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A Fractal Landscape Realizer for Generating Synthetic Maps

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ABSTRACT

A fractal landscape realizer has been developed that generates synthetic landscape maps to user specifications. The alternative landscape realizations are not identical to the actual maps after which they are patterned, but are similar statistically (i.e., the areas and fractal character of each category are replicated). A fractal or self-affine pattern generator is used to provide a spatial probability surface for each category in the synthetic map. The Fractal Realizer arbitrates contentions among categories in a way that makes it possible to preserve the fractal patterns of all the categories in the resulting synthetic landscape. Each synthetic landscape is one equally likely realization from among an infinite ensemble of possible fractal landscape combinations. Synthetic landscapes produced by the Fractal Realizer have been tested using a variant of the Turing Test. More than 100 map experts were presented with a series of 20 selections of paired maps, and asked to distinguish the real map from the synthetic realization. The resulting population of scores was not significantly different from a random binomial, suggesting that the experts were unable to discern the synthetic maps from the actual ones. Statistical landscape indices computed for 25 different synthetic realizations are compared with the values computed for the actual maps. The Fractal Realizer can be used as a stochastic generator of synthetic input maps to a spatially explicit simulation model to test the effects of landscape rearrangement on the uncertainty of model parameter estimates. The sensitivity of stochastic spatial simulations to prescribed input landscapes can be evaluated by supplying them with a series of synthetic maps that obey particular statistical characteristics and by monitoring changes in selected output responses. Statistically similar input landscapes with different spatial arrangements can be generated and supplied to spatial models as a hedge against pseudoreplication.

KEY WORDS: FRAGSTATS, Fractal Realizer, Turing Test, categorical maps, fractal, landscape ecology, neutral model, null model, pattern, pseudoreplication, realization, simulation, synthetic map.

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INTRODUCTION

Often only one or a few actual landscape maps are available as input into spatially explicit simulation models. The availability of limited numbers of prescribed actual landscapes precludes careful sensitivity analysis of the effects of landscape arrangement on the uncertainty of the assumptions used in spatial simulations, making the simulation results subject to the statistical effects of pseudoreplication (Hargrove and Pickering 1992). Interactions between spatial arrangement and juxtaposition in an input landscape and the sensitivity of model parameters may be nonadditive with respect to model output responses.

Neutral landscape models were introduced to generate spatial patterns in the absence of any structuring process (Gardner et al. 1987). Neutral models attempt to capture a minimal set of constraints dictating landscape pattern and to assign the remaining pattern to random processes. As such, neutral models provide a reference baseline and a point of departure for more realistic, but also more complicated, scenarios of landscape change (Milne 1997, Pearson and Gardner 1997, With 1997). Processes resulting in nonstationarity, spatial dependencies, and antecedent conditions complicate simulations of landscape patterns. We use a neutral model approach to model landscape change in the absence of such factors, and then examine the model for systematic errors or biases that might point to the presence of one or more of these factors. If the predictions of a very simple neutral model fit satisfactorily with the data, it may not be necessary to develop more complex approaches. If there are relevant differences, the neutral model can be expanded to determine what additional landscape process features must be included to achieve agreement with observations.

More recently, neutral models have included additional constraints on the spatial patterns generated (Gardner and O'Neill 1991, O'Neill et al. 1992), often so that they could be used as input to spatial simulation models (Palmer 1992, Lavorel et al. 1995, Tyler and Hargrove 1997, With and King 1999). Such constrained models are still neutral in the sense that any one pattern is drawn from an ensemble of random landscapes with similar spatial distributions. Thus, neutral models can be used as a means for generating replicate landscapes that share statistical properties with an empirical landscape of interest. Such replicate landscapes can be used to study statistical expectations over a large ensemble of landscapes.

Simple random percolation maps have been useful as neutral landscape models, particularly as single-category binary maps. However, it has been recognized that simple random maps are unrealistic models of landscape pattern, because they have larger numbers of patches, more edge length, and different cumulative frequency distributions than actual landscapes (Plotnick et al. 1996, Schumaker 1996, With and King 1997).

Visual inspection for realism can anticipate and even surpass the sensitivity of landscape metrics and spatial indices. The human eye and brain are sensitive pattern detectors (Englund 1990), and may exceed the sensitivity of current state-of-the-art landscape metrics (Gustafson 1998). Landscape simulations that control particular aspects of landscape pattern, i.e., contagion (Gardner and O'Neill 1991), patchiness (Gustafson and Parker 1992), Markov transition probabilities (Johnson et al. 1999), and recursive hierarchical curdling (O'Neill et al. 1992, Lavorel et al. 1993) can be readily identified as synthetic by visual examination. In particular, the absence of linear features and lack of nonstationary anisotropic (multidirectional) patterns makes most neutral landscape simulations visually distinguishable from actual maps.

Most existing neutral models produce single-category binary maps rather than multiple-category simulations. Efforts to combine many single-category models can confound the statistical properties of the combined maps. Geostatistics-based approaches require detailed information about statistical properties and tend to be computationally intensive. Another technique generates landscape patterns by adding real patches from a database to a composite map at random locations until the desired percentage of occupancy is obtained (Li and Reynolds 1994, Homer et al. 1997, Hargis et al. 1998). The source and type of actual patches in the database may limit such approaches to simulating patterns from that particular kind of landscape, making these models less than neutral.

Saura and Martinez-Millan (2000) describe a Modified Random Clusters (MRC) neutral model method for simulating more realistic multiple-category maps that requires minimal information, can simulate anisotropic patches, and is computationally efficient. Categories of map patches are assigned depending on adjacency within a spatial neighborhood, thus preserving spatial dependence. However, the percent occupancy of each category in the simulated landscape is only approximately matched, especially as total occupancy approaches the percolation threshold. Although MRC allows separate control of fragmentation and habitat abundance, there is only a single setting that is not independent for individual categories. Thus, all categories in the map must have identical fragmentation. Similarly, anisotropic patterns can be produced, but the pattern of anisotropy is stationary, fixed in direction across the map, and applies equally to all categories.

A FRACTAL LANDSCAPE REALIZER

No technique exists for generating realistic, multiple-category synthetic maps with independently controllable categories that include linear features and nonstationary anisotropic patterns in a computationally modest way. Here we introduce a fractal landscape realizer which generates multiple-category synthetic landscape maps according to user specifications. The alternative landscape realizations produced by the Fractal Realizer (FR) are not identical to the actual maps after which they are patterned, but are visually and statistically similar, i.e., the area and fractal character of each map category are independently and exactly preserved. The FR uses a "recipe" of statistical specifications to produce synthetic landscapes.

The FR can be used to generate replicate landscapes that possess statistical properties similar to those of a particular empirical landscape, and can be used to generate replicated input to spatial simulation models. The sensitivity of stochastic simulations to prescribed input landscapes may be evaluated, or statistically similar landscapes can be generated as a hedge against pseudoreplication. Each synthetic landscape is one realization from an infinite ensemble of possible fractal landscape combinations.

The problem of adequacy

Before the FR could be offered as a landscape pattern generator for statistical testing, we needed to evaluate it in some way. A plethora of landscape pattern metrics exists, but there is no agreement about which aspects of a landscape are most important to match in a synthetic construction, or what magnitude of difference constitutes a formally acceptable degree of fit. We were left with the problem of defining an adequate test for the performance of the FR before the synthetic landscapes that it produces could themselves be used as a statistical null model (Rykiel 1996). This ontological problem arises because of the lack of external standards by which the realism of landscape maps can be tested. Ironically, this lack of external standards is the void that the FR itself is intended to fill.

A Turing Test of the Fractal Realizer

The Turing Test (TT) was devised in 1950 by Alan Turing as a method for determining whether or not a computer program is intelligent (Turing 1950). The TT takes place between an interrogator and two subjects. The interrogator communicates with these subjects via a computer terminal, and must decide which is a human being and which is a computer program. The human being helps the interrogator to make the correct identification, whereas the computer program attempts to trick the interrogator into making the wrong identification. If the computer program succeeds, it is said to be exhibiting intelligence.

Because human experts are capable of recognizing even subtle differences in pattern, we adopted a modified form of the TT to evaluate the performance of the FR. Via the Web, we administered a randomized series of 20 pairwise presentations, and asked human experts to distinguish the map that was real from the synthetic realization. One member of each pair of maps had been clipped from an actual map. The other was a synthetic map generated on the fly using the FR. Thus, no two people experienced exactly the same test. Observers made their selections on the basis of the patterns alone; no information was provided about the empirical maps, spatial scale, land cover types, etc. The map colors were earth tones chosen to avoid the suggestion of particular actual land uses or cover types (i.e., no blue for water). After the TT, the observer was told how many times he/she correctly selected the real map, and was shown the recalculated cumulative results.

Initially, more than 100 landscape ecologists and map experts were individually invited to take the TT of the FR. After the invited experts completed the TT, we opened it to any interested persons. Although additional scores no longer count in the actual analysis, we have created a set of Web pages that will permit the continual monitoring of the cumulative results of the Turing Test of the FR. These pages dynamically generate summary statistics, so that the current state of the continuing Turing Test can be monitored by anyone at any time.

Readers wishing to take the Turing Test of the Fractal Realizer themselves should do so before reading further, because taking the TT after reading this manuscript may affect observer judgment and bias the ongoing results. Please click here to take the Turing Test of the Fractal Realizer.

METHODS

The Fractal Realizer (FR) is written in FORTRAN and based on spatial probability surfaces generated using a fractal approximation. A separate fractal likelihood "topography" map is generated for each requested map category using the midpoint displacement method with successive random additions (Voss 1985, Saupe 1988, Peitgen and Saupe 1988). The user specifies the percentage of occupancy, *p,* for each category in the final map.

The process begins with the assignment of random elevations to the cells at the four corners of the empty probability map. Initially, the line segments formed by the cells at the four corners of the map are broken at their midpoints. The elevation of each midpoint cell is then randomly displaced by a distance that depends on the length or scale of the segment. The map then becomes four subsquares with elevation values at their corners, and the process recursively continues until all the cells in the map are displaced. The process can also be thought of as successively subdividing the resolution of the map until the desired detail is reached. Thus, maps must be square, with sides of length $2^n + 1$, where *n* is any real integer.

The correlation between the scales of successive displacement steps is controlled by a parameter *H* known as the

Hurst exponent (Mandelbrot 1983). The Hurst exponent describes a scaling relation such that $0 < H < 1$, and H values close to 1 produce a spatially autocorrelated, smooth probability topography, whereas H values near 0 produce a negatively correlated, rough topography. Many natural patterns are fractal and have H values close to 0.72 (Mandelbrot 1983, Peitgen and Saupe 1988).

Seven levels of scale recursion are required to fully populate a 129 x 129 cell map using midpoint displacement (sides of length 128, 64, 32, 16, 8, 4, and 2). The H value can be changed at each level, affecting the smoothness of the terrain at that spatial scale of subdivision. The use of different H values at different scales produces a very flexible multifractal probability distribution.

The "elevation" at each location in the topography indicates the likelihood of occurrence of that category at that location. The elevations of each fractal topography are conceptually inverted and lowered into paint until the number of painted cells just equals the percent occupancy requested by the user. Figure 1 shows the result of changing H values while holding p and the random number seed constant. Figure 2 shows the result of changing p values, and Fig. 3 shows different random number realizations with fixed p and H.

The probability-normalized fractal topographies for each requested category are assembled into a vertically aligned stack of maps, and the contents of each cell are examined in turn. If only one category is painted, it is installed in that location in the new synthetic map. Contentions between multiple categories for a particular cell location must be arbitrated. The category with the greatest painted elevation occupies that location in the synthetic map. Then a search is performed on the sorted unpainted locations for each losing contender category, and the next-highest unpainted cell location is located. This cell is assigned the losing category in the output map. The arbitration process is repeated for each losing contender category at this output map cell, in order of elevation priority. These rules are followed to determine categories for all the cells in the output map. The percent occupancy is strictly controlled by trading lost ties with the next-most-likely sites while preserving the fractal distributions of each category (Fig. 4). A sort is performed on unpainted elevations for each requested category to find the tie breaker locations. To allow maximum freedom for the spatial arrangement of the remaining categories on the landscape, the FR swaps the "background" category to be the category with the highest percent occupancy, and generates this category by absence. This reclassification is transparent to the user.

The FR can also generate sloping fractal gradients and edgeless topographies that can be seamlessly wrapped into a torus. Figure 5 shows a two-category gradient map in which the gradients are aligned in the same direction. Contention will be high for cell locations along the left edge of the map in such realizations. Figure 6 shows a two-gradient map in 180-deg. opposition, which minimizes spatial contentions. Figure 7 shows a two-gradient map in 90-deg. opposition. If we increase the H exponent to make both categories smoother, the ecotone between categories becomes a nearly straight 45-deg. line (Fig. 8). The fractal distribution and percent landscape occupancy are strictly maintained in all of these maps.

The FR will also accept externally supplied nonfractal probability surfaces. Constraint layers, a special case of these externally generated surfaces, permit the FR to generate realistic linear and anisotropic features, and can also specify categories that are to remain fixed in every realization. Specifying an absolute constraint layer that contains only extreme probability values deterministically locates category features that will be static and unchanging. Alternatively, an inverted Digital Elevation Model (DEM) used as a gradual constraint layer makes it possible for category features to follow valley bottoms and drainage paths. These linear features are dendritically fractal, but not in the same way as the fractal topographies. If the DEM is not inverted, categories can be made to fall along ridgelines. Such gradually constrained categories show spatial variance among realizations.

Input recipes are constructed to simulate particular maps using an iterative fitting process. The proportion of occupancy, p, for each category in the actual map must be provided, along with the values of H for each category. Estimates of p and H may be obtained using standard map analysis tools, or they may be visually estimated by comparison with a sequential set of maps such as those in Fig. 1 and Fig. 2. Different values of H can be specified for each midpoint recursion level, if desired. Because the FR is fast, many realizations can be quickly created to "fine tune" the recipe. Sample recipes for a gradient map and a constrained map are shown in Appendix 1 and Appendix 2, respectively.

Details of the Turing Test

Seventeen 129 x 129 cell maps (Fig. 9) were clipped from a single source map (Fig. 10). Recipes were developed iteratively to simulate each of the actual maps. The first 15 pairs presented in the Turing Test (TT) were randomly selected from among these 17 actual maps, and the last five were repeats disguised by rotating, inverting, or flipping around the diagonal. Although the synthetic maps for each test were generated dynamically, the random number and orientation were saved so that each test could be regenerated. Multiple observers can take the TT concurrently.

Observers were asked to rate their own expertise in Geographic Information Systems (GIS) and map simulation before taking the TT. After finishing, each observer was given his/her score and shown the collective results, including his/her own. Results were presented as a distribution of test scores and as a percentage of incorrect choices by individual map. Scores were also plotted by self-rated expertise to look for correlations. Finally, observers were asked for comments about their selection strategies.

Landscape spatial indices

FRAGSTATS 2.0 (McGarigal and Marks 1995) was used to calculate a suite of landscape spatial indices for two maps in each of three selection classes: (1) the maps for which the experts most frequently selected the synthetic map over the real one, (2) the maps for which the experts were more or less equally divided, and (3) the maps for which the experts selected the actual map most frequently. These three selection classes of maps were interpreted to represent landscapes that are easy, nominal, and hard to simulate with the FR, and their landscape metrics might indicate what characteristics made them so. Metrics were calculated on each real map in each class and on an ensemble of 25 realizations of the synthetic map, producing a mean and a standard deviation for each metric. Related metrics (see Riitters et al. 1995) were grouped together.

RESULTS

Map choices made by the experts

If we assume that each map choice within the Turing Test (TT) represents a binomial event, i.e., either correct or incorrect, and that successive choices are independent, then the expected random outcome can be expressed as a binomial distribution in which the likelihood of choosing correctly, p, and the likelihood of choosing incorrectly, q, each equal 0.50. Under these circumstances, a one-tailed test requires that a person score at least 14 correct out of 20 to reject the null hypothesis of random. Only 11.9% of the experts achieved such a score. Some experts may have discerned a difference between real and synthetic maps but ascribed the characteristics to the wrong maps, thus consistently choosing incorrectly. To test for such reversed discrimination, a two-tailed binomial distribution requires less than six or more than 14 correct to reject the equally likely hypothesis. Eighteen percent of the experts met this criterion.

The population of TT scores for the 109 experts is shown as a histogram. Three binomial functions are plotted with the histogram: 0.5/0.5 (green), 0.55/0.45 (blue), and 0.6/0.4 (cyan). A log-likelihood ratio goodness-of-fit test fails to reject the null hypothesis for only the 0.55/0.45 binomial (G = 11.97, critical value = 19.67). This test would not reject this null hypothesis as different from the experts' scores even at p = 0.25.

Scores were also recorded in terms of the actual maps that were presented. This histogram plots the percentage of pairs in which each real map was missed. Thus, tall histogram bars indicate maps that were missed almost every time that they were shown. These maps were easy to simulate with the Fractal Realizer (FR). Short histogram bars represent maps that the experts were frequently able to identify as real. Something about these maps was difficult to simulate using the FR. Clicking on individual bars in this histogram shows the real map, along with a synthetic version of it.

There was no apparent relationship between the experts' self-rated expertise on GIS and simulation models and their final TT scores. We also recorded the unedited comments and techniques of the experts after they took the TT. These were more interesting, helpful, and amusing than we expected. Few experts said that they recognized repeated maps.

FRAGSTATS metrics

The FRAGSTATS metrics are shown as a table with a clickable version of each original map from the three map selection classes. Some metrics matched almost exactly, i.e., total area and the diversity and richness group, because the FR controlled these. The match of the patch metrics group and the edge metrics group showed no clear trend across the three map selection classes. The fractal metrics group always showed close agreement, even though these metrics were calculated differently from the *H* used in the recipes for the FR. There was no obvious relationship between the number of constraint layers used in recipes and the three map selection classes.

Ongoing Turing Test

Because the self-ratings of GIS and simulation expertise were not correlated with the experts' scores, and because counts were low in some scoring categories, we allowed other interested persons to take the TT, thus increasing the sample size to nearly 1000 at the time of this writing. The distribution of scores of the ongoing Turing Test is a closer fit with a 0.55/0.45 binomial than with the 0.5/0.5 or 0.6/0.4 model. However, the distribution of ongoing scores appears to be shorter and broader than the strict binomial model.

The percentage of incorrect choices by map for the ongoing Turing Test showed a similar pattern among maps as the expert choices at the time of this writing. Synthetic versions of maps 3 and 10 were still chosen more frequently than their real counterparts, but maps 6 and 12 were chosen more equivocally. Map 16 remained difficult to simulate, whereas map 13 passed map 8 in terms of correct choices by the general testers. Of course, these results may have changed as more observers test the FR. Persons taking the ongoing TT also had interesting unedited comments about the TT. No relationship was evident between scores and either self-assessed expertise level for the ongoing TT.

DISCUSSION

Some experts noted that any pattern could be real and that it would probably be possible to find a spot on the earth that fit any pattern whatsoever. Most experts, however, realized that some patterns are more frequently observed in nature, and that this could form the basis for the Turing Test (TT). Several experts commented that the scale, category types, and geographic area are always provided to viewers of a cartographic product, because, without this, the map cannot be used. In the original TT, the interrogator communicates with the human subject and the computer only via teletype to ensure that the interrogator's choice is based only on the responses and not on ancillary clues. To be analogous, we withheld information about the scale and nature of the source map. Similarly, we constrained certain parts of the synthetic maps to make them appear more realistic. We suspect that divulging information about the scale and source of the maps would have made little difference in the scores.

Elevation-constrained categories sometimes showed a "salt and pepper" speckling because of roughness inherent in the digital terrain model used. Several experts recognized this speckle as a difference between the maps. However, some took it as a result of a classification of a remote image and picked such maps as real. Others suspected that it was the result of an imperfect simulation program and picked such maps as synthetic. This effect may have been responsible for a "hump" in the score distribution around five correct, but this effect disappeared at larger sample sizes. Performing a smoothing pass on the elevation model would have probably eliminated this effect, making the choice among map pairs even more difficult.

As they were presented with more pairs, the experts often devised rules for selecting the real maps (see comments). Even though they were given no feedback during the TT, simply experiencing more pairs of maps may have permitted enough learning to make the pairs no longer represent independent trials, violating one of the assumptions of the binomial model. Nevertheless, the statistics seem unequivocal, and this learning effect is unavoidable with human observers. A simulation model using the output of the Fractal Realizer (FR) as input will not learn, and individual realizations will be truly independent.

That the easy/nominal/hard map selection groups remained similar with increased sample size suggests that there are certain characteristics of the maps that make them easy or difficult to simulate with the FR. Landscape metrics did not resolve or distinguish these unknown characteristics. There were no clear trends in metrics across selection groups, suggesting that these indices may not be measuring the same aspects as human observers. Nevertheless, these aspects seem to be consistent across observers and are perhaps also important to organisms on the landscape. Perhaps the TT measures only differences in the quality of the developed recipes. However, there was no trend among map selection groups, metrics, or number of constraint layers used, suggesting that something is being tested independent of recipes.

Limitations of the Fractal Realizer

Because it generates fractal patterns using midpoint displacement, synthetic maps produced by the FR must be square, with side length $2^n + 1$. Using spectral methods to generate the fractals (Keitt 2000) would eliminate this square map restriction. One cannot take subsets of FR maps and still preserve the percent occupancy for each category. However, the FR can use absolute constraint layers to produce irregular shapes that are not $2^n + 1$ square while preserving *p.* Larger maps with more categories take longer to generate and sort. Currently, the recipe is manually generated, but this process could be automated. The FR is not good at preserving category associations, i.e., amount of edge between categories; indeed, the tool is designed to provide alternative realizations of these spatial associations. Some landscapes, especially anthropogenically shaped ones, may be inherently nonfractal; fortunately, these alternative spatial patterns are usually simpler and easier to simulate using more conventional tools.

CONCLUSIONS

The arbitration method used in the Fractal Realizer (FR) to integrate multiple categories preserves the fractal distribution of each category. In fact, fractals are thought to result in nature from the overlaid spatial juxtaposition of many "random" processes and perturbations (Keitt 2000). These stacked perturbations are reflected in the algorithms used to produce fractal patterns, including Fourier-based spectral techniques and multiple independent cuts (Peitgen and Saupe 1988).

Some might suggest that, by adding topography constraints, we have implicitly incorporated the landscape process of drainage and thus moved away from model neutrality. However, without linear asymmetrical directional features, most neutral maps are obviously unrealistic, and drainage is a process feature common to most natural landscapes.

Although the Turing Test (TT) indicates that maps produced by the FR are nearly indistinguishable observationally from the real maps that they simulate, the scores are skewed positively. The 0.55/0.45 binomial was the best fit of the models tested, but the ongoing score distribution is slightly broader and shorter than this abstract ideal, leaving some room for improvement. Skewness may have resulted from the elevation speckle, learning during the TT, or even discussions with colleagues who had already taken the TT.

A deeper philosophical quandry may be plausible. Can the FR perform *too well* as easily as too poorly? Should "perfect" synthetic maps strive only to reach the 50% incorrect choices line, or should we strive to make maps that are "more real," i.e., more attractive to human eyes, than the real ones? Any difference in histogram bar height from the 50% line indicates some difference between the real maps and the synthetic ones. Perhaps any differences between real and simulated maps should be viewed as a side effect of the FR. This is the equivalent of a two-tailed statistical test within an individual map.

We are not inclined to adopt this two-tailed viewpoint. The hard-to-simulate examples, maps 8, 13, and 16, have predominant linear features in common. These maps showed a northeast-southwest directionality from the Appalachian mountain range that was difficult to simulate. The directionless isotropic characteristics shared by the maps that had tall histogram bars suggests that it was these characteristics that made these maps difficult for experts to select from the synthetic versions. These patterns were amenable to simulation with fractals. Spatial indices and metrics were inadequate to fully characterize the differences in landscape pattern affecting observer choice.

The FR is useful for ecologists who need maps with alternative landscape arrangements whose categories have fixed occupancies and fractal dimensions. Of equal importance is the way in which we have tested this new neutral landscape simulator. The FR code is available from the corresponding author on request.
[**ADDENDUM**: Source code for the Fractal Realizer can be found at: http://research.esd.ornl.gov/~hnw/frdist/]

RESPONSES TO THIS ARTICLE

Responses to this article are invited. If accepted for publication, your response will be hyperlinked to the article. To submit a comment, follow this link. To read comments already accepted, follow this link.

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[Fig. 1] [Fig. 2] [Fig. 3] [Fig. 4] [Fig. 5] [Fig. 6] [Fig. 7] [Fig. 8] [Fig. 9] [Fig. 10] [Appendix 1] [Appendix 2]