realization of estuarine deposition using six TI's (bottom).