Deciphering Renal Cancer Evolution

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CR-UK Translational Cancer Therapeutics Laboratory





Is Cancer a clonal disease evolving in a linear fashion ?

Clonal succession and selective sweeps driving expansion of identical tumour cells



Nature Reviews | Immunology

Curing a tumour composed of **identical** cells ought to be achievable......

Implications for Therapy and Outcome



- Achieving cures in metastatic disease
- Cost of cancer drug development
- Cancer biomarker validation

Burrell, Mcgranahan, Bartek and Swanton Nature 2013



Gerlinger, Rowan, Horswell, Larkin et al NEJM 2012

Branched Evolution in ccRCC



Microevolution: Gradualism

- Darwin argued that nature never makes jumps : natura non facit saltum
- Profound change is the result of a slow but continuous processes
- Gradual accumulation of small mutations as drivers of change (Neo-Darwinism)



Challenge Cancer Macroevolution





Macroevolution: "Hopeful Monsters"

- Goldschmidt argued that large changes in evolution were caused by "macromutations"
- Chromosomal rearrangements result in Macroevolutionary leaps
- Rare events resulting in profound change: "Hopeful monsters"

Speciation





Macroevolution and Hopeful Monsters

"macroevolution must proceed by a different genetic method.... Only the arrangement of the serial chemical constituents of the chromosome into a new, spatially different order; ie. A new chromosomal pattern, is involved". Goldschmidt "Material Basis of Evolution" 1960



Fig 35 Simple types of chromosomal rearrangements

Patterns of Cancer Chromosomal Rearrangements

Structural CIN

Numerical CIN

Chromoplexy (Garraway)







Chromothripsis (Campbell/Meyerson)

Single chromosome fragmented and reassembled





Generates Profound Cell-to-Cell heterogeneity: fuel for phenotypic change (Pavelka Nature 2010)

Intra-metastatic Heterogeneity Driven by Chromosomal Instability





Bottlenecking at Metastatic Sites Is there a Substitute for Diversity ?



Cancer cell population

Time

Ploidy Analysis of Patient 001 Nephrectomy

Tetraploid intermediate in Region 4: Aneuploid progeny at metastatic sites



Allelic Imbalance



Region 4 has Doubled its Genome



Intra-Metastatic Tumour Heterogeneity driven by Chromosomal Instability



Intra-tumour heterogeneity Chromosomal Instability and Poor Clinical Outcome

Cancer Type	Method of measuring CIN	CIN associated with	Reference			
Lung cancer	FISH (n=63)	Poor prognosis (OS & DFS)	Choi et al. (2009)			
(NSCLC)	FISH (n=47)	Poor prognosis (OS)	Yoo et al. (2010)			
	FISH (n=50)	Poor prognosis (OS)	Nakamura et al. (2003)			
	12-gene genomic instability signature (n=647)	Poor prognosis (OS)	Mettu et al.(2010)			
	CIN70 signature (n=62)	Poor clinical outcome	Carter et al. (2006)			
Breast cancer	SSI (n=890)	Poor prognosis (OS)	Kronenwett et al. (2004)			
	SNP (n=313)	Poor prognosis (MFS)	Smid et al. (2010)			
	12-gene signature (n=469)	Poor prognosis (DFS & RFS)	Habermann et al.(2009)			
	CIN70 signature (n=1866)	Poor clinical outcome	Carter et al. (2006)			
	FISH (n=31)	Lymph-node metastasis and ER negativity	Takami et al.(2001)			
Myelodysplastic syndrome	FISH (n=65)	Poor prognosis (DFS)	Heilig et al.(2010)			
Endocrine pancreatic tumors	CGH (n=62)	Metastasis	Jonkers et al.(2005)			
Colon cancer	12 gene genomic instability signature (n=92)	Recurrence	Mettu et al. (2009)			
	Flow cytometry/ image cytometry (n = 10 126)	Poor prognosis	Walther et al.(2008)			
Ovarian cancer	12-gene genomic instability signature (n=124)	Poor prognosis (RFS)	Mettu et al.(2010)			
Endometrial cancer	SNP (n=31)	Poor prognosis (OS)	Murayama-Hosokawa et al. (2010)			
Synovial sarcoma	CGH (n=22)	Poor prognosis (OS)	Nakagawa et al.(2006)			
Oral cancer	FISH (n=77)	Poor prognosis (OS & DFS)	Sato et al.(2010)			
(SCCs)	FISH (n=20)	(loco)regional	Bergshoeff			
		tumour outgrowth	et al. (2008)			
Diffuse Large B-cell Lymphoma	Anaphase segregation errors (n=54)	Poor prognosis (RFS)	Bakhoum et al. (2011)			
Abbreviations: NSCLC, non-small cell lung cancer; SCC, squamous cell carcinoma; FISH, nuorescence in situ hybridization; SSI, stem line scatter index; CGH,						
comparative genome hybridisation; SNP, single-nucleotide polymorphisms; OS, overall survival; DFS, disease-free survival; MFS, metastasis-free survival; RFS,						
relapse free survival						

Opportunities for Clinical Trial Development

Define Actionable Mutations by Clonal Dominance



Marco Gerlinger Stuart Horswell, James Larkin, Max Salm, Nik Matthews UCL Cancer Institute

Target Tumour Phylogenetic Trunks and Resolve Branches



Branched Genetic Events Present in Some Cancer Cells not others Dynamic during disease course

Monitor subclonal events to define drug resistance mechanisms

Trunk Genetic Events Present in Every Cancer Cell

DEFINE and TARGET TRUNK DRIVERS







Private



Non-Synonymous Mutations















Patient 6









Mutations

Patient 10



Subclonal Driver Heterogeneity

Confounding treatment success?











Patient 5



Patient 6







Patient 10



Number of Driver Events under-estimated by Single Biopsy in ccRCC

Driver Prevalence

	Per Biopsy TCGA n=164	Per Biopsy n=79	Per Patient n=10
PBRM1	42%	39%	60%
SETD2	18%	27%	30%
BAP1	21%	24%	40%
KDM5C	7%	11%	10%
P53	5%	5%	40%
ATM	3%	4%	10%
ARID1A	6%	1%	10%
PTEN	5%	10%)	20%)
MTOR PI3K/mTOR	9%	8%	10%
PIK3CA pathway	3% 18%	4% 28%	20%
TSC2	2%	4%	10%

How can the genomic landscape be more efficiently mapped?





Tracking Tumour Subclonal Architecture Dynamics Somatic mutation detection in ctDNA extracted from peripheral blood.



Marco Gerlinger and Andrew Rowan

Exploit Convergence of Driver Events







Evidence for Parallel Evolution SETD2 Loss of Function: H3K36 tri-methylation









Genetic Heterogeneity may affect the same Protein Complex in different branches



SWI/SNF Chromatin remodeling Complex

Disruption of the mTOR Pathway A Common Convergent Event





Number of Driver Events under-estimated by Single Biopsy in ccRCC

		Per Biopsy TCGA n=164	Per Biopsy n=79	Per Patient n=10
	PBRM1	42%	39%	60%
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	ATM	3%	4%	10%
	ARID1A	6%	1%	10%
mTOR pathway	PTEN	5%	10%	20%
	MTOR PI3K/mTOR	9%	8%	10% 60%
	PIK3CA pathway	3%	4%	20%
	TSC2	2%)	4%)	10%)

Genetic Heterogeneity may affect the same Signaling Pathway in different branches



- Genetic heterogeneity may impact the same signalling pathway in different branches
 - PI3K/PTEN/mTOR

Genetic Heterogeneity commonly affects the same Driver in different branches



- 6/10 Tumours have recurrent mutations in the branches in the same gene
 - PIK3CA, PTEN,
 - SETD2, KDM5C, BAP1, PBRM1

Target Tumour Phylogenetic Trunks and Resolve Branches



Target convergent events in the branches

Target lethal subclone(s)

Trunk Genetic Events Present in Every Cancer Cell

DEFINE and TARGET TRUNK DRIVERS

Subclonal SCNA Heterogeneity

Confounding treatment success?







Trunk and Branched SCNAs

Case	Driver CNVs	Heterogeneous driver CNVs (%)
EV001	13	12 (92.3)
EV002	9	7 (77.8)
EV003	5	3 (60.0)
EV005	6	4 (66.7)
EV006	6	2 (33.3)
EV007	8	7 (87.5)
RMH002	8	7 (87.5)
RMH004	12	10 (83.3)
RMH008	4	2 (50.0)
RK26	5	3 (60.0)
Total	76	57 (75)

SCNAs Mapped to Phylogenetic Trees



Tumour Sampling Bias

Difficulties of identifying uniform biomarkers







Heterogeneous Nature

CCB Poor Prognostic Signature and CCA Good Prognostic Signature

Mapping the Genomic Landscape of ccRCC

How deep is the rabbit hole?





How many biopsies to fully map the number of driver events?



RMH004 Driver variants

Clinical Implications of Driver Heterogeneity

- >70% of Drivers are heterogeneous and spatially separated (BAP1, SETD2, PBRM1, KDM5C, MTOR, PIK3CA, PTEN, TSC2, TP53)
- Subclonal drivers cannot be readily distinguished in single biopsies
- Current sampling techniques are underestimating number of driver events in RCC
- Similar trunk driver events but diverse patient outcomes:
 - Branches and subclonal drivers are likely to influence outcome



TRACERx

<u>TRA</u>cking <u>Cancer</u> <u>Evolution</u> through Therapy (<u>**Rx**</u>)

Functional and Genetic Intratumour Heterogeneity

- Optimise Clinical trial development: Target Trunk vs Branched drivers
- Exploit constraints to cancer evolution
 - parallel evolutionary events converging on single genes or pathways
- Define relationships between diversity, clinical stage and cancer outcome
- Autopsy Programs: Define the origins of the lethal subclone
- Impact of therapy on cancer genome evolution
- Develop non-invasive methods to monitor cancer evolution: cfDNA
- Identify sequence of somatic events in relation to genome instability onset:
 - Define drivers of diversity and genome instability in tumours





Renal Cancer Evolution Summary

- Need to address two principles of Darwinian evolution
 - Decipher mechanisms of cancer **diversity**
 - Improve cancer **selection** pressures:
 - Target Clonal Driver VHL loss of function,
 - Resolve subclonal dynamics
- Understand evolutionary pressures resulting in parallel evolution of subclones
 - Develop better animal models of ccRCC
- Longitudinal cancer cohort studies (TRACERx): reveal processes shaping tumour genome evolution
 - Define Origins of lethal subclone





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Rosetrees Trust Helping humanity through medical research

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