

SEDIMENT ROUTING SYSTEM RESPONSE TO
TECTONIC ACTIVITY IN THE ARGENTINE PRECORDILLERA:
SIERRA LAS PENAS-LAS HIGUERAS

by

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A thesis submitted in partial fulfillment
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of

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TABLE OF CONTENTS

1. GENERAL INTRODUCTION	1
2. FIRST MANUSCRIPT	6
Contribution of Authors.....	7
Manuscript Information	8
Title Page	9
Abstract.....	10
Introduction.....	11
Background.....	12
Geologic Setting.....	12
Sediment Routing System.....	14
Terrain Analysis.....	16
Drainage Basin Delineation	16
Extracted Parameters	17
Open Source Geographic Information System	18
Methods.....	18
Data Description	18
DEM Preprocessing	19
Terrain Analysis.....	20
Standard Terrain Analyses.....	20
Identification of Drainage Basin Outlets	20
Delineating Drainage Basins.....	21
Flow Path Length.....	21
Parameters.....	22
Statistical Procedures	22
Results.....	24
Discussion.....	24
Conclusions.....	26
Tables.....	27
Figures.....	28
Acknowledgements.....	36
References.....	37
3. SECOND MANUSCRIPT	41
Contribution of Authors.....	42
Manuscript Information	43
Title Page	44
Abstract.....	45
Introduction.....	46

TABLE OF CONTENTS – CONTINUED

Background	47
Alluvial Fan Classification	47
Image Classification.....	49
Decision Tree Classification	49
Classification Tree Analysis	50
Random Forest Classification	51
Methods.....	52
Study Area	53
Data Description	53
Reference Data Collection	54
Modeling	55
CTA Modeling.....	56
RF Modeling.....	56
Accuracy Assessment	57
Results.....	58
Level 1 Classification	58
Level 2 Classification: Proximal-Synthetic Fans.....	59
Level 2 Classification: Distal-Synthetic Fans.....	60
Discussion.....	61
Level 1 Classification	61
Level 2 Classification	62
Interpretation of Explanatory Variables.....	63
Conclusions.....	64
Tables.....	66
Figures.....	70
Acknowledgements.....	77
References.....	78
4. GENERAL CONCLUSION.....	81
REFERENCES CITED	83
APPENDICES.....	91
APPENDIX A: Terrain Analysis Flow Chart.....	92
APPENDIX B: Remote Sensing Flow Chart.....	94

LIST OF TABLES

Table	Page
2.1 Terrain Analysis Morphometric Parameters	27
3.1 Remote Sensing ASTER Data Description.....	66
3.2 Classification Scheme	67
3.3 Level 1 RF Relative Importance	67
3.4 Level 1 CTA Accuracy Assessment	68
3.5 Level 1 RF Accuracy Assessment	68
3.6 Level 2 Proximal-Synthetic Fans CTA Accuracy Assessment.....	68
3.7 Level 2 Proximal-Synthetic Fans RF Accuracy Assessment.....	69
3.8 Level 2 Distal-Synthetic Fans CTA Accuracy Assessment.....	69
3.9 Level 2 Distal-Synthetic Fans RF Accuracy Assessment.....	69

LIST OF FIGURES

Figure	Page
1.1 Location Map of Study Area.....	4
1.2 Generalized Cross Sections.....	5
2.1 Location Map of Erosional Sector	28
2.2 Drainage Basins	29
2.3 Basin Length	30
2.4 Basin Elevation	31
2.5 Basin Slope	32
2.6 Elongation Ratio Histogram	33
2.7 Fitted Residuals and Normal Q-Q Plot.....	33
2.8 Linear Regression Model.....	34
2.9 Drainage Basin Block Diagrams.....	35
3.1 Location Map of Depositional Sector	70
3.2 Level 1 Unpruned CTA Tree Model.....	71
3.3 Level 1 CTA Cross Validation	71
3.4 Level 1 Pruned CTA Tree Model	72
3.5 Level 1 RF Stability Graph.....	73
3.6 Level 1 Classified Image	74
3.7 Level 2 Proximal-Synthetic Fans Pruned CTA Tree Model.....	75
3.8 Level 2 Proximal-Synthetic Fans Classified Image.....	75
3.9 Level 2 Distal-Synthetic Fans Pruned CTA Tree Model.....	76

LIST OF FIGURES -CONTINUED

Figure	Page
3.10 Level 2 Distal-Synthetic Fans Classified Image.....	76

ABSTRACT

Alluvial fan deposition in the Argentine Central Precordillera is part of a sediment routing system that changes along strike of an active thrust front. This study area is partitioned into erosional and depositional sectors for analysis. The erosional sector drainage basins are analyzed using topographic data from a digital elevation model, to see how morphology changes with fault displacement. Drainage basins become shorter with more displacement. The depositional sector alluvial fans are classified using spectral characteristics from satellite imagery. The fans are classified based on thermal, near infrared, and elevation parameters. Fans close to the thrust front are interpreted to be old sheetflood deposits, with younger fans more distal from the front in the foreland. In this setting, progressive fault displacement causes shortening of the erosional sector, increasing the efficiency of sediment evacuation from the range, and causing a progradation of sheetflood fans into the foreland basin. Remote sensing analysis techniques are useful for characterizing the sediment routing system of alluvial systems where field-based information (geodetic, seismic, structural and lithologic data) is not available.

GENERAL INTRODUCTION

Sedimentation in the foreland basin system of the Argentine Central Precordillera is controlled by active faulting. Fault displacement controls both initiation and development of alluvial fan depositional environments by uplifting thrust sheets, typically forming frontal anticlinal ridges. Sediment provenance and degree of sediment recycling are controlled by basin partitioning with foreland directed dispersal and hinterland directed dispersal in piggyback basins (Ori and Friend, 1984; Schmitt and Steidtmann, 1990; Burbank et al., 1996; DeCelles and Giles, 1996). A topographic barrier at the surface determines drainage pathways, with synthetic sedimentation in the direction of tectonic transport, and antithetic sedimentation directed opposite.

Drainage networks developed at the orogenic front generate complex interactions among localized alluvial fan and regional fluvial systems (Schmitt and Costa, 2006). The competition between small transverse alluvial fans and large trunk lateral drainage systems strongly affects the sedimentation pattern. Fluvial systems are efficient at evacuating sediment from fold and thrust belts, but that efficiency allows the sedimentation locus to move away from the most active thrust faulting. Alluvial fan systems produce deposits that are diagnostic of the most proximal sedimentation pattern in tectonically active settings.

Understanding the way alluvial fans form allows kinematic reconstruction of ancient tectonic settings. Sedimentary rocks serve as the repository of geologic history. Past research (Allen and Hovius, 1998; Leleu et al., 2009) has sought to translate

sedimentation in the rock record to ancient sediment routing systems through palaeocatchment reconstruction. It is precisely this multidisciplinary approach, with integration of the stratigraphy of the rock record and modern hydrologic processes that provides the link between modern and ancient sediment routing systems (Allen, 2008).

Observation of modern systems is critical to the understanding of ancient deposits, which rarely preserve the complete spatial relationships of the sediment routing system. Describing the evolution of sediment routing systems requires observation throughout system development. Few studies have considered the temporal evolution of transverse sediment routing systems along strike of a single emergent propagating fault.

The difficulty of capturing changes in a system evolving over a geologic time scale, with shortening rates of 5-9 mm/yr (Kendrick et al., 2003; Brooks et al., 2003), is surmounted by a space-for-time dimension substitution (ergodic principle) to observe fault-growth related changes in sedimentation. Fault propagation along tectonic strike is used as a proxy for relative timing of uplift, erosion and deposition of associated alluvial fans, with the northern part of the study area analogous to an immature system and the southern part analogous to a mature system. In this setting, the fault loses displacement on the north end of the study area, where it curves on a lateral ramp.

The study area of the Sierra Las Peñas-Las Higueras in the Argentine Central Precordillera between the cities of Mendoza and San Juan (Fig. 1.1) contains pronounced evidence of neotectonic activity. The region is currently seismically active, with several damaging earthquakes occurring in the last century. The city of Mendoza was destroyed

by an earthquake in 1861, and was damaged by a magnitude 5.4 event in 1985, and a magnitude 7.4 earthquake destroyed the city of San Juan in 1944 (Costa et al., 2000b).

The seismic activity accompanied movement on thrust fault structures of the region that are well known from both surface and subsurface data (Vergés et al., 2007) (Fig. 1.2). Numerous scarps from faults intersect the land surface, and thrust-belt structures have been imaged in subsurface seismic data (Costa et al., 2000a). Multiple generations of fan surfaces and Quaternary growth strata have also been recognized as a product of neotectonism (Costa et al., 2006; Schmitt and Costa, 2006).

The objective of this research is to use new remote sensing methods to determine how structural activity influences the sediment routing system. The erosional sector of the sediment routing system consists of the drainage basins developed in the hanging wall of the thrust system. The depositional sector of the sediment routing system consists of alluvial fan deposits below drainage basin outlets. To examine the relationship between fault growth and the transverse alluvial fan sediment routing system, observational studies are conducted of the Sierra Las Peñas-Las Higueras.

This thesis is composed of two separate manuscripts that examine surface characteristics of the system using remotely sensed data. The motivation of this study is to demonstrate whether or not surface characteristics of morphology and spectral reflectance are quantifiable through the transition along the fault. The erosional sector of the sediment routing system is targeted in a morphometric study of the topography of drainage basins. The depositional sector of the sediment routing system is classified based on spectral characteristics of fan surfaces using two decision tree methods.

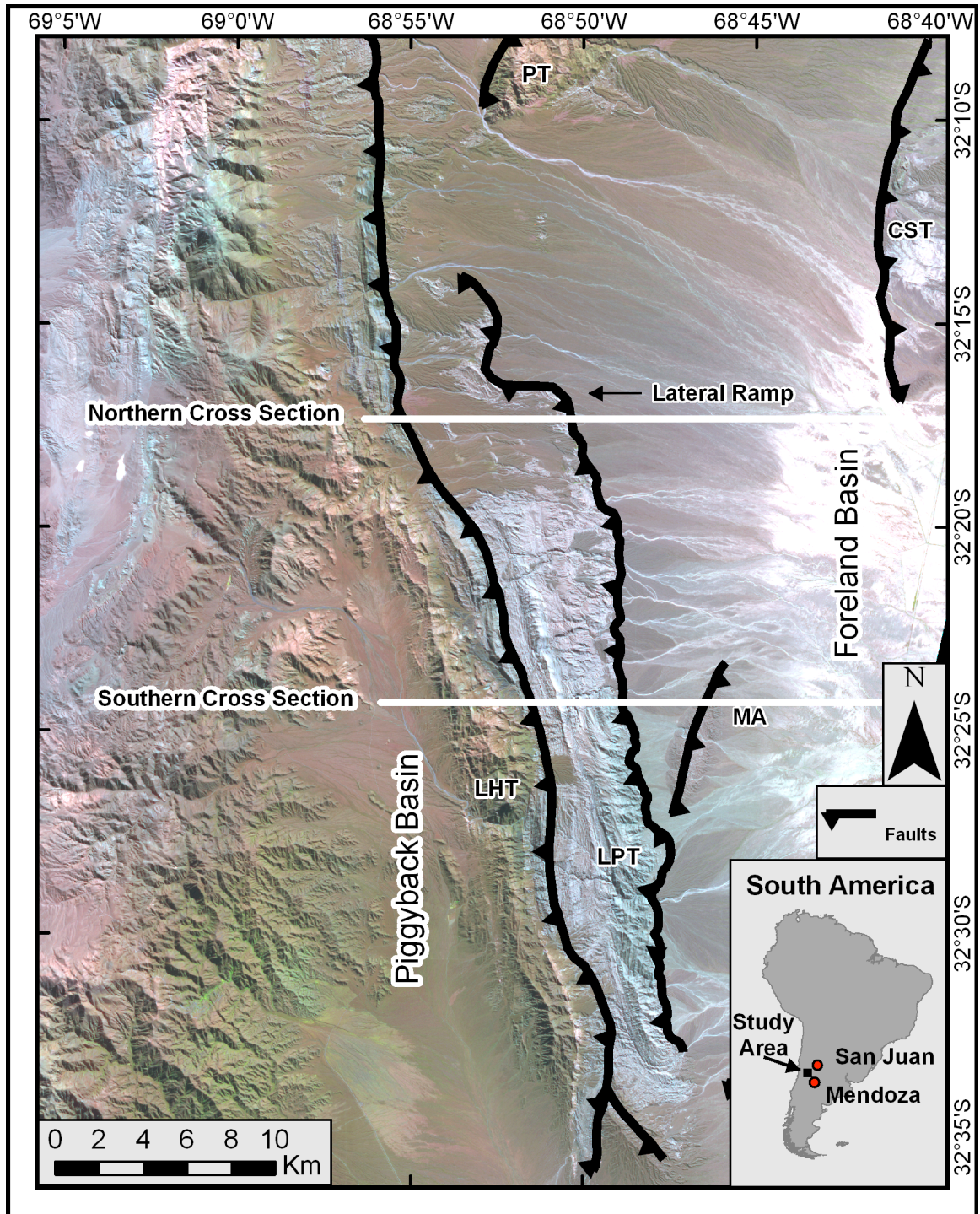


Figure 1.1. Neotectonic features of the study area. Background imagery is standard false-color composite of ASTER bands 4, 3, and 2. Faults are either expressed at the surface, or at depth. LHT, Las Higueras thrust; LPT, Las Peñas thrust; MA, Montecitos anticline; CST, Cerro Salinas thrust; PT, Pedernal thrust.

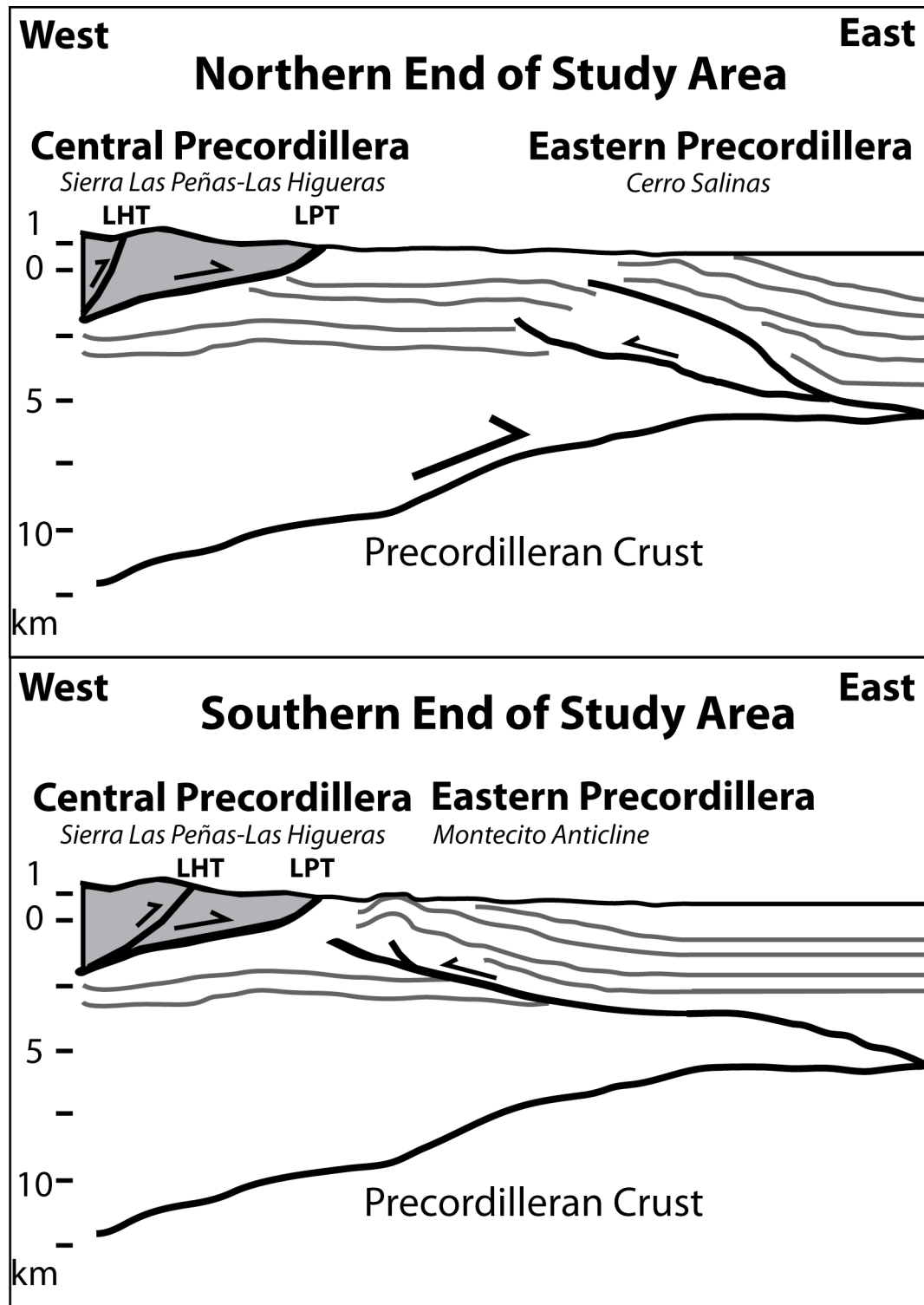


Figure 1.2. Generalized cross section of the north and south ends of the study showing neotectonic faults. After Verges et al., 2007.

FIRST MANUSCRIPT

TERRAIN ANALYSIS OF THE EROSIONAL SEGMENT
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Abstract

Sedimentation in the foreland basin system of the Central Argentine Precordillera is controlled by fault propagation along strike and into the basin. The source area of the sediment routing system changes with displacement along the Las Peñas and Las Higueras thrust faults. Drainage basins develop as a result of uplift and denudation of thrust sheets. Describing the evolution of a sediment routing system requires observation throughout basin development. Since it evolves on a geologic time scale, an appropriate substitution is mapping and evaluation of a system that changes along strike of the propagating thrust faults. Mapping with terrain analysis captures these landscape-scale changes in source areas of sediment routing systems along active ranges.

The objectives of this study were to identify drainage basins using a 30-m resolution digital elevation model and assess how their morphometric parameters change along strike away from a lateral ramp. Hydrologic terrain analyses were used to identify the basins. Statistical summaries and correlations were made with parameters from the basins. Every one km increase away from the lateral ramp is associated with an elongation ratio (of diameter km to length km) increase of 0.021 with a 95% confidence interval from 0.013 to 0.029. Results indicate that elongation ratio is a diagnostic morphometric parameter in the evolution of the sediment routing system. Exogenic surface processes are linked with endogenic tectonic processes to control source area development.

1. Introduction

The Argentine Central Precordillera fold and thrust-belt and associated foreland basin is an evolving orogen-basin system that provides a snapshot of interaction between progressive surface uplift and erosion. Alluvial fan depositional systems are considered to be the most diagnostic sedimentation pattern associated with active tectonism (Fraser and DeCelles, 1992). The frontal ranges result from relative uplift of the hanging wall in relation to the footwall in the basin. Uplift along faults initiates drainage basin development, providing a gradient and a source area for material in the sediment routing system. Increase in relief and in transport potential allows more sediment to exit the drainage basin (Allen, 1997). Drainage basin characterization upstream from the depositional environments provides a context to explore causal factors in fan formation.

The objective of this research is to document how structural activity influences the erosional sector of the sediment routing system. To examine the relationship between fault displacement and sediment dispersal, an observational study of basin morphology is conducted on the Sierra Las Peñas-Las Higueras in Mendoza Province, Argentina. Following the ergodic hypothesis, the entire range is used as an analogue for drainage basin response to thrusting (Burbank et al., 1996). The study attempts to use lateral changes in basin morphology along the fault as a substitute for a time sequence of deformation and erosion.

As fault displacement increases, drainage basins develop in the hanging wall of a thrust. It is difficult to directly measure fault displacement and sediment transport

potential, so proxy morphological parameters are used to represent these variables. Southern basin morphologies are analogous to older, developed basins, and northern basin morphologies are analogous to young basins. Morphology is evidence of the processes competing in active systems.

One of the most important new tools in analysis of modern sediment routing systems is morphometric survey of a drainage basin (Burbank and Verges, 1994; Delcaillau et al., 2006; Singh and Jain, 2009), where parameters describing the geomorphic character of drainage basins are extracted from topographic data. Drainage basins and parameters can be identified and derived from increasingly available 30-m digital elevation models using terrain analysis in a geographic information system. This study provides documentation of drainage basin parameters in the context of modern thrust propagation. It evaluates evidence that drainage basin elongation ratio changes with distance from the lateral ramp along the fault.

2. Background

2.1 Geologic Setting

The present study focuses on the sediment routing system of the Sierra Las Peñas-Las Higueras (Fig. 2.1). This range is at the front of the Argentine Central Precordillera, on two NNW-striking east-verging thrusts, the Las Peñas thrust (LPT) and Las Higueras thrust (LHT) (Costa et al., 2000). Surface deformation and segmentation of sedimentary

deposits equates to uplift of the most proximal parts of the foredeep. The LPT uplifts Neogene (Miocene-Pliocene) rocks in the hanging wall thrust sheet that are mainly fluvial and alluvial sandstone, mudstone and conglomerate. The LHT uplifts Paleozoic (Silurian-Devonian) marine rocks (Verges et al., 2007). The Argentine Central Precordillera is an active system, with documented recent movement along frontal thrusts (<1.6 ka (Costa et al., 2000)).

The geometry of the thrust belt at the south end of the study area ($32^{\circ}45'S$) shows both thrusts gradually losing displacement and becoming thrust-cored anticlines, with a divergent curved splay at the tip of the LHT (Verges et al., 2007) (Fig. 1.1). At the north end of the range ($-32^{\circ}15'S$) the LPT and LHT show gradually decreasing Quaternary deformation, with the LPT folded on a lateral ramp, and the LHT merging into the Pedernal thrust (Ahumada and Costa, 2009).

Juxtaposed with the Central Precordilleran range are the hills of the Eastern Precordillera, cored by the active Cerro Salinas thrust and Montecitos anticline structures (Verges et al., 2007). These structures are west-verging backthrusts of the triangle zone of the fold and thrust belt (Fig. 1.2), deforming Neogene (including Quaternary) foreland basin terrestrial strata. The Montecitos anticline is overthrust by the LPT (Verges et al., 2007), defining the southern boundary of the study area. The northern boundary of the study area is located at the latitude of the Cerro Salinas thrust, where the expression of the LPT curves to the west on a lateral ramp (Fig. 1.1).

The range is an ideal location to study drainage basin patterns because it is geographically segmented from the rest of the Central Precordillera to the north by a

lateral ramp on the LPT and the transfer zone of the LHT to the Pedernal thrust (Ahumada and Costa, 2009). Hydrologically, large transverse drainage loci occur at the north end of the study area, where displacement is transferred to the Pedernal thrust, and at the south end, at the Río de Las Peñas near the Montecito anticline (Fig. 1.1). Thus the study area extends along a uniform stretch of the topographically linear thrust front between two areas of changing structural controls (Keller and Pinter, 1996; Talling et al., 1997). Sheetflood alluvial fan deposition occurs in the proximal foreland basin in this section of the thrust front. Older fans located at the thrust front are incised by young, active sheetflood fans. This moves the locus of sedimentation in the depositional environment eastward into the basin.

Climatically, the study area may be considered uniform at the scale of investigation, with minimal variation along the strike of the thrust fault. The Provinces of Mendoza and San Juan have a hot arid desert climate (Köppen classification BWh (Kottek et al., 2006)). Weather systems from the Pacific Ocean are blocked by the Andes, and moisture-laden air masses from the Atlantic Ocean lose humidity travelling over the Pampas. Total annual rainfall received in Mendoza is about 223 mm, most of which (65%) falls in the months of December to March (Servicio Meteorológico Nacional).

2.2 Sediment Routing System

The interplay of processes in the sediment routing system of a foreland basin pivots on concepts of base level and sediment accommodation with transfer of sediment

from the topographically uplifted parts of the orogenic wedge to depozones both in the wedge top and proximal foreland basin during mountain building (DeCelles and Giles, 1996). Clues to understanding the kinematic history of active areas rely on the assumption that exogenic processes governing the erosional sector of the sediment routing system are sensitive to endogenic uplift along active faults (Schumm, 1986). Common tectonic and lithologic substrates are hypothesized to modulate surface processes in drainage domains (Leeder et al., 1991).

The erosional sector of a sediment routing system is the area where surface processes cause a flux of material from a topographic source drainage basin down gradient (Allen, 1997). Erosive processes responsible for sediment dispersal are based on mechanical and chemical weathering. The intensity of erosion is controlled by the way water moves through the basin (Fraser and DeCelles, 1992). Increasing gradient causes higher energy flows, and incision in the drainage basins.

This study of a modern growing fault system examines the geomorphological response in a deforming terrain. Investigation of drainage system development can be used to describe landscape response to fault activity (Burbank and Anderson, 2000). Geomorphology of drainage basins reflects the hydrologic processes responsible for dispersing sediment out of an uplifted range into the proximal basin. Digital terrain analysis of topography in geomorphologic applications is used as a surrogate for the spatial variation of conditions and processes in the drainage basins (Seibert and McGlynn, 2007).

2.3 Terrain Analysis

2.3.1 Drainage Basin Delineation

The goal of a flow routing technique is to partition the DEM into drainage basins based on drainage divides and flow paths (Band, 1986). The direction of flow follows the surface gradient, and upslope area can be calculated from a low point in the drainage basin. Upslope area from a point is a proxy for flow or discharge. The algorithms process a DEM downwards starting at the highest elevation cell in the grid, and working towards the lowest elevation cell. The boundary between the erosional and depositional sectors, being both the drainage basin outlet and alluvial fan apex, should be used as the low point for drainage delineation. In this study, the objective was to achieve flow paths that join at this single point. This allows calculation of upslope area in the sediment routing system, and delineation of drainage basins (Moore et al., 1991).

There are different algorithms available for flow routing to delineate drainage basins. The eight-flow direction matrix (D8) for a grid dataset by O'Callaghan and Mark (1984) is a simple and commonly used flow algorithm. The D8 method has been criticized for introducing grid bias by having a low resolution of flow directions (Tarboton, 1997). Another more complex method is the infinite number of flow directions D_{∞} method, in which the flow could split and drain into two downslope cells (Tarboton, 1997). Multiple flow direction algorithms (Quinn et al., 1991; Seibert and McGlynn, 2007) allow flow from a pixel to disperse to many neighboring pixels.

The D8 method was chosen over other, more complicated methods because the main objective was to delineate basins that flow to a single point (cell). This algorithm uses the direction of the steepest downward slope on the eight triangular facets formed in a 3 x 3 grid cell window centered on the grid cell of interest to determine the flow direction. Flow direction and slope grids are calculated from this function.

2.3.2 Extracted Parameters

Morphometric parameters are topographic indices measured from individual drainage basins. Basic parameters are area, basin length, and maximum and minimum elevation. Basin area and length are indicators of the size of an individual basin and total amount of potential discharge. The maximum and minimum elevations correspond to the highest and lowest points in each drainage basin and are used to calculate slope and relief parameters.

Several derived parameters are commonly calculated from basic parameters (Delcaillau et al., 2006). Basin length corresponds to the maximum length of the drainage basin measured parallel to the main drainage line. Basin relief is the difference in elevation between the highest and lowest point of the basin. Relief controls stream gradient, and thus the capacity and competence of sediment transport. Basin slope is calculated by dividing relief by basin length. Slope is the angle of a drainage basin, which controls water runoff and infiltration. Elongation ratio is calculated using basin area and length (Schumm, 1956). This ratio is a parameter used to quantify drainage basin shape, which has a strong influence on sediment transport processes.

2.3.3 Open Source Geographic Information System

Terrain analysis was conducted in the open-source System for Automated Geoscientific Analyses (SAGA) software (version 2.0.4). SAGA was chosen to implement terrain analysis in this research for several reasons. This environment was designed to use spatial algorithms in containers called modules, which represent the different geospatial methods. The module libraries contain descriptions of scientific methods, with citations of original authors and journal article references of original publications. Implementation of methods is flexible, with user control on input parameters and algorithm thresholds. Methods are computationally efficient in SAGA because the software was originally developed with a research focus on the analysis of raster data, particularly of Digital Elevation Models (DEM) (Conrad, 2006).

3. Methods

3.1 Data Description

This study utilizes a global DEM generated from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery. The 30-m DEM is derived from 15-m 3N (nadir) and 3B (backward looking) stereoscopic data from the visible near infrared sensor (0.78 to 0.86 μm). The DEM was produced by automatic processing of ASTER Level-1A data, including stereo-correlation, cloud masking to remove clouded

pixels, stacking all cloud-screened DEMs, removing residual bad values and outliers, averaging selected data to create final pixel values, and then correcting residual anomalies before partitioning the data into 1° by 1° tiles (USGS, 2009). Estimated accuracies for this product are 20 m at 95% confidence for vertical data and 30 m at 95% confidence for horizontal data. The ASTER global DEM contains anomalies and artifacts that can introduce large elevation errors on local scales.

3.2 DEM Preprocessing

In conducting the terrain analysis, it was noticed early on that the DEM had striping error on the scale of 10x10 pixels in both the N-S and E-W directions. Striping in a DEM consists of linear parallel ridges and depressions, which alter flow routes, and can be caused by DEM resolution. Spatial filtering of the DEM can remove these stripes, but has a smoothing impact, which alters pixel values. Filtering was useful in this study, since the aim was to extract useful parameters from the DEM, and not just measure the elevation values. Destriping 1 module in SAGA by Perego (2009) was used on the DEM in order to reduce vertical errors associated with striping. To adjust the elevation value of the central cell, the average of the values within a distance of 2 cells was calculated, using only values that were different than the central one, and giving more weight to the nearer cells.

Anomalies and artifacts in the DEM related to processing from imagery can cause pits (extremely low elevation values) that do not exist. These artifacts were removed with

a Fill Sinks module in SAGA, which identifies and fills surface pits in digital elevation models (Wang and Liu, 2006). It also maintains a downward slope in the DEM to allow flow route calculation to the drainage basin outlet. The DEM was checked with and without this step in order to confirm that filling pits and depressions did not mask true topographic basins, concealing temporary storage areas in the sediment routing system.

3.3 Terrain Analysis

3.3.1 Standard Terrain Analyses

After the DEM was preprocessed, standard terrain analyses were conducted in SAGA's Compound Analyses module (Conrad, 2006), including creation of slope, channel network, and length-slope (LS-factor) parameters. The slope (converted to degrees below horizontal) parameter was summarized for each drainage basin. Channel network (showing stream order) and LS-factor (the erosive vs. depositional power of streams) were used in identification of drainage basin outlets.

3.3.2 Identification of Drainage Basin Outlets

Outlet points were located using three factors. First, points were on-screen digitized along the channel network so the catchment area upslope captured the entire basin. Second, outlets were identified on a visible-near infrared image, and moved to the break in slope along the thrust front, separating each drainage basin from its alluvial fan. Finally, the points were adjusted to a pixel where the LS-Factor changed to less than one,

indicating change from erosional to depositional regimes. This caused some of the outlets to shift east of the fault, indicating a migration of the hydrologic knickpoint into the foreland.

3.3.3 Delineating Drainage Basins

Drainage basins were delineated using the interactive Upslope Area Hydrology module in SAGA (Moore et al., 1991). Pixels in the grid that were upslope from the drainage basin outlets were identified in the DEM and separated into individual grids for each basin (Fig. 2.2). Basin area was calculated using the upslope area from drainage basin outlets along the fault.

3.3.4 Flow Path Length

The last parameter derived in SAGA was drainage basin flow path length. The individual basins were parallel processed in a hydrology module in SAGA using the D8 flow algorithm to measure the contributing area to each pixel. Seeds for starts of the flow path length were placed at the point in the drainage basins with the furthest overland flow to the outlet (Fig. 2.3). The seeds were located based on the longest channel reach, and the overland flow distance to channel network (derived from the SAGA module by Conrad, 2006). These seeds were used with the outlets on the DEM using the Flow Path Length Hydrology module in SAGA (O'Callaghan and Mark, 1984). Length was calculated as accumulation along the longest downslope path from the basin seed to the outlet.

3.3.5 Parameters

Parameter grids were clipped to drainage basins to create parameter sets for each basin (Table 1) (Fig. 2.3, Fig 2.4 and Fig 2.5). Elongation ratio was calculated using area and length as the ratio between the diameter of a circle of the same area as the basin and length of the basin (Schumm, 1956).

3.5 Statistical Procedures

The topographic information derived from terrain analyses is used in an observational study. The population in this study is assumed to be representative of a larger population of basins in hanging walls on thrust faults within the region. The observed units are drainage basins (Fig. 2.2), and the sample size is limited to the entire population of basins in the hanging wall block of the Las Peñas thrust fault. The outlet spacing was measured as distance from the fault lateral ramp (Fig. 2.2).

The causal variable of interest in each basin is distance of the outlet from the lateral ramp, which is a proxy for increasing fault displacement. Distance was chosen with a pinning point (0 meters) as the point where the fault curves west on a lateral ramp, and loses displacement. Thus the basins are hypothesized to change with increasing distance from the fault ramp with immature basins located in areas of lower fault displacement (near Basin 1 at the north end) and mature basins located at the areas of greater fault displacement (near Basin 8 at the south end) (Fig. 2.2). The response

parameters of interest, measured from the drainage basins, are proxies for drainage basin development (Table 1). Regression of these data was used to tie the drainage basin response parameters back to a potential causal variable.

This study implemented simple linear regression with the morphometric parameters as a function of position along the fault. Assumptions for the statistical analysis were checked in an exploratory data analysis. The data were explored using several graphical methods. A histogram of the drainage basin response values was checked for population normal distribution and spread (Fig. 2.6). For the simple linear regression model a residual plot was checked for variance and possible cluster effects, and a Normal Q-Q plot was checked again for normal distribution (Fig. 2.7). The small sample size made it difficult to evaluate assumptions of variance and normality, and influenced the decision not to log transform the data.

The slope and intercept of the regression line was estimated by the method of least squares (Fig. 2.8). The variance about the regression was estimated by the sum of squared residuals divided by the degrees of freedom. The null hypothesis is that correlation coefficient for distance along the fault and elongation ratio will be zero.

To see if a richer model would be more appropriate, the following models were also checked: regression with a quadratic term; parallel lines model after accounting for fault block categories; and separate lines model after accounting for fault block categories. In comparing models, none of the richer models were selected in ESS F-tests, so the original simple linear regression model was accepted (conforming to a parsimonious view of the study).

4. Results

A total of 8 drainage basins were delineated from the DEM (Fig. 2.2). Out of these, two basins (basins 6 and 8) drained only the Las Peñas thrust sheet whereas 6 basins drain both the Las Peñas and Las Higueras thrust sheets. A list of extracted/calculated parameters used in the study is given in Table 1. Of all the morphometric parameters analyzed, only elongation ratio was correlated with distance along the fault with statistical significance.

There is convincing evidence of a positive linear relationship between distance from the lateral ramp and drainage basin elongation ratio ($p\text{-value}=0.0008$ from a $t\text{-statistic}=6.157$, on 6 degrees of freedom). It is estimated that every one km distance increase from the lateral ramp is associated with an elongation ratio increase of 0.021 (of diameter km to length km) with a 95% confidence interval from 0.013 to 0.029.

5. Discussion

The association between the elongation ratio response and distance explanatory variable is evidence supporting the hypothesis that fault displacement influences drainage basin development. Causal interpretation of location along the fault affecting mean slope and size of basins cannot be made, as it is impossible to randomize the explanatory variable. This is intrinsic to most geologic statistical analysis, but with strong theoretical

knowledge to rule out confounding factors, the statistical analysis can lend evidence toward causal theories. These data are not a random sample, so they are not necessarily representative of results from measurements of drainage basins from another thrust fault.

This study supports the hypothesis of systematic drainage basins development (increased elongation ratio) with increasing displacement along the fault (distance from the lateral ramp). High elongation ratios are linked with locations of higher displacement, where drainage basins are more developed and efficient at sediment dispersal. Low elongation ratios are linked with locations of little displacement. Basins grow by either lateral stream capture or headwall erosion (Densmore et al., 2005). Since the spacing of drainage outlets on individual thrust sheets is relatively uniform during initiation of drainage basins (Hovius, 1996; Talling et al., 1997), lateral stream capture is ruled out as an influential process governing changes to the elongation ratio.

Low elongation ratios in the northern basins are due to active headwall incision into recently uplifted fan deposits towards the drainage divide. Where the range divide is far away from the active front, basins have low elongation ratios. Both mountain range width and relief are controlled by the geometry and spacing of faults (Densmore et al., 2005). Drainage divide migration causes changes in the range width (Bonnet, 2009). At the fault lateral ramp, the drainage divide is further back in the hinterland, inherited from the older LHT (Fig. 2.9). As fault displacement increases to the south, the rotated thrust sheet causes divide migration towards the thrust front, shortening the basin length (Fig. 2.10). This causes high elongation ratios in the mature southern drainage basins.

The drainage basin position relative to the maximum fault displacement controls

sediment yield and erosion rate (Densmore et al., 2005; Cowie et al., 2006). Uplifting and rotating stratigraphy of the thrust sheets increases potential for plane-parallel mass wasting and increased erosion. These drainage basins are also in an arid environment dominated by ephemeral channels. Dominant sediment transport mechanisms in these settings are hyperconcentrated flow processes and channel bank collapse, which rely on localized contribution of sediment (Pearce et al., 2004). High elongation ratios signify lower transport distances, with increased efficiency of sediment removal out of basins.

6. Conclusions

This study demonstrates a morphometric survey in an open-source GIS using terrain analysis and a DEM. These methods utilize the new freely available global coverage of 30-m DEM, reducing high costs of manually measuring large areas of drainage basin surface features as they change through space.

The correlation of the elongation ratio to position along the thrust front was successful, with elongation ratio increasing with distance from the lateral ramp of the Las Peñas thrust. This quantitative approach of basin characterization supports interpretations of drainage basin development along an active thrust fault. Future work in this setting should focus on investigation of other drainage basin metrics that could be useful in defining dominant processes (such as identifying the relationship between drainage basin shape parameters and stream organization).

Tables

Table 1. Morphometric parameters, with rows as individual basin observations labeled by number. Continuous variables of Distance and Ratio were used in the linear regression model.

Basin (Id)	Distance (km)	Relief (meters)	Slope (degrees)	Area (sq km)	Diameter (km)	Length (km)	Ratio (elongation)
1	2.4	2092.217	15.572	29.774	6.157	20.788	0.296
2	3.9	1929.107	13.979	36.299	6.798	21.681	0.314
3	6.49	1359.220	11.031	21.65	5.25	11.925	0.44
4	8.015	1295.445	14.965	21.596	5.244	12.862	0.408
5	9.665	456.444	7.685	6.709	2.923	5.947	0.491
6	10.665	1270.329	15.788	24.839	5.624	12.117	0.464
7	12.705	373.778	10.057	5.581	2.666	4.805	0.555
8	13.895	1170.444	14.340	13.149	4.092	8.178	0.5

Figures

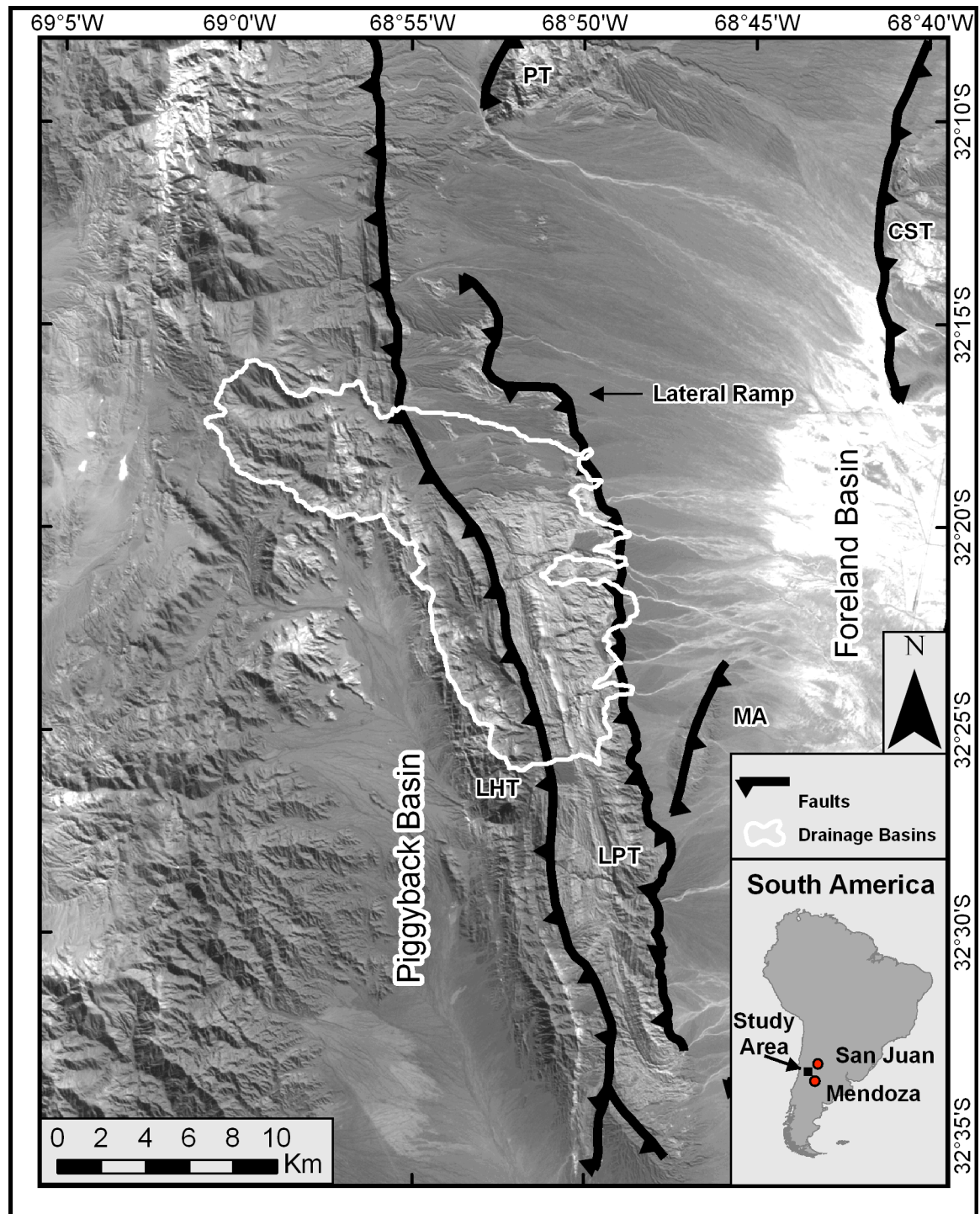


Fig 2.1. The erosional sector of the sediment routing system. Imagery is ASTER Band 4. See Fig. 1.1 for fault acronyms.

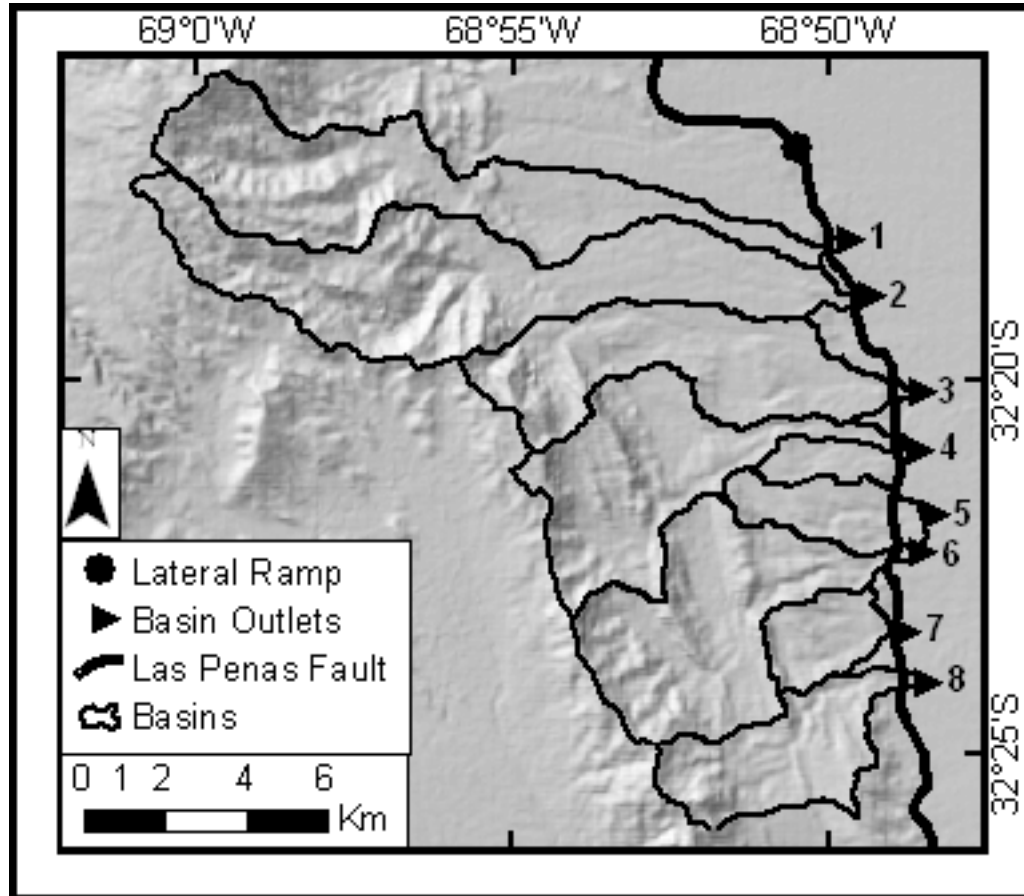


Fig 2.2. Drainage basin identification and location. Basins are numbered with increasing distance from ramp.

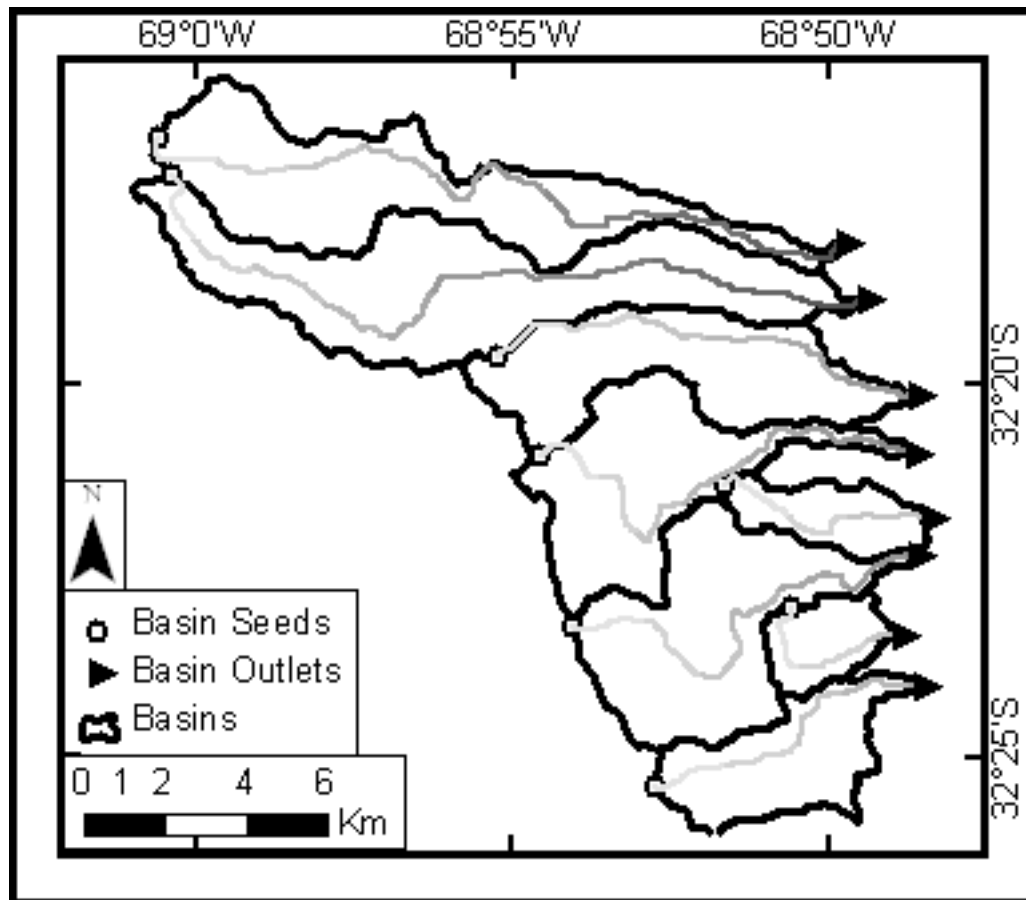


Fig. 2.3. Drainage basin length. The length line becomes darker with accumulated length.

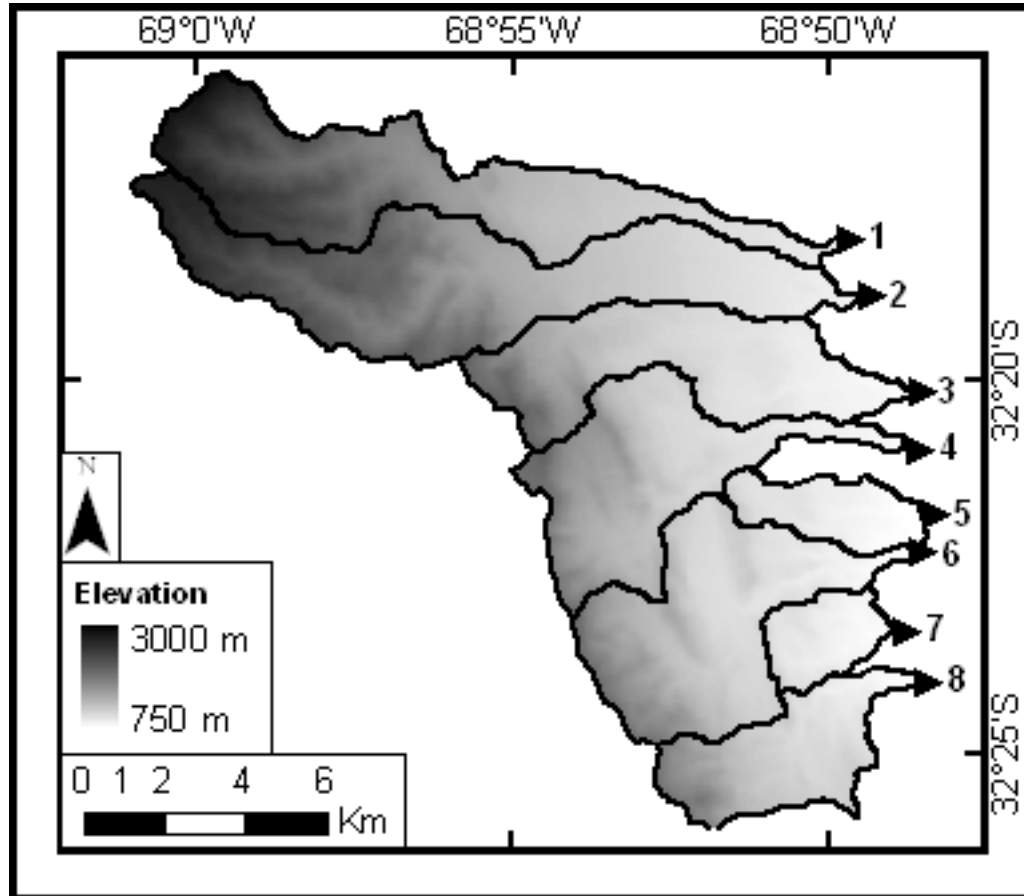


Fig. 2.4. Drainage basin elevation. Elevation for each basin was clipped from the DEM. Elevation is used in calculation of relief.

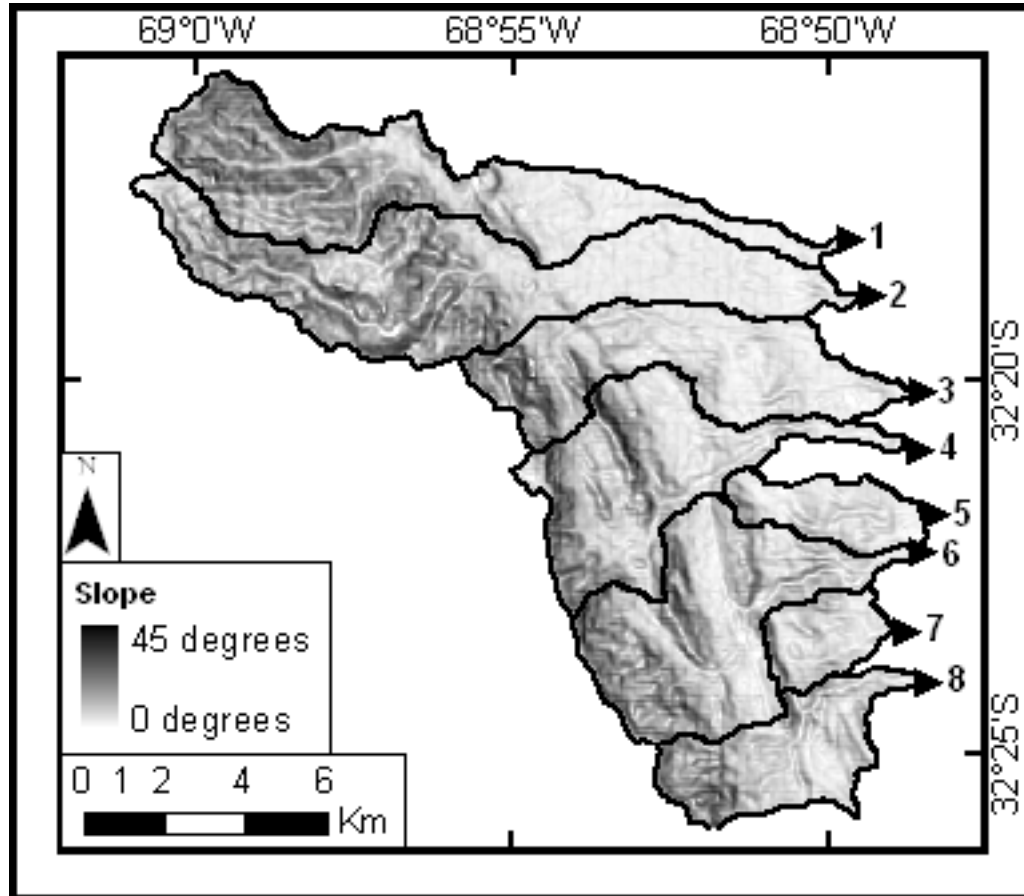


Fig. 2.5. Drainage basin slope. Slope is derived from elevation, and summarized in Table 2.1.

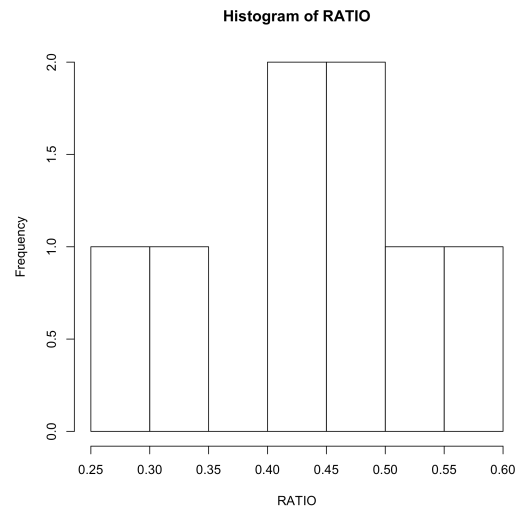


Fig. 2.6. Elongation ratio (RATIO) for each basin. Population is considered to have normal distribution and spread.

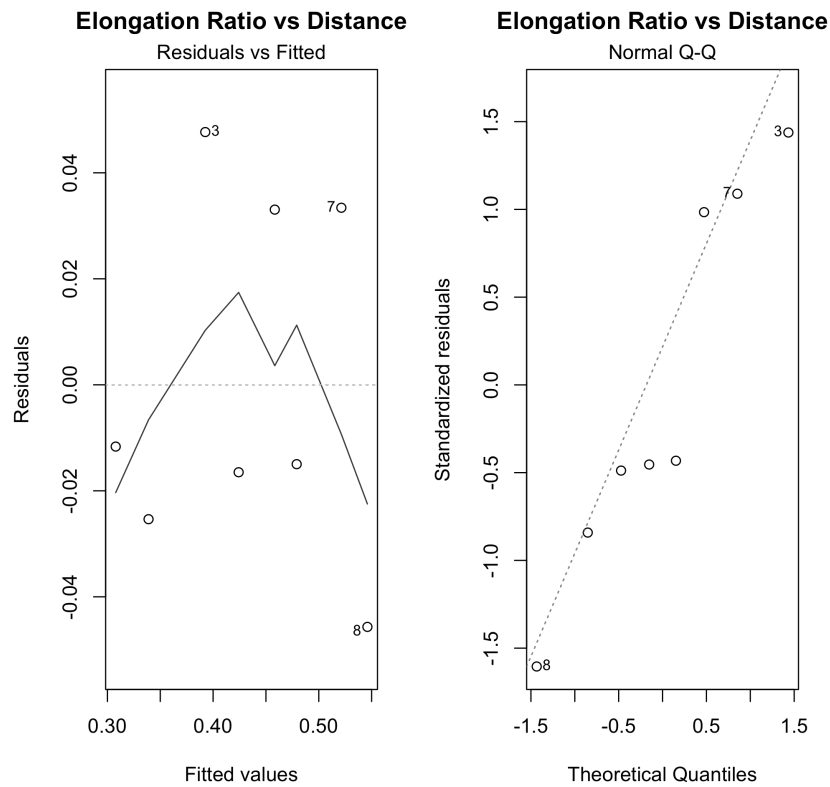


Fig. 2.7. Fitted residuals and Normal Q-Q plot for simple linear regression. Outliers are numbered by basin.

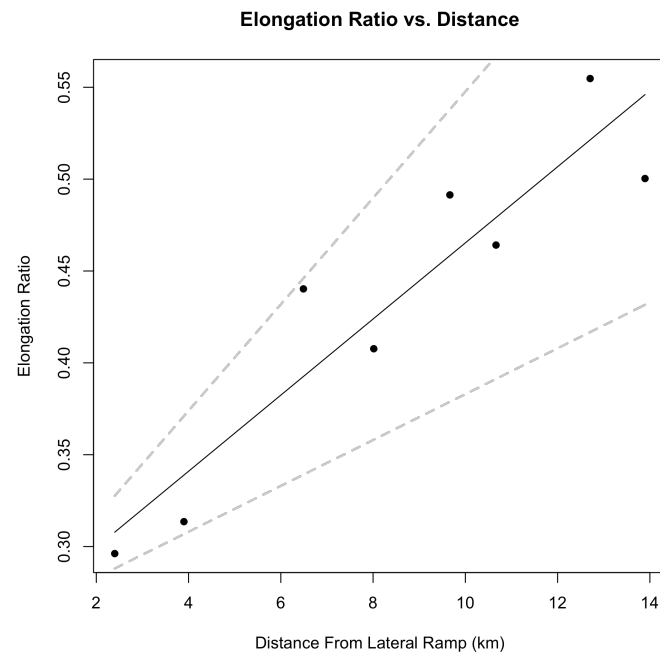


Fig 2.8. Scatterplot of RATIO and DISTANCE with fitted line from simple linear regression (black), and associated 95% confidence interval lines (grey dashed). Note the possibility of the necessity of a log transform of the data, as the CI lines expand with increasing distance.

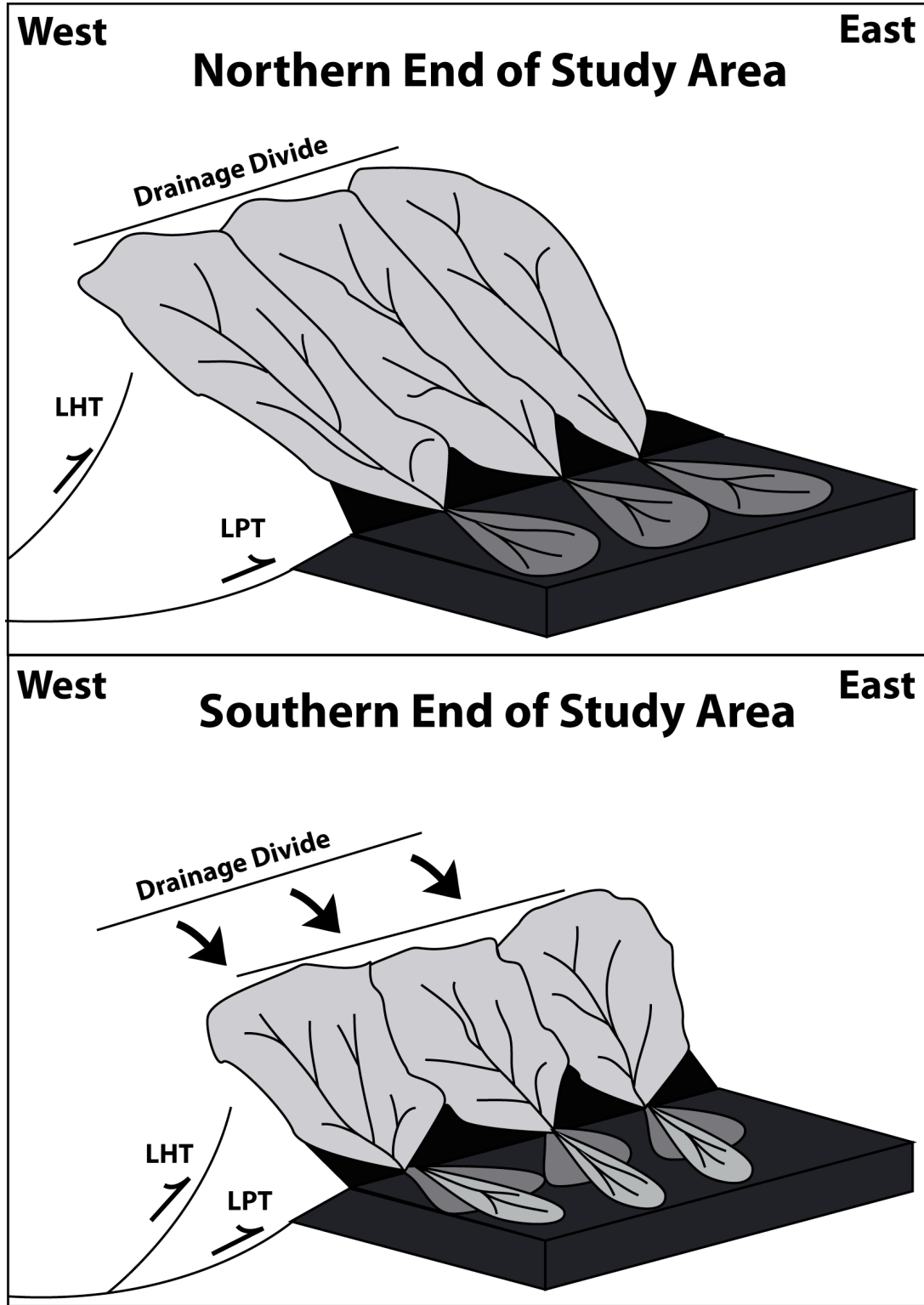


Fig. 2.9. Block diagram cartoon of drainage basin elongation ratio changes with drainage divide migration.

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References

- Ahumada, E.A., Costa, C.H., 2009. Antithetic linkage between oblique Quaternary thrusts at the Andean front, Argentine Precordillera. *Journal of South American Earth Sciences*, 28, 207–216.
- Allen, P.A., 1997. *Earth surface processes*. Blackwell Publishing, Oxford. 416 pp.
- Band, L.E., 1986. Topographic Partition of Watershed with Digital Elevation Models. *Water Resource Research*, 22, 15–24.
- Bonnet, S., 2009. Shrinking and splitting of drainage basins in orogenic landscapes from the migration of the main drainage divide. *Nature Geoscience*, 2, 766–771.
- Burbank, D.W., Anderson, R.S., 2000. *Tectonic Geomorphology*. Blackwell Publishing, Oxford. 270 pp.
- Burbank, D.W., Vergés, J., 1994. Reconstruction of topography and related depositional systems during active thrusting. *Journal of Geophysical Research*, 99, 20281–20297.
- Burbank, D.W., Meigs, A., Brozovic, N., 1996. Interactions of growing folds and coeval depositional systems. *Basin Research*, 8, 199–223.
- Conrad, O., 2006. SAGA – Program Structure and Current State of Implementation. In: Böhner, J., McCloy, K.R., Strobl, J. [Eds.]: *SAGA – Analysis and Modelling Applications*. Göttinger Geographische Abhandlungen, 115, 39–52.
- Costa, C.H., Gardini, C.E., Diederix, H., Cortés, J.M., 2000. The Andean orogenic front at Sierra de Las Penas-Las Higueras, Mendoza, Argentina. *Journal of South American Earth Sciences*, 13, 287–292.
- Cowie, P.A., Attal, M., Tucker, G.E., Whittaker, A.C., Naylor, M., Ganas, A., Roberts, G.P., 2006. Investigating the surface process response to fault interaction and linkage using a numerical modeling approach. *Basin Research*, 18, 231–266.
- DeCelles, P.G., Giles, K.A., 1996. Foreland basin systems. *Basin Research*, 8, 102–123.
- Delcaillau B., Carozza, J.M., Laville, E., 2006. Recent fold growth and drainage development: The Janauri and Chandigarh anticlines in the Siwalik foothills, northwest India. *Geomorphology*, 76, 241–256.

- Densmore, A.L., Dawers, N.H., Gupta, S., Guidon, R., 2005. What sets topographic relief in extensional footwalls? *Geology*, 33, 453-456.
- Fraser, G.S., DeCelles, P.G., 1992. Geomorphic controls on sediment accumulation at margins of foreland basins. *Basin Research*, 4, 233-252.
- Hovius, N., 1996. Regular spacing of drainage outlets from linear mountain belts. *Basin Research*, 8, 29-44.
- Keller, E.A., Pinter, N., 1996. *Active Tectonics: Earthquakes, Uplift, and Landscape*. Prentice Hall, New York. 138-139 pp.
- Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2006. World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, 15, 259-263.
- Leeder, M.R., Seger, M.J., Stark, C.P., 1991. Sedimentation and tectonic geomorphology adjacent to major active and inactive normal faults, southern Greece. *Journal of the Geological Society*, 148, 331-343.
- Moore, I.D., Grayson, R.B., Ladson, A.R., 1991. Digital terrain modelling: a review of hydrological, geomorphological, and biological applications. *Hydrological Processes*, 5, 3-30.
- O'Callaghan, J.F., Mark, D.M., 1984. The extraction of drainage networks from digital elevation data. *Computer Vision, Graphics and Image Processing*, 28, 323-344.
- Pearce, S.A., Pazzaglia, F.J., Eppes, M.C., 2004. Ephemeral stream response to growing folds. *GSA Bulletin*, 116, 1223-1239.
- Quinn, P. F., Beven, K. J., Chevallier, P., Planchon, O., 1991. The prediction of hillslope flowpaths for distributed modelling using digital terrain models. *Hydrological Processes*, 5, 59- 80.
- Schumm S.A., 1956. Evolution of drainage systems and slopes in badlands at Perth Amboy, New Jersey. *Geological Society of America Bulletin*, 67, 597-646.
- Schumm, S.A., 1986. Alluvial river response to active tectonics. In: *Studies in National Research Council (Ed.), Active Tectonics*. National Academy Press, *Studies in Geophysics*, Washington, D.C, 80-94.
- Seibert, J., McGlynn, B.L., 2007. A new triangular multiple flow direction algorithm for computing upslope areas from gridded digital elevation models. *Water Resource Research*, 43, W04501.

- Singh, T., Jain, V., 2009. Tectonic constraints on watershed development on frontal ridges: Mohand Ridge, NW Himalaya, India. *Geomorphology*, 106, 231–241.
- Talling, P.J., Stewart, M.D., Stark, C.P., Gupta, S., Vincent, S.J., 1997. Regular spacing of drainage outlets from linear fault blocks. *Basin Research*, 9, 275– 302.
- Tarboton, D.G., 1997. A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water Resource Research*, 33, 309–319.
- Vergés, J., Ramos, V. A., Meigs, A., Cristallini, E., Bettini, F. H., Cortés, J. M., 2007. Crustal wedging triggering recent deformation in the Andean thrust front between 31°S and 33°S: Sierras Pampeanas-Precordillera interaction. *Journal of Geophysical Research*, 112, B03S15.
- Wang, L., Liu, H., 2006. An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modeling. *International Journal of Geographical Information Science*, 20, 193-213.

Web References

Perego, 2009. SRTM DEM destripping with SAGA GIS: consequences on drainage network extraction. Retrieved April 2, 2010.
<http://www.webalice.it/alper78/>

Servicio Meteorológico Nacional, 2000. Guía Climática para el Turismo, Mendoza. Retrieved April 2, 2010.
<http://www.smn.gov.ar/?mod=clima&id=30&provincia=Mendoza&ciudad=Mendoza>

United States Geological Survey (USGS), 2009. Routine Global Digital Elevation Model. Retrieved April 2, 2010.
https://lpdaac.usgs.gov/lpdaac/products/aster_products_table/routine/global_digital_elevation_model/v1/astgtm

SECOND MANUSCRIPT

REMOTE CLASSIFICATION OF ALLUVIAL FANS
IN A TECTONICALLY ACTIVE AREA USING
MULTISPECTRAL IMAGERY AND DECISION TREE MODELS

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Remote Classification of Alluvial Fans in a Tectonically Active Area Using Multispectral Imagery and Decision Tree Models

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Abstract

Alluvial fans produce a sedimentation pattern diagnostic of landscapes in disequilibrium. Erosional and depositional rates and processes respond to tectonic forcing. This study examines the active Argentine Precordillera foreland basin system to assess whether alluvial fan surface characteristics reflect the response of sedimentary processes to tectonic activity. Differences in surface spectral characteristics are analyzed as the evidence of active processes on alluvial fans.

Alluvial fan surfaces can be distinguished using multispectral (15-m, 30-m, and 90-m resolution) ASTER imagery and topographic data. Classification tree analyses (CTA) in the S-Plus statistical program and random forest classifications (RF) in the randomForest package in the R statistical program were used to classify the imagery. Overall accuracy was greater than 85% for the classification of antithetic and synthetic fans in both CTA and RF. Overall accuracy was not greater than 85% for the classification of individual fan surfaces for either CTA or RF, but RF resulted in 20%-21.6% higher overall accuracies. Results indicate that RF can achieve improvements in accuracy over CTA. Spectral reflectance responses in the thermal (8.925–11.65 μm) and infrared (0.78–0.86 μm) wavelengths, as well as elevation responses are important explanatory variables in classifying alluvial fan surfaces. Sedimentary processes create the conditions reflected by the explanatory variables. Sheetflood and debris flow sedimentation, as well as post-depositional processes are interpreted to control the surface conditions of the alluvial fans in response to growth of a thrust fault.

1. Introduction

Remote sensing techniques are useful in classifying landscape-scale depositional landforms due to reduced costs of manual measurement and the ability to detect slight spectral reflectance differences of large surface features. Reflectance properties of landform surfaces are determined by surface conditions. Remote classification of landforms is a growing field, with data collection and analysis techniques that have the potential to reveal the effects of regional tectonic processes on landscapes that are actively being deformed. Variations in process and rate of deposition on alluvial fans produce patterns of differing sediment and vegetation surface conditions.

Alluvial fan depositional systems are a diagnostic sedimentation style in tectonically active areas (Fraser and DeCelles, 1992). Depositional processes involved in alluvial fan development produce patterns in surface conditions of soil, sediment, and vegetation. Spectral properties of alluvial landforms in different evolutionary stages are reflected in surface conditions. The particular study area, in the Argentine Central Precordillera and foreland basin system, was used because alluvial fans are relatively well exposed and undeformed due to the arid climate and active development. Distinguishing sedimentation processes on alluvial fans may provide insight into the kinematics of active areas.

Alluvial fans may form in any setting where there is a break in slope and an increase in gradient associated with relative high and low land surfaces. Infrequent, intense fluid and sediment gravity flows are sourced in the higher drainage basin and

sediment is deposited in the lower sedimentary basin (Blair and McPherson, 1994a).

Erosion and sedimentation tend toward topography in equilibrium. Flows in the sediment routing system transition from confined within the drainage basin to unconfined at the outlet resulting in erosion, transport and deposition of sediment. The depositional pattern radiates from the outlet into the basin in a fan or conical form. Some examples of alluvial fan settings are fold and thrust belt compressional systems, basin and range extensional systems, active volcanic systems and recently cratered surfaces on earth and elsewhere.

The geologic question of how alluvial fan depositional systems respond to tectonic activity in this area is addressed with a classification of fan surfaces based on spectral and ancillary data. This is accomplished through classification of fan surfaces with explanatory variables using nonmetric rule-based classifiers (decision trees). The objective of this research was to evaluate utility of decision tree methods in classification of spectral reflectance of alluvial fans, and create process-based interpretations of the classifications.

2. Background

2.1 Alluvial Fan Classification

Alluvial fans are classified based on active processes (sediment transport mechanisms, weathering, and vegetation growth), which control their character and morphology (Blair and McPherson, 1994b). Debris flow fans have steep slopes, small

radii, and ropey surfaces. Sheetflood fans are characterized by gentle slopes, large radii, and relatively smooth surfaces. Processes are recorded by environmental variables including soil type, deposit morphology, sediment caliber and texture, and vegetation type that affect fan surface conditions (moisture, roughness, and composition). The surface of a fan may record several of these conditions at a given location.

Traditionally, information about surface conditions is directly measured using qualitative or quantitative data (Blair and McPherson, 1994b). Manual methods including ground surveying and aerial photography interpretation are capable of producing very high spatial resolution data and information, but are not cost effective.

Topographic map and digital elevation model data (slope, aspect, radius, area, hypsometry) may be used to derive information about landscape-scale morphology of alluvial fans (Milana and Ruzyski, 1999), from which active processes can be inferred from a knowledge-based general classification scheme (Blair and McPherson, 1994b) or hydraulically modeled (Pelletier et al., 2005). The resolution of topographic data, however, is often too coarse to recognize elevation patterns directly related to surface conditions.

Brightness values of remotely sensed imagery (digital numbers) relate to actual surface spectral reflectance response, and may be useful for identification of important explanatory variables for classification and interpretation of surfaces. Classified images are interpreted for process and landform classification based on spatial spectral patterns of important explanatory variables. This allows remote mapping (Argialas and Tzotsos, 2004) and measurement (Damanti, 1990; Milana, 2000; Crouvi and Ben-Dor, 2006) of

alluvial fan characteristics. Utility of spectral and ancillary topographic data derived from satellite imagery is demonstrated with classification and interpretation of alluvial fans.

2.2 Image Classification

2.2.1 Decision Tree Classification

Patterns of reflectance properties might be detectable on remotely sensed imagery with nonmetric rule-based (decision tree) classifications implemented in statistical software. Classification trees partition data based on rules and outcome paths by using an object or situation described by a set of variables, creating a rule about the variable value for that entity, and returning a decision based on a value cutoff (Jensen, 2005). Arc branches represent input values of attributes that lead to leaves, which determine output decisions or classifications. This action is recursive, with binary decisions partitioning data into subsets (Breiman et al., 1984). Branches are distributive, increasing homogeneity within classes and decreasing variance away from the root. Decision trees serve to break up complex decisions into a compilation of simpler decisions (Safavian and Landgrebe, 1991).

Machine learning efficiently derives rules for decision trees. Computers can create rules from associated attribute conditions directly from training data (Huang and Jensen, 1997). This method mimics human generalization (induction) by heuristically searching data for general descriptions that are true to training data and can be used as production rules for new data (Jensen, 2005). These rules become the knowledge base for

an expert system in place of an expensive and unreliable human knowledge expert. In comparison to classifications using conventional methods, accuracy assessments suggest that this rule production method is reliable (Huang and Jensen, 1997; Lawrence and Wright, 2001).

The ability to use ancillary data, which can be both numerical and categorical, has proved to be one of the most important aspects of this classifier (Lawrence and Wright, 2001). Decision trees from multi-source data have been used for soil mapping on alluvial fans by developing environmental variables to serve as proxies for soil forming processes (Scull et al., 2005).

2.2.2 Classification Tree Analysis

Classification Tree Analysis (CTA) is one type of decision tree model developed using training data for each landcover class. Rules are created that are true to training data and can be used in a model to predict values for new data (classification). CTA selects a split by minimizing deviance at a node. The logic of splitting rules can be checked directly from the decision tree. Rules developed from explanatory variables serve as proxies for environmental conditions. Tree-model rules can be transferred to a decision-tree engineer in imaging software, and original images can be classified.

CTA uses tree growing-pruning (splits classes until they are pure or nearly pure, and then selectively prunes the tree) to prevent overfitting or explanation of all deviance in the data. This is accomplished using a cross validation method that randomly divides original training data into 10 equal subsets of which 9 are validated against the tenth to

select the pruned tree size.

This classification method has several advantages over traditional methods in that it is easy to interpret, does not require data normalization, can handle both numerical and categorical data, and has resulted in higher accuracies than many other methods (Safavian and Landgrebe, 1991; Lawrence et al., 2004). Disadvantages that may preclude use are negative influence of unbalanced data, accumulation of errors in large trees, non-automatic optimization, and potentially strong influence on variability by training data outliers (Safavian and Landgrebe, 1991; Lawrence et al., 2004).

Some of these disadvantages can be overcome using voting or ensemble methods (Gislason et al., 2006), where multiple trees are created, and the best outcome is determined based on a plurality of outcomes (tree voting). Bagging methods use training data to repeatedly select random subsets of original training data, which reduces variance of the classification (Breiman, 1996). In boosting methods, training data are assigned different weights (misclassified = high weighting) in iterative retraining (Lawrence et al., 2004), reducing variance and bias. However, boosting methods can be slow and sensitive to noise.

2.2.3 Random Forest Classification

Random Forest Classification (RF) is a decision tree classification method that uses voting. Many decision trees are developed by training on a bootstrapped sample of original training data and the method searches across random subsets of input variables to determine splits (Breiman, 2001). Each decision tree casts a vote for an input class, and

the output of a RF model is thus the mode class of many individual decision tree outputs. Error rate stability can be plotted against number of trees, with 500 trees per model usually providing adequate stability. Variable importance, indicating relative importance of each explanatory variable, can be plotted. Actual interactions, or rules upon which splits are based, are not indicated, making this method somewhat of a black-box operation. Variable importance is useful if repeated RF models are developed, because in successive runs, only important variables may be used.

Out-Of-Bag (OOB) error estimation in RF is developed in an internal accuracy assessment of incorrectly classified pixels by withholding a third of the training data from construction of each tree, and excluding a different third of the data from each classification tree for comparison (Breiman, 2001). An OOB error matrix, based on correctly classified pixels, can be output from the model. The model developed using training data can be combined with validation data to predict values and develop a traditional accuracy assessment as well.

One disadvantage of RF is a high memory requirement for large data sets. Furthermore, rules based on tree decisions are not always easy to interpret. There are also advantages including increased accuracy and efficiency, ability to handle large data sets and numbers of variables, estimates of variable importance, generation of an internal accuracy assessment, detection of outliers, and requirement of little input and supervision.

3. Methods

3.1 Study Area

The geographic location of study is Mendoza Province, Argentina along the Central Precordilleran mountain front (Figure 3.1). Active structures influencing the sediment routing system are the east-vergent Las Peñas and Las Higueras thrusts of the Precordilleran fold and thrust belt (Costa et al., 2000). This is an arid region where thrust faults create an uplifted range that divides the landscape into watersheds along the range and alluvial fans into a foreland basin and a piggyback basin on the hanging wall (Figure 3.1). Dominant alluvial sedimentation patterns bordering the mountain range are synthetic sedimentation along the eastern slopes (foreland basin) in the direction of tectonic transport, and antithetic sedimentation on the western slopes (piggyback basin).

3.2 Data Description

The single scene of imagery used in this study was acquired from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor on May 1, 2002 from the first Earth Observing System satellite Terra. Sensor swath of ASTER imagery (60 km) records the extent of the depositional system under scrutiny. The scene was chosen for its cloud-free nature and to avoid recent (since May 1, 2007) saturation and striping in the shortwave infrared (SWIR) range caused by detector temperature peaks.

The scene downloaded from the USGS Land Processes Distributed Access Archive was the Orthorectified Digital Elevation Model and Registered Radiance at the Sensor (AST14DMO) data product. This data set includes fourteen radiometrically-calibrated and geometrically co-registered (Level-1B) nadir looking radiance bands at 15-m visible near infrared (VNIR), 30-m shortwave infrared (SWIR) and 90-m thermal infrared (TIR) resolution. The data are orthorectified to a path-oriented Universal Transverse Mercator (UTM) projection. AST14DMO also includes the ASTER 30-m Digital Elevation Model (DEM) derived from the 3N (nadir) and 3B (backward looking) stereoscopic data from the VNIR sensor (0.78 to 0.86 μm). The DEM was generated by the USGS with a bilinear resampling method, and all bands were orthorectified by cubic convolution. Slope was derived from the DEM for use as ancillary data. The sixteen layers of explanatory variables (Table 3.1) were stacked into one image for input into classification.

3.3 Reference Data Collection

The study area was mapped visually using aerial photograph interpretation and field assessment of example fan surface characteristics including vegetation, surface roughness, and sediment size. The depositional system was split into surfaces based on spatial texture. The three major depositional patterns identified were antithetic fans, and proximal and distal synthetic fans. Synthetic fans were separated into eight individual surfaces (Table 3.2). The first level of the hierarchy (Level 1) was designed to detect

differences in major depositional processes (debris flows and sheetfloods). The second level aimed to separate the synthetic fans into lithotopes (individual landform surfaces) (Level 2) to see if variation was recognizable along strike of the thrust front. This hierarchy served to characterize spectral signatures of depositional environments, as well as variations within environments along the active fault.

Areas of interest (AOIs) for each category in the classification scheme were delineated in imaging software (ERDAS Imagine). Each pixel of the stacked image contained location information (x and y coordinates), as well as values for each of the 16 explanatory variables. Pixel data were exported to table format for each of the 11 categories, data were inspected for excess fields and entries, and a type field was added where classes were assigned to each pixel.

A stratified random sample of pixels was extracted from the entire study area (total set of exported pixels) for reference data. Classes were stratified into separate tables, and samples were selected using a random number generator. Sample size for the Level 1 classification was 500 pixels and size for Level 2 classification was 100 pixels. The sample reference data from each class were split into two equal sets and then compiled into training data and validation data tables. Training data were used in building statistical models for classification, and validation data were used in accuracy assessments of classifications.

3.4 Modeling

3.4.1 CTA Modeling

Training data were imported into S+ statistical software and tree models were developed using the “type” field as a dependent variable and the 16 independent explanatory variables. Unpruned tree models were developed (Figure 3.2) and cross validation was plotted (Figure 3.3) and assessed for amount of variability explained with each successive split. Pruned tree models were developed based on cross validation and logic of splitting rules. Splitting rules from the pruned tree models were transferred to Knowledge Engineer decision trees in ERDAS Imagine. The Knowledge Classifier function was used in classification of AOIs of the original 16-layer image.

Comparing reserved validation data with classified values of the image provided the accuracy assessment. Validation pixel classes were imported into the Accuracy Assessment tool in ERDAS Imagine, and the real values were compared to the classified image values. Summaries of real versus classified values were exported as error matrices with descriptive statistics.

3.4.2 RF Modeling

This study also used the randomForest package in R statistical software to develop tree models. The same equation with dependent and independent variables used for CTA in the S+ program was applied to the training data in R statistical program (R Development Core Team, 2005). A classification type of random forest was used, with 500 trees and 4 variables tried at each split. Error rate vs. number of trees was used to display stability. If the error did not change significantly throughout the number of trees,

500 trees were adequate. Importance of the explanatory variables was plotted, showing relative importance, rather than actual splitting rules of the trees. An OOB error internal estimate was automatically generated with an error matrix.

Validation data were used to create a traditional error matrix for comparison with CTA. The predict command in randomForest was used with models developed from training data to predict values for validation pixels. Traditional error matrices were summarized from predicted and actual validation values.

3.5 Accuracy Assessment

Common remote sensing descriptive and multivariate statistical measurements were used in accuracy assessment. Error matrices from classifications show errors of omission and commission, and descriptive statistics of users, producers, and overall accuracies. User's accuracies indicate reliability of the classification method in reference to correctly classified pixels (commission errors). Producer's accuracies reflect the chances that reference pixels are incorrectly classified (omission errors). Overall accuracies are a measure of total correctly classified reference data with respect to the total amount of reference data. OOB error estimation of the RF classification was compared to the traditional accuracy assessment.

Error matrices were converted to mathematical terms to measure multivariate statistics of the classifications. Kappa analysis was conducted to determine KHAT (coefficient of agreement) statistics, which are a measurement of accuracy based on

actual agreement of the error matrix (major diagonals) and the chance agreement (row and column totals) (Jensen, 2005). The KHAT statistic is asymptotically normally distributed and ranges from +1 to -1 (Congalton and Green, 1999). The large sample variance of KHAT ($\text{var}(\text{KHAT})$) was computed using the Delta method to determine confidence intervals around the KHAT value. The KHAT and $\text{var}(\text{KHAT})$ were used in z-tests to test statistical significance of a single error matrix and in a pair-wise comparison z-test to test if the two error matrices, and thus the two algorithms, were significantly different.

4. Results

4.1 Level 1 Classification

In the Level 1 classification, the system was split into depositional environments with three terminal nodes (antithetic fans, proximal synthetic fans and distal synthetic fans), on two rules in CTA based on explanatory variables and values B13 (<1581) and B3 (<38.5) designating paths through the tree environment (Figure 3.4). Important variables in the RF model were B15 (68.3), B3 (58.3), B14 (49.3), and B13 (48.1) (Table 3.3). Stability plots of error vs. trees used showed error not changing significantly after approximately 100 trees used (Figure 3.5).

Image classification from CTA was sound on a visual check (Figure 3.6). Overall classification accuracies for CTA and RF were 94.67% and 96.27%, respectively. The

internal RF OOB error estimate for the RF approach was 3.07% (96.93% accuracy), which is less than 1% different from the traditional error matrix approach and consistent with previous studies (Lawrence et al., 2006). Class accuracies for CTA ranged from 85.20%-100% producers and 87.28%-100% users (Table 3.4), and for RF 92.4%-100% producers and 92.70%-100% users (Table 3.5), with antithetic fans most accurately classified, and distal-synthetic fans most inaccurately. KHAT statistics were 0.92 for CTA and 0.94 for RFC. The z statistics for CTA and RF were 11.35 and 16.58 respectively. A z statistic of 0.24 (p-value 0.81) was calculated in a pair-wise comparison of CTA and RF.

4.2 Level 2 Classification: Proximal-Synthetic Fans

The proximal-synthetic fan environment (Fig. 3.6) was split into individual surfaces, with three terminal nodes (ps1, ps2, and ps3), on two rules in CTA based on explanatory variables B13 (<1668.5) and B15 (<752.5) (Figure 3.7). Important variables in the proximal-synthetic fan RF model were B13 (14), B12 (13.5), B14 (11.9), and B15 (9.7). Stability plots of the error vs. trees used showed error changing more throughout the plots than in the Level 1 plot.

The classified image shows three surfaces (AOIs) that are classified into the three categories. Note the inclusion of non-ps3 classified pixels in the ps3 AOI, and the blocky patterns in ps1 AOI (Figure 3.8). Overall classification accuracies for CTA and RF were 54.00% and 74.00%, respectively. The internal RF OOB error estimate for the RF

approach was 26.67% (73.33% accuracy). Class accuracies for CTA ranged from 52.00%-58.00% producers and 40.63%-76.47% users (Table 3.6), and for RF 54.00%-96.00% producers and 66.67%-87.10% users (Table 3.7). KHAT statistics were 0.31 for CTA and 0.61 for RF. The z statistics for CTA and RF were 0.52 and 1.50 respectively. A z statistic of 0.41 was calculated in a pair-wise comparison of CTA and RF error matrices.

4.3 Level 2 Classification: Distal-Synthetic Fans

The distal-synthetic fan environment was split into individual surfaces, with six terminal nodes (ds1, ds2, ds3, ds3, ds4, and ds5), on five rules in CTA based on variables B12 (<1360.5), B14 (<1764.5), B15 (<679.5), B14 (<1750), and B12 (<1349.5) (Figure 3.9). Important variables in the distal-synthetic fan RF model were B12 (26.25), B15 (26.1), B13 (21.9), and B14 (18.7). Stability plots of error vs. trees used showed error changing more throughout the plots than in the Level 1 plot.

The classified image exhibited blocky patterns (Figure 3.10). Overall classification accuracies for CTA and RF were 47.20% and 68.80%, respectively. The internal RF OOB error estimate for the RF approach was 32.80% (67.20% accuracy). This is 1.6% different from the traditional approach. Class accuracies for CTA ranged from 22.00%-82.00% producers and 29.63%-68.75% users (Table 3.8), and for RF 58.00%-76.00% producers and 60.67%-76.00% users (Table 3.9). KHAT statistics were 0.34 for CTA and 0.61 for RF. The z statistics for CTA and RF were 0.90 and 2.90

respectively. A z statistic of 0.62 was calculated in a pair-wise comparison of CTA and RF error matrices.

5. Discussion

5.1 Level 1 Classification

The objective of this project was to evaluate utility of decision tree methods in classification of spectral reflectance of alluvial fans, and interpret the classification rules. The first criteria for this evaluation was whether or not each method was able to classify the alluvial fan depositional system with at least 85% overall accuracy, and roughly equivalent class accuracy measurements. For the Level 1 classification at least 85% overall accuracy and roughly equivalent class accuracy measurements were achieved for both CTA and RF models.

CTA and RF models were then tested for their statistical significance using Kappa analysis. Individual error matrices from the Level 1 classification were tested and resulted in KHAT statistics that represent strong agreement between the remotely sensed classification and reference data. Z statistics for CTA and RF were greater than the 1.96 critical value and significantly better than random. A z-test was used to test if the two error matrices were significantly different. The z statistic in a pair-wise comparison of CTA and RF was close to zero, showing that the two KHATs, and thus the two algorithms, are not statistically significantly different.

Decisions for creating binary trees and splitting data into homogenous subsets were similar between the two model types, as shown by a comparison of variable value rules of CTA and importance of variables of RF. Differentiation of antithetic fans from all synthetic fans in CTA used B13, a 90-m resolution TIR band with a spectral range of 10.25–10.95 μm . The proximal and distal synthetic fans were split based on B3, a 15-m resolution VNIR band with a range of 0.78–0.86 μm . The B15 30-m DEM and the B14 90-m TIR band (10.95–11.65 μm) were also important factors in RF.

5.2 Level 2 Classification

For Level 2 classification at least 85% overall accuracy and class accuracy measurements were not achieved for either proximal-synthetic or distal-synthetic fans. Even though this analysis failed the accuracy criteria, disparity between CTA and RF measurements was apparent, with RF overall accuracy 20.00% higher than CTA for older sheetflood fans, and 21.60% higher than CTA for younger sheetflood fans.

The CTA and RF classifications were then tested for their statistical significance using Kappa analysis. The individual error matrices from Level 2 classification were tested and resulted in KHAT statistics that did not represent strong agreement between remotely sensed classification and reference data. Z statistics for CTA and RF were not significantly better than random, with the exception of RF classification for the distal-synthetic fans.

Decisions were similar between the two model types, and between the proximal-synthetic or distal-synthetic fans. Rules of CTA and importance of variables of RF generated from the Level 2 classification focused on 90-m thermal band differences in B12, B13, and B14 (8.925–11.65 μm) as well as elevation in the B15 30-m DEM.

5.3 Interpretation of Explanatory Variables

Decisions based on thermal band criteria prevalent throughout this study may indicate grain size changes (Hardgrove et al., 2009), a product of primary depositional processes. Soil density, controlled by a greater degree of compaction of surface materials and particle size with grading, may influence thermal signature (Cracknell and Hayes, 1991). Field observations support the interpretation that antithetic fans are the result of debris flow deposition and synthetic fans are the result of sheetflood deposition. Secondary reworking caused by soil development or eolian winnowing may also affect the thermal character of the surfaces. In addition to these dominant process-based characteristics, changes in vegetation, topographic undulations, and soil and mineralogical differences influence thermal emittance.

Values from the visible near infrared (0.78–0.86 μm) B3 variable are usually responsive to the amount of vegetation biomass (Jensen, 2005). Post-depositional vegetation growth is strongly influenced by length of time the surface has been inactive (age of the surface) as well as substrate characteristics. Both vegetation quantity and type were observed in the field, and are determined by conditions of underlying materials,

such as compaction, moisture, grain size, and sorting. The proximal-synthetic fans are interpreted to be older sheetflood fans based on this variable, and the distal-synthetic fans are interpreted to be younger sheetflood fans.

Decisions based on the 30-m DEM variable relate to the environment elevation. Distinction between the antithetic and synthetic fans in Level 1 is due to the setting in either the high piggyback basin on the hanging wall of the thrust or the low foreland basins on the footwall. Between synthetic fans, this difference is due to the progressive uplift and rotation of the proximal fans, which are closer to the locus of thrust faulting. Decisions based on elevation in the Level 2 model may indicate an along-strike tilt of the foreland surface related to fault propagation, raising fans that are further north.

6. Conclusions

These analyses demonstrated development and implementation of decision tree models in remote sensing using two statistical techniques. CTA proved an excellent method for understanding relationships and values of variables, and should be used as an exploratory tool to test variable interaction. CTA might be a more efficient approach to remote classification, due to the availability of actual decision rules, as well as ease of creating classified maps. RF was not as transparent, but important variables were identified. Based on accuracies, it is advised the more accurate RF method be used.

The classification was effective at Level 1, successfully classifying three depositional environment extents, interpreted to represent debris flow deposition on

antithetic fans and sheetflood deposition on synthetic fans, with younger sheetflood fans prograding into the foreland, more distal to the thrust front. These different depositional environments have specific geographic extents determined by location and growth of the thrust fault. The debris flow fans were all located in the piggyback basin, antithetically depositing sediment. The sheetflood fans were all classified in the foreland basin, synthetically depositing sediment. The two generations of sheetflood fan showed a progressive step towards the foreland with uplift and movement along the fault. Subtle variations in development of individual sheetflood fans at Level 2, however, were not recognized based on the classification.

Unsuccessful classification could be due to inaccurate training data upon which the models were built, choices of explanatory variables used in the decision trees, or patterns and conditions produced by processes on individual fans not correlated with explanatory variables. Accuracy for individual classifications could increase with addition of more ancillary data, refinement of training data, and use of spatial pattern recognition algorithms.

These methods improve efficiency and accuracy by reducing high costs of manually measuring large areas of surface features and detecting spectral reflectance differences of landscapes as they change through time and space. The methods are not influenced by insufficient expert knowledge, and they have the ability to incorporate ancillary data as influential variables in determining classification of surfaces. Future work should focus on identifying the relationship between spectral reflectance responses and environmental variables on the surfaces of the alluvial fans.

Tables

Table 3.1 Data description of ASTER AST14DMO data products and ancillary components developed from imagery (<https://lpdaac.usgs.gov/lpdaac/products>). The variables column indicates the name of each explanatory variable for the modeling.

ASTER DATA DESCRIPTION			
Swath Area	~60 km x 60 km		
Input Resolution	15, 30, 90 m		
DEM Output Resolution	30 m		
Image Output Resolution	15, 30, 90 m		
DEM Resampling Method	Bilinear		
Image Resampling	Cubic		
Data Format	GeoTIFF		
Map Projection	UTM		
Layers	Variables	Range	Data Type
VNIR (15-m)			
Spectral Range		μm	
Band	B1	(0.52-0.60)	8-bit
Band	B2	(0.63-0.69)	8-bit
Band	B3	(0.78-0.86)	8-bit
Band	B3 aft (not used)	(0.78-0.86)	8-bit
SWIR (30-m)			
Band	B4	(1.600-1.700)	8-bit
Band	B5	(2.145-2.185)	8-bit
Band	B6	(2.185-2.225)	8-bit
Band	B7	(2.235-2.285)	8-bit
Band	B8	(2.295-2.365)	8-bit
Band	B9	(2.360-2.430)	8-bit
TIR (90-m)			
Band	B10	(8.125-8.475)	16-bit
Band	B11	(8.475-8.825)	16-bit
Band	B12	(8.925-9.275)	16-bit
Band	B13	(10.25-10.95)	16-bit
Band	B14	(10.95-11.65)	16-bit
Ancillary Data (30-m)			
Elevation Component	B15	meters	16-bit
Slope Component	B16	degrees	16-bit

Table 3.2 Classification scheme detailing one Level 1 classification of depositional environments, and two Level 2 classifications of individual fan surfaces.

Level 1- Environments	Level 2- Proximal Surfaces	Level 2- Distal Surfaces
Antithetic	ps1	ds1
Proximal Synthetic	ps2	ds2
Distal Synthetic	ps3	ds3
		ds4
		ds5

Table 3.3 Relative importance plot of explanatory variables in Level 1 RF model. Important variables are bolded.

Variable	Relative Importance
B1	22.084342
B2	33.142694
B3	58.263881
B4	25.764172
B5	28.336292
B6	27.989805
B7	29.708269
B8	31.353259
B9	14.343932
B10	25.953897
B11	17.904821
B12	16.38047
B13	48.10537
B14	49.33493
B15	68.289279
B16	2.407575

Table 3.4 Error matrix and accuracy totals for Level 1 Environments (CTA).

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Undefined	0	1	0	---	---
antithetic	250	250	250	100.00%	100.00%
distal synthetic	250	216	213	85.20%	98.61%
proximal synthetic	250	283	247	98.80%	87.28%
Totals	750	750	710		
Overall Classification Accuracy = 94.67%					

Table 3.5 Error matrix and accuracy totals for Level 1 Environments (RF).

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Undefined	0	0	0	---	---
antithetic	250	250	250	100.00%	100.00%
distal synthetic	250	260	241	96.40%	92.70%
proximal synthetic	250	240	231	92.40%	96.25%
Totals	750	750	722		
Overall Classification Accuracy = 96.27%					

Table 3.6 Error matrix and accuracy totals for Level 2 Proximal-Synthetic Fans (CTA).

Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Undefined	0	1	0	---	---
ps1	50	34	26	52.00%	76.47%
ps2	50	64	26	52.00%	40.63%
ps3	50	51	29	58.00%	56.86%
Totals	150	150	81		
Overall Classification Accuracy = 54.00%					

Table 3.7 Error matrix and accuracy totals for Level 2 Proximal-Synthetic Fans (RF).

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
-----	-----	-----	-----	-----	-----
Undefined	0	0	0	---	---
ps1	50	31	27	54.00%	87.10%
ps2	50	54	36	72.00%	66.67%
ps3	50	65	48	96.00%	73.85%
Totals	150	150	111		
Overall Classification Accuracy =		74.00%			

Table 3.8 Error matrix and accuracy totals for Level 2 Distal-Synthetic Fans (CTA).

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
-----	-----	-----	-----	-----	-----
Undefined	0	1	0	---	---
ds1	50	25	11	22.00%	44.00%
ds2	50	32	22	44.00%	68.75%
ds3	50	88	41	82.00%	46.59%
ds4	51	50	28	54.90%	56.00%
ds5	49	54	16	32.65%	29.63%
Totals	250	250	118		
Overall Classification Accuracy =		47.20%			

Table 3.9 Error matrix and accuracy totals for Level 2 Distal-Synthetic Fans (RF).

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
-----	-----	-----	-----	-----	-----
Undefined	0	0	0	---	---
ds1	50	61	37	74.00%	60.66%
ds2	50	51	38	76.00%	74.51%
ds3	50	42	30	60.00%	71.43%
ds4	50	50	38	76.00%	76.00%
ds5	50	46	29	58.00%	63.04%
Totals	250	250	172		
Overall Classification Accuracy =		68.80%			

Figures

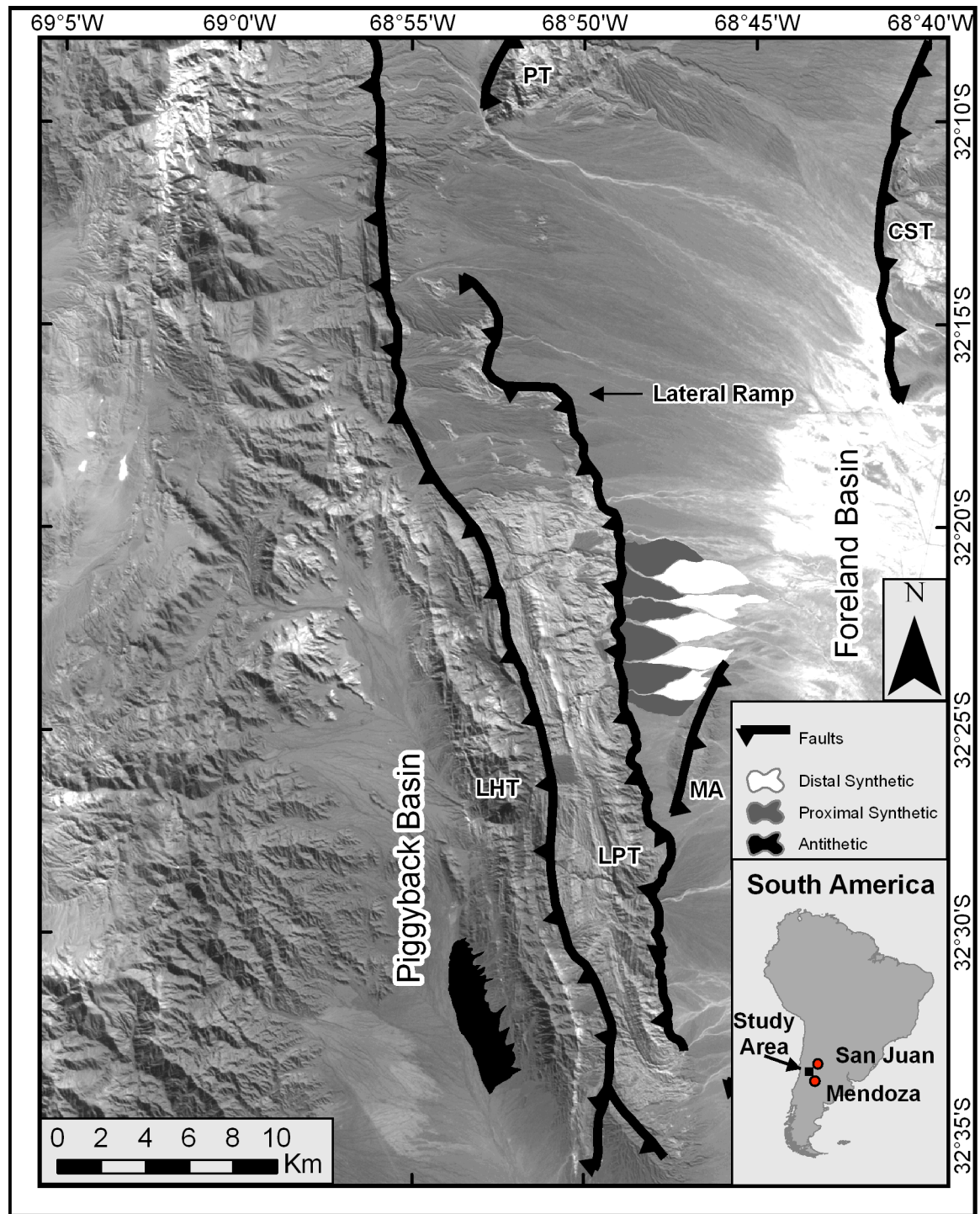


Fig. 3.1. Depositional environments of the Sierra Las Peñas-Las Higueras. Imagery is ASTER Band 4. See Fig. 1.1 for fault acronyms.

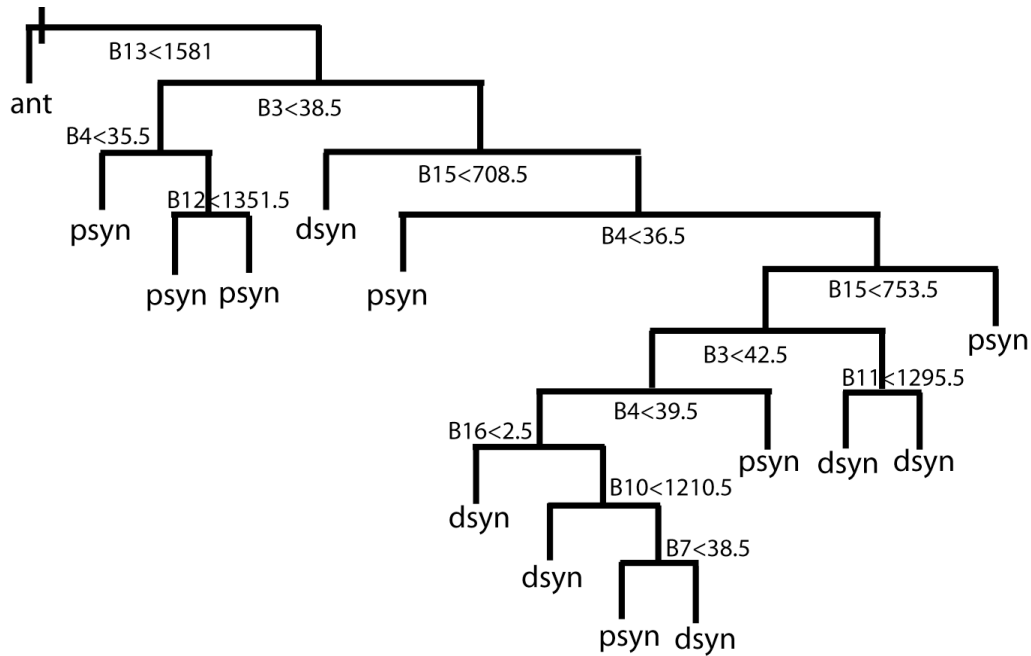


Fig. 3.2. Full unpruned tree for Level 1 classification showing variables and values for split locations. Antithetic fans are labeled ant, Synthetic fans are either dsyn for Distal or psyn for Proximal.

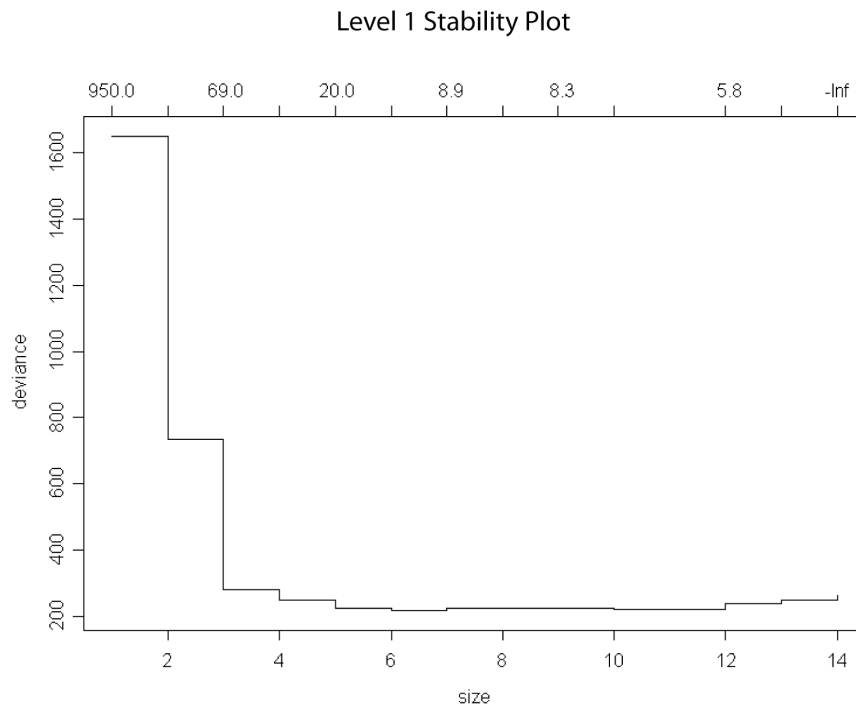


Fig. 3.3. Cross validation plot for Level 1 CTA showing deviance relating to size of tree (number of splits).

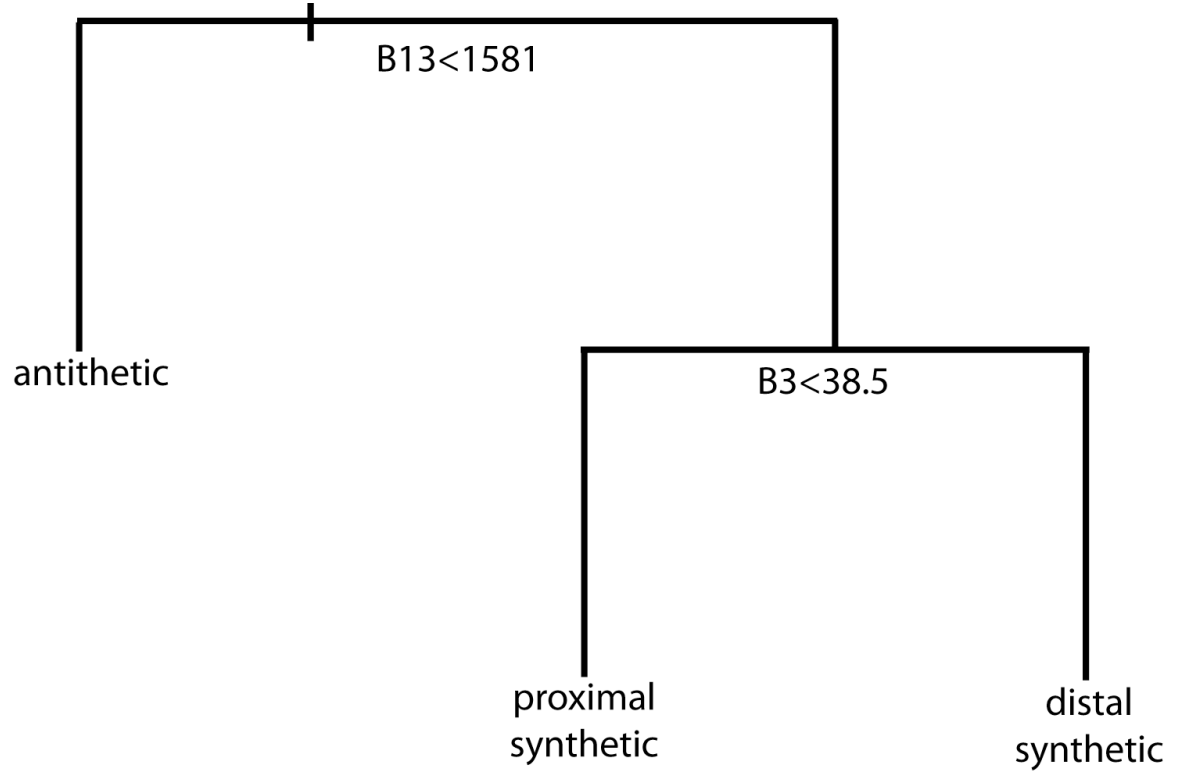


Fig. 3.4. Pruned tree for Level 1 CTA showing variables and values for split locations.

Level 1 Stability Plot

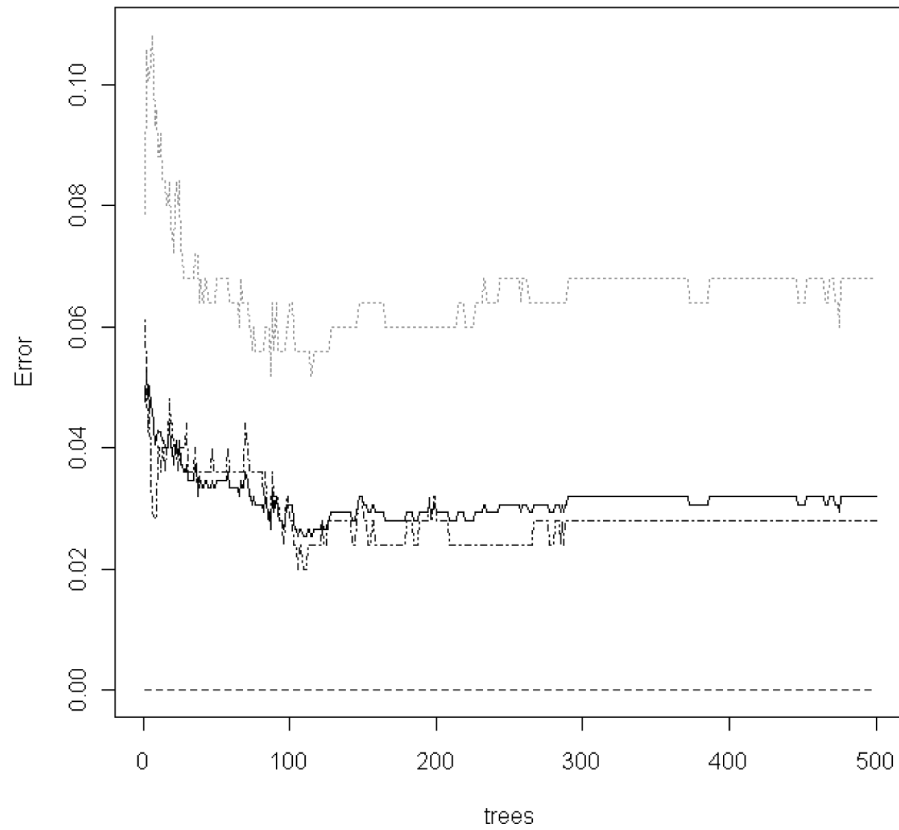


Fig. 3.5. Graph showing change in Level 1 RF model OOB error estimation with number of trees used. Black line represents overall error, and dashed lines are individual class errors.

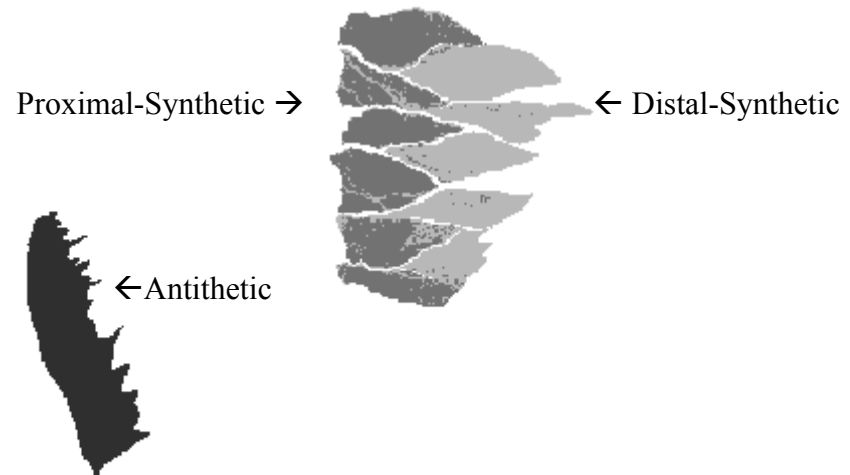


Fig. 3.6. CTA classification of Level 1. The 3 classes are colored in order from Antithetic (darkest) to Proximal-Synthetic (middle grey) and Distal-Synthetic (lightest).

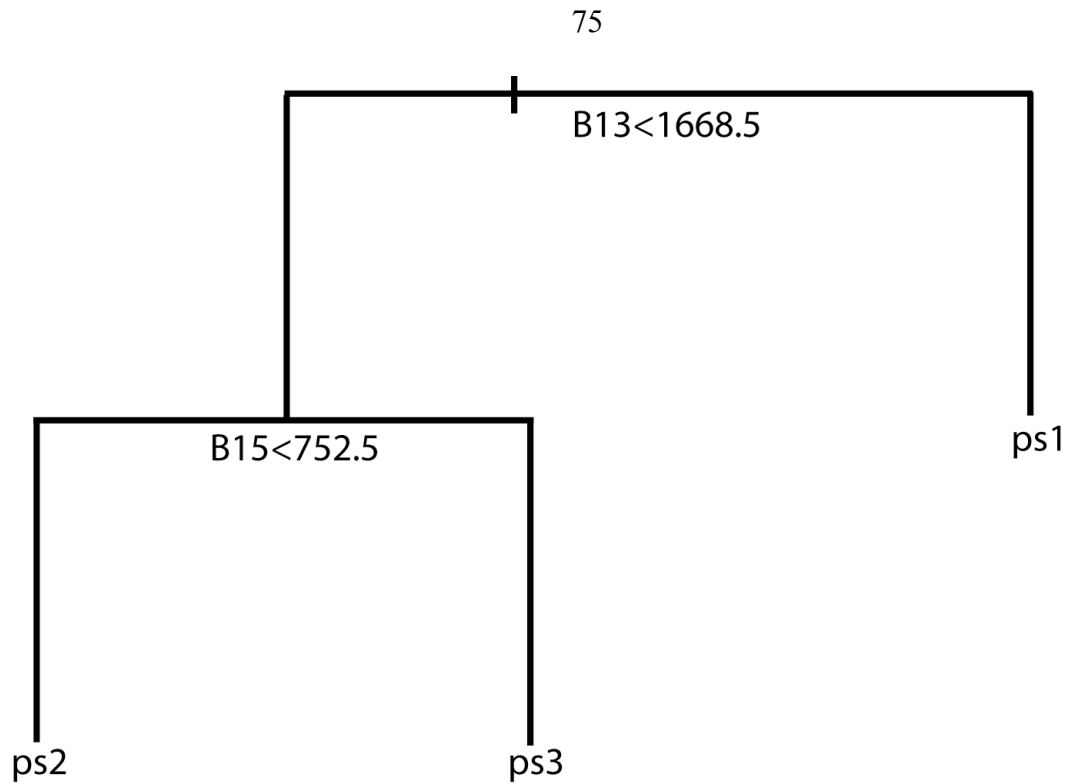


Fig. 3.7. Pruned tree for Level 2 Proximal-Synthetic Fans CTA showing variables and values for split locations.

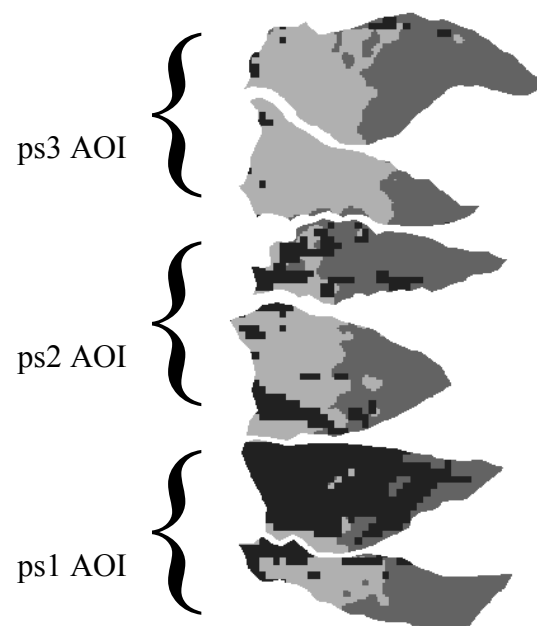


Fig. 3.8. CTA classification of Level 2 Proximal-Synthetic Fans. The 3 classified pixel colors are ps1 (darkest) to ps2 (middle grey) to ps3 (lightest).

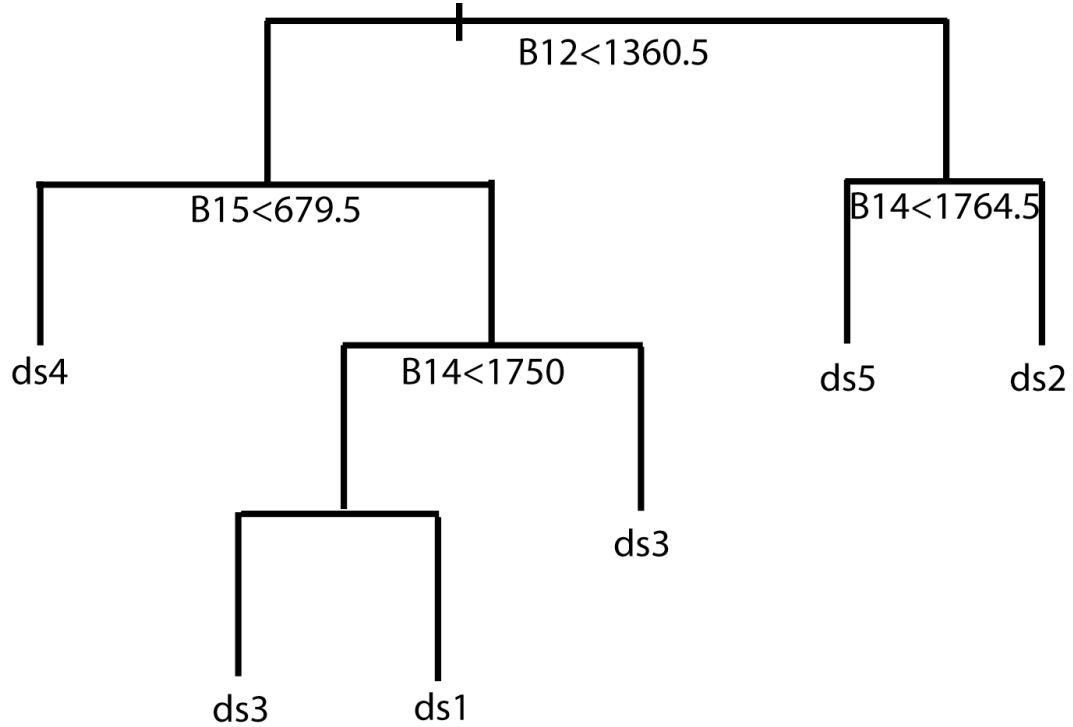


Fig. 3.9. Pruned tree for Level 2 Distal-Synthetic Fans CTA showing variables and values for split locations.

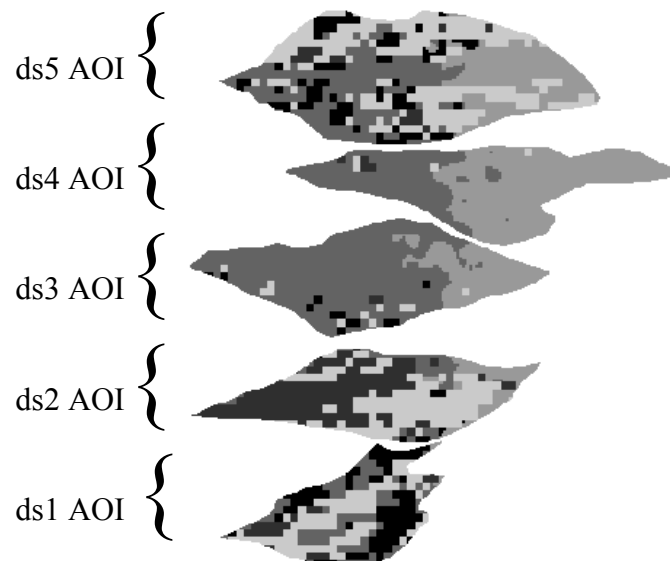


Figure 3.10. CTA classification of Level 2 Distal-Synthetic Fans. The 5 classified pixel colors are in order from ds1 (darkest) to ds5 (lightest).

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References

- Argialas, D.P., & Tzotsos, A., (2004). Automatic extraction of alluvial fans from ASTER L1 Satellite Data and a Digital Elevation Model using object-oriented image analysis. *International Society for Photogrammetry and Remote Sensing, Congress 20, Commission 7, 35, no. 251.*
- Blair, T.C., & McPherson, J.G., (1994a). Alluvial fan processes and forms. In: Abrahams, A.D., Parson, A.J. (Eds.), *Geomorphology of Desert Environments*. London, England, Chapman and Hall, pp. 354–402.
- Blair, T.C., & McPherson, J.G., (1994b). Alluvial fans and their natural distinction from rivers based on morphology, hydraulic processes, sedimentary processes, and facies assemblages. *Journal of Sedimentary Research, A64*, 450–489.
- Breiman, L., (1996). Bagging predictors. *Machine Learning, 26*, 123–140.
- Breiman, L., (2001). Random Forests. *Machine Learning, 40*, 5–32.
- Breiman, L., Friedman, J.H., Olshen, R.A. & Stone, C.J., (1984). *Classification and Regression Trees*. Monterey, CA, Wadsworth, 358 pp.
- Congalton, R., & Green, K., (1999). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton, Florida, CRC Press, Inc., 183 pp.
- Costa, C.H., Gardini, C.E., Diederix, H., & Cortés, J.M., (2000). The Andean orogenic front at Sierra de Las Penas-Las Higueras, Mendoza, Argentina. *Journal of South American Earth Sciences, 13*, 287–292.
- Cracknell, A.P., & Hayes, L.W.B., (1991). *Introduction to Remote Sensing*. London, England, Taylor and Francis, 293 pp.
- Crouvi, O., & Ben-Dor, E., (2006). Quantitative mapping of arid alluvial fan surfaces using field spectrometer and hyperspectral remote sensing, *Remote Sensing of Environment, 104*, 103–117.
- Damanti, J.F., (1990). Lithologic mixing in a modern foreland basin: Evidence from Landsat thematic mapper images. *Geology, 18*, 835–838.
- Fraser, G.S., & DeCelles, P.G., (1992). Geomorphic controls on sediment accumulation at margins of foreland basins. *Basin Research, 4*, 233–252.

- Gislason, P.O., Benediktsson, J.A., & Sveinsson, J.R., (2006). Random Forests for land cover classification. *Pattern Recognition Letters*, 27, 294–300.
- Hardgrove, C., Moersch, J., & Whisner, S., (2009). Thermal imaging of alluvial fans: A new technique for remote classification of sedimentary features. *Earth and Planetary Science Letters*, 285, 124-130.
- Huang, X., & Jensen, J.R., (1997). A machine-learning approach to automated knowledge-base building for remote sensing image analysis with GIS data. *Photogrammetric Engineering & Remote Sensing*, 63, 1185–1194.
- Jensen, J.R., (2005). *Introductory Digital Image Processing*. Upper Saddle River, NJ, Pearson Prentice Hall, 526 pp.
- Lawrence R.L., & Wright, A., (2001). Rule-based classification system using classification and regression tree (CART) Analysis. *Photogrammetric Engineering and Remote Sensing*, 67, 1137-1142.
- Lawrence, R.L., Bunn, A., Powell, S., & Zambon, M., (2004). Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment*, 90, 331– 336.
- Lawrence, R.L., Wood, S.D., & Sheley, R.L., (2006). Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). *Remote Sensing of Environment*, 100, 356–362.
- Milana, J.P., (2000). Characterization of alluvial bajada facies distribution using TM imagery. *Sedimentology*, 47, 741–760.
- Milana, J.P. & Ruzzycki, L. de B., (1999). Alluvial fan slope as a function of sediment transport efficiency. *Journal of Sedimentary Research*, 69, 553-562.
- Pelletier, J.D., Mayer, L., Pearthree, P.A., House, P.K., Demsey, K.A., Klawon, J.E., & Vincent, K.R., (2005). An integrated approach to flood hazard assessment on alluvial fans using numerical modeling, field mapping, and remote sensing. *Geological Society of America Bulletin*, 117, 1167–1180.
- R Development Core Team, (2005). R: A language and environment for statistical computing. Vienna, Austria, R Foundation for Statistical Computing, URL <http://www.R-project.org>.
- Safavian, S.R., & Langrebe, D., (1991). A survey of decision tree classifier methodology. *IEEE Transactions on Systems, Man and Cybernetics*, 21, 660–674.

Scull, P., Franklin, J., & Chadwick, O.A., (2005). The application of classification tree analysis to soil type prediction in a desert landscape. *Ecological Modeling*, 181, 1-15.

GENERAL CONCLUSION

This study successfully demonstrated the use of remotely sensed data to quantify transition in surface characteristics of the sediment routing system with changing displacement along the fault system. The sediment routing system shows changes in both the erosional and depositional sectors along strike of the active thrust. Moving south along the thrust front, with increasing displacement, drainage basins become shorter and the locus of sedimentation moves eastward into the foreland basin, incising older fan surfaces (Fig. 2.9).

Results from terrain analysis of the erosional sector of the sediment routing system indicate that elongation ratio is a diagnostic morphometric in the evolution of the thrust-sheet drainage basins. Drainage basin shape affects hydrologic processes in the source area, and how efficiently sediment is evacuated from the range. Statistical analysis suggests that every one km increase away from the fault lateral ramp is associated with an elongation ratio (of diameter km to length km) increase of 0.021 with a 95% confidence interval from 0.013 to 0.029.

Results from the spectral classification of imagery from the depositional sector of the sediment routing system indicate that spectral reflectance responses in the thermal (8.925–11.65 μm) and infrared (0.78–0.86 μm) wavelengths, as well as elevation responses are important explanatory variables in classifying alluvial fan surfaces. These responses are interpreted to be related to differences in grain size and compaction, vegetation growth, and fan progradation, respectively. Overall accuracy was greater than

85% for the classification of antithetic and synthetic fans in both classification tree analysis and random forest models.

Mapping with remote sensing of satellite images and terrain analysis of digital elevation models captures landform-scale changes in alluvial fan depositional systems along the Argentine Precordillera. Satellite image and digital elevation model coverage is becoming almost ubiquitous on Earth and expanding with access to other planets. The terrain analysis and remote sensing techniques used in this study may be applied to alluvial fan depositional systems in other locations where field-based information (geodetic, seismic, structural and lithologic data) is not available.

REFERENCES CITED

- Ahumada, E.A., and Costa, C.H., 2009. Antithetic linkage between oblique Quaternary thrusts at the Andean front, Argentine Precordillera. *Journal of South American Earth Sciences*, 28, 207–216.
- Allen, P.A., 1997. *Earth surface processes*. Blackwell Publishing, Oxford, 416 pp.
- Allen, P.A., 2008. From landscapes into geological history. *Nature*, 451, 274 – 276.
- Allen, P.A., and Hovius, N., 1998. Sediment supply from landslide-dominated catchments: implications for basin margin fans. *Basin Research*, 10, 19–35.
- Argialas, D.P., and Tzotsos, A., 2004. Automatic extraction of alluvial fans from ASTER L1 Satellite Data and a Digital Elevation Model using object-oriented image analysis. *International Society for Photogrammetry and Remote Sensing, Congress 20, Commission 7*, 35, no. 251.
- Band, L.E., 1986. Topographic Partition of Watershed with Digital Elevation Models. *Water Resource Research*, 22, 15-24.
- Blair, T.C., and McPherson, J.G., 1994a. Alluvial fan processes and forms. In: Abrahams, A.D., Parson, A.J. Eds.), *Geomorphology of Desert Environments*. Chapman and Hall, London, pp. 354–402.
- Blair, T.C., and McPherson, J.G., 1994b. Alluvial fans and their natural distinction from rivers based on morphology, hydraulic processes, sedimentary processes, and facies assemblages. *Journal of Sedimentary Research*, A64, 450–489.
- Bonnet, S., 2009. Shrinking and splitting of drainage basins in orogenic landscapes from the migration of the main drainage divide. *Nature Geoscience*, 2, 766-771.
- Breiman, L., 1996. Bagging predictors. *Machine Learning*, 26, 123–140.
- Breiman, L., 2001. Random Forests. *Machine Learning*, 40, 5–32.
- Breiman, L., Friedman, J.H., Olshen, R.A. and Stone, C.J., 1984. *Classification and Regression Trees*. Wadsworth, Monterey, CA, 358 pp.
- Brooks, B.A., Bevis, M., Smalley, R., Kendrick, E., Manceda, R., Lauria, E., Maturana, R., and Araujo, M., 2003. Crustal motion in the Southern Andes (26 degrees-36 degrees S): Do the Andes behave like a microplate? *Geochemistry, Geophysics, Geosystems*, 4, 1085.
- Burbank, D.W., and Anderson, R.S., 2000. *Tectonic Geomorphology*. Blackwell Publishing, Oxford, 270 pp.

- Burbank, D.W., and Vergés, J., 1994. Reconstruction of topography and related depositional systems during active thrusting. *Journal of Geophysical Research*, 99, 20281–20297.
- Burbank, D.W., Meigs, A., and Brozovic, N., 1996. Interactions of growing folds and coeval depositional systems. *Basin Research*, 8, 199–223.
- Congalton, R., and Green, K., 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. CRC Press, Inc., Boca Raton, Florida, 183 pp.
- Conrad, O., 2006. SAGA – Program Structure and Current State of Implementation. In: Böhner, J., McCloy, K.R., Strobl, J. [Eds.]: *SAGA – Analysis and Modelling Applications*. Göttinger Geographische Abhandlungen, 115, 39-52.
- Costa, C.H., Gardini, C.E., Diederix, H., and Cortés, J.M., 2000a. The Andean orogenic front at Sierra de Las Penas-Las Higueras, Mendoza, Argentina. *Journal of South American Earth Sciences*, 13, 287–292.
- Costa, C., Machette, M.N., Dart, R.L., Bastias, H.E., Paredes, J.D., Perucca, L.P., Tello, G.I., and Haller, K.M., 2000b. Map and Database of Quaternary Faults and Folds in Argentina: U.S. Geological Survey Open-File Report 00-0108, 76 p., 90 p., 1 plate (1:4,000,000 scale).
- Costa, C.H., Gardini, C.E., Diederix, H., Cisneros, H.A., and Ahumada, E.A., 2006. The active Andean orogenic front at the southernmost Pampean flat-slab. *Geological Society of America Abstracts with Programs, Backbone of the Americas* (Specialty Meeting No. 2), p. 110.
- Cowie, P.A., Attal, M., Tucker, G.E., Whittaker, A.C., Naylor, M., Ganas, A., and Roberts, G.P., 2006. Investigating the surface process response to fault interaction and linkage using a numerical modeling approach. *Basin Research*, 18, 231–266.
- Cracknell, A.P., and Hayes, L.W.B., 1991. *Introduction to Remote Sensing*. Taylor and Francis, London, England, 293 pp.
- Crouvi, O., and Ben-Dor, E., 2006. Quantitative mapping of arid alluvial fan surfaces using field spectrometer and hyperspectral remote sensing. *Remote Sensing of Environment*, 104, 103-117.
- Damanti, J.F., 1990. Lithologic mixing in a modern foreland basin: Evidence from Landsat thematic mapper images. *Geology*, 18, 835-838.

- DeCelles, P.G., and Giles, K.A., 1996. Foreland basin systems. *Basin Research*, 8, 102-123.
- Delcaillau B., Carozza, J.M., and Laville, E., 2006. Recent fold growth and drainage development: The Janauri and Chandigarh anticlines in the Siwalik foothills, northwest India. *Geomorphology*, 76, 24-256.
- Densmore, A.L., Dawers, N.H., Gupta, S., and Guidon, R., 2005. What sets topographic relief in extensional footwalls? *Geology*, 33, 453-456.
- Fraser, G.S., and DeCelles, P.G., 1992. Geomorphic controls on sediment accumulation at margins of foreland basins. *Basin Research*, 4, 233-252.
- Gislason, P.O., Benediktsson, J.A., and Sveinsson, J.R., 2006. Random Forests for land cover classification. *Pattern Recognition Letters*, 27, 294-300.
- Hardgrove, C., Moersch, J., and Whisner, S., 2009. Thermal imaging of alluvial fans: A new technique for remote classification of sedimentary features. *Earth and Planetary Science Letters*, 285, 124-130.
- Hovius, N., 1996. Regular spacing of drainage outlets from linear mountain belts. *Basin Research*, 8, 29-44.
- Huang, X., and Jensen, J.R., 1997. A machine-learning approach to automated knowledge-base building for remote sensing image analysis with GIS data. *Photogrammetric Engineering and Remote Sensing*, 63, 1185-1194.
- Jensen, J.R., 2005. *Introductory Digital Image Processing*. Pearson Prentice Hall, Upper Saddle River, NJ, 526 pp.
- Keller, E.A., and Pinter, N., 1996. *Active Tectonics: Earthquakes, Uplift, and Landscape*. Prentice Hall, New York, pp. 138-139.
- Kendrick, E., Bevis, M., Smalley, R., Brooks, B., Vargas, R.B., Lauría, E., and Souto Fortes, L.P., 2003. The Nazca-South America Euler vector and its rate of change. *Journal of South American Earth Sciences*, 16, 125-131.
- Kottek, M., Grieser, J., Beck, C., Rudolf, B., and Rubel, F., 2006. World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, 15, 259-263.
- Lawrence R.L., and Wright, A., 2001. Rule-based classification system using classification and regression tree (CART) Analysis. *Photogrammetric Engineering and Remote Sensing*, 67, 1137-1142.

- Lawrence, R.L., Bunn, A., Powell, S., and Zambon, M., 2004. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment*, 90, 331-336.
- Lawrence, R.L., Wood, S.D., and Sheley, R.L., 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). *Remote Sensing of Environment*, 100, 356-362.
- Leeder, M.R., Seger, M.J., and Stark, C.P., 1991. Sedimentation and tectonic geomorphology adjacent to major active and inactive normal faults, southern Greece. *Journal of the Geological Society*, 148, 331-343.
- Leleu, S., Ghienne, J.-F., and Manatschal, G., 2009. Alluvial fan development and morpho-tectonic evolution in response to contractional fault reactivation (Late Cretaceous-Palaeocene), Provence, France. *Basin Research*, 21, 157-187.
- Milana, J.P., 2000. Characterization of alluvial bajada facies distribution using TM imagery. *Sedimentology*, 47, 741-760.
- Milana, J.P. and Ruzycki, L. de B., 1999. Alluvial fan slope as a function of sediment transport efficiency. *Journal of Sedimentary Research*, 69, 553-562.
- Moore, I.D., Grayson, R.B., and Ladson, A.R., 1991. Digital terrain modelling: a review of hydrological, geomorphological, and biological applications. *Hydrological Processes*, 5, 3-30.
- O'Callaghan, J.F., and Mark, D.M., 1984. The extraction of drainage networks from digital elevation data. *Computer Vision, Graphics and Image Processing*, 28, 323-344.
- Ori, G.G., and Friend, P.F., 1984. Sedimentary basins formed and carried piggyback on active thrust sheets. *Geology*, 12, 478-478.
- Pearce, S.A., Pazzaglia, F.J., and Eppes, M.C., 2004. Ephemeral stream response to growing folds. *GSA Bulletin*, 116, 1223-1239.
- Pelletier, J.D., Mayer, L., Pearthree, P.A., House, P.K., Demsey, K.A., Klawon, J.E., and Vincent, K.R., 2005. An integrated approach to flood hazard assessment on alluvial fans using numerical modeling, field mapping, and remote sensing. *Geological Society of America Bulletin*, 117, 1167-1180.
- Quinn, P. F., Beven, K. J., Chevallier, P., and Planchon, O., 1991. The prediction of hillslope flowpaths for distributed modelling using digital terrain models. *Hydrological Processes*, 5, 59- 80.

- R Development Core Team, 2005. R: A language and environment for statistical computing. Vienna, Austria, R Foundation for Statistical Computing, URL <http://www.R-project.org>.
- Safavian, S.R., and Langrebe, D., 1991. A survey of decision tree classifier methodology. *IEEE Transactions on Systems, Man and Cybernetics*, 21, 660–674.
- Schmitt, J.G., and Costa, C.H., 2006, Tectogenic sediment dispersal from retroarc foreland orogenic wedges: Examples from the Cordillera of North and South America. *Geological Society of America Abstracts with Programs, Backbone of the Americas (Specialty Meeting No. 2)*, 112.
- Schmitt, J.G., and Steidtmann, J.R., 1990, Interior ramp-supported uplifts: Implications for sediment provenance in foreland basins. *Geological Society of America Bulletin*, 102, 494-501.
- Schumm S.A., 1956. Evolution of drainage systems and slopes in badlands at Perth Amboy, New Jersey. *Geological Society of America Bulletin*, 67, 597–646.
- Schumm, S.A., 1986. Alluvial river response to active tectonics. In: *Studies in National Research Council (Ed.), Active Tectonics*. National Academy Press, Studies in Geophysics, Washington, D.C, 80–94.
- Scull, P., Franklin, J., and Chadwick, O.A., 2005. The application of classification tree analysis to soil type prediction in a desert landscape. *Ecological Modeling*, 181, 1-15.
- Seibert, J., and McGlynn, B.L., 2007. A new triangular multiple flow direction algorithm for computing upslope areas from gridded digital elevation models. *Water Resource Research*, 43, W04501.
- Singh, T., and Jain, V., 2009. Tectonic constraints on watershed development on frontal ridges: Mohand Ridge, NW Himalaya, India. *Geomorphology*, 106, 231–241.
- Talling, P.J., Stewart, M.D., Stark, C.P., Gupta, S., and Vincent, S.J., 1997. Regular spacing of drainage outlets from linear fault blocks. *Basin Research*, 9, 275– 302.
- Tarboton, D.G., 1997. A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water Resource Research*, 33, 309–319.
- Vergés, J., Ramos, V.A., Meigs, A., Cristallini, E., Bettini, F.H., and Cortés, J.M., 2007. Crustal wedging triggering recent deformation in the Andean thrust front between

31 degrees S and 33 degrees S: Sierras Pampeanas-Precordillera interaction.
Journal of Geophysical Research, 112, B03S15.

Wang, L., and Liu, H., 2006. An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modeling. International Journal of Geographical Information Science, 20, 193-213.

WEB REFERENCES

Perego, 2009. SRTM DEM destripping with SAGA GIS: consequences on drainage network extraction. Retrieved April 2, 2010.
<http://www.webalice.it/alper78/>

Servicio Meteorológico Nacional, 2000. Guía Climática para el Turismo, Mendoza. Retrieved April 2, 2010.
<http://www.smn.gov.ar/?mod=clima&id=30&provincia=Mendoza&ciudad=Mendoza>

United States Geological Survey (USGS), 2009. Routine Global Digital Elevation Model. Retrieved April 2, 2010.
https://lpdaac.usgs.gov/lpdaac/products/aster_products_table/routine/global_digital_elevation_model/v1/astgtm

APPENDICES

APPENDIX A

TERRAIN ANALYSIS FLOW CHART

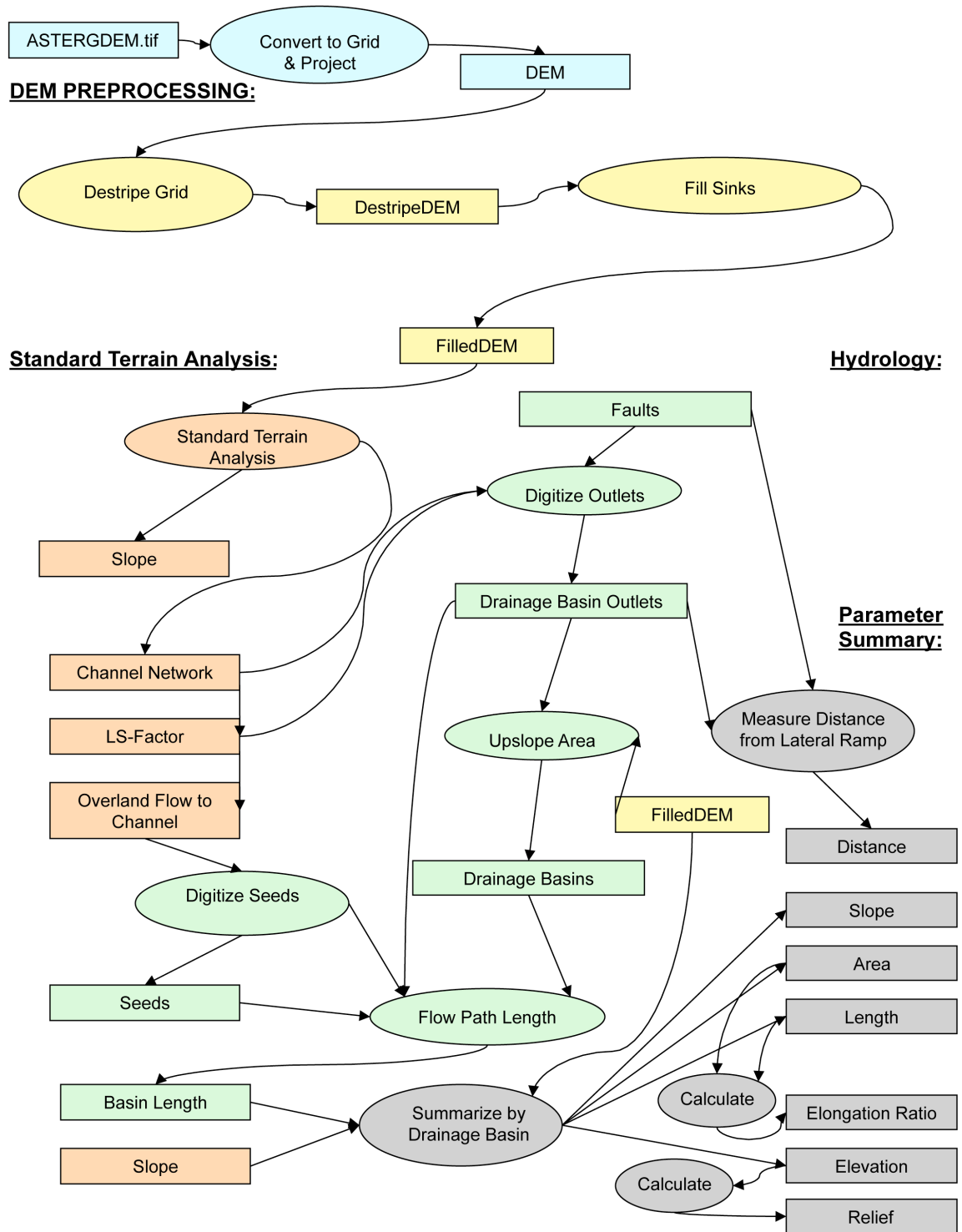


Diagram explanation of the processing steps used in terrain analysis (Manuscript 1). Circles indicate processing steps and squares indicate data.

APPENDIX B

REMOTE SENSING FLOW CHART

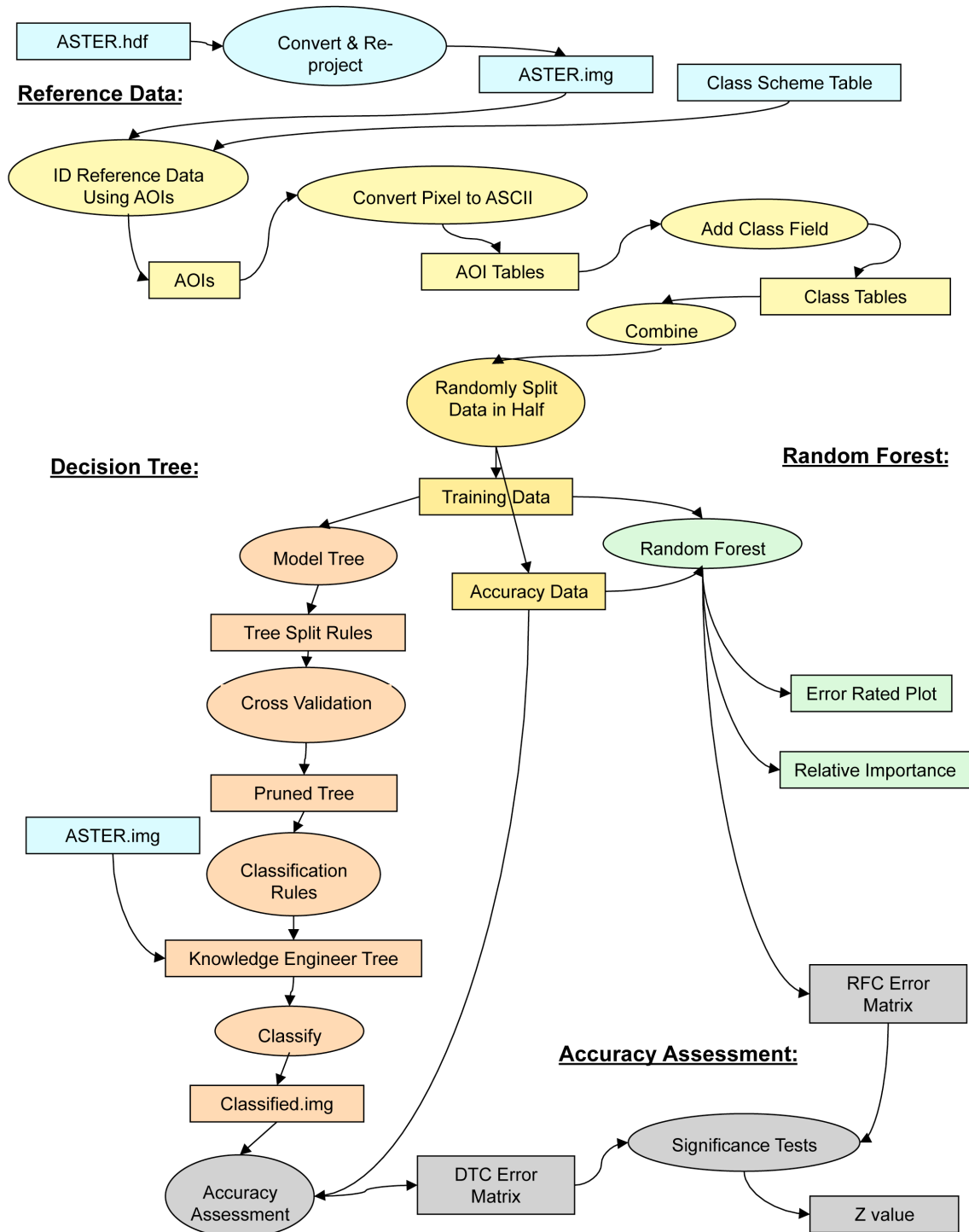


Diagram explanation of the processing steps used in remote sensing (Manuscript 2). Circles indicate processing steps and squares indicate data.