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### Abstract

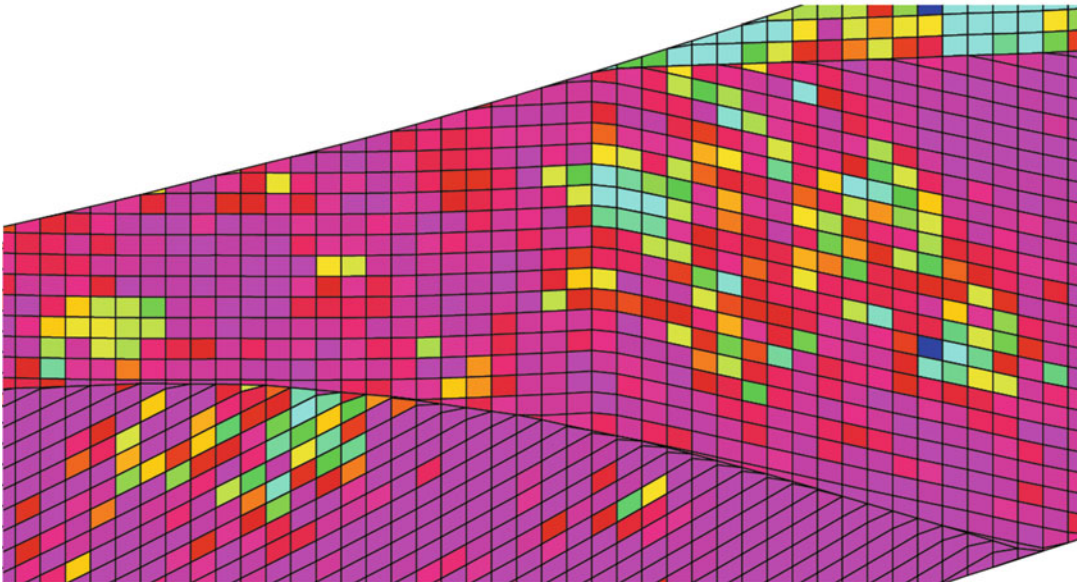
This topic concerns the difference between a reservoir model and a geological model. *Model representation* is the essential issue – ask yourself whether the coloured cellular graphics we see on the screen truly resemble the reservoir as exposed in outcrop:

*WYSIWYG (computing acronym).*

Our focus is on achieving a reasonable representation.

Most of the outputs from reservoir modelling are quantitative and derive from property models, so the main purpose of a rock model is to get the properties in the right place – to guide the spatial property distribution in 3D.

For certain model designs, the rock model component is minimal, for others it is essential. In all cases, the rock model should be the guiding framework and should offer predictive capacity to a project.



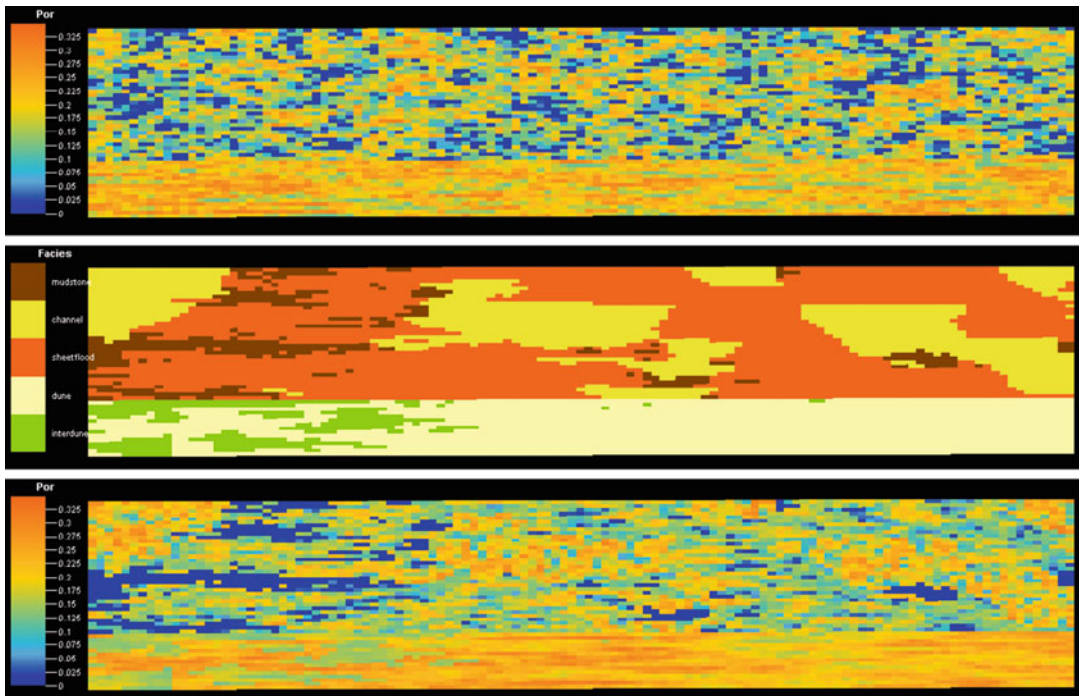
Outcrop view and model representation of the Hopeman Sandstone at Clashach Quarry, Moray Firth, Scotland

## 2.1 Rock Modelling

In a generic reservoir modelling workflow, the construction of a rock or ‘facies’ model usually precedes the property modelling. Effort is focussed on capturing contrasting rock types identified from sedimentology and representing

these in 3D. This is often seen as the most ‘geological’ part of the model build along with the fault modelling, and it is generally assumed that a ‘good’ final model is one which is founded on a thoughtfully-constructed rock model.

However, although the rock model is often essential, it is rarely a model deliverable in itself,



**Fig. 2.1** To model rocks, or not to model rocks? *Upper image*: porosity model built directly from logs; *middle image*: a rock model capturing reservoir heterogeneity; *lower image*: the porosity model rebuilt, conditioned to the rock model

and many reservoirs *do not require* rock models. Figure 2.1 shows a porosity model which has been built with and without a rock model. If the upper porosity model is deemed a reasonable representation of the field, a rock model is not required. If, however, the porosity distribution is believed to be significantly influenced by the rock contrasts shown in the middle image, then the lower porosity model is the one to go for. Rock modelling is therefore a means to an end rather than an end in itself, an optional step which is useful if it helps to build an improved property model.

The details of rock model input are software-specific and are not covered here. Typically the model requires specification of variables such as sand body sizes, facies proportions and reference to directional data such as dip-logs. These are part of a standard model build and need consideration, but are not viewed here as critical to the higher level issue of model design. Moreover, many of these variables cannot be specified

precisely enough to guide the modelling: rock body databases are generally insufficient and dip-log data too sparse to rely on as a model foundation. Most critical to the design are the issues identified below, mishandling of which is a common source of a poor model build:

- **Reservoir concept** – is the architecture understood in a way which readily translates into a reservoir model?
- **Model elements** – from the range of observed structural components and sedimentological facies types, has the correct selection of elements been made on which to base the model?
- **Model Build** – is the conceptual model carried through *intuitively* into the statistical component of the build?
- **Determinism and probability** – is the balance of determinism and probability in the model understood, and is the conceptual model firmly carried in the deterministic model components?

These four questions are used in this chapter to structure the discussion on the rock model, followed by a summary of more specific rock model build choices.

## 2.2 Model Concept

The best hope of building robust and sensible models is to use conceptual models to guide the model design. We favour this in place of purely data-driven modelling because of the issue of under-sampling (see later). The geologist should have a mental picture of the reservoir and use modelling tools to convert this into a quantitative geocellular representation. Using system defaults or treating the package as a black box that somehow adds value or knowledge to the model will always result in models that make little or no geological sense, and which usually have poor predictive capacity.

The form of the reservoir concept is not complex. It may be an image from a good outcrop analogue or, better, a conceptual sketch, such as those shown in Fig. 2.2.

It should, however, be specific to the case being modelled, and this is best achieved by drawing a simple section through the reservoir showing the key architectural elements – an example of which is shown in Fig. 2.3.

Analogue photos or satellite images are useful and often compelling but also easy to

adopt when not representative, particularly if modern dynamic environments are being compared with ancient preserved systems. It is possible to collect a library of analogue images yet still be unclear exactly how these relate to the reservoir in hand, and how they link to the available well data. By contrast, the ability to draw a conceptual sketch section is highly informative and brings clarity to the mental image of the reservoir held by the modeller. If this conceptual sketch is not clear, the process of model building is unlikely to make it any clearer. If there is no clear up-front conceptual model then the model output is effectively a random draw:

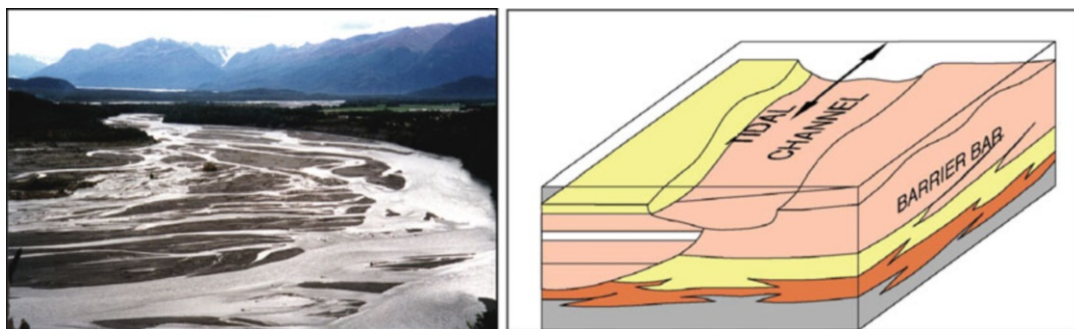
*If you can sketch it, you can model it*

An early question to address is: “*what are the fundamental building blocks for the reservoir concept?*” These are referred to here as the ‘model elements’ and discussed further below. For the moment, the key thing to appreciate is that:

*model elements  $\neq$  facies types*

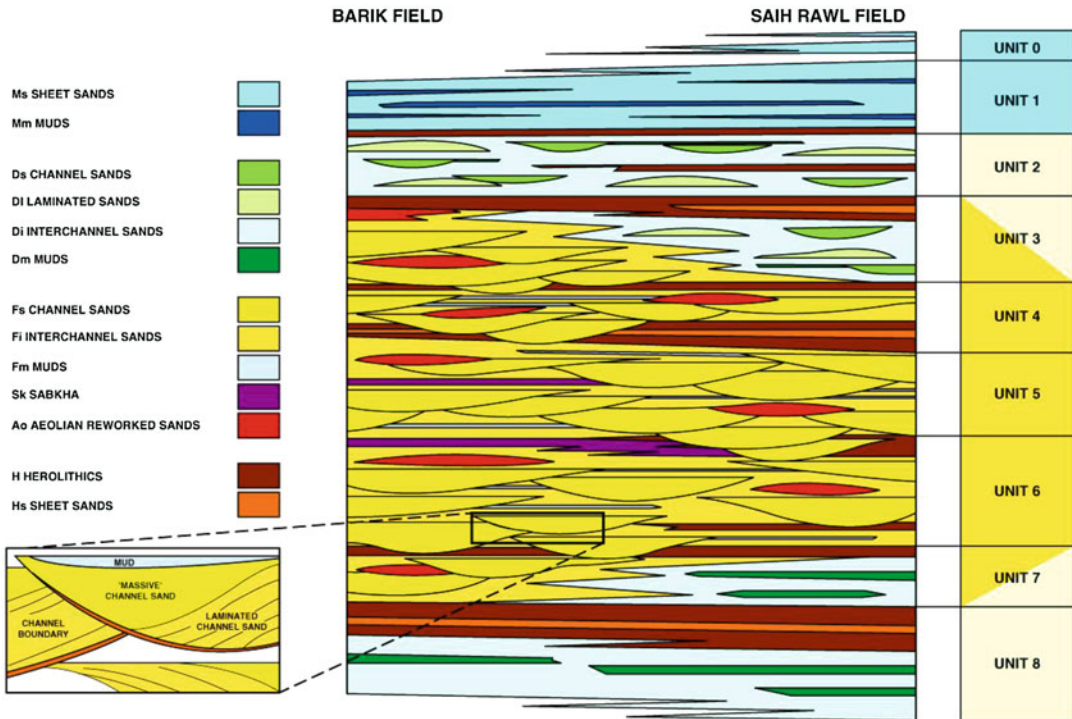
Selection of model elements is discussed in Sect. 2.4.

With the idea of a reservoir concept as an architectural sketch constructed from model elements established, we will look at the issues surrounding the build of the model framework then return to consider how to select elements to place within that framework.



**Fig. 2.2** Capturing the reservoir concept in an analogue image or a block diagram sketch





**Fig. 2.3** Capturing the reservoir concept in a simple sketch showing shapes and stacking patterns of reservoir sand bodies and shales (From: van de Leemput et al. 1996)

## 2.3 The Structural and Stratigraphic Framework

The structural framework for all reservoir models is defined by a combination of structural inputs (faults and surfaces from seismic to impart gross geometry) and stratigraphic inputs (to define internal layering).

The main point we wish to consider here is *what are the structural and stratigraphic issues that a modeller should be aware of when thinking through a model design?* These are discussed below.

### 2.3.1 Structural Data

Building a fault model tends to be one of the more time-consuming and manual steps in a modelling workflow, and is therefore commonly done with each new generation of seismic interpretation. In

the absence of new seismic, a fault model may be passed on between users and adopted simply to avoid the inefficiency of repeating the manual fault-building.

Such an inherited fault framework therefore requires quality control (QC). The principal question is whether the fault model reflects the seismic interpretation directly, or whether it has been modified by a conceptual structural interpretation.

A direct expression of a seismic interpretation will tend to be a conservative representation of the fault architecture, because it will directly reflect the resolution of the data. Facets of such data are:

- Fault networks tend to be incomplete, e.g. faults may be missing in areas of poor seismic quality;
- Faults may not be joined (under-linked) due to seismic noise in areas of fault intersections;
- Horizon interpretations may stop short of faults due to seismic noise around the fault zone;

- Horizon interpretations may be extended down fault planes (i.e. the fault is not identified independently on each horizon, or not identified at all)
- Faults may be interpreted on seismic noise (artefacts).

Although models made from such ‘raw’ seismic interpretations are honest reflections of that data, the structural representations are incomplete and, it is argued here, a structural interpretation should be overlain on the seismic outputs as part of the model design. To achieve this, the workflow similar to that shown in Fig. 2.4 is recommended.

Rather than start with a gridded framework constructed directly from seismic interpretation, the structural build should start with the raw, depth-converted seismic picks and the fault sticks. This is preferable to starting with horizon grids, as these will have been gridded without access to the final 3D fault network. Working with pre-gridded surfaces means the starting inputs are smoothed, not only within-surface but, more importantly, around faults, the latter tending to have systematically reduced fault displacements.

A more rigorous structural model workflow is as follows:

1. Determine the structural concept – are faults expected to die out laterally or to link? Are *en echelon* faults separated by relay ramps? Are there small, possibly sub-seismic connecting faults?
2. Input the fault sticks and grid them as fault planes (Fig. 2.4a)
3. Link faults into a network consistent with the concept (1, above, also Fig. 2.4b)
4. Import depth-converted horizon picks as points and remove spurious points, e.g. those erroneously picked along fault planes rather than stratigraphic surfaces (Fig. 2.4c)
5. Edit the fault network to ensure optimal positioning relative to the raw picks; this may be an iterative process with the geophysicist, particularly if potentially spurious picks are identified
6. Grid surfaces against the fault network (Fig. 2.4d).

## 2.3.2 Stratigraphic Data

There are two main considerations in the selection of stratigraphic inputs to the geological framework model: *correlation* and *hierarchy*.

### 2.3.2.1 Correlation

In the subsurface, correlation usually begins with markers picked from well data – *well picks*. Important information also comes from correlation surfaces picked from seismic data. Numerous correlation picks may have been defined in the interpretation of well data and these picks may have their origins in lithological, biostratigraphical or chronostratigraphical correlations – all of these being elements of sequence stratigraphy (see for example Van Wagoner et al. 1990; Van Wagoner and Bertram 1995). If multiple stratigraphic correlations are available these may give surfaces which intersect in space. Moreover, not all these surfaces are needed in reservoir modelling. A selection process is therefore required. As with the structural framework, the selection of surfaces should be made with reference to the conceptual sketch, which is in turn driven by the model purpose.

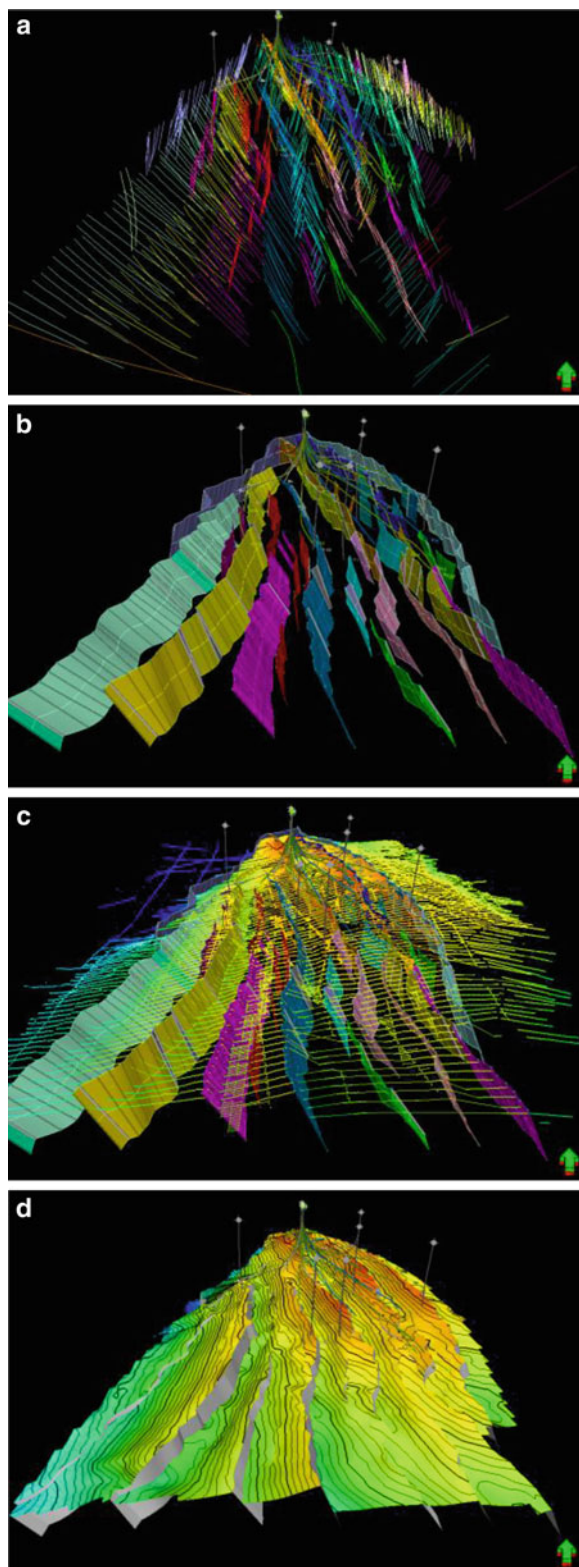
As a guideline, the ‘correct’ correlation lines are generally those which most closely govern the fluid-flow gradients during production. An exception would be instances where correlation lines are used to guide the distribution of reservoir volumes in 3D, rather than to capture correct fluid flow units.

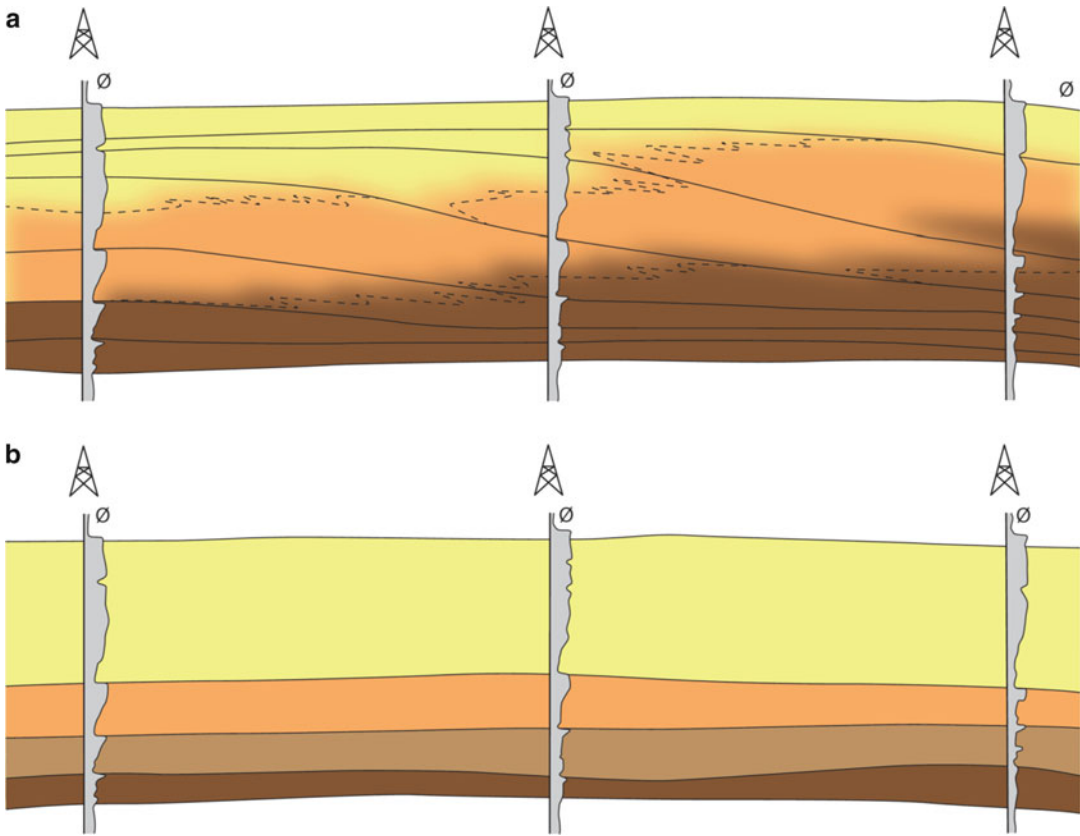
The choice of correlation surfaces used hugely influences the resulting model architecture, as illustrated in Fig. 2.5, and in an excellent field example by Ainsworth et al. (1999).

### 2.3.2.2 Hierarchy

Different correlation schemes have different influences on the key issue of hierarchy, as the stratigraphy of most reservoir systems is inherently hierarchical (Campbell 1967). For example, for a sequence stratigraphic correlation scheme, a low-stand systems tract might have a length-scale of tens of kilometres and might contain within it numerous stacked sand systems

**Fig. 2.4** A structural build based on fault sticks from seismic (a), converted into a linked fault system (b), integrated with depth-converted horizon picks (c) to yield a conceptually acceptable structural framework which honours all inputs (d). The workflow can equally well be followed using time data, then converting to depth using a 3D velocity model. The key feature of this workflow is the avoidance of intermediate surface gridding steps which are made independently of the final interpreted fault network. Example from the Douglas Field, East Irish Sea (Bentley and Elliott 2008)





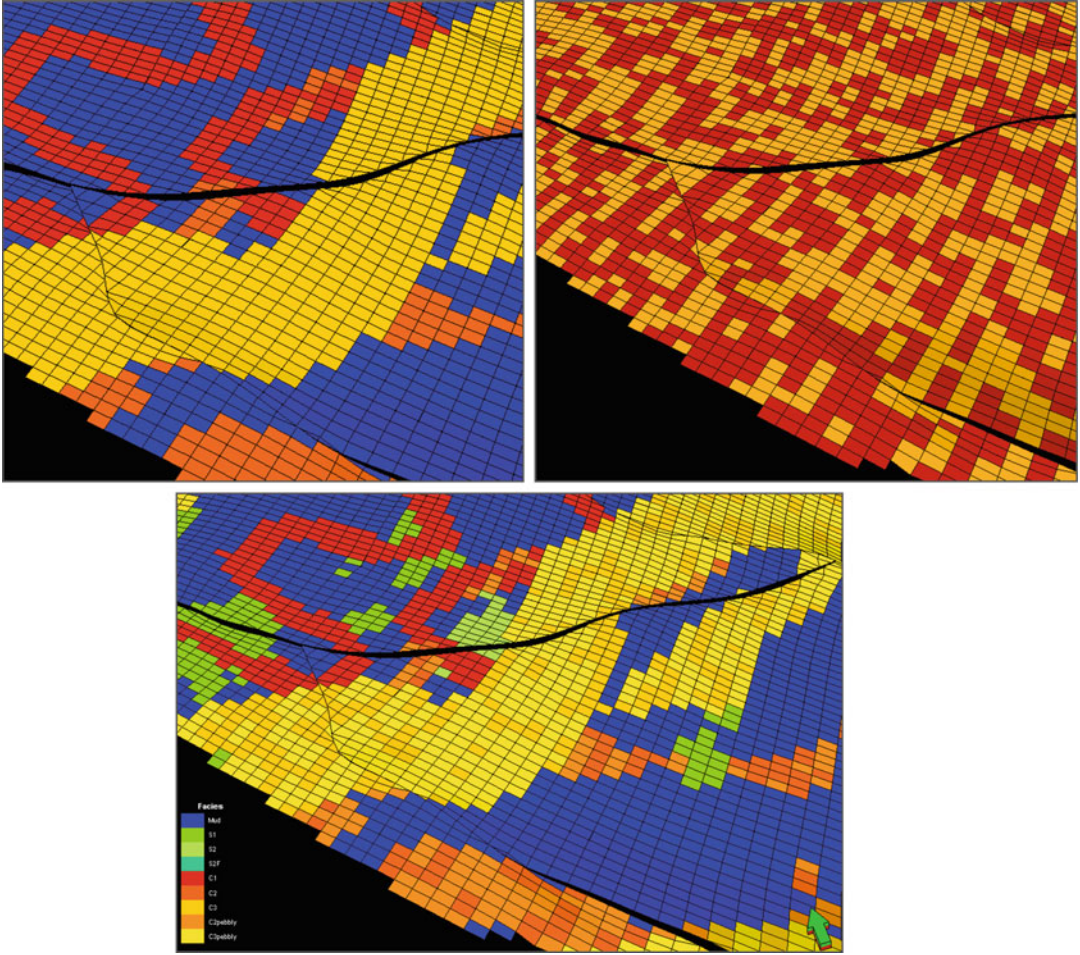
**Fig. 2.5** Alternative (a) chronostratigraphic and (b) lithostratigraphic correlations of the same sand observations in three wells; the chronostratigraphic correlation invokes an additional hierarchical level in the stratigraphy

with a length-scale of kilometres. These sands in turn act as the bounding envelope for individual reservoir elements with dimensions of tens to hundreds of metres.

The reservoir model should aim to capture the levels in the stratigraphic hierarchy which influence the spatial distribution of significant heterogeneities (determining ‘significance’ will be discussed below). Bounding surfaces within the hierarchy may or may not act as flow barriers – so they may represent important model elements in themselves (e.g. flooding surfaces) or they may merely control the distribution of model elements within that hierarchy. This applies to structural model elements as well as the more familiar sedimentological model elements, as features such as fracture density can be controlled by mechanical stratigraphy – implicitly related to the stratigraphic hierarchy.

So which is the preferred stratigraphic tool to use as a framework for reservoir modelling? The quick answer is that it will be the framework which most readily reflects the conceptual reservoir model. Additional thought is merited, however, particularly if the chronostratigraphic approach is used. This method yields a framework of timelines, often based on picking the most shaly parts of non-reservoir intervals. The intended shale-dominated architecture may not automatically be generated by modelling algorithms, however: a rock model for an interval between two flooding surfaces will contain a shaly portion at both the top and the base of the interval. The probabilistic aspects of the subsequent modelling can easily degrade the correlatable nature of the flooding surfaces, inter-well shales becoming smeared out incorrectly throughout the zone.





**Fig. 2.6** The addition of hierarchy by logical combination: single-hierarchy channel model (*top left*, blue = mudstone, yellow = main channel) built in parallel with a probabilistic model of lithofacies types (*top*

*right*, yellow = better quality reservoir sands), logically combined into the final rock model with lithofacies detail in the main channel only – an additional level of hierarchy

Some degree of hierarchy is implicit in any software package. The modeller is required to work out if the default hierarchy is sufficient to capture the required concept. If not, the workflow should be modified, most commonly by applying logical operations.

An example of this is illustrated in Fig. 2.6, from a reservoir model in which the first two hierarchical levels were captured by the default software workflow: tying layering to seismic horizons (first level) then infilled by sub-seismic stratigraphy (second level). An additional hierarchical level was required because an important permeability heterogeneity existed between

lithofacies types *within* a particular model element (the main channels). The chosen solution was to build the channel model using channel objects and creating a separate, in this case probabilistic, model which contained the information about the distribution of the two lithofacies types. The two rock models were then combined using a logical property model operation, which imposed the texture of the fine-scale lithofacies, but only within the relevant channels. Effectively this created a third hierarchical level within the model.

One way or another hierarchy can be represented, but only rarely by using the default model workflow.

## 2.4 Model Elements

Having established a structural/stratigraphic model framework, we can now return to the model concept and consider how to fill the framework to create an optimal architectural representation.

### 2.4.1 Reservoir Models Not Geological Models

The rich and detailed geological story that can be extracted from days or weeks of analysis of the rock record from the core store need not be incorporated directly into the reservoir model, and this is a good thing. There is a natural tendency to ‘include all the detail’ just in case something minor turns out to be important. Models therefore have a tendency to be over-complex from the outset, particularly for novice modellers. The amount of detail required in the model can, to a large extent, be anticipated.

There is also a tendency for modellers to seize the opportunity to build ‘real 3D geological pictures’ of the subsurface and to therefore make these as complex as the geology is believed to be. This is a hopeless objective as the subsurface is considerably more complex in detail than we are capable of modelling explicitly and, thankfully, much of that detail is irrelevant to economic or engineering decisions. We are building *reservoir models* – reasonable representations of the detailed geology – *not* geological models.

### 2.4.2 Building Blocks

Hence the view of the components of a reservoir model as *model elements* – the fundamental building blocks of the 3D architecture. The use of this term distinguishes model elements from geological terms such as ‘facies’, ‘lithofacies’, ‘facies associations’ and ‘genetic units’. These geological terms are required to capture the richness of the geological story, but do not necessarily describe the things we need to put into reservoir models. Moreover, key elements of the reservoir model may be small-scale structural

or diagenetic features, often (perhaps incorrectly) excluded from descriptions of ‘facies’.

Modelling elements are defined here as:

*three-dimensional rock bodies which are petrophysically and/or geometrically distinct from each other in the specific context of the reservoir fluid system.*

The fluid-fill factor is important as it highlights the fact that different levels of heterogeneity are important for different types of fluid, e.g. gas reservoirs behave more homogeneously than oil reservoirs for a given reservoir type.

The identification of ‘model elements’ has some parallels with discussions of ‘hydraulic units’ although such discussions tend to be in the context of layer-based well performance. Our focus is on the building blocks for 3D reservoir architecture, including parts of a field remote from well and production data. It should be spatially predictive.

### 2.4.3 Model Element Types

Having stepped beyond a traditional use of depositional facies to define rock bodies for modelling, a broader spectrum of elements can be considered for use, i.e. making the sketch of the reservoir as it is intended to be modelled. Six types of model element are considered below.

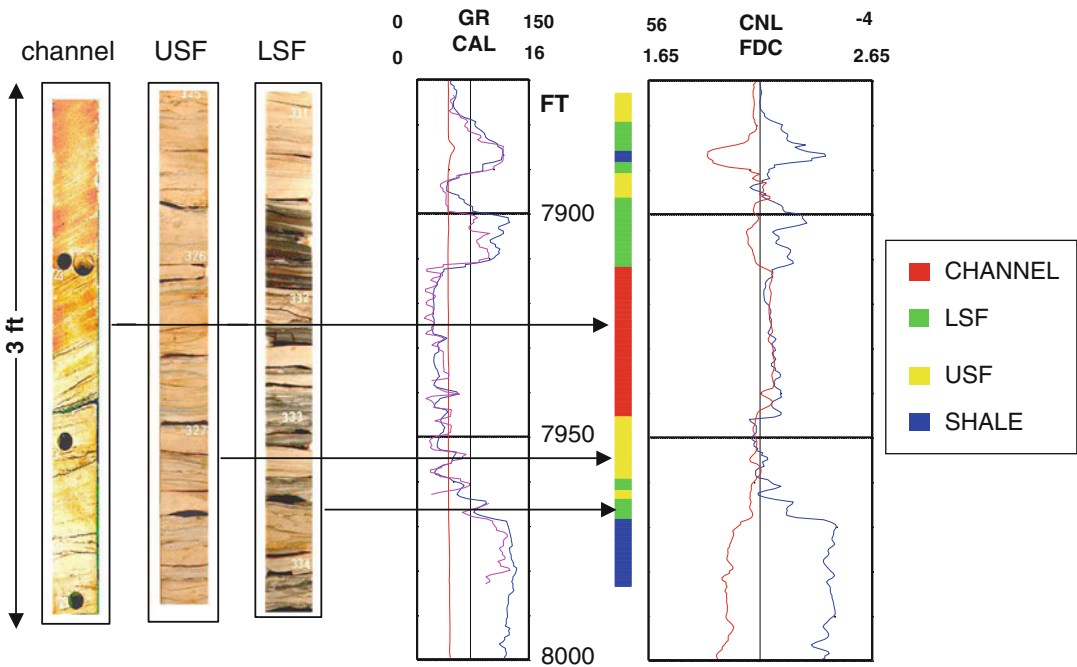
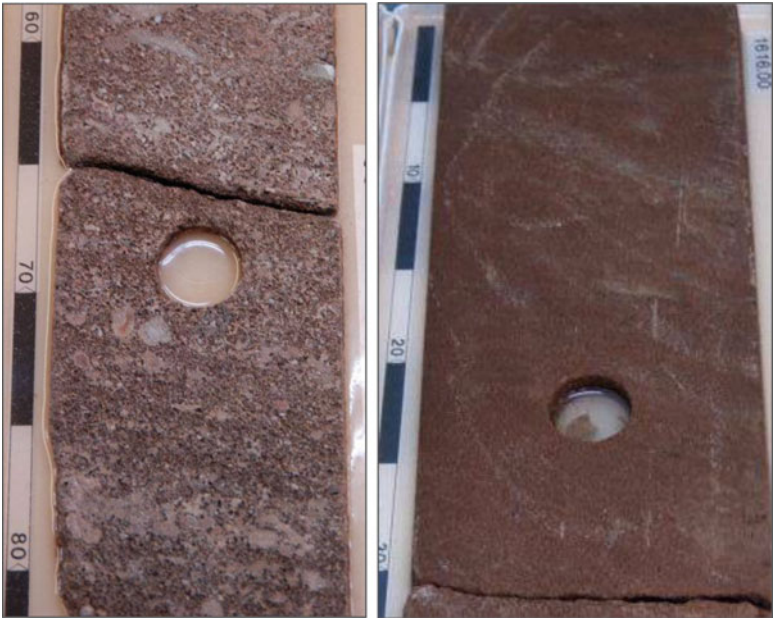
#### 2.4.3.1 Lithofacies Types

This is sedimentologically-driven and is the traditional way of defining the components of a rock model. Typical lithofacies elements may be coarse sandstones, mudstones or grainstones, and will generally be defined from core and or log data (e.g. Fig. 2.7).

#### 2.4.3.2 Genetic Elements

In reservoir modelling, genetic elements are a component of a sedimentary sequence which are related by a depositional process. These include the rock bodies which typical modelling packages are most readily designed to incorporate, such as channels, sheet sands or heterolithics. These usually comprise several lithofacies, for example, a fluvial channel might

**Fig. 2.7** Example lithofacies elements; *left*: coarse, pebbly sandstone; *right*: massively-bedded coarse-grained sandstone



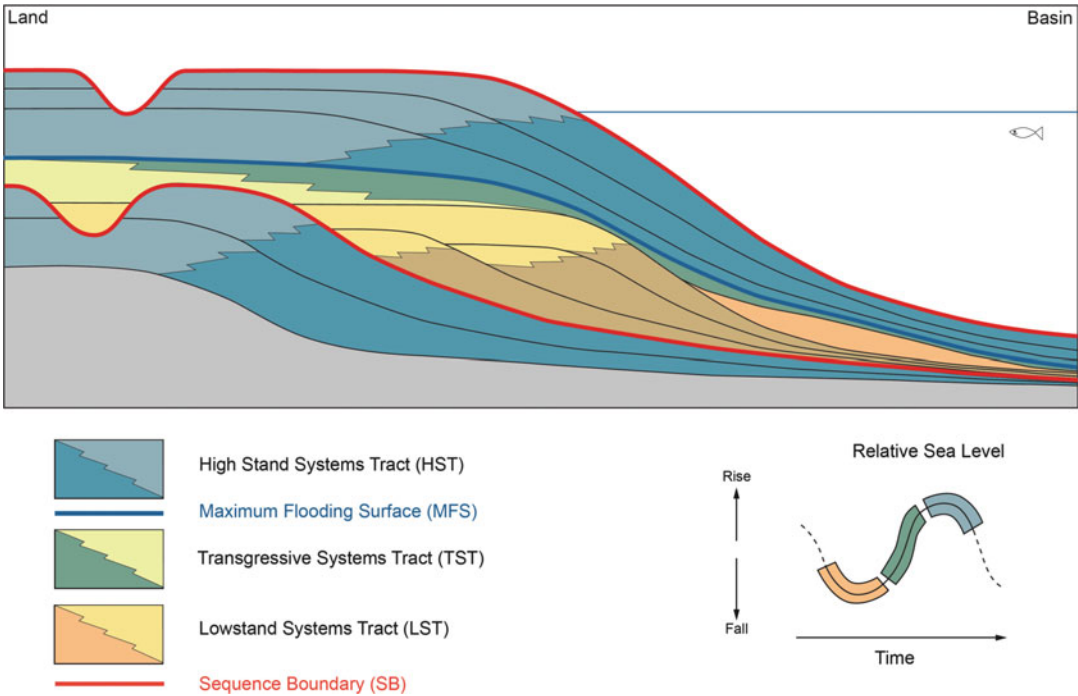
**Fig. 2.8** Genetic modelling elements; lithofacies types grouped into channel, upper shoreface and lower shoreface genetic depositional elements (Image courtesy of Simon Smith)

include conglomeratic, cross-bedded sandstone and mudstone lithofacies. Figure 2.8 shows an example of several genetic depositional elements interpreted from core and log observations.

### 2.4.3.3 Stratigraphic Elements

For models which can be based on a sequence stratigraphic framework, the fine-scale components of the stratigraphic scheme may also be the





**Fig. 2.9** Sequence stratigraphic elements

predominant model elements. These may be parasequences organised within a larger-scale sequence-based stratigraphic framework which defines the main reservoir architecture (e.g. Fig. 2.9).

#### 2.4.3.4 Diagenetic Elements

Diagenetic elements commonly overprint lithofacies types, may cross major stratigraphic boundaries and are often the predominant feature of carbonate reservoir models. Typical diagenetic elements could be zones of meteoric flushing, dolomitisation or de-dolomitisation (Fig. 2.10).

#### 2.4.3.5 Structural Elements

Assuming a definition of model elements as three-dimensional features, structural model elements emerge when the properties of a volume are dominated by structural rather than sedimentological or stratigraphic aspects. Fault damage zones are important volumetric structural elements (e.g. Fig. 2.11) as are mechanical layers (strata-bound fracture sets) with properties driven by small-scale jointing or cementation.

#### 2.4.3.6 Exotic Elements

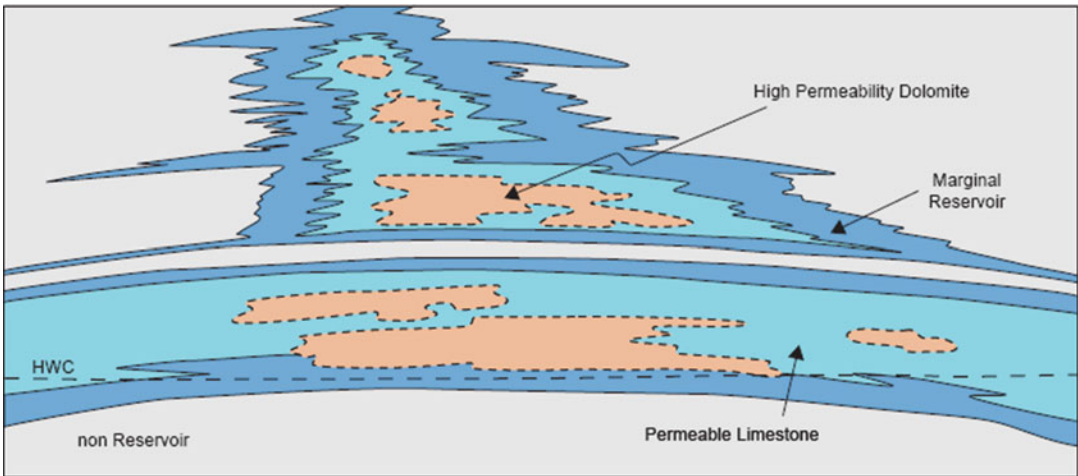
The list of potential model elements is as diverse as the many different types of reservoir, hence other ‘exotic’ reservoir types must be mentioned, having their own model elements specific to their geological make-up. Reservoirs in volcanic rocks are a good example (Fig. 2.12), in which the key model elements may be zones of differential cooling and hence differential fracture density.

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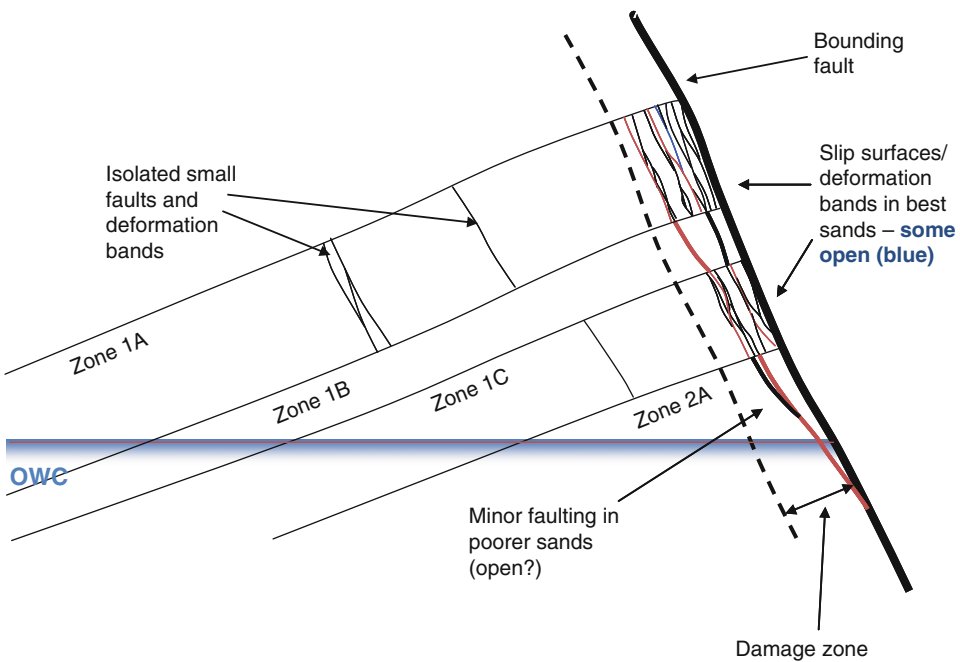
The important point about using the term ‘model element’ is to stimulate broad thinking about the model concept, a thought process which runs across the reservoir geological sub-disciplines (stratigraphy, sedimentology, structural geology, even volcanology). For avoidance of doubt, the main difference between the model framework and the model elements is that 2D features are used to define the model framework (faults, unconformities, sequence boundaries, simple bounding surfaces) whereas it is 3D model elements which fill the volumes within that framework.

Having defined the framework and identified the elements, the next question is how much information to carry explicitly into the modelling process. Everything that can be identified need not be modelled.





**Fig. 2.10** Diagenetic elements in a carbonate build-up; where reservoir property contrasts are driven by differential development of dolomitisation



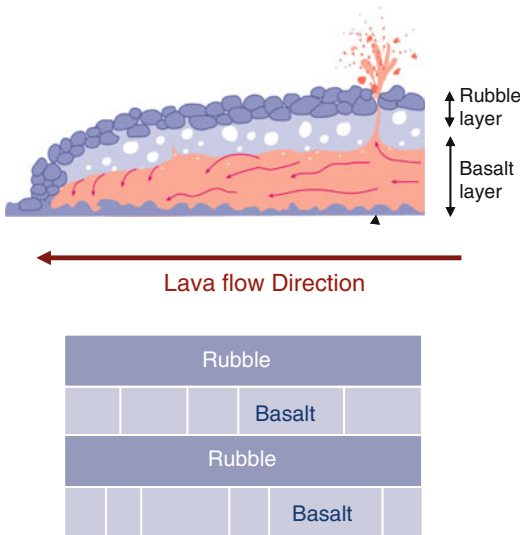
**Fig. 2.11** Structural elements: volumes dominated by minor fracturing in a fault damage zone next to a major block-bounding fault (Bentley and Elliot 2008)

#### 2.4.4 How Much Heterogeneity to Include?

The ultimate answer to this fundamental question depends on a combined understanding of geology and flow physics. To be more specific,

the key criteria for distinguishing which model elements are required for the model build are:

1. The identification of potential model elements – a large number may initially be selected as ‘candidates’ for inclusion;



**Fig. 2.12** Exotic elements: reservoir breakdown for a bimodal-permeability gas-bearing volcanic reservoir in which model elements are driven by cooling behaviour in a set of stacked lava flows (Image courtesy of Jenny Earnham)

2. The interpretation of the architectural arrangement of those elements represented in a simple sketch – the ‘concept sketch’;
3. The reservoir quality contrasts between the elements, addressed for example by looking at permeability/porosity contrasts between each;
4. The fluid type (gas, light oil, heavy oil);
5. The production mechanism.

The first steps are illustrated in Fig. 2.13 in which six potential elements have been identified from core and log data (step 1), placed in an analogue context (step 2) and their rock property contrasts compared (step 3). The six candidate elements seem to cluster into three, but is it right to lump these together? How great does a contrast have to be to be ‘significant’? Here we can invoke some useful guidance.

#### 2.4.4.1 Handy Rule of Thumb

A simple way of combining the factors above is to consider what level of permeability contrast would generate significant flow heterogeneities for a given fluid type and production mechanism. The handy rule of thumb is as follows (Fig. 2.14):

- Gas reservoirs are sensitive to 3 orders of magnitude of permeability variation per porosity class;

- Oil reservoirs under depletion are sensitive to 2 orders of magnitude of permeability variation per porosity class;
- Heavy oil reservoirs, or lighter crudes under secondary or tertiary recovery, tend to be sensitive to 1 order of magnitude of permeability variation.

This simple rule of thumb, which has become known as ‘Flora’s Rule’ (after an influential reservoir engineering colleague of one of the authors), has its foundation in the viscosity term in the Darcy flow equation:

$$u = \frac{-k}{\mu} \nabla(P) \quad (2.1)$$

where:

$u$  = fluid velocity

$k$  = permeability

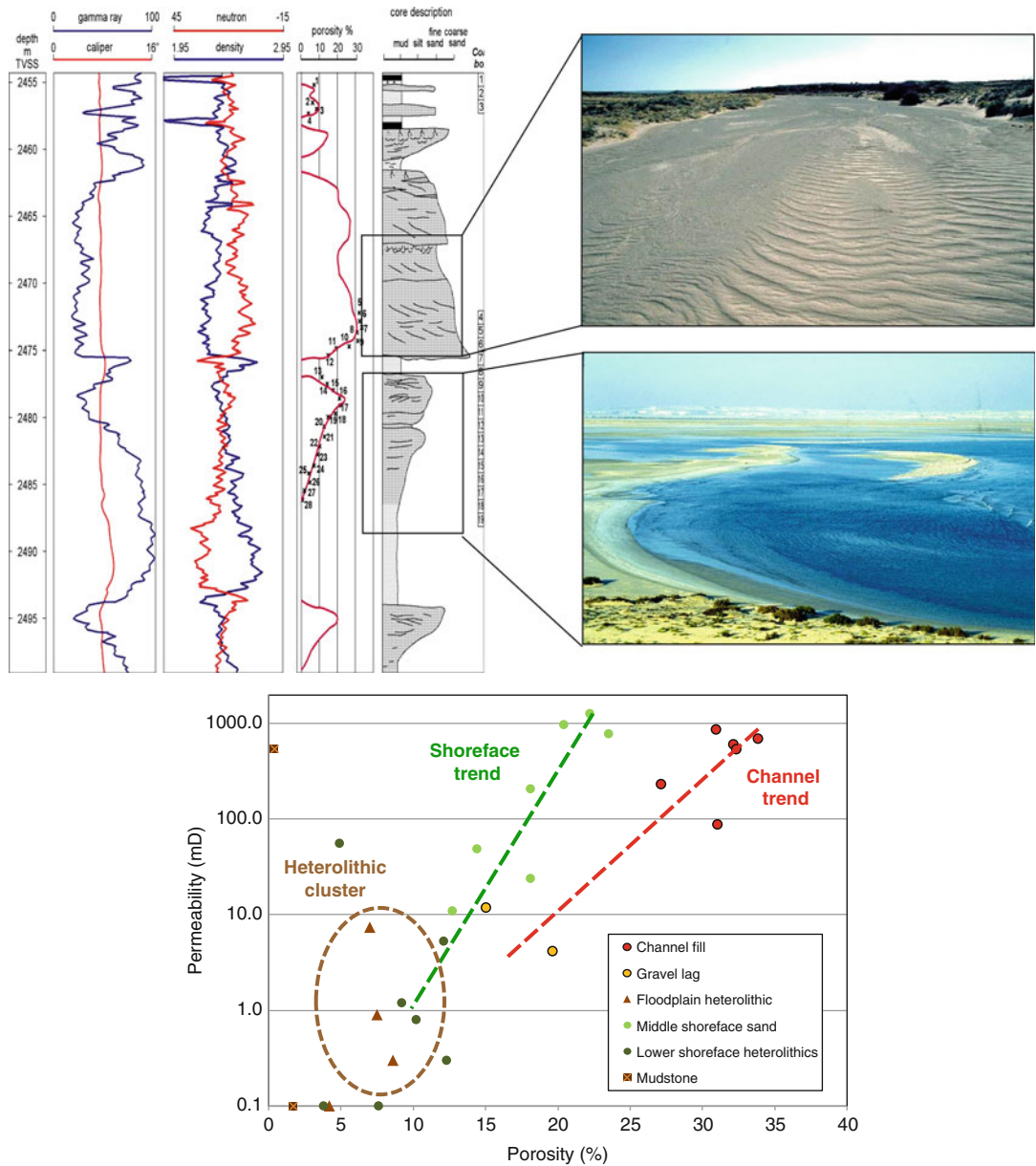
$\mu$  = fluid viscosity

$\nabla P$  = pressure gradient

Because the constant of proportionality between flow velocity and the pressure gradient is  $k/\mu$ , low viscosity results in a weaker dependence of flow on the pressure gradient whereas higher viscosities give increasingly higher dependence of flow on the pressure gradient. Combine this with a consideration of the mobility ratio in a two-phase flow system, and the increased sensitivity of secondary and tertiary recovery to permeability heterogeneity becomes clear.

Using these criteria, some candidate elements which contrast geologically in core may begin to appear rather similar – others will clearly stand out. The same heterogeneities that are shown to have an important effect on an oilfield waterflood may have absolutely no effect in a gas reservoir under depletion. The importance of some ‘borderline’ heterogeneities may be unclear – and these could be included on a ‘just in case’ basis. Alternatively, a quick static/dynamic sensitivity run may be enough to demonstrate that a specific candidate element can be dropped or included with confidence.

Petrophysically similar reservoir elements may still need to be incorporated if they have different 3D shapes (the geometric aspect) if, for example, one occurs in ribbon shapes and another in sheets. The reservoir architecture is influenced by the geometric stacking of such elements.



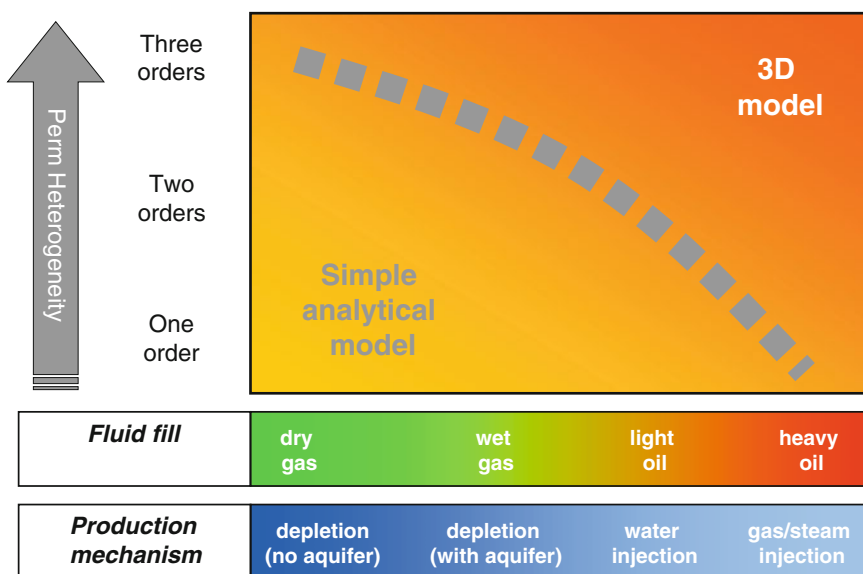
**Fig. 2.13** Six candidate model elements identified from core and log data and clustered into three on a k/phi cross plot – to lump or to split?

The outcome of this line of argument is that some reservoirs may not require complex 3D reservoir models at all (Fig. 2.15). Gas-charged reservoirs require high degrees of permeability heterogeneity in order to justify a complex modelling exercise – they often deplete as simple tanks. Fault compartments and active aquifers may stimulate heterogeneous flow production in

gas fields, but even in this case the model required to capture key fault blocks can be quite coarse. At the other end of the scale, heavy oil fields under water or steam injection are highly susceptible to minor heterogeneities, and benefit from detailed modelling. The difficulty here lies in assessing the scale of these heterogeneities, which can often be on a very fine, poorly-sampled scale.

<b>Critical permeability contrast</b>	3 orders      2 orders      1 order			
<b>Fluid fill</b>	dry gas	wet gas	light oil	heavy oil
<b>Production mechanism</b>	depletion (no aquifer)	depletion (with aquifer)	water injection	gas/steam injection

**Fig. 2.14** Critical order of magnitude permeability contrasts for a range of fluid and production mechanisms – ‘Flora’s Rule’



**Fig. 2.15** What type of reservoir model? A choice based on heterogeneity and fluid type

The decision as to which candidate elements to include in a model is therefore not primarily a geological one. Geological and petrophysical analyses are required to define the degree of permeability variation and to determine the spatial architecture, but it is the fluid type and the selected displacement process which determine the level of geological detail needed in the reservoir model and hence the selection of ‘model elements’.

## 2.5 Determinism and Probability

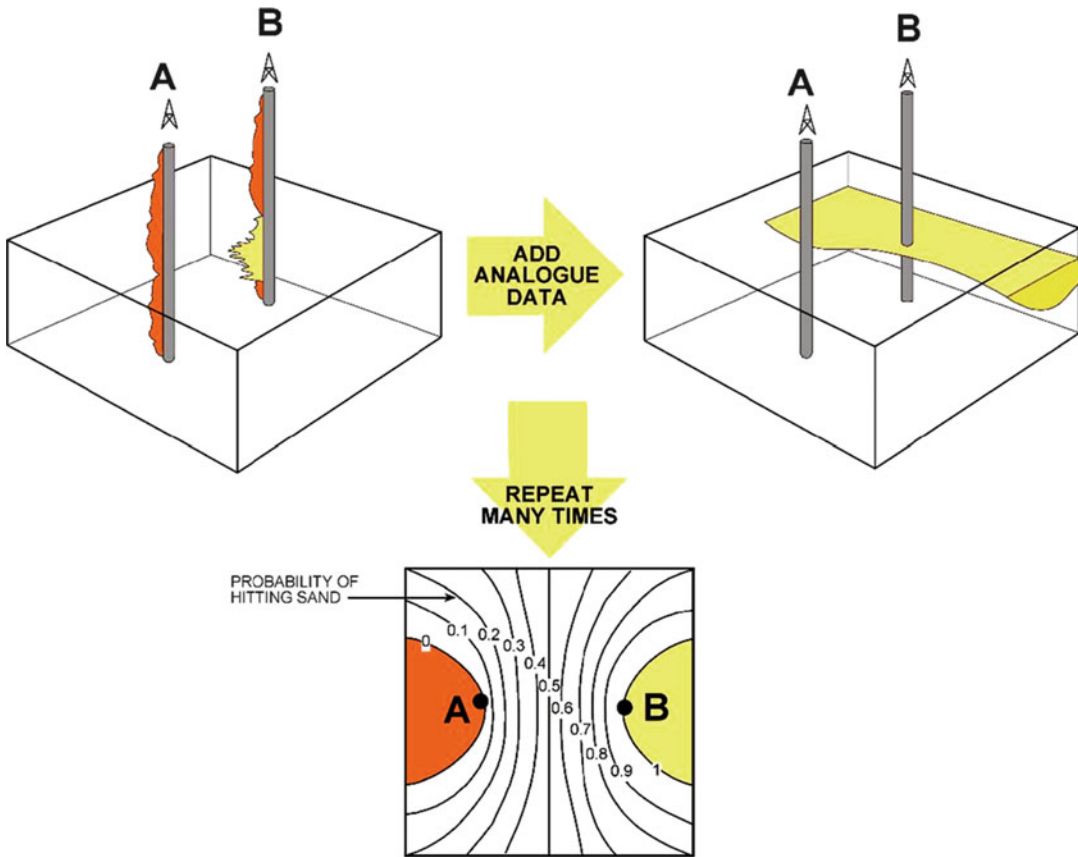
The use of geostatistics in reservoir modelling became widely fashionable in the early 1990s (e.g. Haldorsen and Damsleth 1990; Journel and

Alabert 1990) and was generally received as a welcome answer to some tricky questions such as how to handle uncertainty and how to represent geological heterogeneities in 3D reservoir models.

However, the promise of geostatistics (and ‘knowledge-based systems’) to solve reservoir forecasting problems sometimes led to disappointment. Probabilistic attempts to predict desirable outcomes, such as the presence of a sand body, yield naïve results if applied blindly (Fig. 2.16).

This potential for disappointment is unfortunate as the available geostatistical library of tools is excellent for applying quantitative statistical algorithms rigorously and routinely, and is essential for filling the inter-well volume in a 3D





**Fig. 2.16** A naïve example of expectation from geostatistical forecasting – the final mapped result simply illustrates where the wells are

reservoir model. Furthermore, geostatistical methods need not be over-complex and are not as opaque as sometimes presented.

### 2.5.1 Balance Between Determinism and Probability

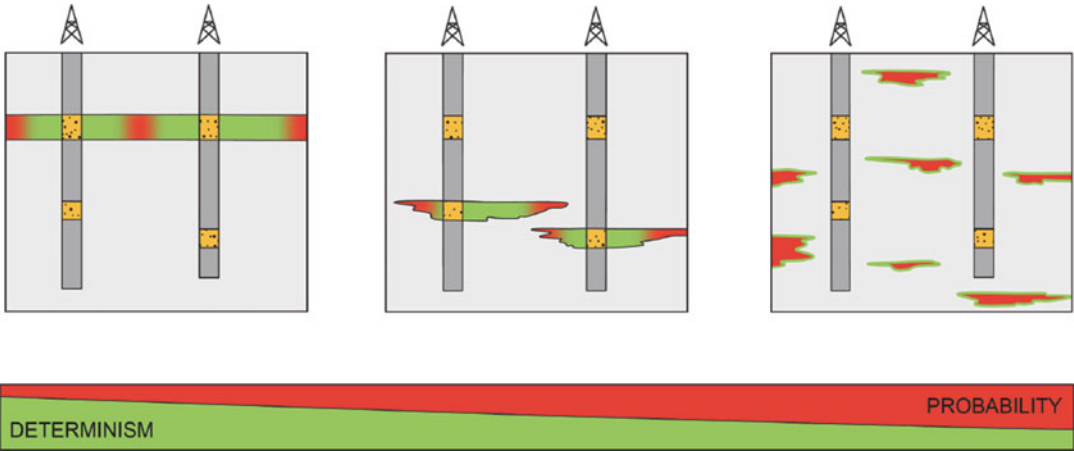
The underlying design issue we stress is the balance between determinism and probability in a model, and whether the modeller is aware of, and in control of, this balance.

To define the terminology as used here:

- **Determinism** is taken to mean an aspect of a model which is fixed by the user and imposed on the model as an absolute, such as placing a fault in the model or precisely fixing the location of a particular rock body;

- **Probability** refers to aspects of the model which are specified by a random (stochastic) outcome from a probabilistic algorithm.

To complete the terminology, a *stochastic process* (from the Greek *stochas* for ‘aiming’ or ‘guessing’) is one whose behaviour is completely non-deterministic. A *probabilistic* method is one in which likelihood or probability theory is employed. *Monte Carlo* methods, referred to especially in relation to uncertainty handling, are a class of algorithms that rely on repeated random sampling to compute a *probabilistic* result. Although not strictly the same, the terms *probabilistic* and *stochastic* are often treated synonymously and in this book we will restrict the discussion to the contrast between deterministic and probabilistic approaches applied in reservoir modelling.



**Fig. 2.17** Different rock body types as an illustration of the deterministic/probabilistic spectrum

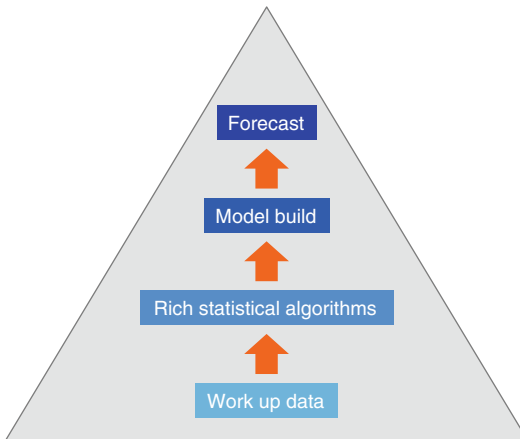
The balance of deterministic and probabilistic influences on a reservoir model is not as black and white as it may at first seem. Consider the simple range of cases shown in Fig. 2.17, showing three generic types of rock body:

1. *Correlatable bodies* (Fig. 2.17, left). These are largely determined by correlation choices between wells, e.g. sand observations are made in two wells and interpreted as occurrences of the same extensive sand unit and are correlated. This is a deterministic choice, not an outcome of a probabilistic algorithm. The resulting body is not a 100 % determined 'fact', however, as the interpretation of continuity between the wells is just that – an interpretation. At a distance from the wells, the sand body has a probabilistic component.
2. *Non-correlated bodies* (Fig. 2.17, centre). These are bodies encountered in one well only. At the well, their presence is determined. At increasing distances from the well, the location of the sand body is progressively less well determined, and is eventually controlled almost solely by the outcome from a probabilistic algorithm. These bodies are each partly deterministic and partly probabilistic.
3. *Probabilistic bodies* (Fig. 2.17, right). These are the bodies not encountered by wells, the position of which will be chosen by a probabilistic algorithm. Even these, however, are not 100 % probabilistic as their appearance

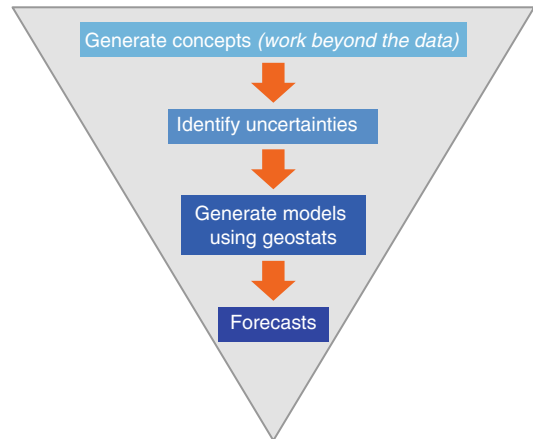
in the model is not a complete surprise. Deterministic constraints will have been placed on the probabilistic algorithm to make sure bodies are not unrealistically large or small, and are appropriately numerous.

So, if everything is a mixture of determinism and probability, what's the problem? The issue is that although any reservoir model is rightfully a blend of deterministic and probabilistic processes, the richness of the blend is a choice of the user so this is an issue of model design. Some models are highly deterministic, some are highly probabilistic and which end of the spectrum a model sits at influences the uses to which it can be put. A single, highly probabilistic model is not suitable for well planning (rock bodies will probably not be encountered as prognosed). A highly deterministic model may be inappropriate, however, for simulations of reservoirs with small rock bodies and little well data. Furthermore, different modellers might approach the same reservoir with more deterministic or more probabilistic mindsets.

The balance of probability and determinism in a model is therefore a subtle issue, and needs to be understood and controlled as part of the model design. We will also suggest here that greater happiness is generally to be found in models which are more strongly deterministic, as the deterministic inputs are the direct carrier of the reservoir concept.



**Fig. 2.18** The data-driven approach to reservoir modelling



**Fig. 2.19** The concept-driven approach to reservoir modelling

### 2.5.2 Different Generic Approaches

To emphasise the importance of user choice in the approach to determinism and probability, two approaches to model design are summarised graphically (Fig. 2.18).

The first is a data-driven approach to modelling. In this case, the model process starts with an analysis of the data, from which statistical guidelines can be drawn. These guidelines are input to a rich statistical model of the reservoir which in turn informs a geostatistical algorithm. The outcome of the algorithm is a model, from which a forecast emerges. This is the approach which most closely resembles the default path in reservoir modelling, resulting from the linear workflow of a standard reservoir modelling software package.

The limit of a simple data-driven approach such as this is that there is a reliance on the rich geostatistical algorithm to generate the desired model outcome. This in turn relies on the statistical content of the underlying data set, *yet for most of our reservoirs, the underlying data set is statistically insufficient*. This is a critical issue and distinguishes oil and gas reservoir modelling from other types of geostatistical modelling in earth sciences such as mining and soil science. In the latter cases, there is often a much richer underlying data set, which can indeed yield clear

statistical guidelines for a model build. In reservoir modelling we are typically dealing with much more sparse data, an exception being direct conditioning of the reservoir model to high quality 3D seismic data (e.g. Doyen 2007).

An alternative is to take a more concept-driven approach (Fig. 2.19). In this case, the modelling still starts with an analysis of the data, but the analysis is used to generate alternative conceptual models for the reservoir. The reservoir concept should honour the data but, as the dataset is statistically insufficient, the concepts are not limited to it. The model build is strongly concept-driven, has a strong deterministic component, and less emphasis is placed on geostatistical algorithms. The final outcome is not a single forecast, but a set of forecasts based on the uncertainties associated with the underlying reservoir concepts.

The difference between the data- and concept-driven approaches described above is the expectation of the geostatistical algorithm in the context of data insufficiency. The result is a greater emphasis on deterministic model aspects, which therefore need some more consideration.

### 2.5.3 Forms of Deterministic Control

The deterministic controls on a model can be seen as a toolbox of options with which to realise an architectural concept in a reservoir model.

These will be discussed further in the last section of this chapter, but are introduced below.

### 2.5.3.1 Faulting

With the exception of some (relatively) specialist structural modelling packages, large scale structural features are strongly deterministic in a reservoir model. Thought is required as to whether the structural framework is to be geophysically or geologically led, that is, are only features resolvable on seismic to be included, or will features be included which are kinematically likely to occur in terms of structural rock deformation. This in itself is a model design choice, introduced in the discussion on model frameworks (Sect. 2.3) and the choice will be imposed deterministically.

### 2.5.3.2 Correlation and Layering

The correlation framework (Sect. 2.3) is deterministic, as is any imposed hierarchy. The probabilistic algorithms work entirely within this framework – layer boundaries are not moved in common software packages. Ultimately the flowlines in any simulation will be influenced by the fine layering scheme and this is all set deterministically.

### 2.5.3.3 Choice of Algorithm

There are no hard rules as to which geostatistical algorithm gives the ‘correct’ result yet the choice of pixel-based or object-based modelling approaches will have a profound effect in the model outcome (Sect. 2.7). The best solution is the algorithm or combination of algorithms which most closely reflects the desired reservoir concept, and this is a deterministic choice.

### 2.5.3.4 Boundary Conditions for Probabilistic Algorithms

All algorithms work within limits, which will be given by arbitrary default values unless imposed. These limits include correlation models, object dimensions and statistical success criteria (Sect. 2.6). In the context of the concept-driven logic described above these limits need to be deterministically chosen, rather than left as a

simple consequence of the limits apparent from the (statistically insufficient) well data set.

### 2.5.3.5 Seismic Conditioning

The great hope for detailed deterministic control is exceptionally good seismic data. This hope is often forlorn, as even good quality seismic data is not generally resolved at the level of detail required for a reservoir model. All is not lost, however, and it is useful to distinguish between *hard* and *soft* conditioning.

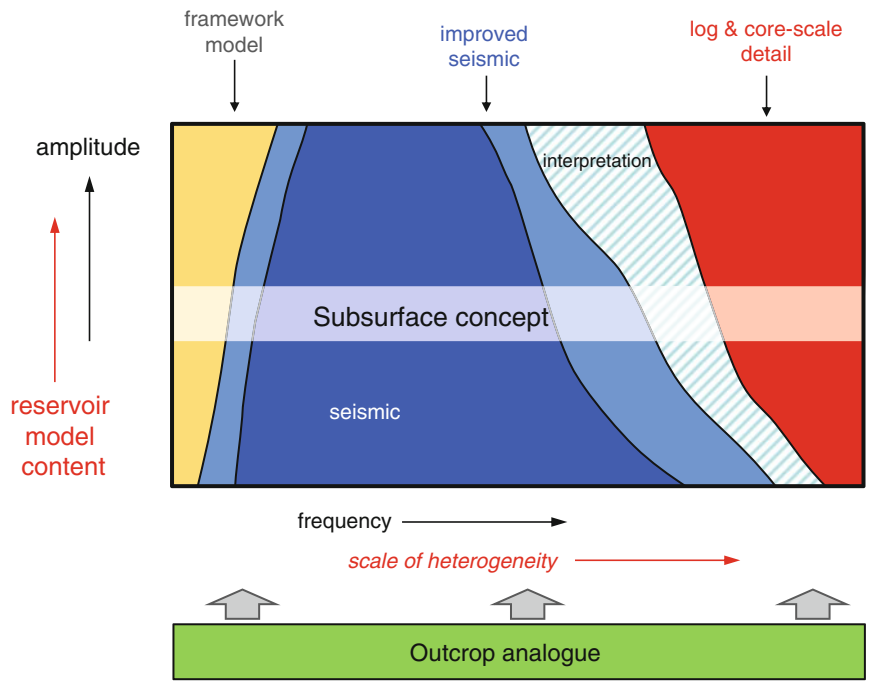
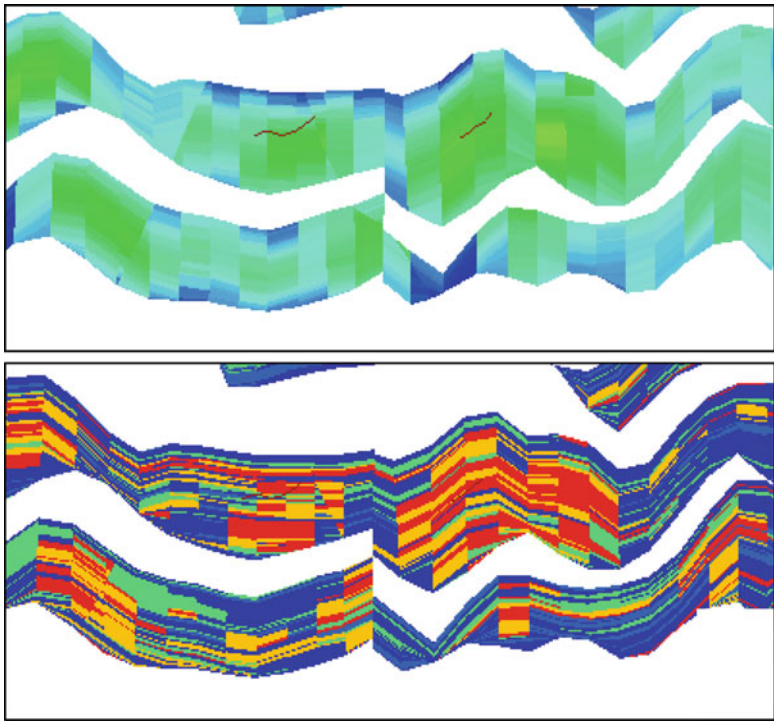
*Hard conditioning* is applicable in cases where extremely high quality seismic, sufficiently resolved at the scale of interest, can be used to directly define the architecture in a reservoir model. An example of this is seismic geobodies in cases where the geobodies are believed to directly represent important model elements. Some good examples of this have emerged from deepwater clastic environments, but in many of these cases detailed investigation (or more drilling) ends up showing that reservoir pay extends sub-seismically, or that the geobody is itself a composite feature.

The more generally useful approach for rock modelling is *soft conditioning*, where information from seismic is used to give a general guide to the probabilistic algorithms (Fig. 2.20). In this case, the link between the input from seismic and the probabilistic algorithm may be as simple as a correlation coefficient. It is the level of the coefficient which is now the deterministic control; and the decision to use seismic as either a hard or soft conditioning tool is also a deterministic one.

One way of viewing the role of seismic in reservoir modelling is to adapt the frequency/amplitude plot familiar from geophysics (Fig. 2.21). These plots are used to show the frequency content of a seismic data set and typically how improved seismic acquisition and processing can extend the frequency content towards the ends of the spectrum. Fine scale reservoir detail, often sits beyond the range of the seismic data (extending the blue area in Fig. 2.21). The low end of the frequency spectrum – the large scale layering – is also typically beyond the range of the seismic sample, hence the requirement to construct a low frequency ‘earth model’ to support seismic inversion work.



**Fig. 2.20** Deterministic model control in the form of seismic ‘soft’ conditioning of a rock model. *Upper image:* AI volume rendered into cells. *Lower image:* Best reservoir properties (red, yellow) preferentially guided by high AI values (Image courtesy of Simon Smith)



**Fig. 2.21** Seismic conditioning: deterministic and probabilistic elements of a reservoir model in the context of frequency & scale versus amplitude & content

The plot is a convenient backdrop for arranging the components of a reservoir model, and the frequency/amplitude axes can be alternatively labelled for ‘reservoir model scale’ and ‘content’. The reservoir itself exists on all scales and is represented by the full rectangle, which is only partially covered by seismic data. The missing areas are completed by the framework model at the low frequency end and by core and log-scale detail at the high frequency end, the latter potentially a source for probabilistic inversion studies which aim to extend the influence of the seismic data to the high end of the spectrum.

The only full-frequency data set is a good outcrop analogue, as it is only in the field that the reservoir can be accessed on all scales. Well facilitated excursions to outcrop analogues are thereby conveniently justified.

Is all the detail necessary? Here we can refer back to Flora’s Rule and the model purpose, which will inform us how much of the full spectrum is required to be modelled in any particular case.

In terms of seismic conditioning, it is only in the case where the portion required for modelling exactly matches the blue area in Fig. 2.21 that we can confidently apply hard conditioning using geobodies in the reservoir model, and this is rarely the case.

\*\*\*

With the above considered, there can be some logic as to the way in which deterministic control is applied to a model, and establishing this is part of the model design process. The probabilistic aspects of the model should be clear, to the point where the modeller can state whether the design is strongly deterministic or strongly probabilistic and identify where the deterministic and probabilistic components sit.

Both components are implicitly required in any model and it is argued here that the road to happiness lies with strong deterministic control. The outcome from the probabilistic components of the model should be largely predictable, and should be a clear reflection of the input data combined with the deterministic constraints imposed on the algorithms.

Disappointment occurs if the modeller expects the probabilistic aspects of the software to take on the role of model determination.

## 2.6 Essential Geostatistics

Good introductions to the use of statistics in geological reservoir modelling can be found in Yarus and Chambers (1994), Holden et al. (1998), Dubrule and Damsleth (2001), Deutsch (2002) and Caers (2011).

Very often the reservoir modeller is confounded by complex geostatistical terminology which is difficult to translate into the modelling process. Take for example this quotation from the excellent but fairly theoretical treatment of geostatistics by Isaaks and Srivastava (1989):

*in an ideal theoretical world the sill is either the stationary infinite variance of the random function or the dispersion variance of data volumes within the volume of the study area*

The problem for many of us is that we don’t work in an *ideal theoretical world* and struggle with the concepts and terminology that are used in statistical theory. This section therefore aims to extract just those statistical concepts which are essential for an *intuitive* understanding of what happens in the statistical engines of reservoir modelling packages.

### 2.6.1 Key Geostatistical Concepts

#### 2.6.1.1 Variance

The key concept which must be understood is that of variance. Variance,  $\sigma^2$ , is a measure of the average difference between individual values and the mean of the dataset they come from. It is a measure of the *spread* of the dataset:

$$\sigma^2 = \Sigma(x_i - \mu)^2 / N \quad (2.2)$$

where:

$x_i$  = individual value for the variable in question,

$N$  = the number of values in the data set, and

$\mu$  = the mean of that data set

Variance-related concepts underlie much of reservoir modelling. Two such occurrences are summarised below: the use of correlation coefficients and the variogram.

### 2.6.1.2 Correlation Coefficients

The correlation coefficient measures the strength of the dependency between two parameters by comparing how far pairs of values ( $x$ ,  $y$ ) deviate from a straight line function, and is given by the function:

$$\rho = \frac{1/N \sum_{i=1}^N (x_i - \mu_x)(y_i - \mu_y)}{\sigma_x \sigma_y} \quad (2.3)$$

where

$N$  = number of points in the data set

$x_i$ ,  $y_i$  = values of point in the two data sets

$\mu_x$ ,  $\mu_y$  = mean values of the two data sets, and

$\sigma_x$ ,  $\sigma_y$  = standard deviations of the two data sets  
(the square of the variance)

If the outcome of the above function is positive then higher values of  $x$  tend to occur with higher values of  $y$ , and the data sets are said to be ‘positively correlated’. If the outcome is  $\rho = 1$  then the relationship between  $x$  and  $y$  is a simple straight line. A negative outcome means high values of one data set correlate with low values of the other: ‘negative correlation’. A zero result indicates no correlation.

Note that correlation coefficients assume the data sets are both linear. For example, two data sets which have a log-linear relationship might have a very strong correlation but still display a poor correlation coefficient. Of course, a coefficient can still be calculated if the log-normal data set (e.g. permeability) is first converted to a linear form by taking the logarithm of the data.

Correlation between datasets (e.g. porosity versus permeability) is typically entered into reservoir modelling packages as a value between 0 and 1, in which values of 0.7 or higher generally indicate a strong relationship. The value may be described as the ‘dependency’.

### 2.6.1.3 The Variogram

Correlation coefficients reflect the variation of values within a dataset, but say nothing about how these values vary spatially. For reservoir modelling we need to express spatial variation of parameters, and the central concept controlling this is the variogram.

The variogram captures the relationship between the difference in value between pairs of

data points, and the distance separating those two points. Numerically, this is expressed as the averaged squared differences between the pairs of data in the data set, given by the empirical variogram function, which is most simply expressed as:

$$2\gamma = (1/N) \sum (z_i - z_j)^2 \quad (2.4)$$

where  $z_i$  and  $z_j$  are pairs of points in the dataset.

For convenience we generally use the semivariogram function:

$$\gamma = (1/2N) \sum (z_i - z_j)^2 \quad (2.5)$$

The semivariogram function can be calculated for all pairs of points in a data set, whether or not they are regularly spaced, and can therefore be used to describe the relationship between data points from, for example, irregularly scattered wells.

The results of variogram calculations can be represented graphically (e.g. Fig. 2.22) to establish the relationship between the separation distance (known as the lag) and the average  $\gamma$  value for pairs of points which are that distance apart. The data set has to be grouped into distance bins to do the averaging; hence only one value appears for any given lag in Fig. 2.22.

A more formal definition of semi-variance is given by:

$$\gamma(h) = \frac{1}{2} E \{ [Z(x+h) - Z(x)]^2 \} \quad (2.6)$$

where

$E$  = the expectation (or mean)

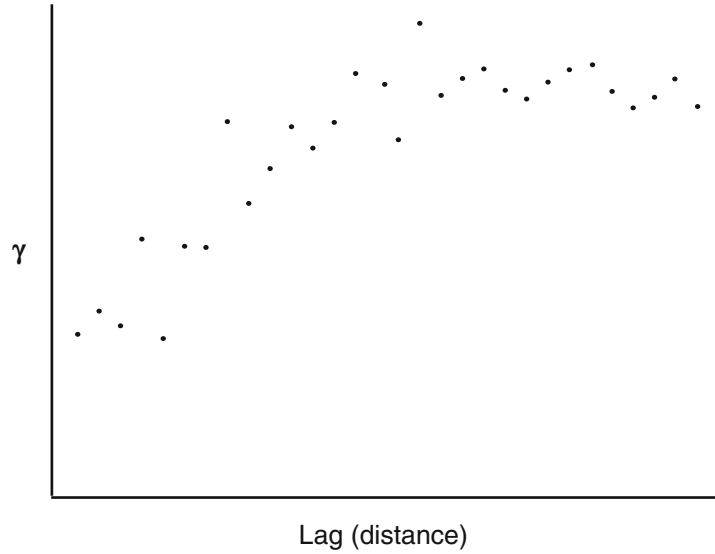
$Z(x)$  = the value at a point in space

$Z(x+h)$  = the value at a separation distance,  $h$  (the lag)

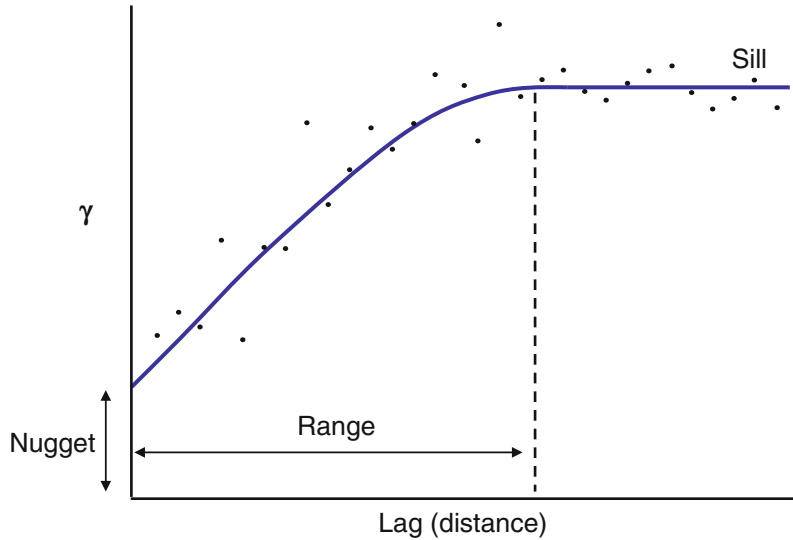
Generally,  $\gamma$  increases as a function of separation distance. Where there is some relationship between the values in a spatial dataset,  $\gamma$  shows smaller values for points which are closer together in space, and therefore more likely to have similar values (due to some underlying process such as the tendency for similar rock types to occur together). As the separation distance increases the difference between the paired samples tends to increase.

Fitting a trend line through the points on a semivariogram plot yields a *semivariogram*

**Fig. 2.22** The raw data for a variogram model: a systematic change in variance between data points with increasing distance between those points



**Fig. 2.23** A semivariogram model fitted to the points in Fig. 2.22



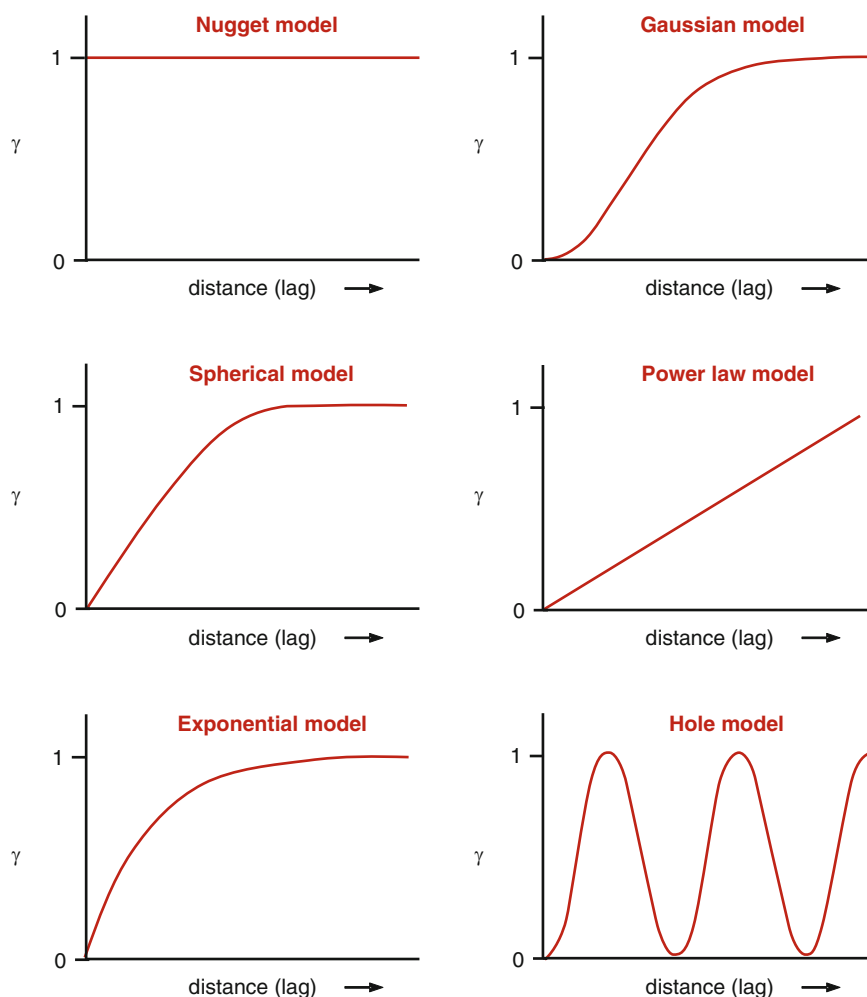
model (Fig. 2.23) and it is this model which may be used as input to geostatistical packages during parameter modelling.

A semivariogram model has three defining features:

- *the sill*, which is a constant  $\gamma$  value that may be approached for widely-spaced pairs and approximates the variance;
- *the range*, which is the distance at which the sill is reached, and
- *the nugget*, which is the extrapolated  $\gamma$  value at zero separation.

Now recall the definition of the sill, from Isaaks and Srivastava (1989), quoted at the start of this section. In simpler terms, the sill is the point at which the semivariogram function is equal to the variance, and the key measure for reservoir modelling is the range – the distance at which pairs of data points no longer bear any relationship to each other. A large range means that data points remain correlated over a large area, i.e. they are more homogeneously spread; a small range means the parameters are highly variable over short distances i.e. they are





**Fig. 2.24** Standard semi variogram models, with  $\gamma$  normalised to 1 (Redrawn from Deutsch 2002, © Oxford University Press, by permission of Oxford University Press, USA ([www.oup.com](http://www.oup.com)))

spatially more heterogeneous. The presence of a nugget means that although the dataset displays correlation, quite sudden variations between neighbouring points can occur, such as when gold miners come across a nugget, hence the name. The nugget is also related to the sample scale – an indication that there is variation at a scale smaller than the scale of the measurement.

There are several standard functions which can be given to semivariogram models, and which appear as options on reservoir modelling software packages. Four common types are illustrated in Fig. 2.24. The spherical model is probably the most widely used.

A fifth semivariogram model – the power law – describes data sets which continue to

get more dissimilar with distance. A simple example would be depth points on a tilted surface or a vertical variogram through a data set with a porosity/depth trend. The power law semivariogram has no sill.

It should also be appreciated that, in general, sedimentary rock systems often display a ‘hole effect’ when data is analysed vertically (Fig. 2.24e). This is a feature of any rock system that shows cyclicity (Jensen et al. 1995), where the  $\gamma$  value decreases as the repeating bedform is encountered. In practice this is generally not required for the vertical definition of layers in a reservoir model, as the layers are usually created deterministically from log data, or introduced using vertical trends (Sect. 2.7).

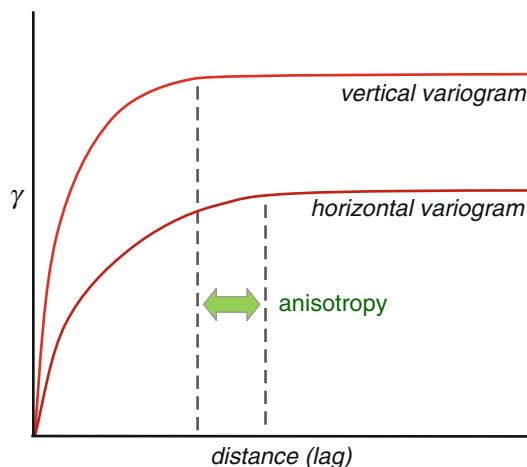
The shape of the semivariogram model can be derived from any data set, but the dataset is only a sample, and most likely an imperfect one. For many datasets, the variogram is difficult to estimate, and the modeller is therefore often required to choose a variogram model ‘believed’ to be representative of the system being modelled.

#### 2.6.1.4 Variograms and Anisotropy

A final feature of variograms is that they can vary with direction. The spatial variation represented by the variogram model can be orientated on any geographic axis, N-S, E-W, etc. This has an important application to property modelling in sedimentary rocks, where a trend can be estimated based on the depositional environment. For example, reservoir properties may be more strongly correlated along a channel direction, or along the strike of a shoreface. This directional control on spatial correlation leads to anisotropic variograms. Anisotropy is imposed on the reservoir model by indicating the direction of preferred continuity and the strength of the contrast between the maximum and minimum continuity directions, usually represented as an oriented ellipse.

Anisotropic correlation can occur in the horizontal plane (e.g. controlled by channel orientation) or in the vertical plane (e.g. controlled by sedimentary bedding). In most reservoir systems, vertical plane anisotropy is stronger than horizontal plane anisotropy, because sedimentary systems tend to be strongly layered.

It is generally much easier to calculate vertical variograms directly from subsurface data, because the most continuous data come from sub-vertical wells. Vertical changes in rock properties are therefore more rapid, and vertical variograms tend to have short ranges, *often less than that set by default in software packages*. Horizontal variograms are likely to have much longer ranges, and may not reach the sill at the scale of the reservoir model. This is illustrated conceptually in Fig. 2.25, based on work by Deutsch (2002). The manner in which horizontal-vertical anisotropy is displayed (or calculated) depends very much on how the well data is split zonally. If different stratigraphic



**Fig. 2.25** Horizontal-vertical anisotropy ratio in semivariograms (Redrawn from Deutsch 2002, © Oxford University Press, by permission of Oxford University Press, USA ([www.oup.com](http://www.oup.com)))

**Table 2.1** Typical ranges in variogram anisotropy ratios

Element	Anisotropy ratio
Point bars	10:1–20:1
Braided fluvial	20:1–100:1
Aeolian	30:1–120:1
Estuarine	50:1–150:1
Deepwater	80:1–200:1
Deltaic	100:1–200:1
Platform carbonates	200:1–1000:1

From Deutsch (2002)

zones are mixed within the same dataset, this can lead to false impressions of anisotropy. If the zones are carefully separated, a truer impression of vertical and horizontal semivariograms (per zone) can be calculated.

At the reservoir scale, vertical semivariograms can be easier to estimate. One approach for geostatistical analysis which can be taken is therefore to *measure* the vertical correlation (from well data) and then estimate the likely horizontal semivariogram using a vertical/horizontal anisotropy ratio based on a general knowledge of sedimentary systems. Considerable care should be taken if this is attempted, particularly to ensure that the vertical semivariograms are sampled within distinct (deterministic) zones. Deutsch has estimated ranges of typical anisotropy ratios by sedimentary environment (Table 2.1) and these offer a general guideline.

**Fig. 2.26** Image of a present-day sand system – an analogue for lower coastal plain fluvial systems and tidally-influenced deltas (Brahmaputra Delta (NASA shuttle image))



## 2.6.2 Intuitive Geostatistics

In the discussion of key geostatistical concepts above we have tried to make the link between the underlying geostatistical concepts (more probabilistic) and the sedimentological concepts (more deterministic) which should drive reservoir modelling. Although this link is difficult to define precisely, an intuitive link can always be made between the variogram and the reservoir architectural concept.

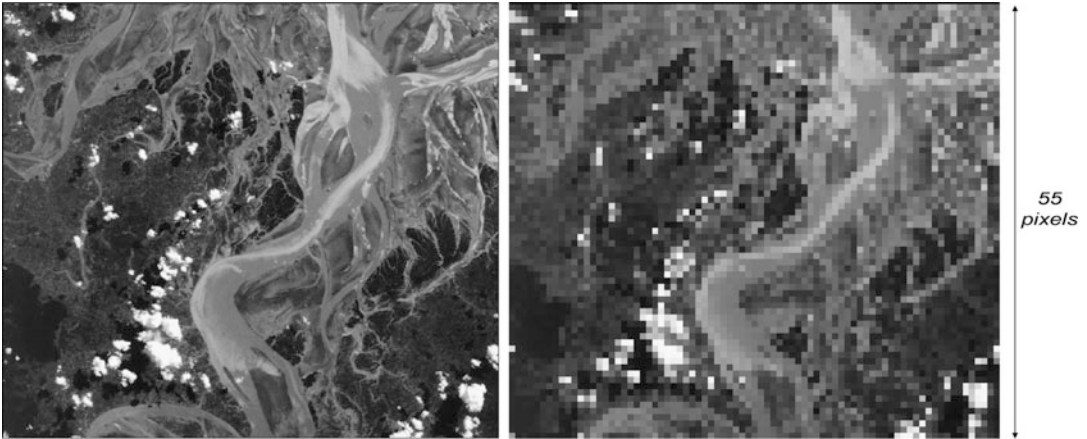
In the discussion below we try to develop that link using a satellite image adopted as a conceptual analogue for a potential reservoir system. The image is of a wide fluvial channel complex opening out into a tidally-influenced delta. Assuming the analogue is appropriate, we extract the guidance required for the model design by estimating the variogram range and anisotropy from this image. We assume the image intensity is an indicator for sand, and extract this quantitatively from the image by pixelating the image, converting to a greyscale and treating the greyscale as a proxy for ‘reservoir’. This process is illustrated in Figs. 2.26, 2.27, 2.28, 2.29, 2.30, and 2.31.

This example shows how the semivariogram emerges from quite variable line-to-line transects over the analogue image to give a picture of

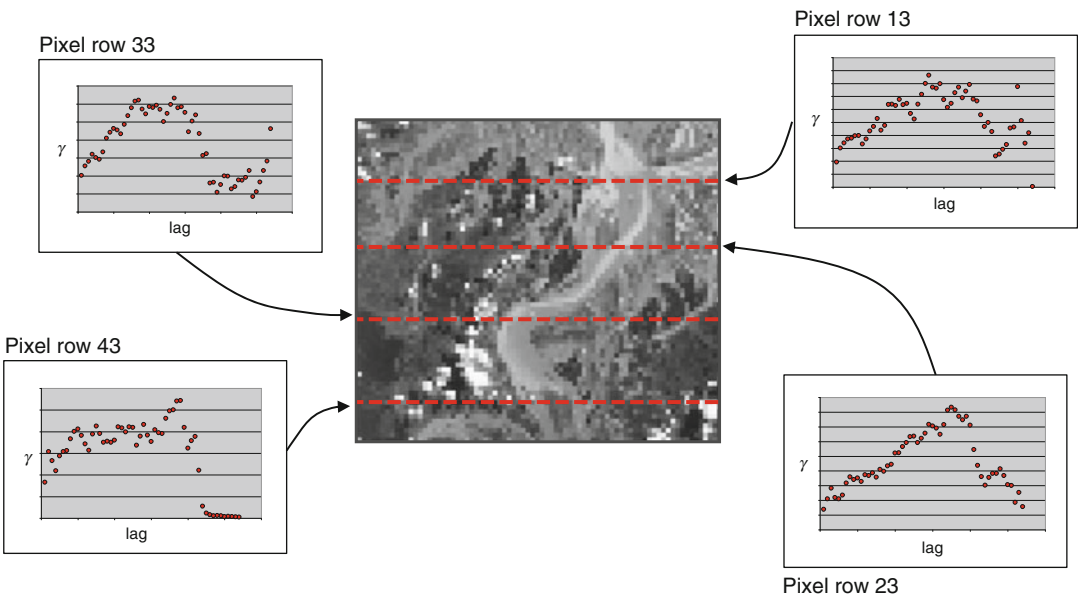
average variance. The overall result suggests pixel ranges of 25 in an E-W direction (Fig. 2.30) and 35 in a N-S direction (Fig. 2.31), reflecting the N-S orientation of the sand system and a 35:25 (1.4:1) horizontal anisotropy ratio.

This example is not intended to suggest that quantitative measures should be derived from satellite images and applied simply to reservoir modelling: there are issues of depositional vs. preserved architecture to consider, and for a sand system such as that illustrated above the system would most likely be broken down into elements which would not necessarily be spatially modelled using variograms alone (see next section).

The example is designed to guide our thinking towards an intuitive connection between the variogram (geostatistical variance) and reservoir heterogeneity (our concept of the variation). In particular, the example highlights the role of *averaging* in the construction of variograms. Individual transects over the image vary widely, and there are many parts of the sand system which are not well represented by the final averaged variogram. The variogram is in a sense quite crude and the application of variograms to either rock or property modelling assumes it is reasonable to convert actual spatial variation to a representative average and



**Fig. 2.27** Figure 2.26 converted to greyscale (*left*), and pixelated (*right*)



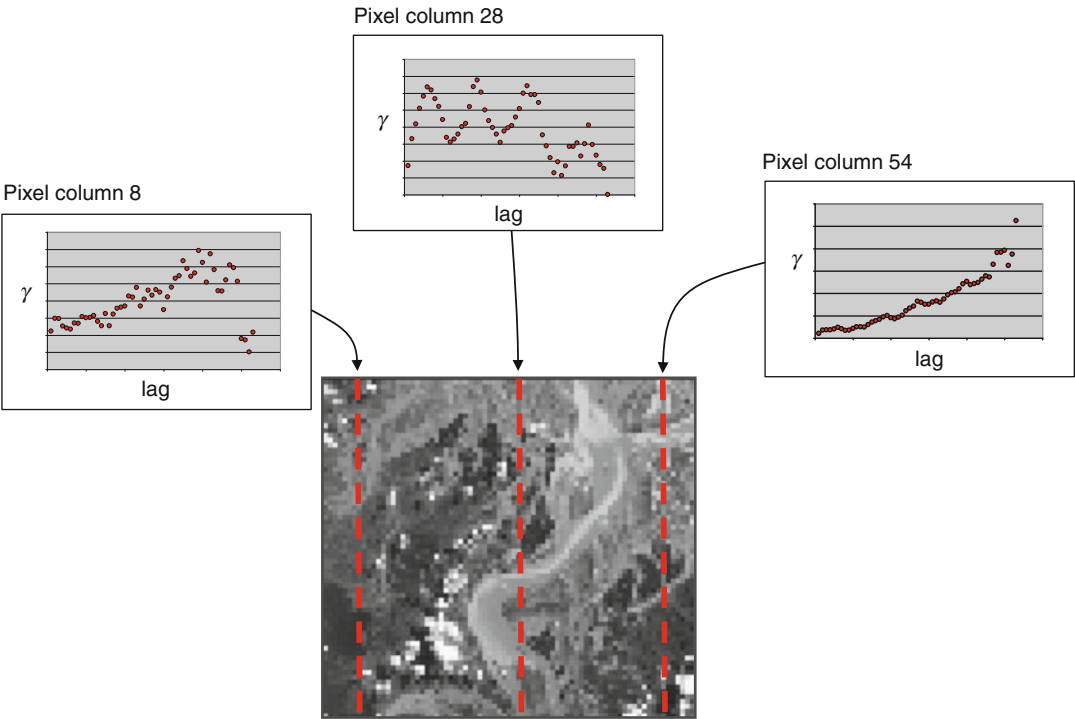
**Fig. 2.28** Semivariograms for pixel pairs on selected E-W transects

then apply this average over a wide area. Using sparse well data as a starting point this is a big assumption, and its validity depends on the architectural concept we have for the reservoir. The concept is not a statistical measure; hence the need to make an intuitive connection between the reservoir concept and the geostatistical tools we use to generate reservoir heterogeneity.

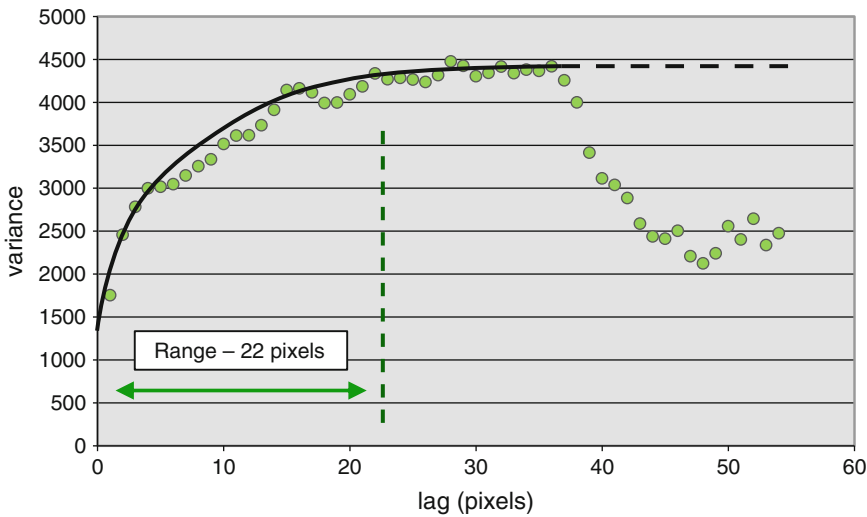
The intuitive leap in geostatistical reservoir modelling is therefore to repeat this exercise for

an analogue of the reservoir being modelled and use the resulting variogram to guide the geostatistical model, *assuming* it is concluded that the application of an average variogram model is valid. The basic steps are as follows:

1. Select (or imagine) an outcrop analogue;
2. Choose the rock model elements which appropriately characterise the reservoir
3. Sketch their spatial distribution (the architectural concept sketch) or find a suitable analogue dataset;

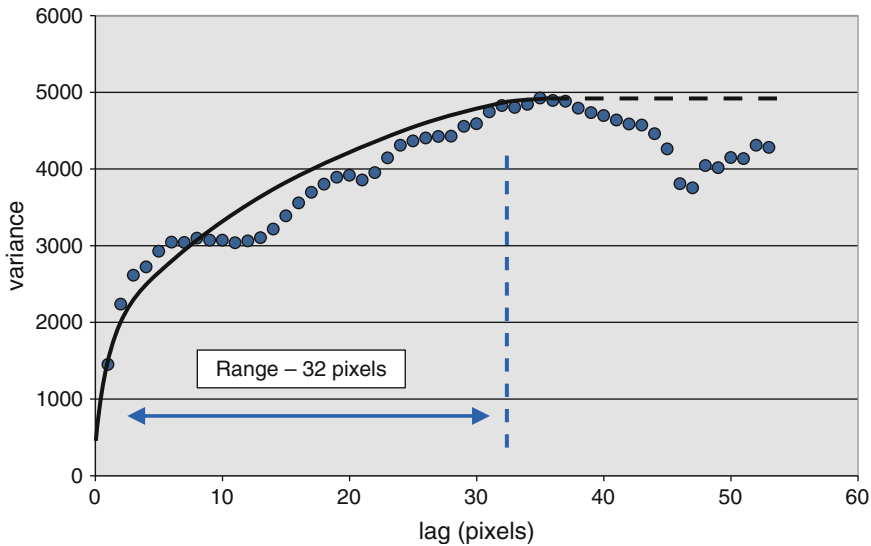


**Fig. 2.29** Semivariograms for pixel pairs on selected N-S transects



**Fig. 2.30** Semivariogram based on all E-W transects





**Fig. 2.31** Semivariogram based on all N-S transects

4. Estimate appropriate variogram ranges for individual elements (with different variogram ranges for the horizontal and vertical directions);
5. Estimate the anisotropy in the horizontal plane;
6. Input these estimates directly to a variogram-based algorithm if pixel-based techniques are selected (see next section);
7. Carry through the same logic for modelling reservoir properties, if variogram-based algorithms are chosen.

The approach above offers an intuitive route to the selection of the key input parameters for a geostatistical rock model. The approach is concept-based and deterministically steers the probabilistic algorithm which will populate the 3D grid.

There are some generalities to bear in mind:

- There should be greater variance across the grain of a sedimentary system (represented by the shorter EW range for the example above);
- Highly heterogeneous systems, e.g. glacial sands, should have short ranges and are relatively isotropic in (x, y);

- Shoreface systems generally have long ranges, at least for their reservoir properties, and the maximum ranges will tend to be along the strike of the system;
- In braided fluvial systems, local coarse-grained components (if justifiably extracted as model elements) may have very short ranges, often only a nugget effect;
- In carbonate systems, it needs to be clear whether the heterogeneity is driven by diagenetic or depositional elements, or a blend of both; single-step variography described above may not be sufficient to capture this.

Often these generalities may not be apparent from a statistical analysis of the well data, but they make intuitive sense. The outcome of an 'intuitive' variogram model should of course be sense-checked for consistency against the well data – any significant discrepancy should prompt a re-evaluation of either the concept or the approach to handling of the data (e.g. choice of rock elements). However, this intuitive approach to geostatistical reservoir modelling is recommended in preference to simple conditioning of the variogram model to the well data – which is nearly always statistically unrepresentative.

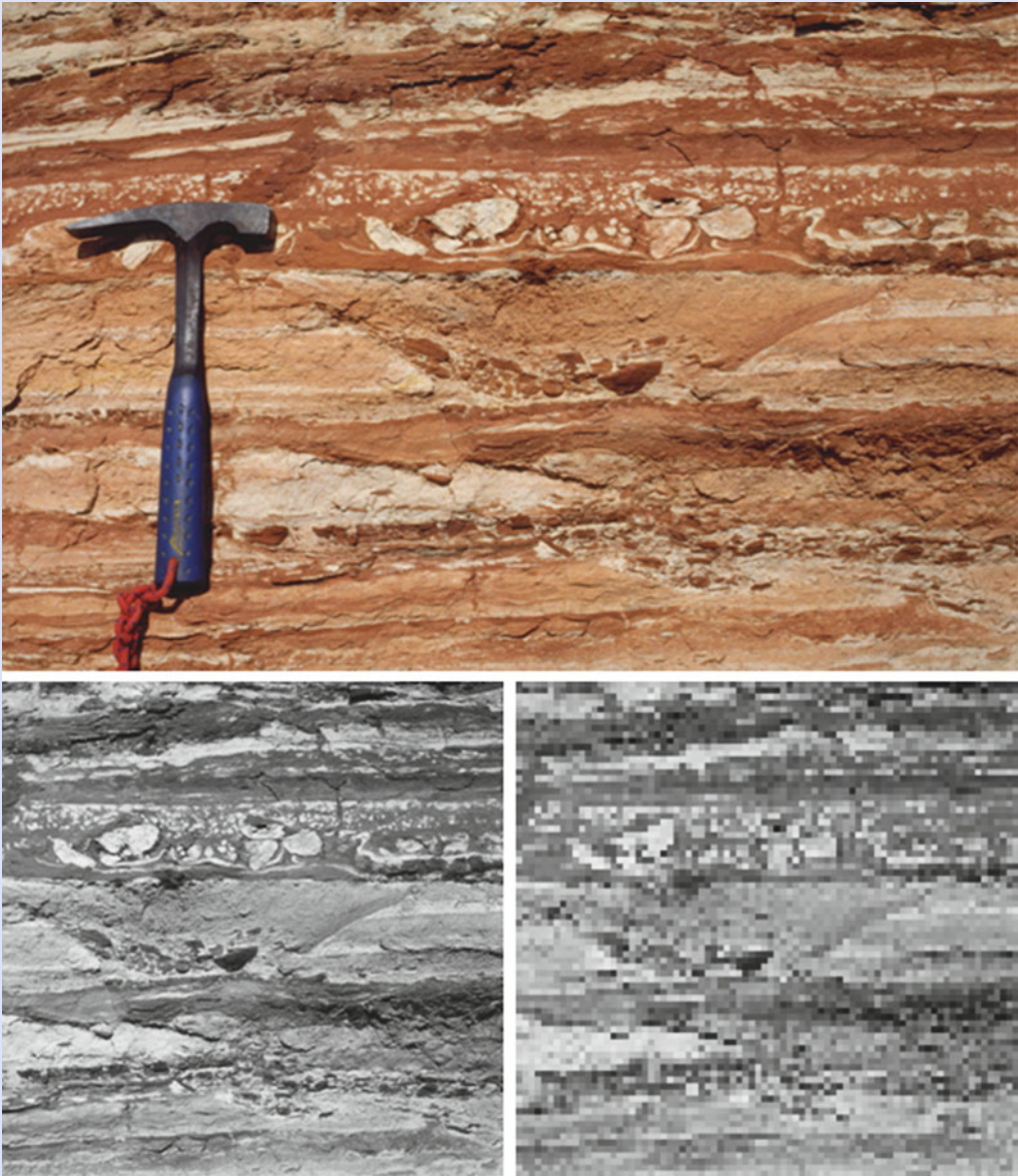
**Exercise 2.1.**

Estimate variograms for an outcrop image.

The image below shows an example photo of bedding structures from an outcrop section of a fluvial sedimentary sequence. Redox reactions (related to paleo-groundwater flows) give a strong visible contrast between high porosity (white) and low porosity (red) pore types. Micro

channels with lag deposits and soft-sediment deformation features are also present.

Sketch estimated semivariogram functions for the horizontal and vertical directions assuming that colour (grey-scale) indicates rock quality. The hammer head is 10 cm across. Use the grey-scale image and pixelated grey-scale images to guide you.



Grey scale image is  $22.5 \times 22.5$  cm; pixelated grey-scale image is 55 by 55 pixels

## 2.7 Algorithm Choice and Control

The preceding sections presented the basis for the design of the rock modelling process:

- Form geological concepts and decide whether rock modelling is required;
- Select the model elements;
- Set the balance between determinism and probability;
- Intuitively set parameters to guide the geostatistical modelling process, consistent with the architectural concepts.

The next step is to select an algorithm and decide what controls are required to move beyond the default settings that all software packages offer. Algorithms can be broadly grouped into three classes:

- *Object modelling* places bodies with discrete shapes in 3D space for which another model element, or group of elements, has been defined as the background.
- *Pixel-based methods* use indicator variograms to create the model architecture by assigning the model element type on a cell-by-cell basis. The indicator variable is simply a variogram that has been adapted for discrete variables. There are several variants of pixel modelling

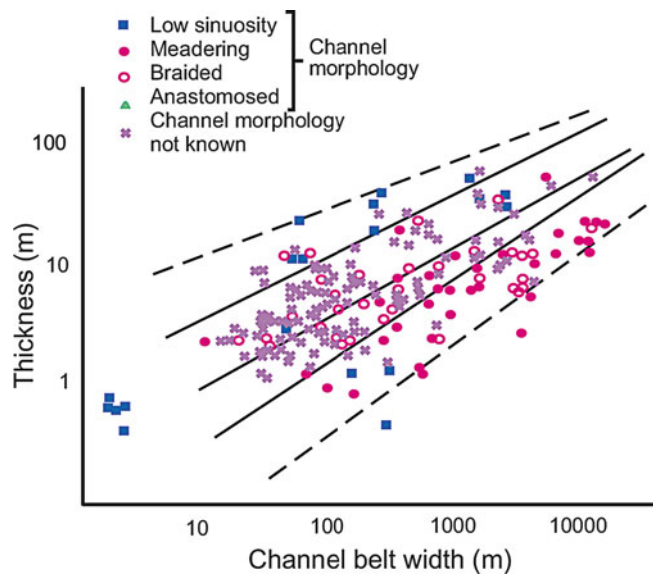
including sequential indicator simulation (SIS), indicator kriging and various facies trend or facies belt methods which attempt to capture gradational lateral facies changes. The most common approach is the SIS method.

- *Texture-based methods* use training images to recreate the desired architecture. Although this has been experimented with since the early days of reservoir modelling this has only recently ‘come of age’ through the development of multi-point statistical (MPS) algorithms (Strebelle 2002).

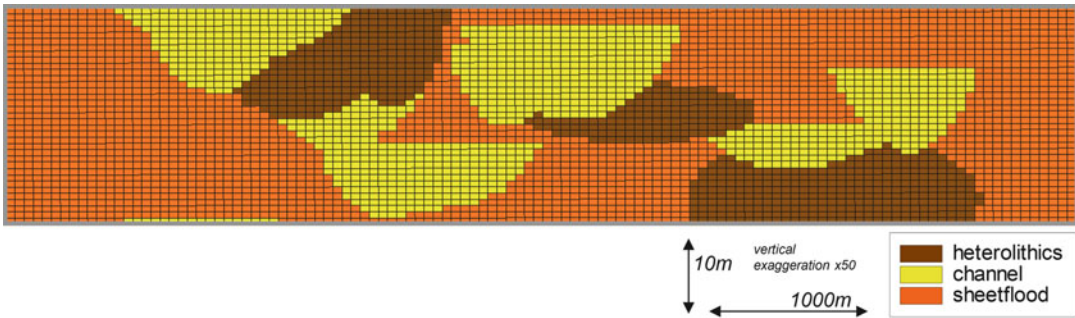
The pros and cons of these algorithms, including some common pitfalls, are explored below.

### 2.7.1 Object Modelling

Object modelling uses various adaptations of the ‘marked point process’ (Holden et al. 1998). A position in the 3D volume, the marked point, is selected at random. To this point the geometry of the object (ellipse, half moon, channel etc.) is assigned. The main inputs for object modelling are an upscaled element log, a shape template and a set of geometrical parameter distributions such as width, orientation and body thickness, derived from outcrop data (e.g. Fig. 2.32).



**Fig. 2.32** An early example of outcrop-derived data used to define geometries in object models (Fielding and Crane 1987) (Redrawn from Fielding and Crane 1987, © SEPM Society for Sedimentary Geology [1987], reproduced with permission)



**Fig. 2.33** Cross section through the 'Moray Field' model, an outcrop-based model through Triassic fluvial clastics in NE Scotland. Figures 2.35, 2.36, 2.38 and 2.39

follow the same section line through the models and each model is conditioned to the same well data, differing only in the selection of rock modelling algorithm

The algorithms work by selecting objects from the prescribed distribution and then rejecting objects which do not satisfy the well constraints (in statistics, the 'prior model'). For example, a channel object which does not intersect an observed channel in a well is rejected. This process continues iteratively until an acceptable match is reached, constrained by the expected total volume fraction of the object, e.g. 30 % channels. Objects that do not intersect the wells are also simulated if needed to achieve the specified element proportions. However, spatial trends of element abundance or changing body thickness are not automatically honoured because most algorithms assume stationarity (no interwell trends). Erosional, or intersection, rules are applied so that an object with highest priority can replace previously simulated objects (Fig. 2.33).

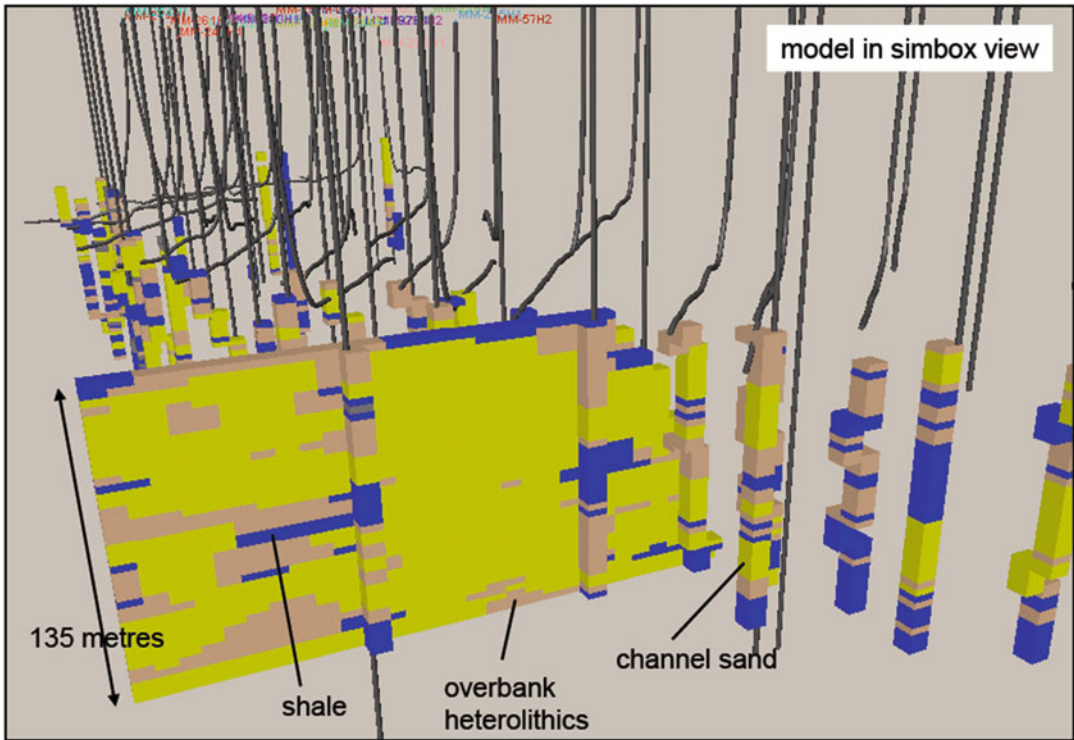
There are issues of concern with object modelling which require user control and awareness of the algorithm limitations. Firstly, it is important to appreciate that the algorithm can generate bodies that cross multiple wells if intervals of the requisite element appear at the right depth intervals in the well. That is, the algorithm can generate probabilistic correlations without user guidance – something that may or may not be desirable. Some algorithms allow the user to control multiple well intersections of the same object but this is not yet commonplace.

Secondly, the distribution of objects at the wells does not influence the distribution of inter-well objects because of the assumption of

stationarity in the algorithm. Channel morphologies are particularly hard to control because trend maps only affect the location of the control point for the channel object and not the rest of the body, which generally extends throughout the model. A key issue with object modelling, therefore, is that things can easily go awry in the inter-well area. Figure 2.34 shows an example of 'funnelling', in which the algorithm has found it difficult to position channel bodies without hitting wells with no channel observations; the channels have therefore been preferentially funnelled into the inter-well area. Again, some intuitive geological sense is required to control and if necessary reject model outcomes. The issue illustrated in Fig. 2.34 can easily be exposed by making a net sand map of the interval and looking for bulls-eyes around the wells.

Thirdly, the element proportions of the final model do *not* necessarily give guidance as to the quality of the model. Many users compare the element ('facies') proportions of the model with those seen in the wells as a quantitative check on the result, but matching the well intersections is the main statistical objective of the algorithm so there is a circular logic to this type of QC. The key thing to check is the degree of 'well match' *and* the spatial distributions *and* the total element proportions (together). Repeated mismatches or anomalous patterns point to inconsistencies between wells, geometries and element proportions.





**Fig. 2.34** ‘Funnelling’ – over-concentration of objects (channels, yellow) in between wells which have lower concentrations of those objects; a result of inconsistencies

between well data, guidance of the model statistics and the model concept (Image courtesy of Simon Smith)

Moreover, it is highly unlikely that the element proportions seen in the wells truly represent the distribution in the subsurface as the wells dramatically under-sample the reservoir. It is always useful to check the model element distributions against the well proportions, and the differences should be explainable, but differences should be expected. The ‘right’ element proportion is the one which matches the underlying concept.

The following list of observations and tips provides a useful checklist for compiling body geometries in object modelling:

1. Do not rely on the default geometries.
2. Remember that thickness distributions have to be customised for the reservoir. The upscaled facies parameter includes *measured* thickness from deviated wells – they are not stratigraphic thicknesses.
3. Spend some time customising the datasets and collating your own data from analogues.

There are a number of excellent data sources available to support this; they do not provide instant answers but do give good guidance on realistic *preserved* body geometries.

4. The obvious object shape to select for a given element is not always the best to use. Channels are a good example of this, as the architecture of a channel belt is sometimes better constructed using ellipse- or crescent-shaped objects rather than channel objects *per se*. These body shapes are less extensive than the channel shapes, rarely go all the way through a model area and so reflect the trend map inputs more closely and are less prone to the ‘bull’s eye’ effect.
5. There may be large differences between the geometry of a modern feature and that preserved in the rock record. River channels are a good example: the geomorphological expression of a modern river is typically much narrower and more sinuous than the geometry of the sand body that is preserved. This is



because the channels have a component of lateral migration and deposit a broader and lower sinuosity belt of sands as they do so. Carbonate reservoirs offer a more extreme example of this as any original depositional architecture can be completely overprinted by subsequent diagenetic effects. Differential compaction effects may also change the vertical geometry of the original sediment body.

6. Do not confuse uncertainty with variability. Uncertainty about the most appropriate analogue may result in a wide spread of geometrical constraints. It is incorrect, however, to combine different analogue datasets and so create spuriously large amounts of variation. It is better to make two scenarios using different data sets and then quantify the differences between them.
7. Get as much information as possible from the wells and the seismic data sets. Do well correlations constrain the geometries that can be used? Is there useful information in the seismic?
8. We will never know what geometries are correct. The best we can do is to use our conceptual models of the reservoir to select a series of different analogues that span a plausible range of geological uncertainty and quantify the impact. This is pursued further in Chap. 5.

## 2.7.2 Pixel-Based Modelling

Pixel-based modelling is a fundamentally different approach, based on assigning properties using geostatistical algorithms on a cell-by-cell basis, rather than by implanting objects in 3D. It can be achieved using a number of algorithms, the commonest of which are summarised below.

### 2.7.2.1 Indicator Kriging

Kriging is the most basic form of interpolation used in geostatistics, developed by the French mathematician Georges Matheron and his student Daniel Krige (Matheron 1963). The technique is applicable to property modelling (next chapter) but rock models can also be made using

an adaptation of the algorithm called *Indicator Kriging*.

The algorithm attempts to minimise the estimation error at each point in the model grid. This means the most likely element at each location is estimated using the well data and the variogram model – there is no random sampling. Models made with indicator kriging typically show smooth trends away from the wells, and the wells themselves are often highly visible as ‘bulls-eyes’. These models will have different element proportions to the wells because the algorithm does not attempt to match those proportions to the frequency distribution at the wells. Indicator kriging can be useful for capturing lateral trends *if* these are well represented in the well data set, or mimicking correlations between wells.

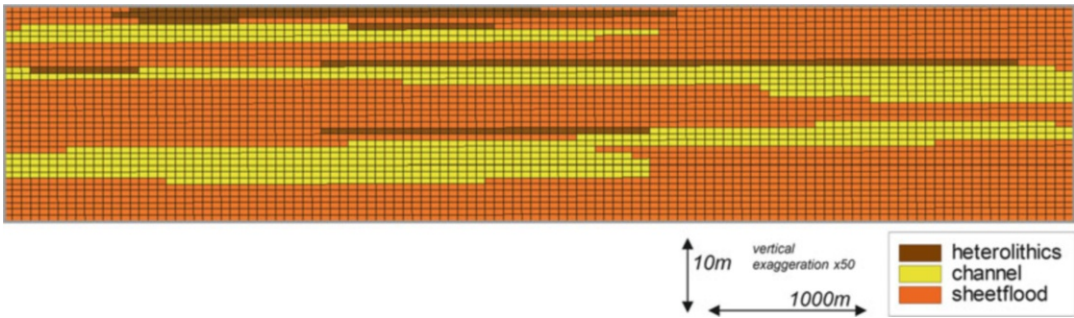
In general, it is a poor method for representing reservoir heterogeneity because the heterogeneity in the resulting model is too heavily influenced by the well spacing. For fields with dense, regularly-spaced wells and relatively long correlation lengths in the parameter being modelling, it may still be useful.

Figure 2.35 shows an example of indicator Kriging applied to the Moray data set – it is first and foremost an interpolation tool.

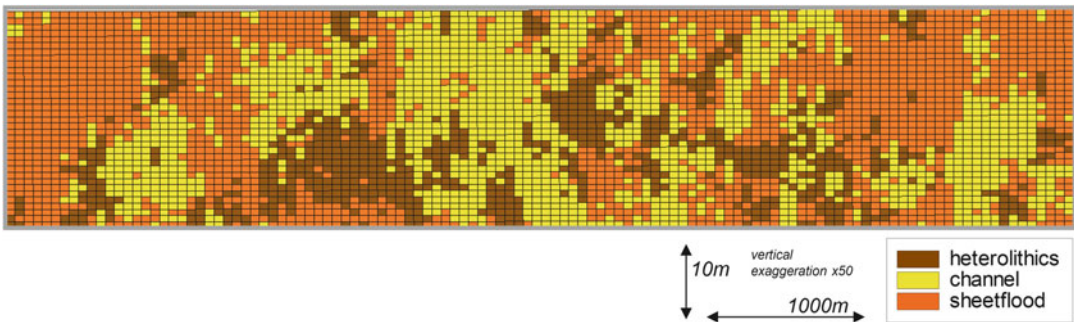
### 2.7.2.2 Sequential Indicator Simulation (SIS)

Sequential Gaussian Simulation, SGS is most commonly used for modelling continuous petrophysical properties (Sect. 3.4), but one variant, Sequential Indicator Simulation (SIS), is quite commonly used for rock modelling (Journel and Alabert 1990). SIS builds on the underlying geostatistical method of kriging, but then introduces heterogeneity using a sequential stochastic method to draw Gaussian realisations using an indicator transform. The indicator is used to transform a continuous distribution to a discrete distribution (e.g. element 1 vs. element 2).

When applied to rock modelling, SIS will generally assume the reservoir shows no lateral or vertical trends of element distribution – the principle of stationarity again – although trends can be superimposed on the simulation (see the important comment on trends at the end of this section).



**Fig. 2.35** Rock modelling using indicator kriging



**Fig. 2.36** Rock modelling using SIS

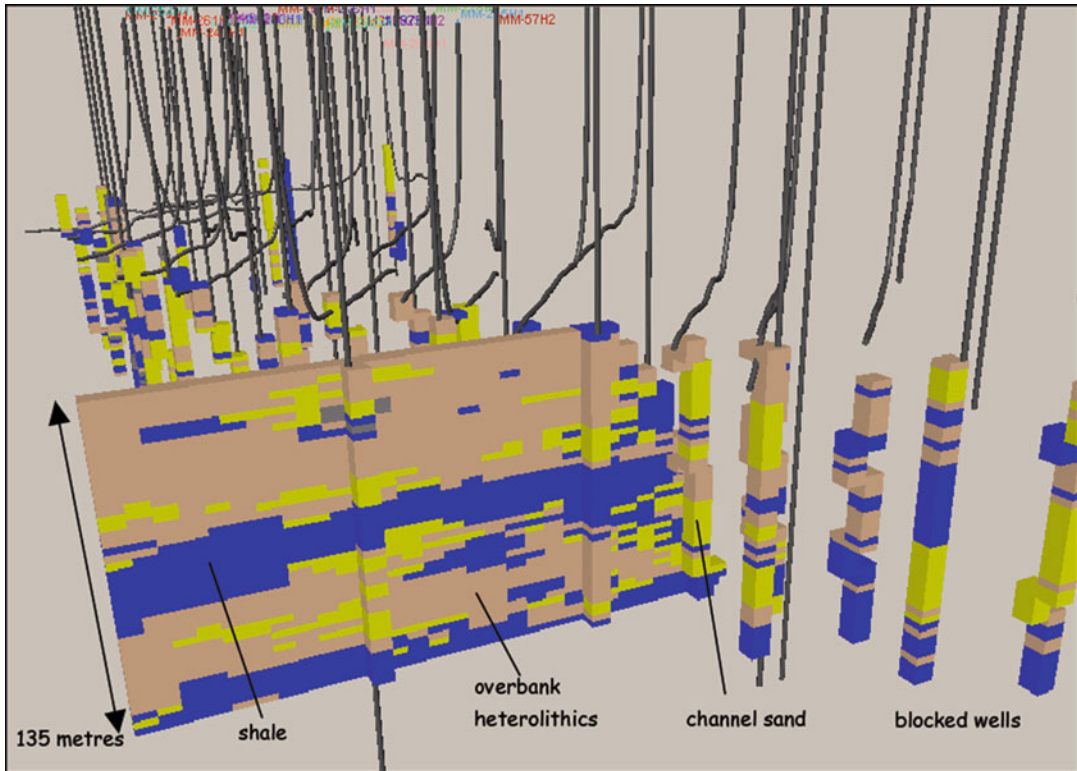
Models built with SIS should, by definition, honour the input element proportions from wells, and each geostatistical realisation will differ when different random seeds are used. Only when large ranges or trends are introduced will an SIS realisation differ from the input well data.

The main limitation with such pixel-based methods is that it is difficult to build architectures with well-defined margins and discrete shapes because the geostatistical algorithms tend to create smoothly-varying fields (e.g. Fig. 2.36). Pixel-based methods tend to generate models with limited linear trends, controlled by the principal axes of the variogram. Where the rock units have discrete, well-defined geometries or they have a range of orientations (e.g. radial patterns), object-based methods are preferable to SIS.

SIS is useful where the reservoir elements do not have discrete geometries either because they have

irregular shapes or variable sizes. SIS also gives good models in reservoirs with many closely-spaced wells and many well-to-well correlations. The method is more robust than object modelling for handling complex well-conditioning cases and the funnelling effect is avoided. The method also avoids the bulls-eyes around wells which are common in Indicator Kriging.

The algorithm can be used to create correlations by adjusting the variogram range to be greater than the well spacing. In the example in Fig. 2.37, correlated shales (shown in blue) have been modelled using SIS. These correlations contain a probabilistic component, will vary from realisation to realisation and will not necessarily create 100 % presence of the modelled element between wells. Depending on the underlying concept, this may be desirable.



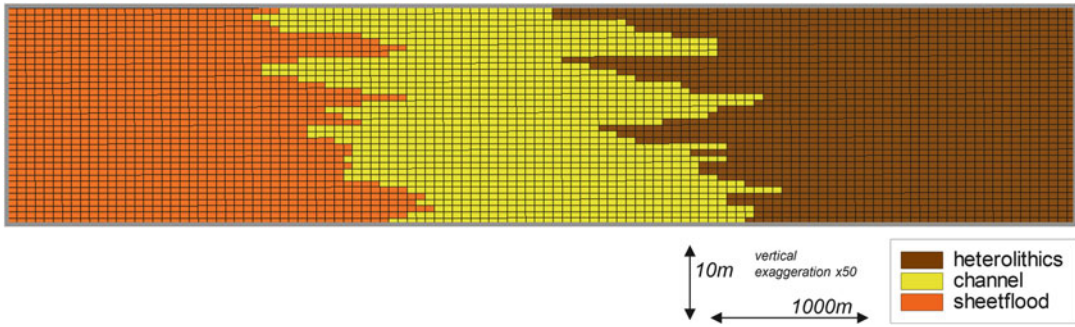
**Fig. 2.37** Creating correlatable shale bodies (shown in blue) in a fluvial system using SIS (Image courtesy of Simon Smith)

When using the SIS method as commonly applied in commercial packages, we need to be aware of the following:

1. Reservoir data is generally statistically insufficient and rarely enough to derive meaningful experimental variograms. This means that the variogram used in the SIS modelling must be derived by intuitive reasoning (see previous section).
2. The range of the variogram is not the same as the element body size. The range is related to the *maximum* body size, and actual simulated bodies can have sizes anywhere along the slope of the variogram function. The range should therefore *always* be set larger than your expected average body size, as a rule of thumb – twice the size.
3. The choice of the type of kriging used to start the process off can have a big effect. For simple kriging a universal mean is used and the algorithm assumes stationarity. For ordinary kriging the mean is estimated locally throughout the model, and consequently allows lateral trends to be captured. Ordinary kriging works well with large numbers of wells and well-defined trends, but can produce unusual results with small data sets.
4. Some packages allow the user to specify local azimuths for the variogram. This information can come from the underlying architectural concept and can be a useful way of avoiding the regular linear striping which is typical for indicator models, especially those conditioned to only a small number of wells.

### 2.7.2.3 Facies Trend Algorithms

The facies trend simulation algorithm is a modified version of SIS which attempts to honour a logical lateral arrangement of elements,



**Fig. 2.38** Rock modelling using facies trend simulation

for example, an upper shoreface passing laterally into a lower shoreface and then into shale.

Figure 2.38 shows an example applied to the Moray data set. The facies trend approach, because it uses SIS, gives a more heterogeneous pattern than indicator kriging and does not suffer from the problem of well bulls-eyes. The latter is because the well data is honoured at the well position, but not necessarily in the area local to the well.

The user can specify stacking patterns, directions, angles and the degree of inter-fingering. The approach can be useful, but it is often very hard to get the desired inter-fingering throughout the model. The best applications tend to be shoreface environments where the logical sequence of elements, upper to lower shoreface, transition on a large scale. Similar modelling effects can also be achieved by the manual application of trends (see below).

### 2.7.3 Texture-Based Modelling

A relatively new development is the emergence of algorithms which aim to honour texture directly. Although there are parallels with very early techniques such as simulated annealing (Yarus and Chambers 1994, Ch. 1 by Srivistava) the approach has become more widely available through the multi-point statistics (MPS) algorithm (Strebelle 2002; Caers 2003).

The approach starts with a pre-existing training image, typically a cellular model, which is

analysed for textural content. Using a geometric template, the frequency of instances of a model element occurring next to similar and different elements are recorded, as is their relative position (to the west, the east, diagonally etc.). As the cellular model framework is sequentially filled, the record of textural content in the training image is referred to in order to determine the likelihood of a particular cell having a particular model content, given the content of the surrounding cells.

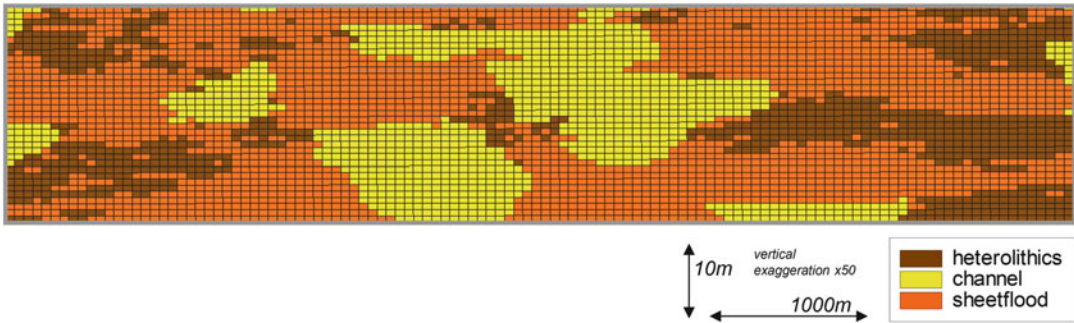
Although the approach is pixel-based, the key step forward is the emphasis on potentially complex texture rather than relatively simple geostatistical rules. The term ‘multi-point’ statistics compares with the ‘two-point’ statistics of variography. The prime limitation of variogram-based approaches – the need to derive simple rules for *average* spatial correlation – is therefore surmounted by modelling instead an average texture.

In principle, MPS offers the most appropriate algorithm for building 3D reservoir architecture, because architecture itself is a heterogeneous textural feature and MPS is designed to model heterogeneous textures directly.

In spite of this there are two reasons why MPS is not necessarily the algorithm of choice:

1. A training image is required, and this is a 3D architectural product in itself. MPS models are therefore not as ‘instantaneous’ as the simpler pixel-based techniques such as SIS, and require more pre-work. The example shown in Fig. 2.39 was built using a training data set which was itself extracted from a





**Fig. 2.39** Rock modelling using MPS

model combining object- and SIS-based architectural elements. The MPS algorithm did not ‘work alone.’

2. The additional effort of generating and checking a training image may not be required in order to generate the desired architecture.

Despite the above, the technique can provide very realistic-looking architectures which overcome both the simplistic textures of older pixel-based techniques and the simplistic shapes and sometimes unrealistic architectures produced by object modelling.

#### 2.7.4 The Importance of Deterministic Trends

All of the algorithms above involve a probabilistic component. In Sect. 2.5 the balance between determinism and probability was discussed and it was proposed that strong deterministic control is generally required to realise the desired architectural concept.

Having discussed the pros and cons of the algorithms, the final consideration is therefore how to overlay deterministic control. In statistical terms, this is about overcoming the *stationarity* that probabilistic algorithms assume as a default. Stationarity is a prerequisite for the algorithms and assumes that elements are randomly but homogeneously distributed in the inter-well space. This is at odds with geological systems, in which elements are heterogeneously distributed and show significant non-stationarity: they are commonly clustered and show patterns

in their distribution. Non-stationarity is the geological norm, indeed, *Walther’s Law* – the principle that vertical sequences can be used to predict lateral sequences – is a statement of non-stationarity.

Deterministic trends are therefore *required*, whether to build a model using object- or pixel-based techniques, or to build a training image for a texture-based technique.

##### 2.7.4.1 Vertical Trends

Sedimentary systems typically show vertical organisation of elements which can be observed in core and on logs and examined quantitatively in the data-handling areas of modelling packages. Any such vertical trends are typically switched *off* by default – the assumption of stationarity.

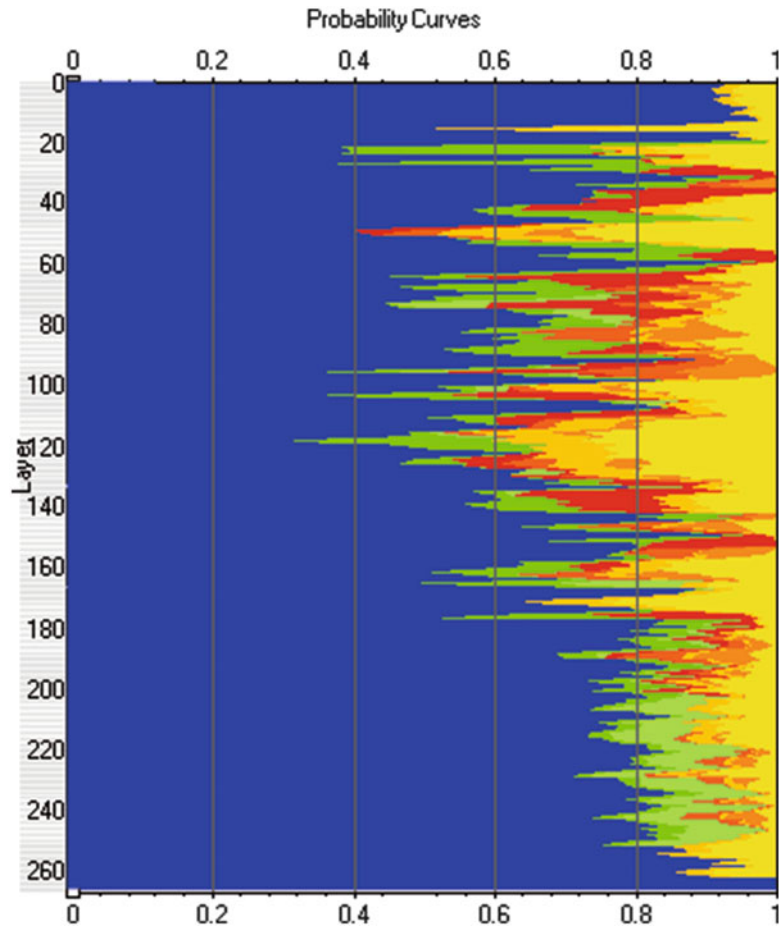
As a first assumption, observed trends in the form of vertical probability curves, should be switched *on*, unless there are compelling reasons not to use them. More significantly, these trends can be manually adjusted to help realise an architectural concept perhaps only partly captured in the raw well data.

Figure 2.40 shows an edited vertical element distribution which represents a concept of a depositional system becoming sand-prone upwards. This is a simple pattern, common in sedimentary sequences, but will not be integrated in the modelling process by default.

Thought is required when adjusting these profiles because the model is being consciously steered away from the statistics of the well data. Unless the well data is a perfect statistical sample



**Fig. 2.40** Vertical probability trends; each colour represents a different reservoir element and the probability represents the likelihood of that element occurring at that point in the cell stratigraphy (*blue* = mudstone; *yellow* = sandstone)



of the reservoir (rarely the case and never provable) this is not a problem, but the modeller should be aware that hydrocarbon volumes are effectively being adjusted up and down away from well control. The adjustments therefore require justification which comes, as ever, from the underlying conceptual model.

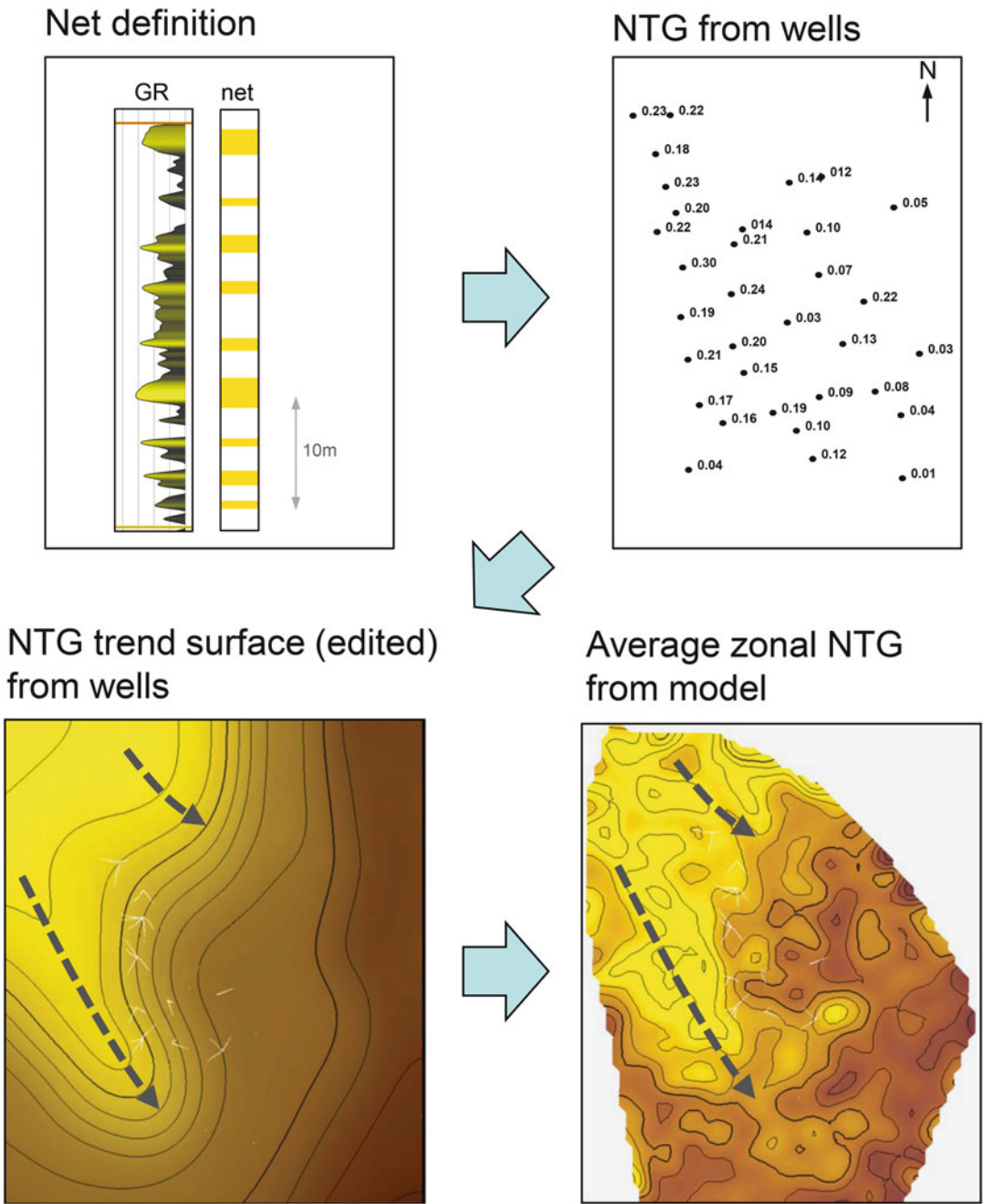
#### 2.7.4.2 Horizontal Trends

Horizontal trends are mostly simply introduced as 2D maps which can be applied to a given interval. Figure 2.41 shows the application of a sand trend map to a low net-to-gross system following the steps below:

1. Sand elements are identified in wells based on core and log interpretation;
2. A net-to-gross (sand) value is extracted at each well and gridded in 2D to produce a map illustrating any sand trend apparent from well data alone;

3. The 2D map is hand-edited to represent the desired concept, with most attention being paid to the most poorly sampled areas (in the example shown, the trend grid is also smoothed – the level of detail in the trend map should match the resolution of the sand distribution concept);
4. The trend map is input to, in this case, an SIS algorithm for rock modelling;
5. As a check, the interval average net-to-gross is backed-out of the model as a map and compared with the concept. The map shows more heterogeneity because the variogram ranges have been set low and the model has been tied to the actual well observations; the desired deterministic trends, however, clearly control the overall pattern.

The influence of the trend on the model is profound in this case as the concept is for the sand system to finger eastwards into a poorly drilled, mud-dominated environment. The oil



**Fig. 2.41** Deterministic application of a horizontal trend

volumes in the trended case are half that calculated for a model with the trends removed, with all other model variables unchanged. Stationarity is overcome and the concept dominates the modelling.

The source of the trend can be an extension of the underlying data, as in the example above, or a less data-independent concept based on a regional model, or a trend surface derived from

seismic attributes – the ‘soft conditioning’ described in Sect. 2.5.

### 2.7.4.3 3D Probability Volumes

The 3D architecture can be directly conditioned using a 3D volume – a natural extension of the process above. The conditioning volume can be built in a modelling exercise as a combination of

the horizontal/vertical trends described above, or derived from a 3D data source, typically a seismic volume.

Seismic conditioning directly in 3D raises some issues:

1. The volume needs QC. It is generally easier to check simpler data elements, so if the desired trends are separately captured in 2D trend surfaces and vertical proportion curves then combination into a 3D trend volume is not necessary.
2. If conditioning to a 3D seismic volume, the resolution of the model framework needs to be consistent with the intervals the seismic attribute is derived from. For example, if the parameter being conditioned is the sand content within a 25 m thick interval, it must be assumed that the seismic data from which the seismic attribute is derived is also coming from that 25 m interval. This is unlikely to be the case from a simple amplitude extraction and a better approach is to condition from inverted seismic data. The questions to ask are therefore what the seismic inversion process was inverting for (was it indeed the sand content) and, crucially, was the earth model used for the inversion the same one as the reservoir model is being built on?
3. If the criteria for using 3D seismic data (2, above) are met, can a probabilistic seismic inversion be called upon? This is the ideal input to condition to.
4. If the criteria in point 2, above, are not met, the seismic can still be used for soft conditioning, but will be more artefact-free and easier to QC if applied as a 2D trend. The noisier the data, the softer the conditioning will need to be, i.e. the lower the correlation coefficient.

### 2.7.5 Alternative Rock Modelling Methods – A Comparison

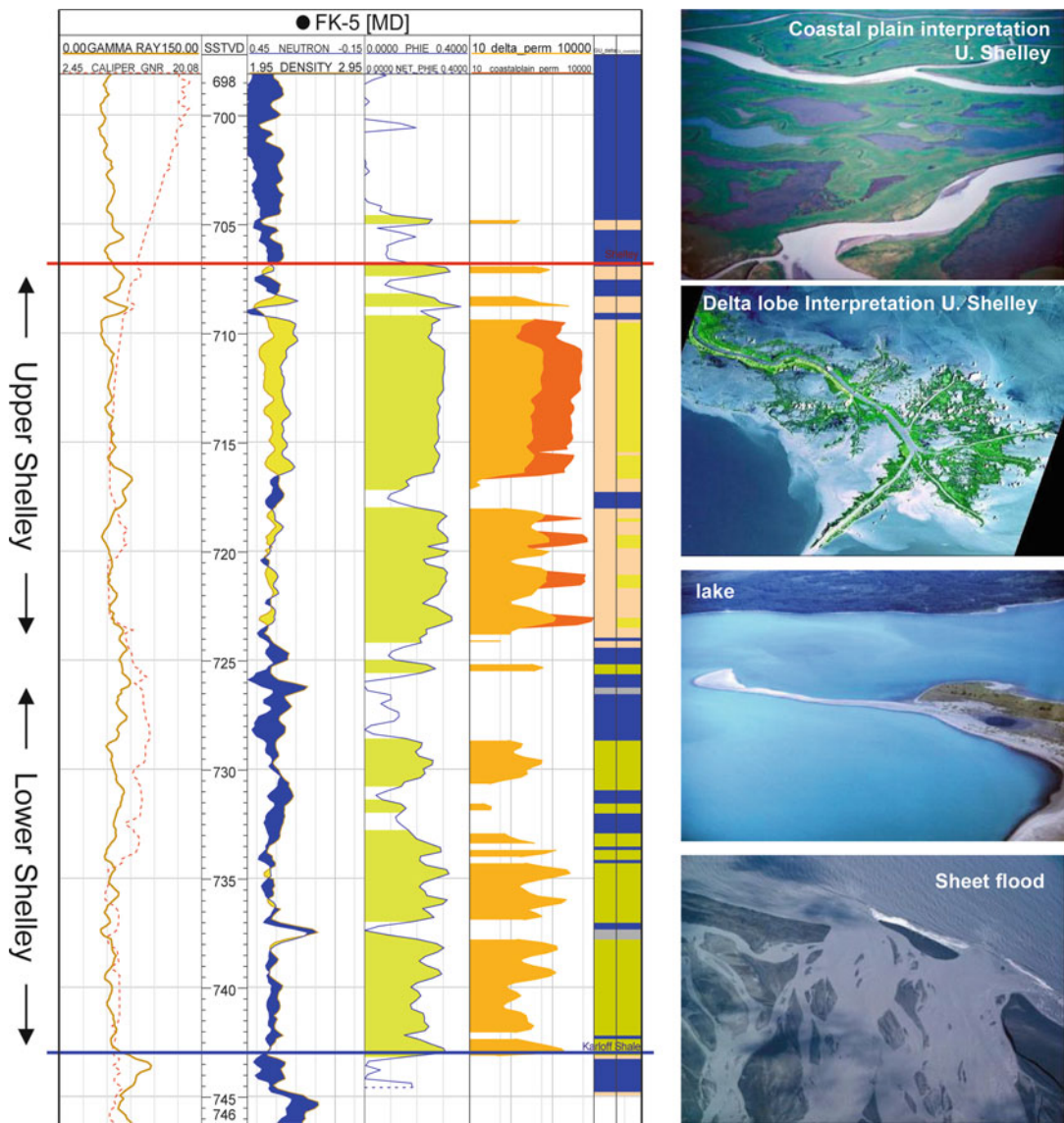
So which algorithm is the one to use? It will be the one that best reflects the starting concept – the architectural sketch – and this may require the application of more than one algorithm, and almost certainly the application of deterministic trends.

To illustrate this, an example is given below, to which alternative algorithms have been applied. The case is taken from a fluvio-deltaic reservoir – the Franken Field – based on a type log with a well-defined conceptual geological model (Fig. 2.42). The main reservoir is the Shelley, which divides into a clearly fluvial Lower Shelley characterised by sheetfloods, and an Upper Shelley, the sedimentology for which is less clear and can be viewed as either a lower coastal plain or a river-dominated delta.

Rock model realisations have been built from element distributions in 19 wells. Cross-sections taken at the same location through the models are illustrated in Figs. 2.43, 2.44 and 2.45 for a 2-, 4- and 7-interval correlation, respectively. The examples within each layering scheme explore object vs. pixel (SIS) modelling and the default model criteria (stationarity maintained) vs. the use of deterministic trends (stationarity overwritten).

The models contrast greatly and the following observations can be made:

1. The more heavily subdivided models are naturally more ‘stripey’. This is partly due to the ‘binning’ of element well picks into zones, which starts to break down stationarity by picking up any systematic vertical organisation of the elements, irrespective of the algorithm chosen and without separate application of vertical trends.
2. The stripey architecture is further enhanced in the 7-zone model because the layering is based on a flooding surface model, the unit boundaries for which are preferentially picked on shales. The unit boundaries are therefore shale-rich by definition and prone to generating correlatable shales if the shale dimension is big enough (for object modelling) or shale variogram range is long enough (for SIS).
3. Across all frameworks, the object-based models are consistently more ‘lumpy’ and the SIS-based models consistently more ‘spotty’, a consequence of the difference between the algorithms described in the sections above.



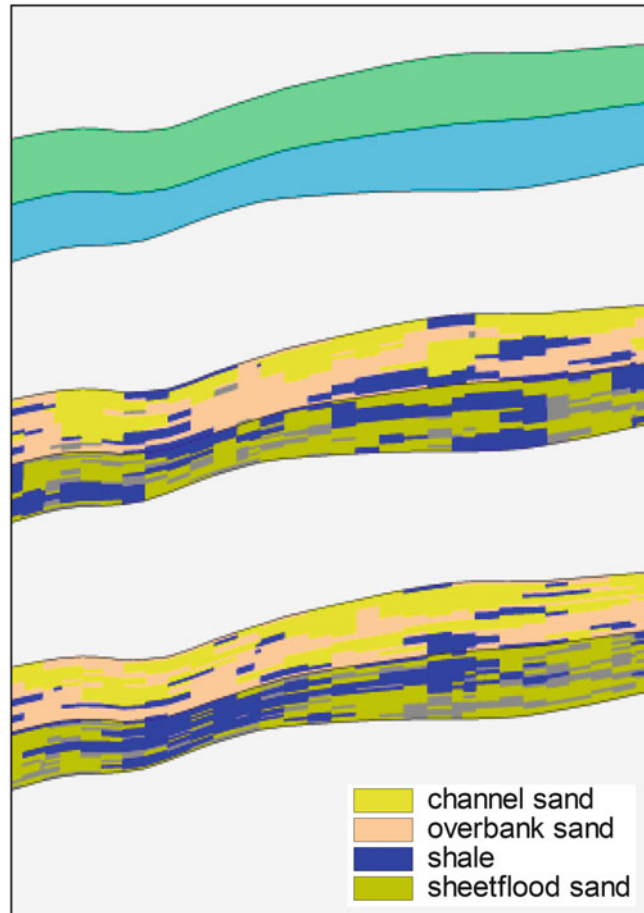
**Fig. 2.42** The Franken Field reservoir – type log and proposed depositional environment analogues. The model elements are shown on the *right-hand coloured logs*, one of which is associated with a delta interpretation for the

Upper Shelley, the other for an alternative coastal plain model for the Upper Shelley. Sands are marked in *yellow*, muds in *blue*, intermediate lithologies in intermediate colours (Image courtesy of Simon Smith)

4. The untrended object model for the two zone realisation is the one most dominated by stationarity, and looks the least realistic geologically.
5. The addition of deterministic trends, both vertical and lateral, creates more ordered, less random-looking models, as the assumption of stationarity is overridden by the conceptual model.

Any of above models presented in Figs. 2.43, 2.44, and 2.45 could be offered as a ‘best guess’, and could be supported at least superficially with an appropriate story line. Presenting multiple models using different layering schemes and alternative algorithms also appears thorough and in a peer-review it would be hard to know whether these models are ‘good’ or ‘bad’ representations of the reservoir. However, a

**Fig. 2.43** The Franken Field. *Top image:* the two zone subdivision; *middle image:* object model (no trends applied, stationarity maintained); *bottom image:* trended object model



number of the models were made quickly using system defaults and have little substance; stationarity (within zones) is dominant and although the models are statistically valid, they lack an underlying concept and have poor deterministic control. Only the lower models in each Figure take account of the trends associated with the underlying reservoir concept, and it is these which are the superior representations – at least matching the quality of the conceptual interpretation.

The main point to take away from this example is that all the models match the well data and no mechanical modelling errors have been made in their construction, yet the models differ drastically. The comparison reinforces the importance of the underlying reservoir concept as the tool for

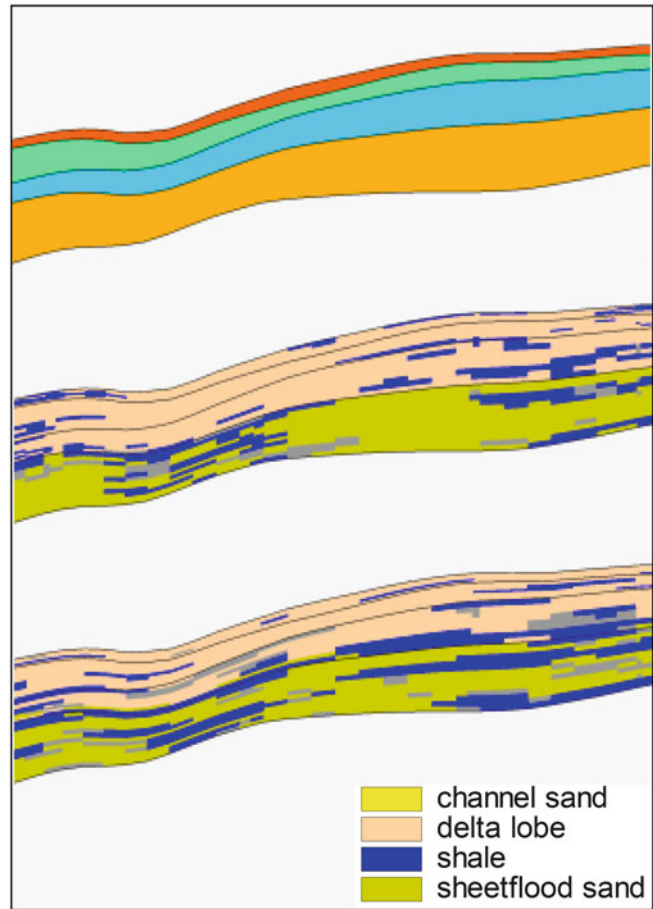
assessing which of the resulting rock models are acceptable representations of the reservoir.

## 2.8 Summary

In this chapter we have offered an overview of approaches to rock modelling and reviewed a range of geostatistically-based methods, whilst holding the balance between probability and determinism and the primacy of the underlying concept as the core issues. Reservoir modelling is not simply a process of applying numerical tools to the available dataset – there is always an element of subjective design involved. Overall the rock model must make geological sense and to



**Fig. 2.44** The Franken Field: *Top image*: the four zone subdivision; *middle image*: pixel (SIS) model (no trends applied, stationarity maintained); *bottom image*: trended pixel (SIS) model

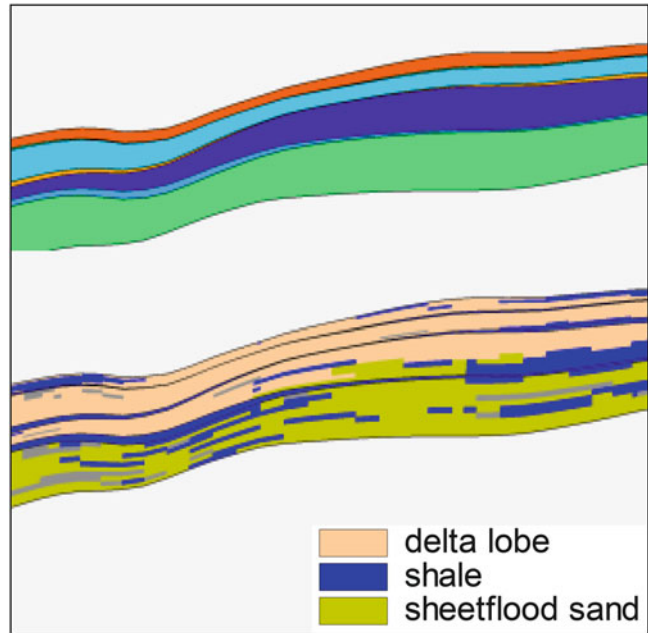


summarise this, we offer a brief resume of practical things which can be done to check the quality of the rock model – the QC process.

### 2.8.1 Sense Checking the Rock Model

- (a) Make architectural sketches along depositional strike and dip showing the key features of the conceptual models. During the model build switch the model display to stratigraphic (*simbox*) view to remove the structural deformation. How do the models compare with the sketches?
- (b) Watch out for the individual well matches – well by well. These are more useful and diagnostic than the overall ‘facies’ proportions. Anomalous wells point to weaknesses in the model execution.
- (c) Make element proportion maps for each element in each zone and check these against well data and the overall concept. This is an important check on the inter-well probabilistic process.
- (d) Check the statistics of the modelled element distribution against that for the well data alone; they should not necessarily be the same, but the differences should be explicable in terms of any applied trends and the spatial location of the wells.
- (e) Make net sand isochore maps for each zone without wells posted; imposed trends should be visible and the well locations should not (no bulls-eyes around wells).

**Fig. 2.45** The Franken Field: *Top image*: the seven zone subdivision; *bottom image*: trended SIS model



- (f) Make full use of the visualisation tools, especially the ability to scroll through the model vertically, layer by layer, to look for anomalous geometries, e.g. spikes and pinch-outs.

### 2.8.2 Synopsis – Rock Modelling Guidelines

The first decision to be made is whether or not a rock model is truly required. If rock modelling can add important controls to the desired distribution of reservoir properties, then it is clearly needed. If, however, the desired property distributions can be achieved directly by property modelling, then rock modelling is probably not necessary at all.

If it is decided that a rock model is required, it then needs some thought and design. The use of system default values is unlikely to be successful.

This chapter has attempted to stress the following things:

1. The *model concept* needs to be formed before the modelling begins, otherwise the modeller is ‘flying blind’. A simple way of checking your (or someone else’s) grasp of the conceptual reservoir model is to make a sketch section of the reservoir, or request a sketch, showing the desired architecture.
2. The model concept needs to be expressed in terms of the chosen *modelling elements*, the selection of which is based on not only a consideration of the heterogeneity, but with a view to the fluid type and production mechanism. Some fluid types are more sensitive to heterogeneity than others; if the fluid molecules do not sense the heterogeneity, there is no need to model it – this is ‘Flora’s Rule.’
3. Rock models are mixtures of *deterministic* and *probabilistic* inputs. Well data tends to be statistically insufficient, so attempts to extract statistical models from the well data are often not successful. The road to happiness therefore generally lies with strong deterministic control, as determinism is the most direct method of carrying the underlying reservoir concept into the model.
4. To achieve the desired reservoir architecture, the *variogram model* has a leading influence if pixel-based methods are employed. Arguably the *variogram range* is the most important geostatistical input.

5. To get a reasonable representation of the model concept it is generally necessary to impose *trends* (vertical and lateral) on the modelling algorithm, irrespective of the chosen algorithm.
6. Given the above controls on the reservoir model concepts, it is necessary to guide the geostatistical algorithms during a rock model build using an intuitive understanding of the relationship between the underlying reservoir concept and the geostatistical rules which guide the chosen algorithm.
7. It is unlikely that the element proportions in the model will match those seen in the wells – do not expect this to be the case; the data and the model are statistically different – more on this in the next section.

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