Conceptual Framework of LTM (Pijanowski et al, 1997)

Six interacting modules:

Policy Framework

- Organizes the goals for the watershed's stakeholders (e.g. resource managers, landowners, planners)
- Goals made with certain expectations of outcomes and specific spatial and temporal scales in mind
    - example: township planner making decisions within township

Driving Variables

- Management Authority
    - institutional components and policies of land use (e.g. landowner)
- Socioeconomic
    - population change
    - economics of land ownership
    - transportation
    - agricultural economics
    - locations of employment
- Environmental
    - abiotic (e.g. distribution of soil types and elevation)
    - biotic (e.g. locations of T&E species)

Land Transformation

- change in
    - land use (urban, agriculture/pasture, forest, wetlands, open water, barren, non-forested vegetation)
    - land cover (types of agriculture, deciduous and coniferous forests, non-forested vegetation)

Intensity of Use

- land management practices, resource use & human activities
    - can be measured as chemical inputs (e.g. herbicides, salting roads) or natural resource use (e.g. subsurface water for irrigation)

Processes and Distributions

- Processes: groundwater & surface water flows, chemical and sediment transport, and geochemistry
- Distributions: plants and animals

Assessment endpoints

- indicators of ecological integrity and economic sustainability that should be:
    - relatively easy to quantify
    - unambiguous
    - correlated with changes to land use
    - reflect qualitative aspects of landscapes

LTM Spatial Framework

- Spatial extent
  - Watersheds (though it can be any definable region)
  - future model developments will focus on coupling land use change and hydrogeologic and geochemical processes

- Land use and features characterized as raster
  - Four classes: Parcel (30 x 30m), Plat (100 x 100m), Block (300 x 300 m), Local (1 km x 1 km)
  - Selection of resolution determined by:
    - process (land ownership changes versus hydrologic process)
    - availability of data
  - Anderson Level I land uses

GIS Integration: Six step

1A: Create driver variable grids to represent "relative transition urban probabilities"
1B: Calculate spatial interactions for each cell in grid
  - Neighborhood
    - trends and patterns in neighboring locations influence a cell's land use transition probability
  - Distance
    - Euclidian distance converted to relative probabilities of land transition
  - Patch Size
    - size of the parcel of land will influence land use conversion
  - Site Specific Characteristics
    - natural qualities (e.g. soil type or elevation) influence suitability
    - policy may "lock up" or "promote" conversion

1C: Determine "raw" values for each grid cell
1D: Scale raw values so that there are an equal number of values between 10 (greatest probability of urbanization) and 1 (least probability)
1E: Produce "driving variable grids"
1F: Multiply by driving variable weight

2: Sum all driving variable grids and create final driving variable grid

3a: Identify "non-buildable" sites (due to policy, ownership, environment)
  - Non-buildable = 0, Buildable = 1

3b: Produce "building exclusion" grid

4: Produce "urban pressure grid"
  - Multiply "building exclusion grid" with the "integrated driving variable grid"

5a: Produce “area to be transformed grid”
- Multiply “nonurban grid” and “urban pressure grid”

5b: Scale values into percentile classes so that each percentile is represented by equal number of cells

5c: Produce primary output

6: Determine “critical threshold value”(# cells to be transformed)
- Amount of future urban land
- $U_i(t) = (d_i P / d_i t) * A_i (t)$
- U = amount of new urban land required in time interval *t*
- *i* = spatial extent of population statistics
- *P* = # new people
- *A* = per capita requirements for urban land
- Critical threshold value is proportion of current non-urban land use to the amount of new urban land use required in the future

Pilot Test
- Saginam Bay Watershed, Michigan
- Two modules: driving variables and land transformation
- 10 year time steps; change projected for next fifty years

Land Transformation Model Coupled with ANN (Pijanowski, in press)
- Four step process

Step 1: Processing spatial data
- inputs generated from a series of base layers with GIS
- represent land uses (agriculture parcels, urban areas) or landscape features (roads, rivers, lakeshores)
- binary cells (presence/absence)

Step 2: Applying spatial transition rules
- Four classes that quantify the spatial effects that predictor cells have on land use transitions
  - neighborhoods or densities
  - patch size
  - site specific characteristics
  - distance from location of predictor cell
- Certain locations coded to avoid transition (“exclusion zones”)

Step 3: integration of predictor variables
- ANN
  - “feedforward network” (three layers: input, hidden, output)
  - Stuttgart’s Neural Network Simulator version 4.2 used for design, training and prediction of the ANN
  - differ from statistical or algorithm models

        - do not require formal mathematical specification
        - not highly sensitive to noise
        - generate information that can be applied to data “it hasn’t seen before”
    - Four phases of ANN in land use prediction
        1. design of network and of inputs from historical data
        2. network training using subset of inputs
        3. testing of neural network using full dataset of inputs
        4. forecast change
    - output is a map of “change likelihood values”

Step 4: temporal indexing
- amount of land expected to transition to urban using “principle index driver”
- determined either by comparison of 1980 to 1990 change with GIS, or by population driver equation above
- projections made for ten-year time step

Case Study One: Michigan Grand Transverse Bay Watershed (GTBW)

LTM applied in two runs:

First (control run)
- project the pattern of urban development in 1990
- use an ANN trained on actual changes between 1980 and 1990 in one county

Second run
- extension of same ANN to project 1990 urban land development across all six counties in watershed

Ten “predictor variables” (slide)

ANN tested:

$$\frac{\text{\# of cells correctly predicted to change}}{\text{\# of cells that transitioned (based on GIS PID)}}$$

Evaluation
1. Does the model accurately predict the locations of urban development?
2. What predictor variables were found most influential in the model’s ability to identify urban land use change?

Results:

1. Land use change forecast

   0 = no observed change
   1 = observed change but not predicted by the model
   2 = no observed change but change predicted by the model
   3 = observed change and predicted change

   - Proportion of correct predictions was 0.46 (941/2073)
   - ANN has a more difficult time learning the characteristics that lead to change than those that lead to no change
   - critical threshold value of 0.28 used to transition enough cells to urban

2. Trained ANN on ten different nine-predictor variable models (each with one omission)
   - Used a scalable window goodness of fit algorithm to assess predictability across spatial scales (slide)
   - "quality of view" = most influential predictor variable at small scales
   - Two major inflection points
     - 700 m: nearly all predictor variables change direction from negative to positive slope (ranking is volatile)
     - 1900m: stabilization of effects

Model Assumptions

1. The patterns of each predictor variable remained constant beyond 1990
   - locations of roads and highways likely to change
2. The spatial rules used to build interactions between predictor cells and potential locations for transition remain constant over time
3. ANN remains constant over time
4. Amount of urban area per capita undergoing a transition is assumed to be fixed over time.

Case Study Two: Twin Cities Metropolitan Area (TCMA) & Detroit Metropolitan Area (DMA)

Poses two interesting questions:

1. Can neural nets generate network files that can be applied between two study areas?
   - "internal" versus "external" learning
   - network files created by the training of the TCMA and DMA regional driving variables sets are swapped

2. Is "learning" using the entire regional dataset and applied to a local dataset was better than learning directly from driving variables grids created from a subset or the regional dataset?
    - Is a network file generated from regional training as good as a network file created by training and testing on a single county (subset)?

Results:

Internal & External Exercise

Network file generated from DMA and TCMA driving variable grids were a good match, while TCMA network file was much less accurate when applied to DMA data.

- DMA neural net may be more generalized
- pattern of urban development may be less complex in TCMA than in DMA
- driving factors of change differ between the two: TCMA lacks a coastline

Regional and Local Exercise

Neural net does not bias itself when presented with a dataset from a larger area

- able to generalize across a region

Pijanowski, B.C., D.T. Long, S.H. Sage and W.E. Cooper. (1997). A Land Transformation Model: Conceptual Elements, Spatial Object Class Hierarchies, GIS Command Syntax and an Application to Michigan's Saginaw Bay Watershed. *Land Use Modeling Workshop.* Sioux Falls, South Dakota, June 3-5, 1997.

Pijanowski, B.C., Shellito, B.A., Bauer, M.E. and K.E. Sawaya. (2001). Using GIS, Artificial Neural Networks and Remote Sensing to Model Urban Change in the Minneapolis-St. Paul and Detroit Metropolitan Areas. *ASPRS Proceedings.* St Louis, Mo, April 21-26, 2001.

Pijanowski, B.C., D. Brown, B. Shellito and G. Manik. (in press). Using neural networks and GIS to forecast land use changes: A Land Transformation Model. *Computers, Environment, and Urban Systems.*