Learning with Resource Capacity Constraints

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The Application:

Recent research suggests that migration is the primary and most effective risk management tool employed by pastoralists (animal herders) in the east African ASAL, where rainfall is typically insufficient and too variable to support crop agriculture, so pastoralists instead maintain large livestock (cattle, camels, sheep, goats) herds. Each year the region experiences biannual dry seasons, so pastoralists form mobile "satellite camps" constituted by most of their herd, which travel throughout the region, sometimes up to hundreds of kilometers, searching for water and forage resources. Less mobile household members and a few lactating animals are commonly left behind at an immobile "base camp". Herd splitting and migration behaviors thereby drive livestock population dynamics and determine the standards of living for pastoralist communities. When herds thrive, the people thrive, and when herds crash, the people suffer, often falling into long-term destitution.

Huts in Logologo, Kenya.

A boy goat herder.

Camels at a watering trough in the Chalbi desert.

Main Objective:

To model the spatio-temporal herd allocation choices of pastoralists (livestock herders) in the arid and semi-arid lands (ASAL) of east Africa. The objective is to use data on herd movement choices to estimate the parameters of a spatially explicit dynamic model of household herd allocation over space and time and then use the parameterized model to simulate alternative policy or project interventions that might affect pastoralist behavior and resulting rangeland and herd dynamics.

An empty streambed during the dry season near Kargi, Kenya.

Importance of the Problem:

The research is important for multiple reasons. First, for those interested in the well-being of pastoralist people in the region, maintaining herds through migration is essential; herds constitute their primary asset stock and source of flow income, and those who fail to reach adequate water and forage typically lose their herds and then fall into long-term destitution. But little is known about the structural parameters that guide herder decision making and thus researchers and policymakers have little capacity to predict the consequences of changing patterns of rainfall, violence or forage availability on herd movements and population dynamics, and on resulting pastoralist well-being.

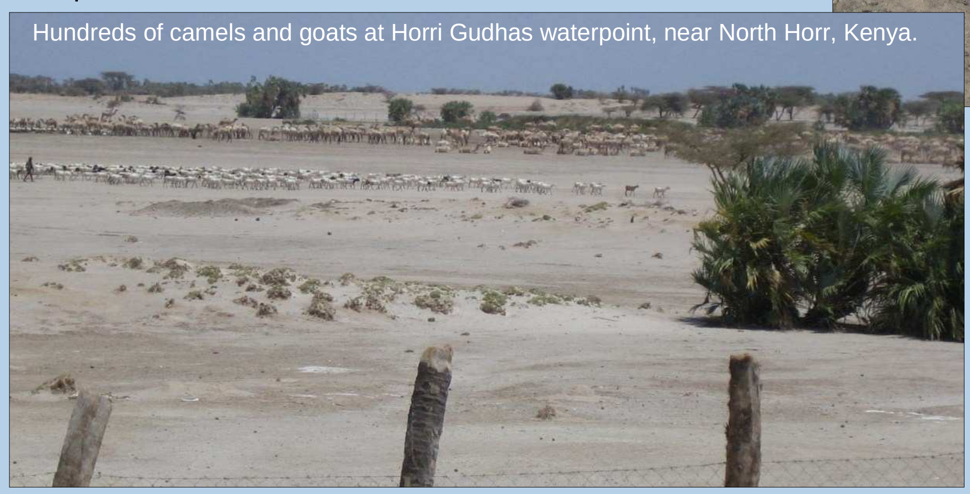
Second, herders' migratory behavior also has strong implications for environmental management. Pastoralists' herds regulate the natural environment of the east African ASAL, competing with wild ungulates for forage and water and affecting rangeland and high forest ecology in common property or open access rangelands. Given that land tenure arrangements are mostly open access, in practice we observe significant, localized environmental degradation from overgrazing. Herd movements can also lead to violent resource conflict between neighboring tribes and also with roving cattle bandits.

At El Dharo hand-dug well, near North Horr, Kenya.

Treating sheep for scrapies (disease) in a boma (corral).

Data Sources:

This effort will use data collected every three months over a period of three years (2000-2) from 150 households in northern Kenya by the USAID Global Livestock Collaborative Research Support Program (GL CRSP) Improving Pastoral Risk Management on East African Rangelands (PARIMA) project. The data include detailed household and herd composition data as well as the locations of all the water points used by sample herders each period.



Hundreds of camels and goats at Horri Gudhas waterpoint, near North Horr, Kenya.

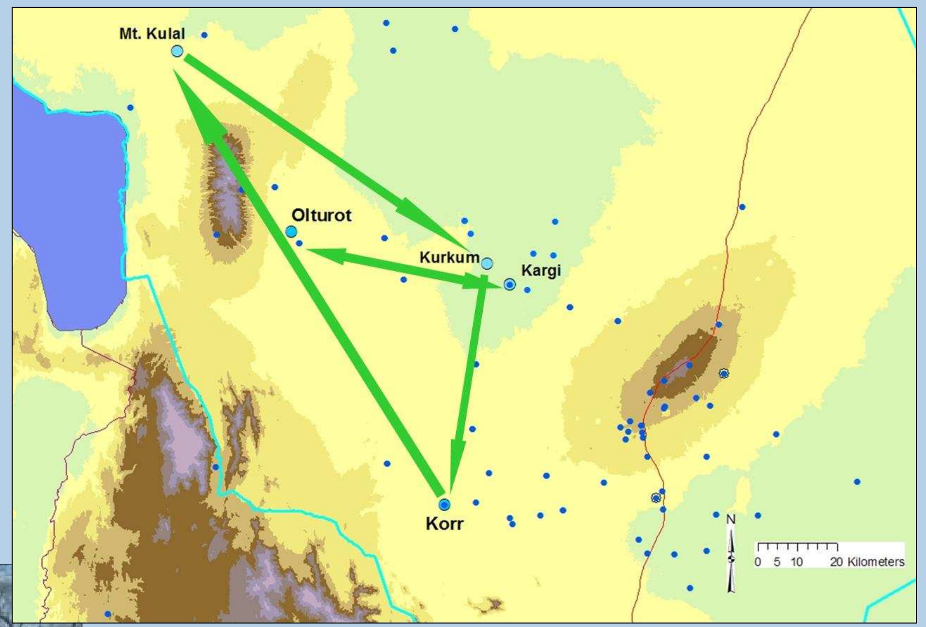
Funding Sources

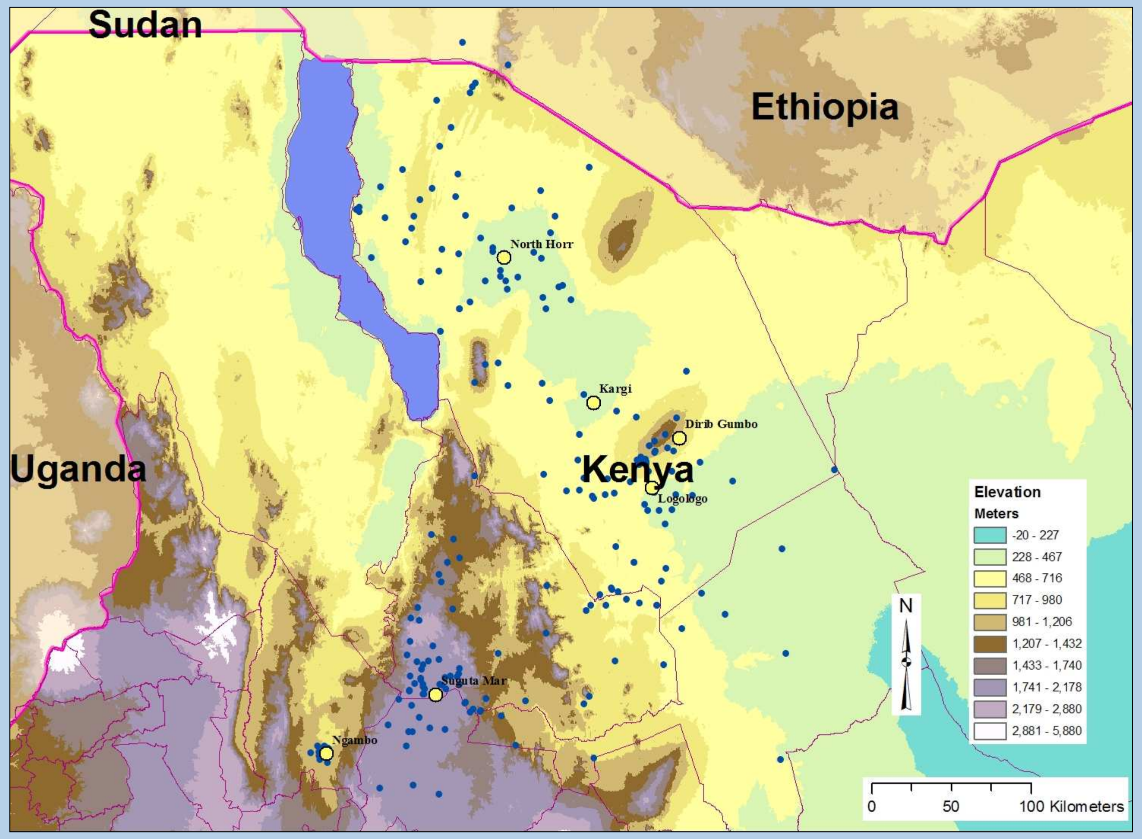
NSF Expeditions Award 0832782

USAID Global Livestock Collaborative Research

Support Program (GL CRSP) Improving Pastoral Risk

Management on East African Rangelands (PARIMA) project.





Small Stock Routes Dec. 2000 – Nov.2001

The Modeling:

We consider the problem of learning while enforcing resource capacity constraints. In our problem setting, each instance requires a certain amount of a resource and each class has a finite resource capacity. The sum of the required resources from all instances assigned to a class should not exceed the class resource capacity. The goal is to learn a model that classifies as accurately as possible for new instances while enforcing the class resource capacity constraints.

SVMCAP OPTIMIZATION

$$min_{w,\xi\geq 0,\delta\geq 0} \quad \frac{1}{2}\|w\|^2 + \frac{l_1}{n}\sum_{i=1}^{n}\xi_i + \frac{l_2}{m}\sum_{j=1}^{m}\delta_j$$

$$s.t. \quad \forall 1\leq i\leq n, \forall \widehat{y}\in \mathbf{S}:$$

$$w^\top\phi(x_i,y_i) \geq w^\top\phi(x_i,\widehat{y}) + \Delta(y_i,\widehat{y}) - \xi_i \qquad (1)$$

$$\forall y_j\in \mathbf{S}, 1\leq j\leq m:$$

$$\sum_{i=1}^{n} L_i \mathbf{1}_{\{arg\max_y w^\top\phi(x_i,y)=y_j\}} \leq C_j + \delta_j \qquad (2)$$

Algorithm 1 SVM$_{cap}$ Training Algorithm

Input: $\mathbf{x}$, C, ϕ, Δ, T, λ
w_0=**0**
for t = 1, 2, . . ., T **do**
  A=$\emptyset$
  for i = 1, 2, . . ., $|\mathbf{x}|$ **do**
    $\widehat{y}$= $arg\max_{y\neq y_i}(w_{t-1}^T\phi(x_i,y)+\Delta(y_i,y))$
    if $w_{t-1}^T\phi(x_i,y_i) < w_{t-1}^T\phi(x_i,\widehat{y})+\Delta(y_i,\widehat{y})$ **then**
      A=$A\cup(x_i,y_i,\widehat{y})$
    end if
  end for
  w_t=(1-$\frac{1}{t}$)w_{t-1}+$\frac{1}{\lambda t|\mathbf{x}|}\sum_{(x_i,y_i,\widehat{y})\in A}(\phi(x_i,y_i)-\phi(x_i,\widehat{y}))$
  for j = 1, 2, . . ., $|\mathbf{y}|$ **do**
    if $\sum_{i=1}^{|x|} L_i\mathbf{1}_{\{arg\max_y w_t^\top\phi(x_i,y)=y_j\}} > C_j$ **then**
      UpdateCapacityViolation(j,t);
    end if
  end for
  if $\|w_t\| > \frac{1}{\sqrt{\lambda}}$ **then**
    w_t=$\frac{1}{\sqrt{\lambda}}\frac{\mathbf{w}_t}{\|\mathbf{w}_t\|}$
  end if
end for
Output: $\mathbf{w}_T$

Results on accuracy and resource capacity violation:

Table 2: 9-fold cross validation results on the Pastoral Dataset (λ=0.1)

Method	Acc.	σ	AV	σ	CV	σ	t
Ground Truth	100	0	86.6	4.2	44.0	4.8	-
Bin-packing	4.9	1.5	<1	<1	<1	<1	<5
SVM	20.8	6.5	96.6	1.9	58.5	4.2	398
SVM$_{cap}$	**21.2**	6.9	**9.2**	10.3	**5.2**	6.3	512

Table 3: 10-fold cross validation results on the Forest Fire Dataset (λ=0.01)

Method	Acc.	σ	AV	σ	CV	σ	t
Bin-packing	25.7	9.1	18.6	24.3	<1	<1	<1
SVM	**76.2**	4.1	74.7	16.0	12.3	6.1	1.6
SVM$_{cap}$	64.0	13.8	**35.7**	18.6	**1.4**	1.9	2.7