Ing. Ana Laura Diedrichs
ana.diedrichs@frm.utn.edu.ar

UTN FACULTAD REGIONAL MENDOZA

IoT en agricultura: Predicción de heladas Mediante IoT y ML

SASE 2019
SIMPOSIO ARGENTINO DE SISTEMAS EMBEBIDOS
17 | 18 | 19 DE JULIO

¡Buenos días!
Me presento

Ing. Ana Laura Diedrichs
ana.diedrichs@frm.utn.edu.ar
Web https://anadiedrichs.github.io/
Twitter @anadiedrichs

DHARMA

INVESTIGACIÓN, INNOVACIÓN Y EDUCACION EN SISTEMAS INTELIGENTES

DHARMA.FRM.UTN.EDU.AR

Desarrollo (de)

Herramientas (de)

Aprendizaje (y)

Razonamiento (de)

Maquinas

http://dharma.frm.utn.edu.ar/

Inteligencia artificial – aprendizaje automático

Clasificación de imágenes para detección de yemas

Importancia de la yema

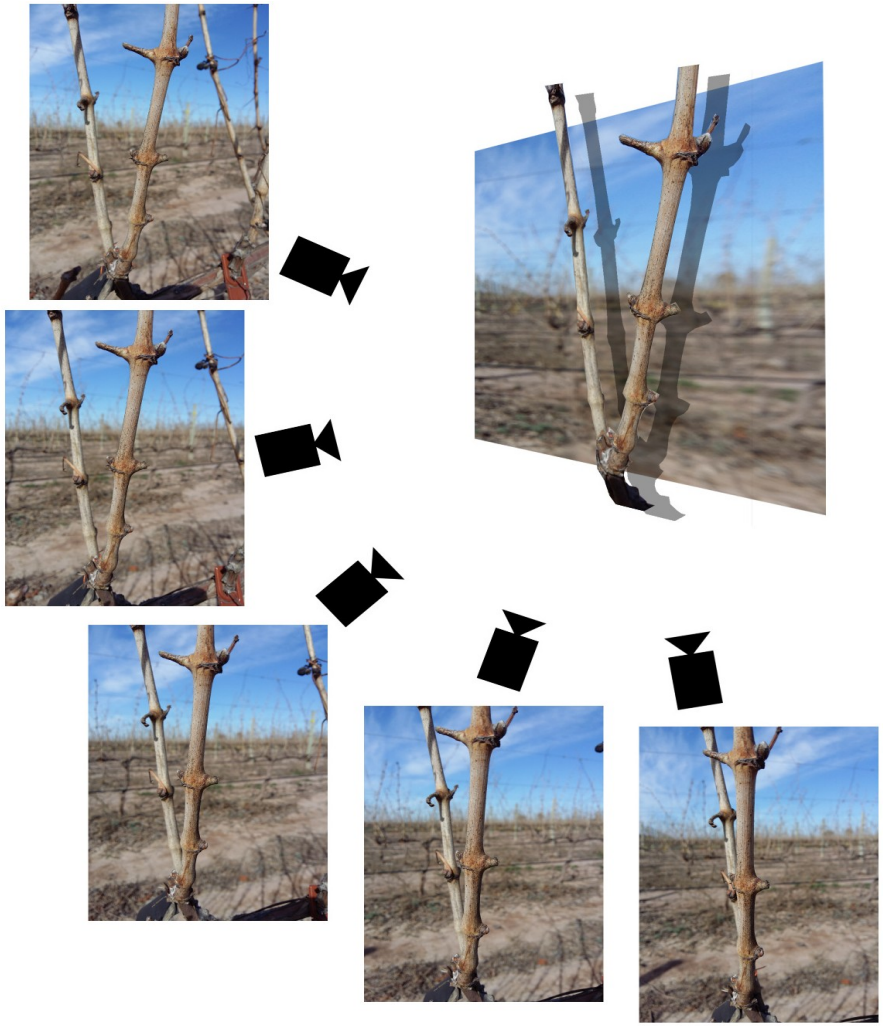
- Punto de crecimiento: brotes, hojas, racimos, zarcillos
- Aplicaciones de interés: medición de variables, poda, fenotipado

Enfoque para la clasificación/detección

- Clasificador SIFT+BoF+SVM y detección tipo scanning-window

http://dharma.frm.utn.edu.ar/

Reconstrucción de escenas para detección de yemas en 3D

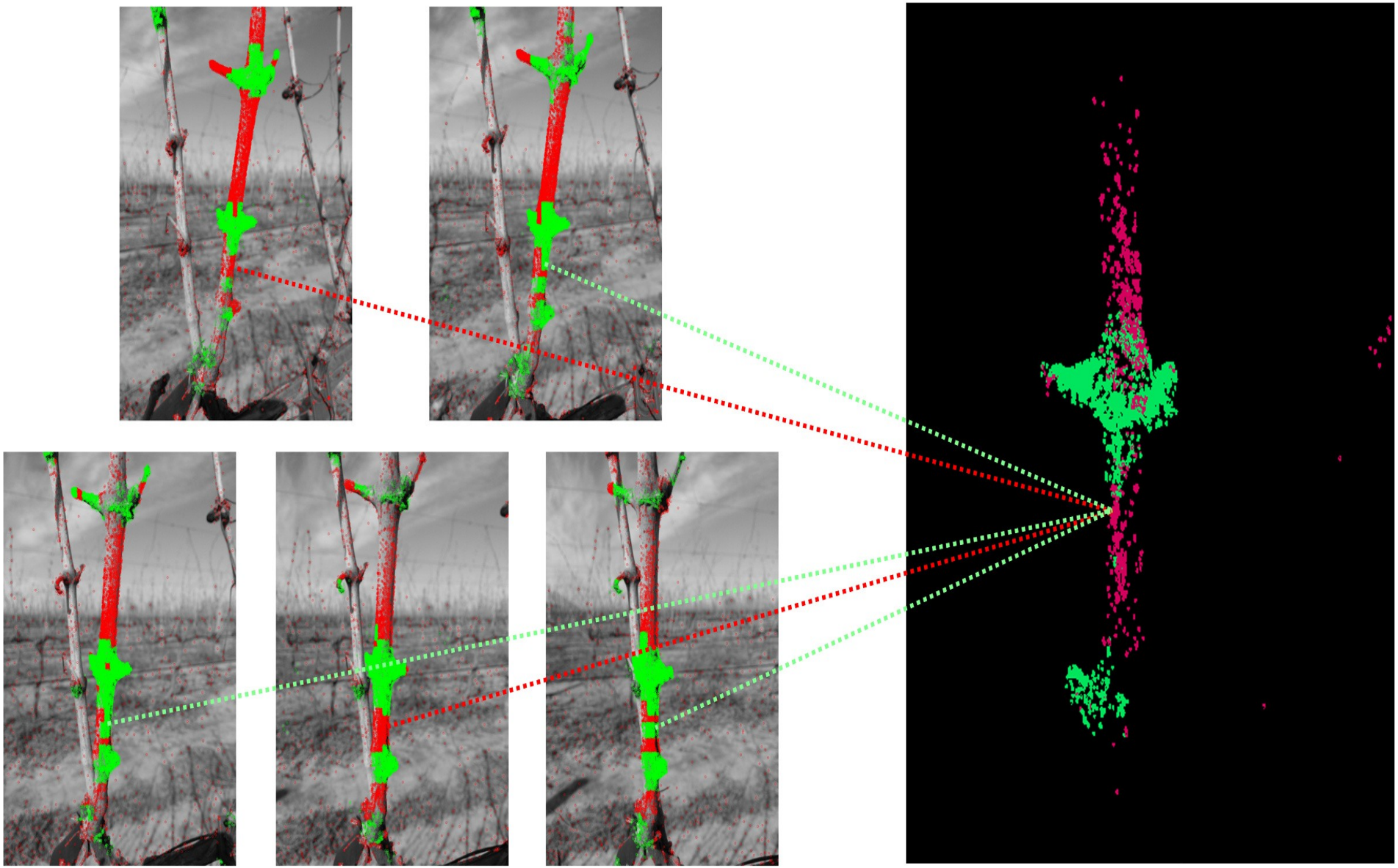


http://dharma.frm.utn.edu.ar/

Reconstrucción de escenas para detección de yemas en 3D

Stage 2- Scanning Windows 2D

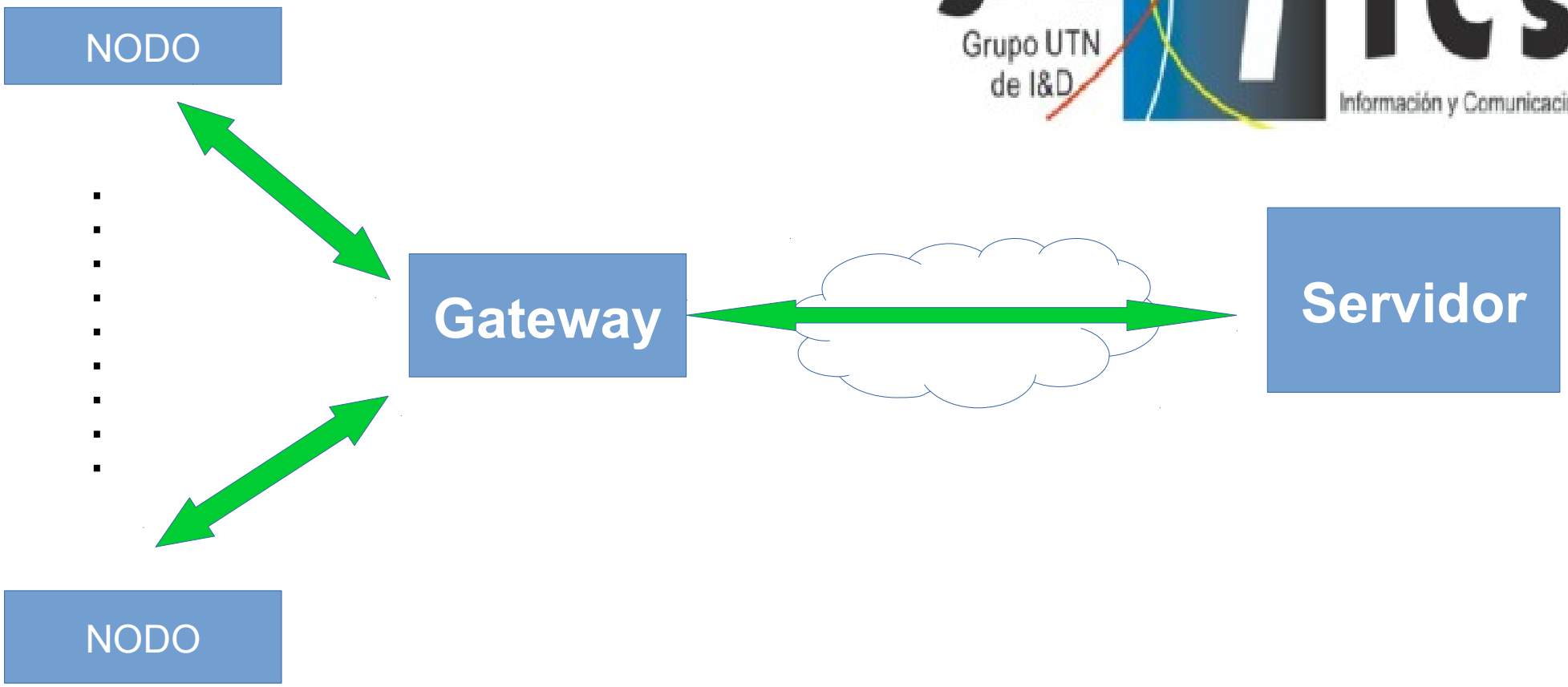
Stage 3 - Voting 3D



Tecnologías: ORB, DAISY, FLANN, SIFT, BoF, SVM

Arquitectura del Internet de las cosas

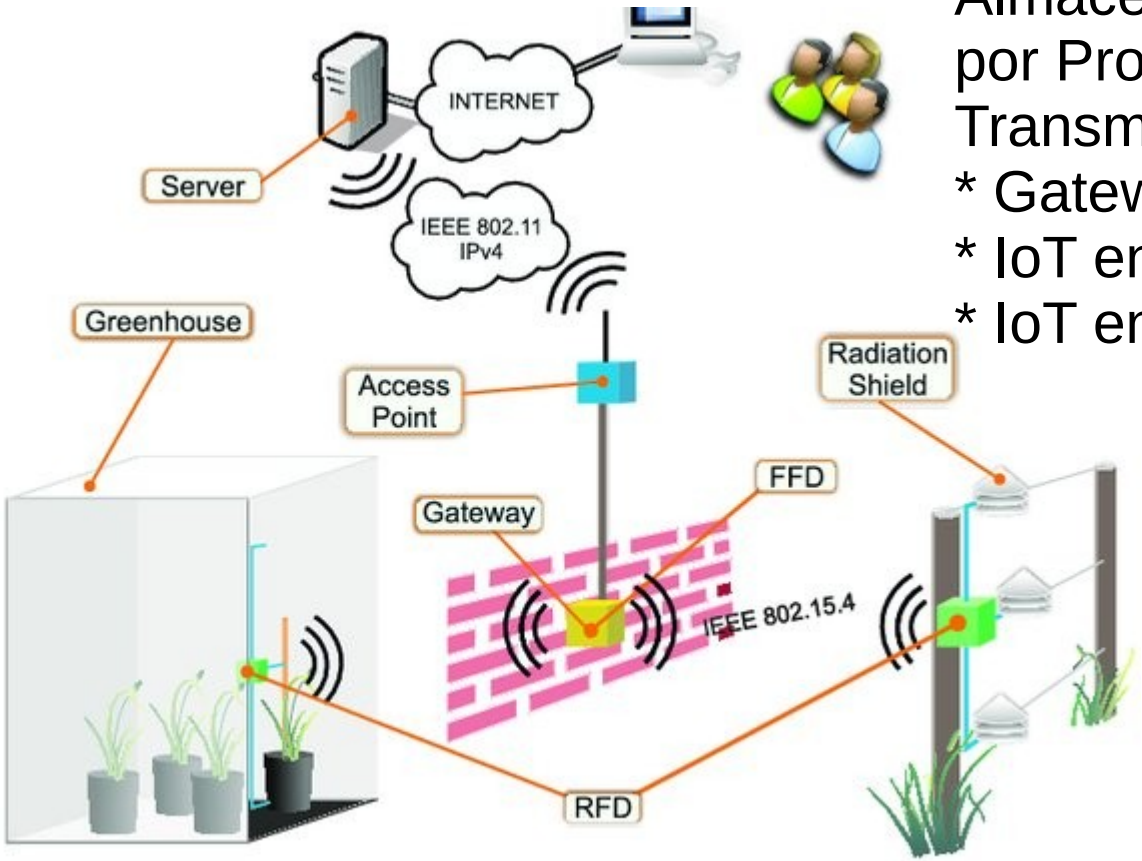
1. cosas = dispositivos + sensores/actuadores + comunicación inalámbrica



GridTICs

https://twitter.com/GridTICs

* Red SIPIA
* SADA - Sat Sistema de Adquisición y Almacenamiento de Datos Ambientales por Protocolo SDI-12 con Transmisión Satelital
* Gateway IoT CIAA
* IoT en agricultura
* IoT en general (OpenMote, Contiki)



Diedrichs, A. L., Tabacchi, G., Grünwaldt, G., Pecchia, M., Mercado, G., & Antivilo, F. G. (2014, June). Low-power wireless sensor network for frost monitoring in agriculture research. In 2014 IEEE Biennial Congress of Argentina (ARGENCON) (pp. 525-530). IEEE.

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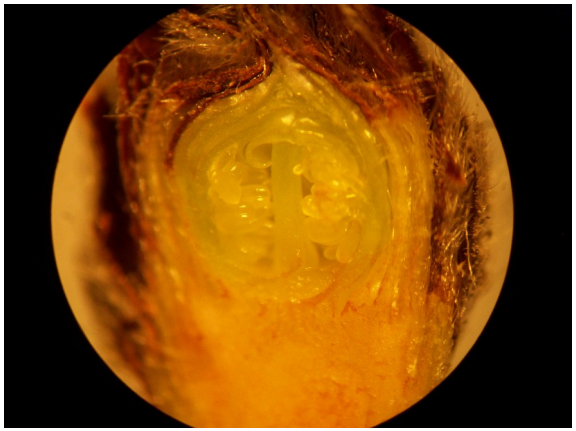
¿De dónde vienen los frutos?



vegetativo

floración

Flor abierta

Viñedos

Viñedo afectado por helada presentando la mayoría de los daños en la extremidad de los brotes.
Foto: Arturo Hernández. EEA Mendoza INTA

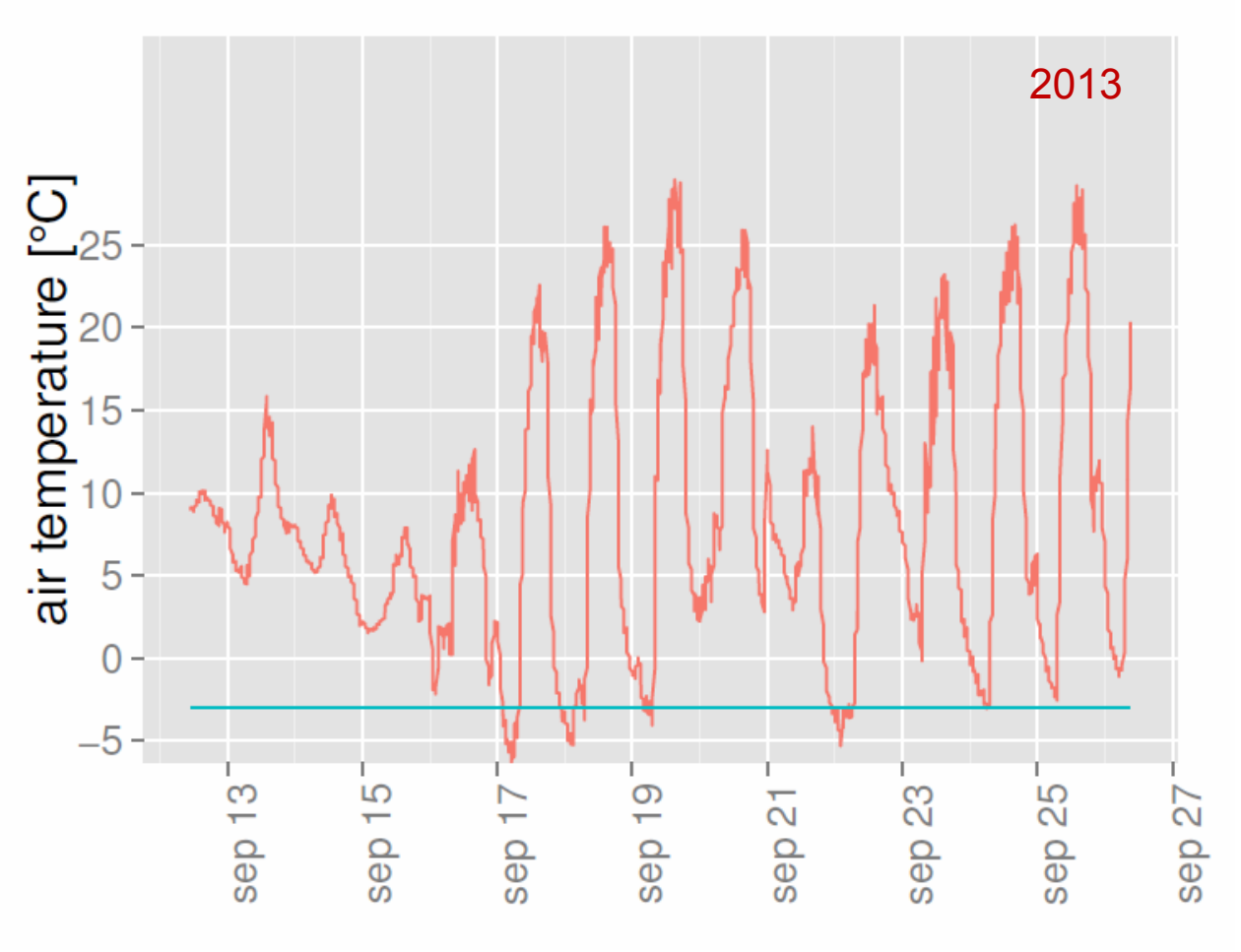
Planta afectada gravemente por helada con daños totales en brotes e inflorescencias.
Foto: Arturo Hernández. EEA Mendoza INTA

Receso Invernal	***Yemas Cerradas Mostrando Color***	***Plena Floración***	***Pequeños Frutos Verdes***
-17 ºC	-1,1 ºC	-0,6 ºC	-0,6 ºC

Temperaturas que podrían causar daño a la vid según su estado fenológico.
Fuente: Dirección de Agricultura y Contingencias Climáticas.

- https://inta.gob.ar/sites/default/files/script-tmp-hoja_divulgacin_helada.pdf

A los cultivos no les agradan las heladas



antes

después

Impacto económico-social

2013 - 85% producción durazno perdida · 10,000 puestos de trabajos

Campaña 2016-2017
Denunciaron daños unos 6.041 productores
· 53.647 hectáreas afectadas por heladas
· La mitad son de viñedos

- http://www.contingencias.mendoza.gov.ar/web1/pdf/camp1617hel.pdf

Combatir un evento de helada

molinos

calentadores

rociadores

Sábado, 1 de octubre de 2016 | Edición impresa

Casi 30 mil hectáreas afectadas por heladas

Se trata de un relevamiento estimativo hecho por la Provincia por las heladas que se registraron el mes pasado. La fruta de carozo es la más afectada.

| Archivo Los Andes

Hay muchas formas de combatir la helada, lo que es complicado es predecirla.

La helada como fenómeno microclimático

- Datos climáticos de estaciones meteorológicas.
- Usualmente hay 1 por finca y ésta puede tener miles de hectáreas.
- La helada es un fenómeno microclimático, es decir, parte de la finca pudo verse afectada y parte no.
- **Fenómeno de inversión térmica**

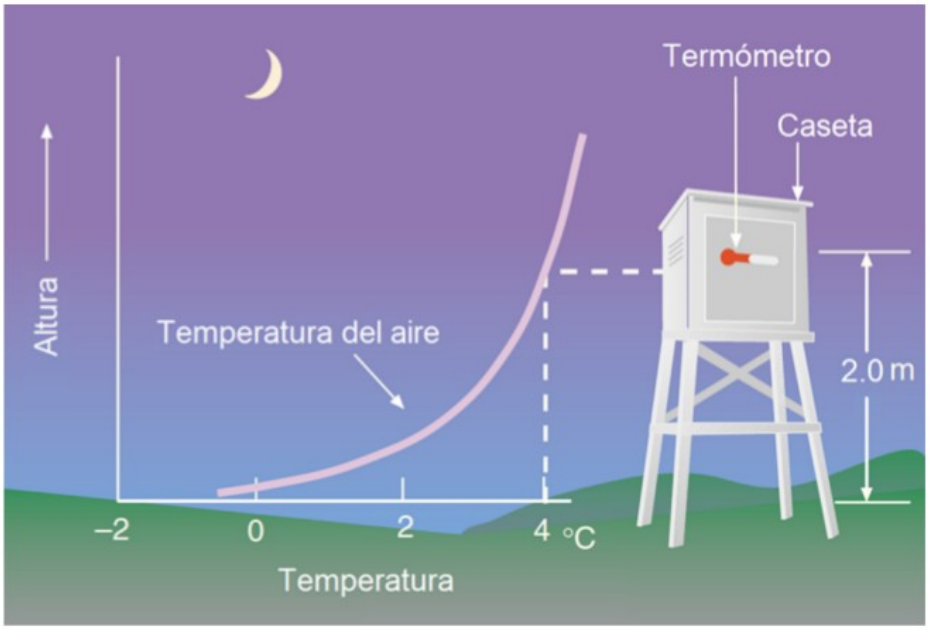
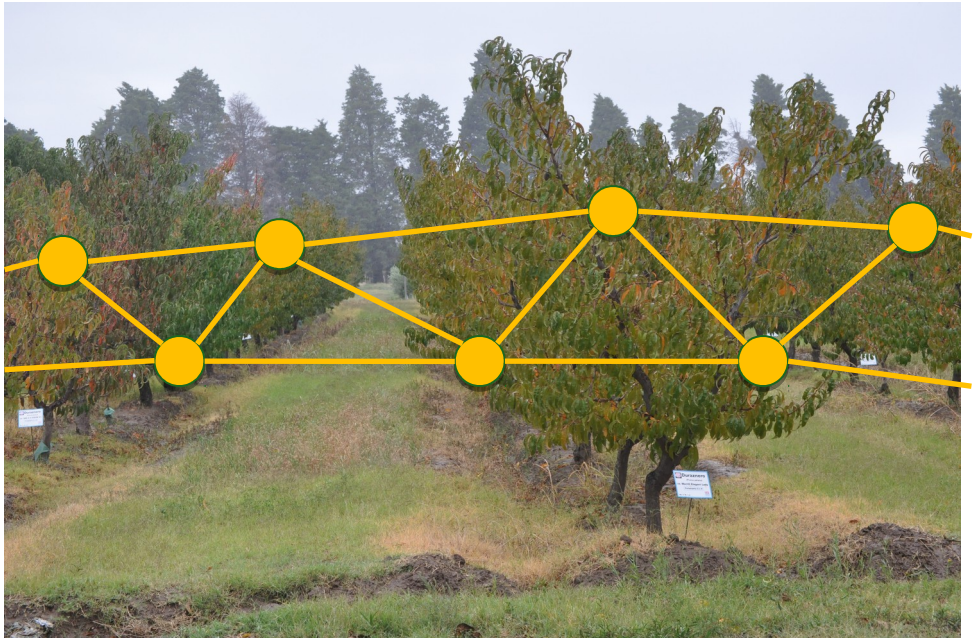


Figure 2.4.: Perfil característico de la temperatura cerca a la superficie durante la ocurrencia de una helada radiativa [2].

Sistema de monitoreo en tiempo real



- Temp. aire
- RH
- otros

state-of-the-art

Solución propuesta

1. Una red inalámbrica de sensores de bajo consumo
2. Recolección de datos en tiempo real
3. Aprendizaje automático para la predicción de heladas

• PrEcision Agriculture through Climate researcH

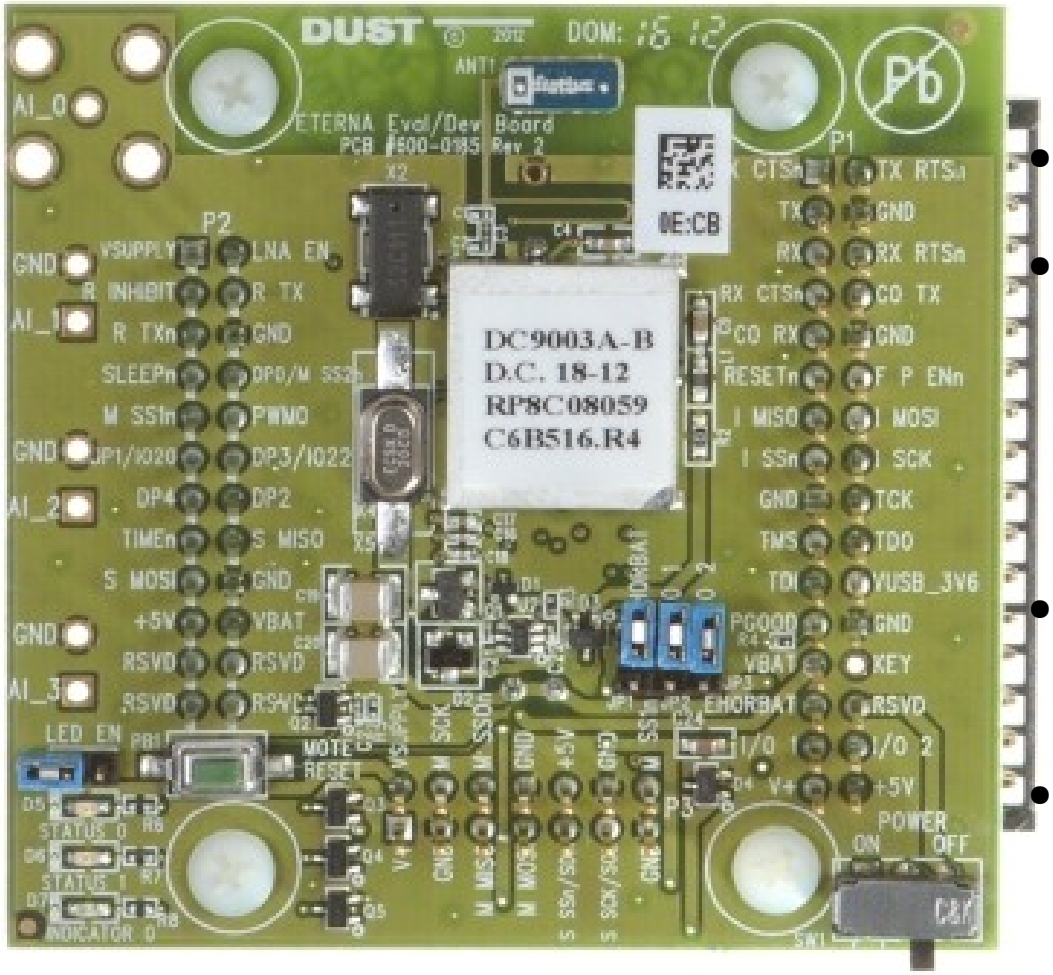
- Funding by mobility STIC-AmSud programm 16STIC08-PEACH (29000 euros), during 2016-2017
- Participantes: Thomas Watteyne, Ana Laura Diedrichs, Keoma Brun-Laguna, Javier Emilio Chaar, Diego Dujovne, Juan Carlos Taffernaberry, Gustavo Mercado, Nicolás Altamiranda, Matías Grünwaldt

PEACH: Objetivos

Instalar una red IoT para Caracterización microclimática

Construcción de módulo predictor de heladas

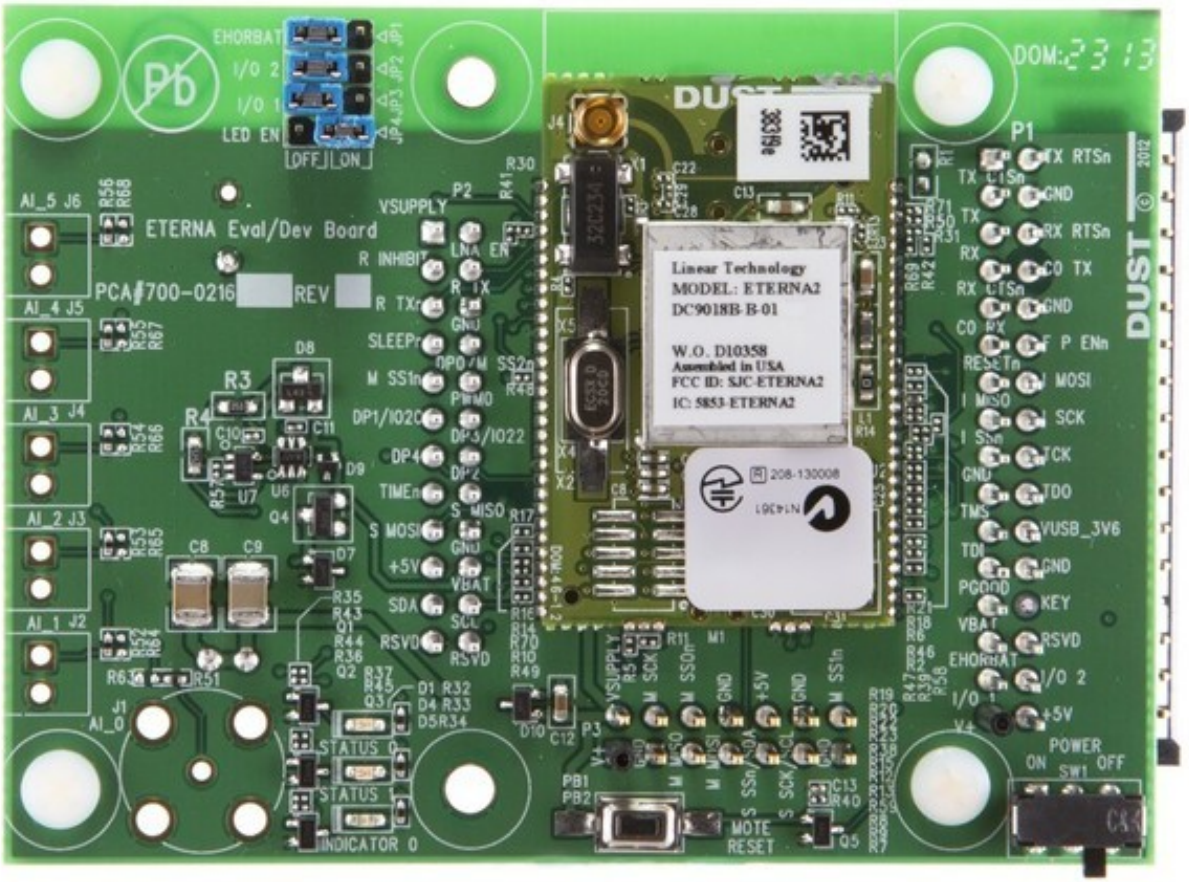
Motes: DC9003



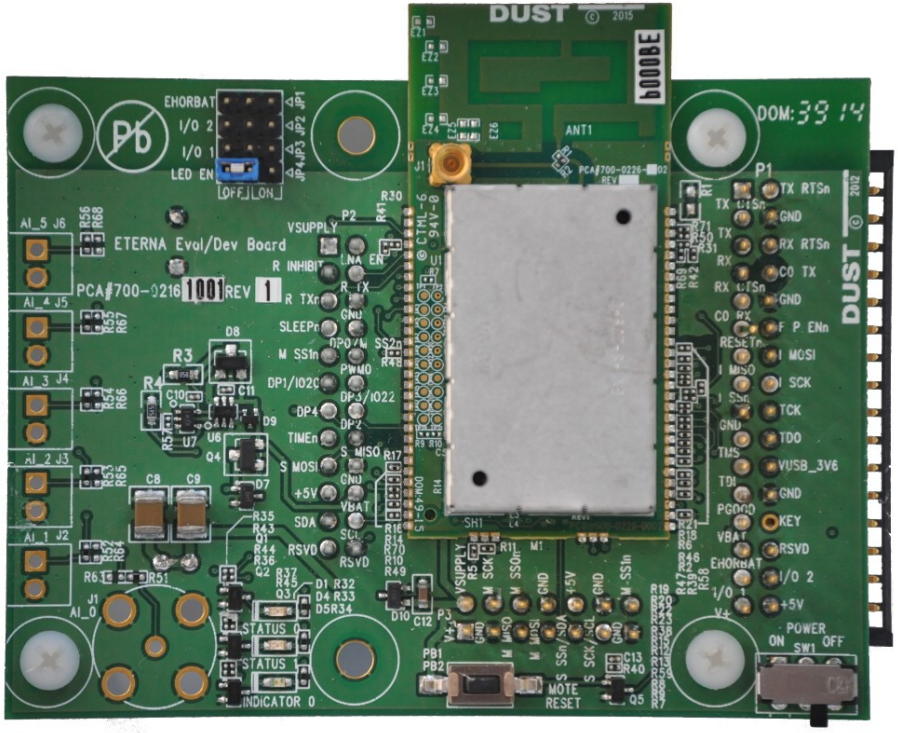
- Placa desarrollo off-the-shelf
- SmartMesh IP networks
- LTC5800 Chip (SoC con ARM Cortex-M3 y radio IEEE 802.15.4) conectado a una antena chip
- Consumo: Tx 5-9.5 mA, Rx: 4.5 mA, activo 2 mA
- Alimentación: 3,5 V

DC9018

- Igual a DC9003
- Antena 2 dBi



Mote de largo alcance



- Prototipo de Linear Technologies
- Alcance 2 km

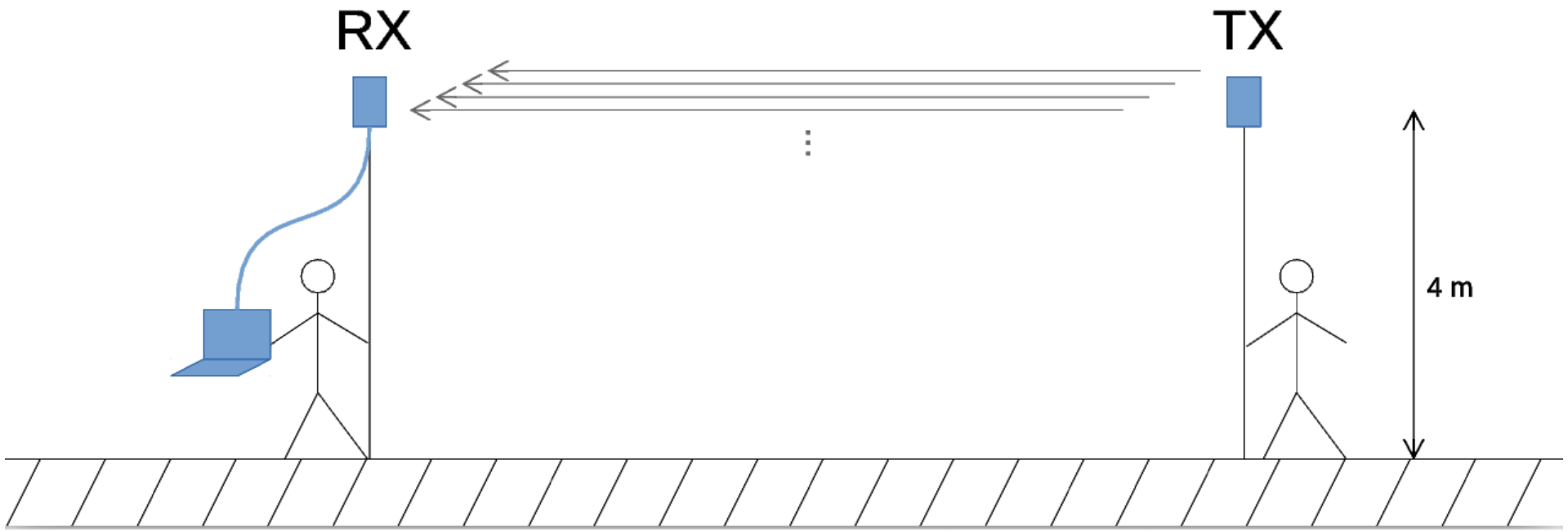
DC2274

- Coordinador de la red
- Sincronización
- Estadísticas
- Direccionamiento
- Antena de mayor alcance (2 dBi)

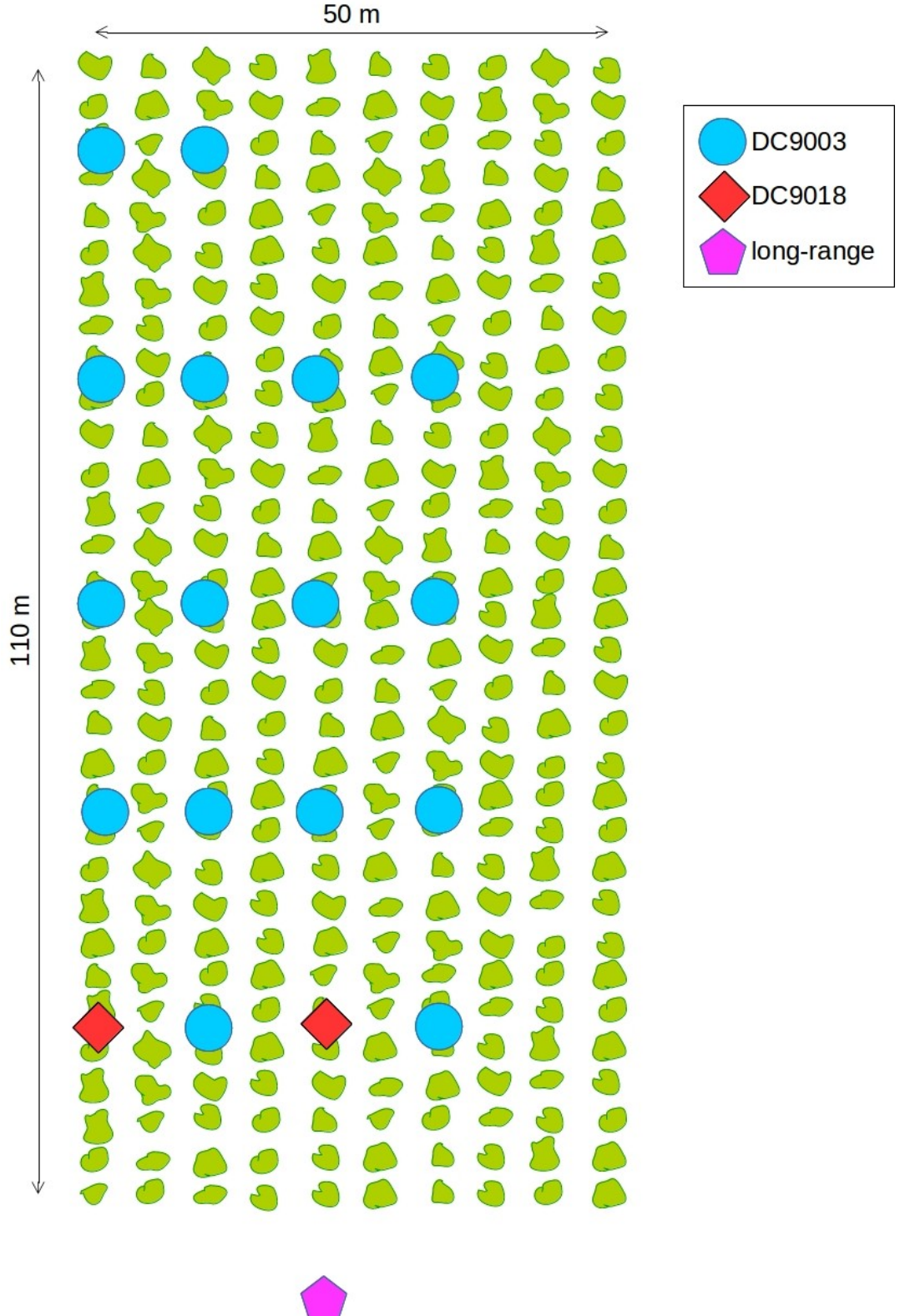
Área de interés

Estimación alcance

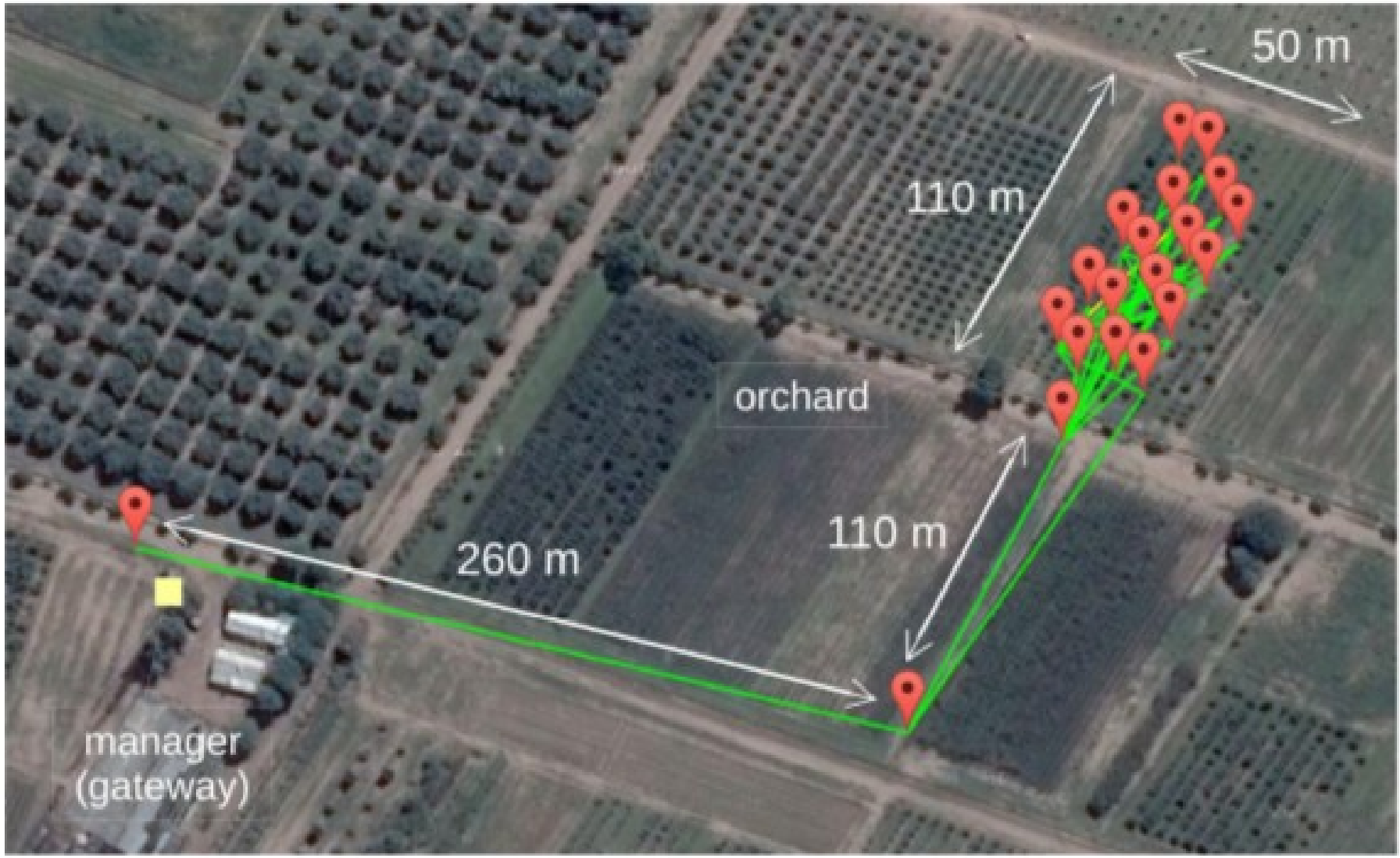
Range testing setup




50 m
110 m
G
H
K
F
J
I
D
L
M
E
C
good
medium
bad


50 m
110 m
DC9003
DC9018
long-range

Wireless links



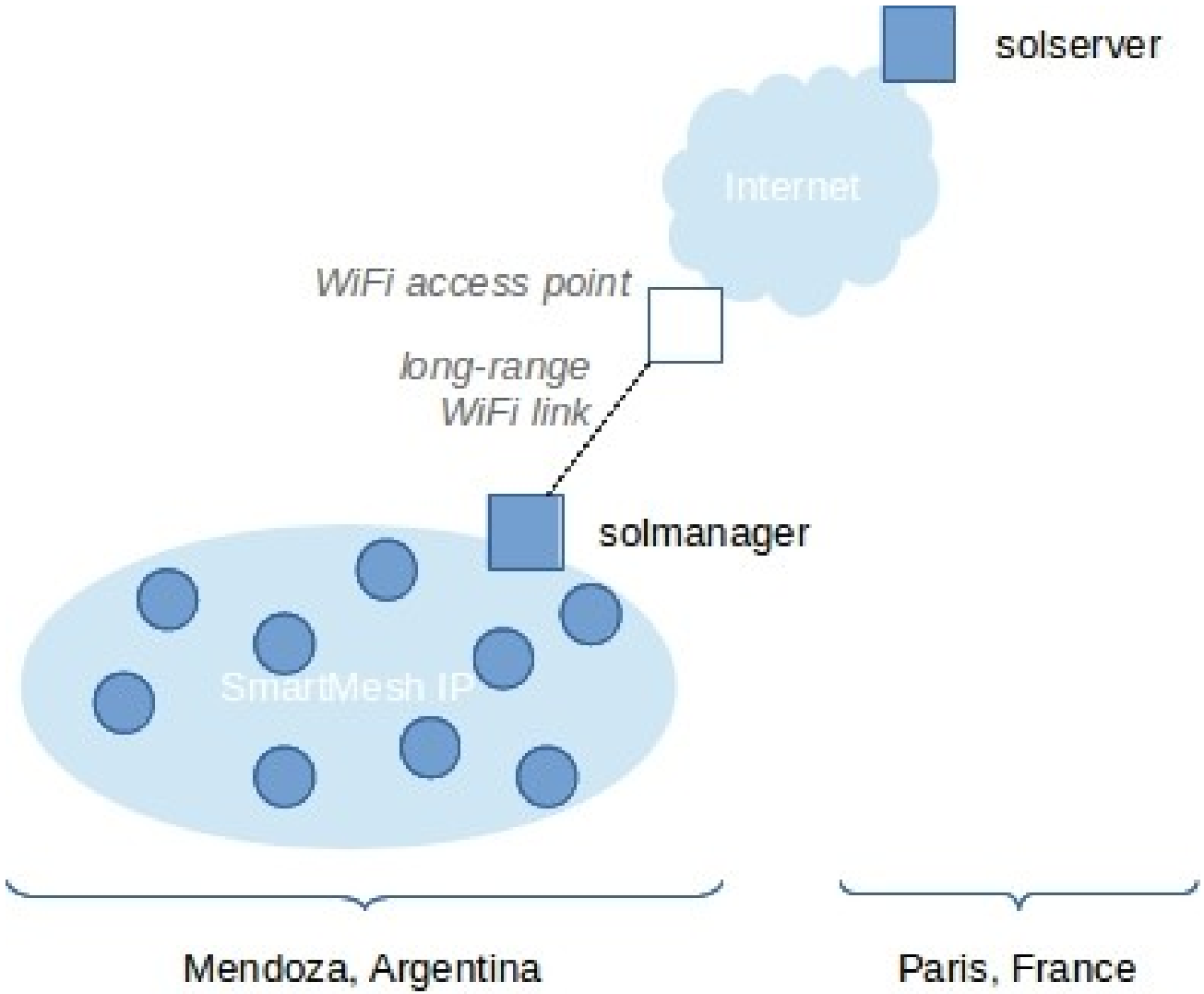
The nodes and wireless links of the PEACH deployment

Manager box

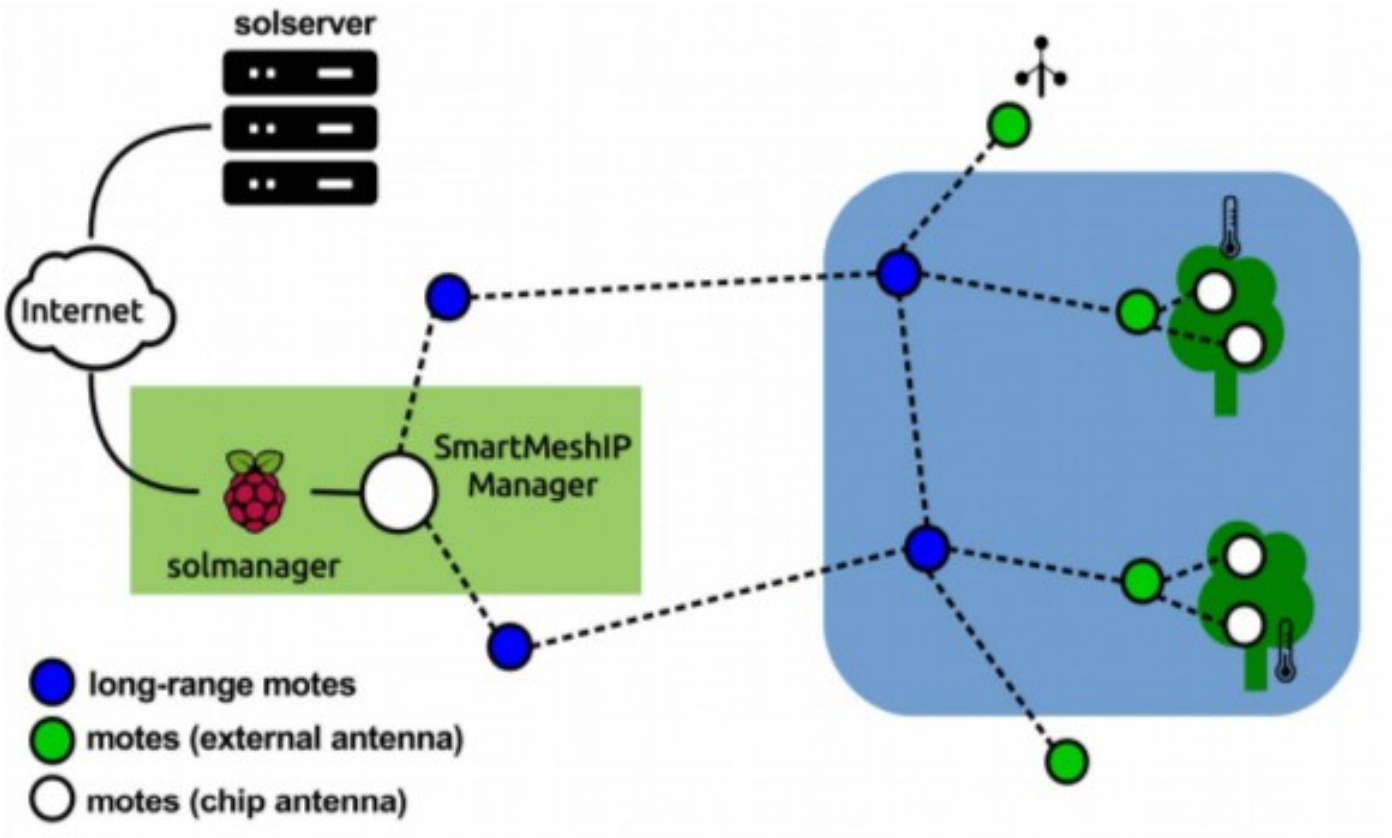
Mote box

Instalando

Arquitectura

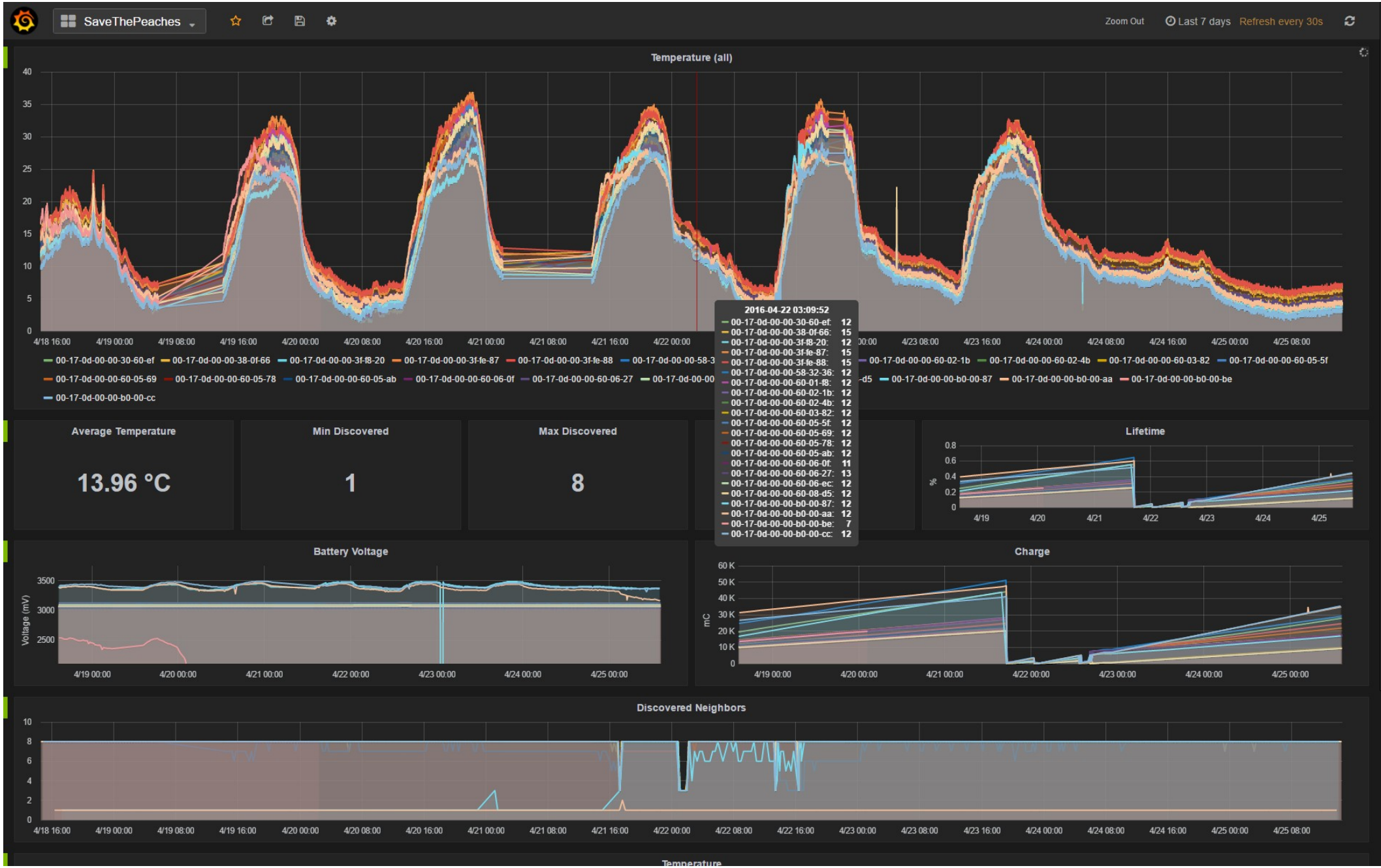


Arquitectura



The deployment architecture

Front-end


SaveThePeaches
Zoom Out
Last 7 days
Refresh every 30s
Temperature (all)
2016-04-22 03:09:52
00-17-0d-00-00-30-60-ef: 12
00-17-0d-00-00-38-0f-66: 15
00-17-0d-00-00-3f-f8-20: 12
00-17-0d-00-00-3f-fe-87: 15
00-17-0d-00-00-3f-fe-88: 15
00-17-0d-00-00-58-32-36: 12
00-17-0d-00-00-60-01-f8: 12
00-17-0d-00-00-60-02-1b: 12
00-17-0d-00-00-60-02-4b: 12
00-17-0d-00-00-60-03-82: 12
00-17-0d-00-00-60-05-5f: 12
00-17-0d-00-00-60-05-69: 12
00-17-0d-00-00-60-05-78: 12
00-17-0d-00-00-60-05-ab: 12
00-17-0d-00-00-60-06-0f: 11
00-17-0d-00-00-60-06-27: 13
00-17-0d-00-00-60-06-ec: 12
00-17-0d-00-00-60-08-d5: 12
00-17-0d-00-00-b0-00-87: 12
00-17-0d-00-00-b0-00-aa: 12
00-17-0d-00-00-b0-00-be: 7
00-17-0d-00-00-b0-00-cc: 12
Average Temperature
13.96 °C
Min Discovered
1
Max Discovered
8
Lifetime
Battery Voltage
Voltage (mV)
Charge
mC
Discovered Neighbors
Temperature

Desempeño

Resumimos el desempeño del funcionamiento de la red en los primeros cinco días y 6 horas de operación.

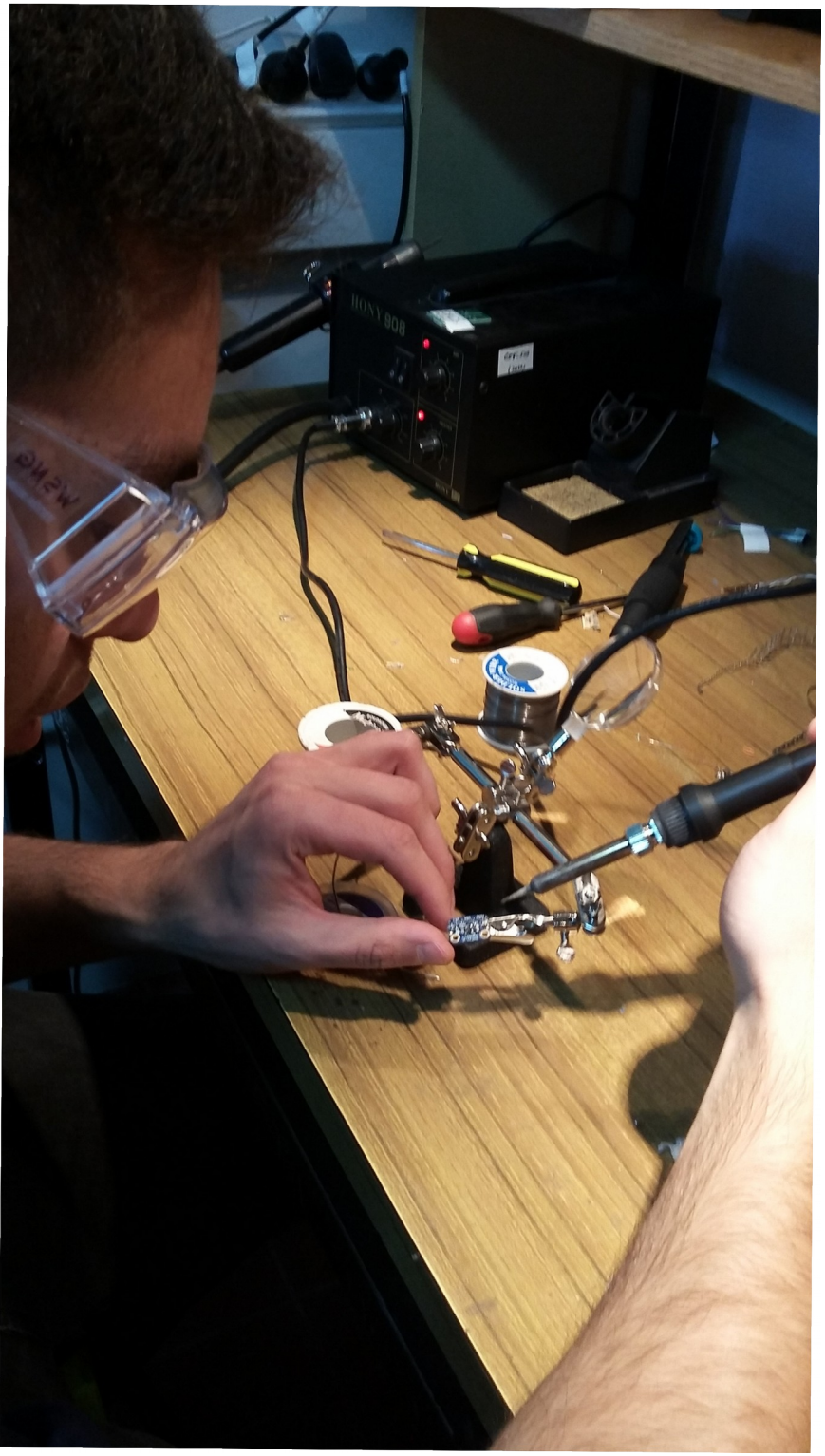
reliability	100% (Arrived/Lost: 243089/0)
stability	93% (Transmit/Fails: 1462435/96923)
latency	800 ms

Table : Key network performance indicators.

Resultados

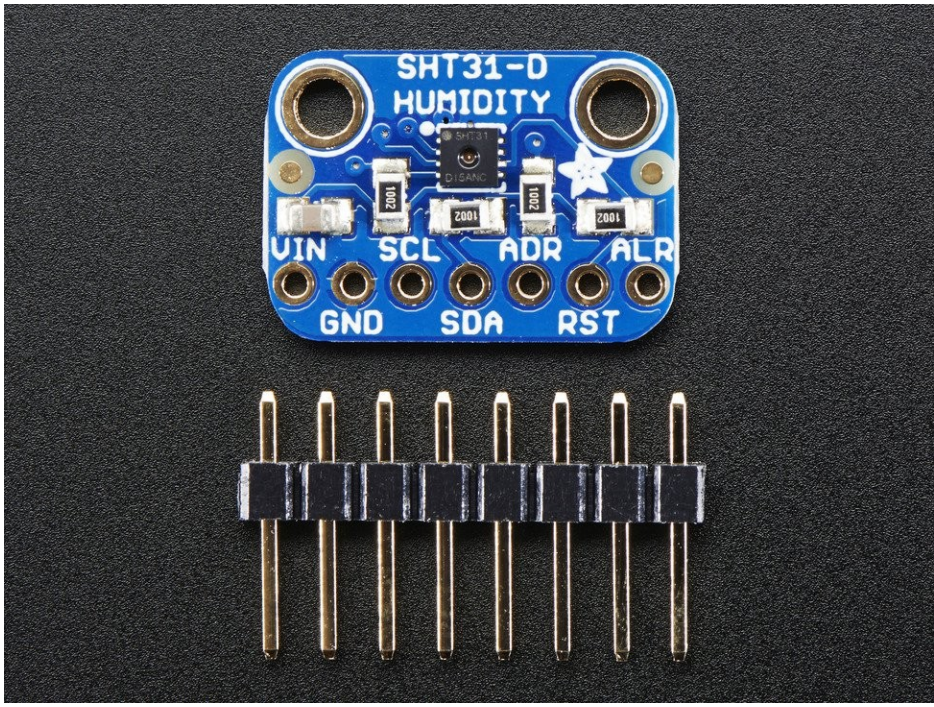
MAC	Uptime	Neig.	Cells	Hops	Latency	Recv'd	Lost	Relia.	Charge	Lifetime
60-3C-D9*	5-06:57:07	2	40	*N.A.*	*N.A.*	*N.A.*	*N.A.*	*N.A.*	*N.A.*	*N.A.*
B0-00-AA	5-06:56:06	3	20	1.0	170 ms	16450	0	100%	33263 mC	4.42 years
B0-00-CC	5-06:54:55	5	18	2.7	280 ms	16657	0	100%	28396 mC	5.18 years
58-32-36	3-09:29:11	10	21	3.0	420 ms	10788	0	100%	27546 mC	3.43 years
B0-00-BE	3-10:17:42	6	15	2.8	670 ms	10560	0	100%	15147 mC	6.30 years
60-06-0F	3-09:01:05	4	11	3.5	1020 ms	10386	0	100%	15759 mC	5.96 years
B0-00-87	3-10:06:30	6	37	1.2	120 ms	10628	0	100%	20038 mC	4.75 years
3F-F8-20	3-09:21:15	2	9	3.6	1180 ms	10428	0	100%	11907 mC	7.92 years
30-60-EF	3-09:16:26	9	24	2.7	340 ms	10551	0	100%	22471 mC	4.19 years
60-03-82	3-09:11:22	4	11	3.5	740 ms	10409	0	100%	15977 mC	5.89 years
60-08-D5	3-09:04:03	2	9	3.5	810 ms	10389	0	100%	11173 mC	8.41 years
3F-FE-88	3-08:56:18	3	10	3.5	1210 ms	10384	0	100%	12924 mC	7.26 years
3F-FE-87	3-08:51:28	2	9	4.2	1440 ms	10372	0	100%	11900 mC	7.88 years
60-05-5F	3-08:45:53	2	9	4.4	1860 ms	10346	0	100%	10867 mC	8.61 years
60-06-27	3-08:45:09	4	12	3.6	770 ms	10368	0	100%	14629 mC	6.40 years
60-05-69	3-08:40:17	2	9	3.6	1100 ms	10334	0	100%	10915 mC	8.57 years
60-01-F8	3-08:37:02	3	10	3.6	640 ms	10322	0	100%	11292 mC	8.28 years
60-02-4B	3-08:31:59	2	9	4.3	1520 ms	10326	0	100%	13186 mC	7.08 years
60-02-1B	3-08:28:39	6	14	3.5	650 ms	10301	0	100%	14700 mC	6.35 years
60-05-AB	3-08:22:30	3	10	4.0	920 ms	10298	0	100%	12808 mC	7.27 years
60-06-EC	3-08:21:17	2	9	4.4	1740 ms	10289	0	100%	10964 mC	8.50 years
38-0F-66	3-08:03:38	2	9	4.4	1430 ms	10254	0	100%	10781 mC	8.61 years
60-05-78	3-08:00:26	2	9	3.6	950 ms	10247	0	100%	10710 mC	8.66 years

* the manager



Integración sensores

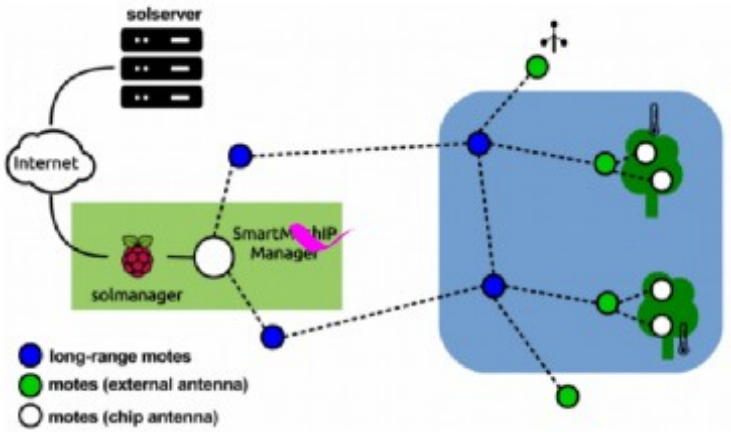
- SHT-31



• PrEcision Agriculture through Climate researcH

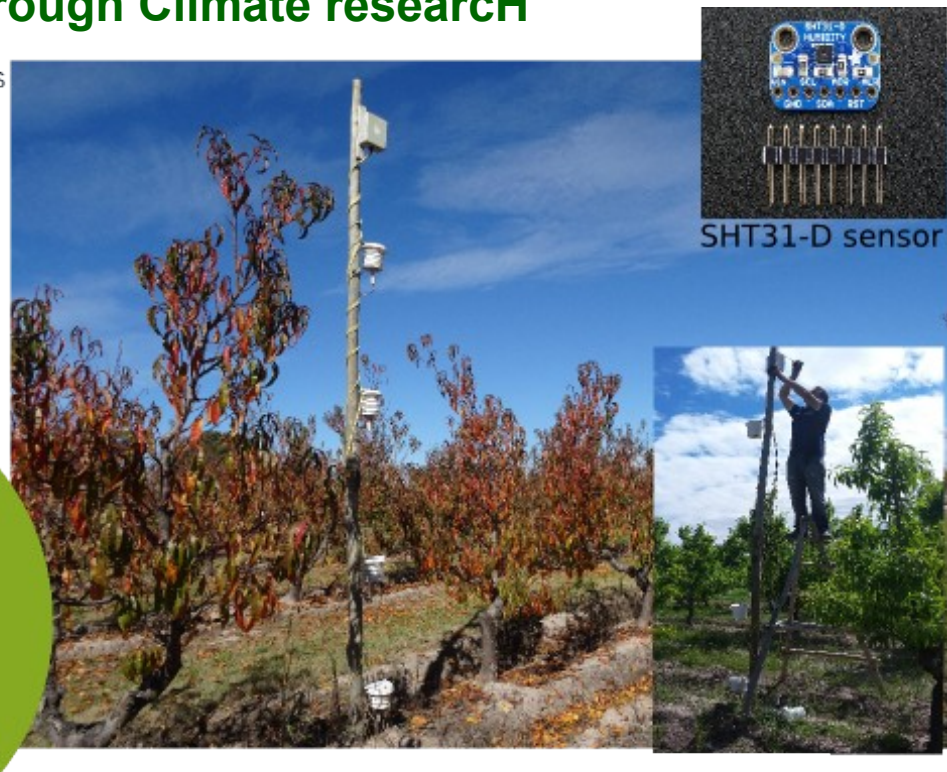
(a) DC2274: Low-power wireless manager (2 deployed) (b) Long-range prototype board (3 deployed) (c) DC9018: External antenna mote (2 deployed) (d) DC9003: chip antenna mote (16 deployed)

- In parallel to sensor measurements, each device produces large amounts of network statistics
- Every 15min, each device produces
  - Packet counters
  - Charge consumed
  - Battery state
  - Neighbors heard
  - Neighbors communicating with
  - Link quality
  - Etc.

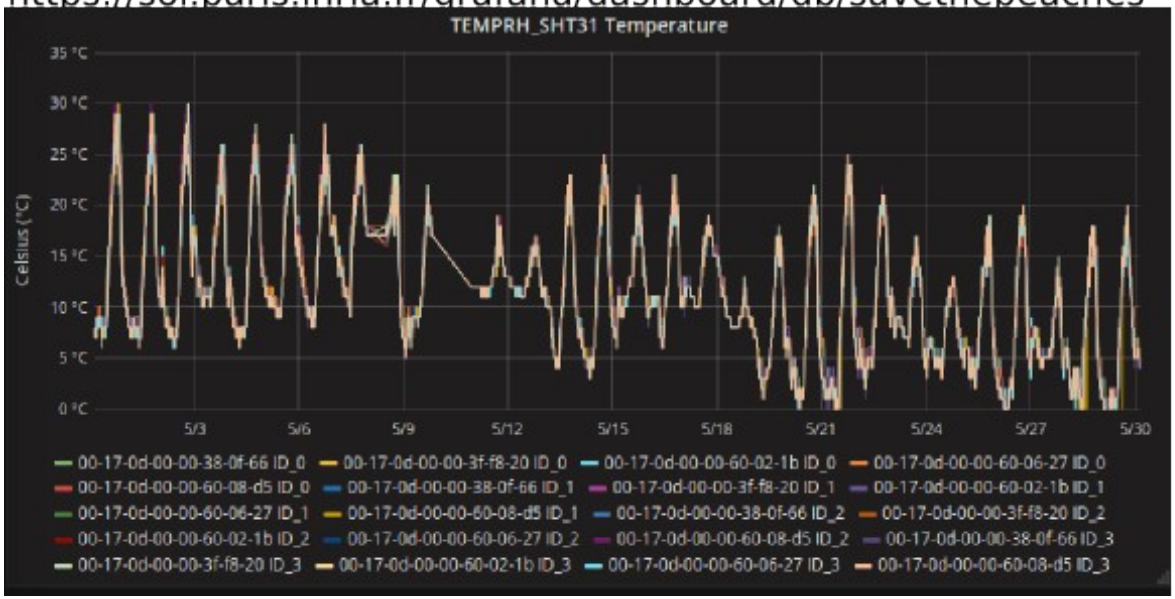


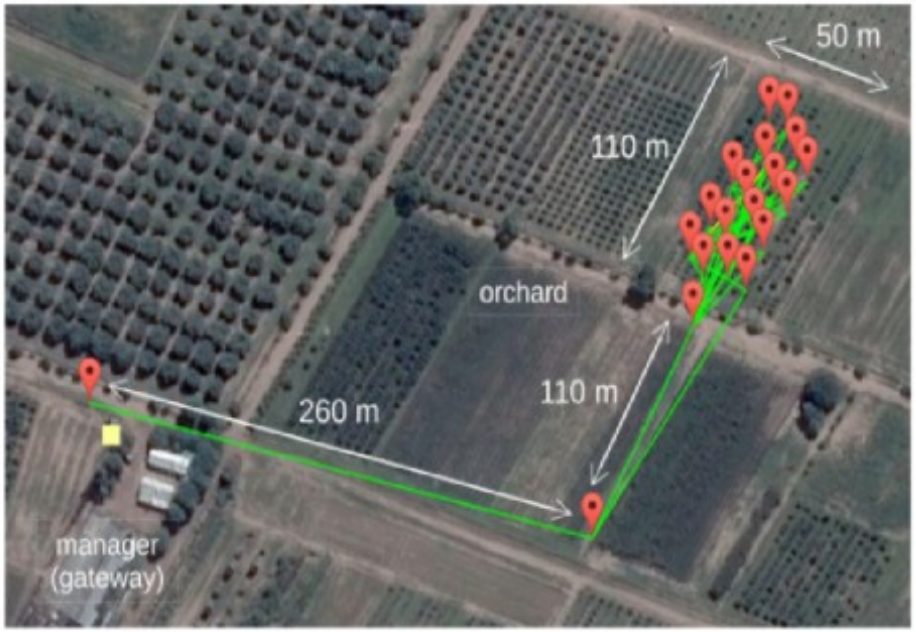
The deployment architecture

SAVETHEPEACHES.COM



https://sol.paris.inria.fr/grafana/dashboard/db/savethepeaches

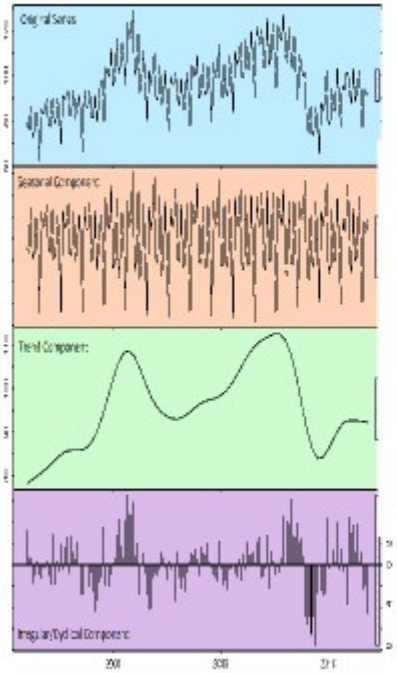




The nodes and wireless links of the PEACH deployment

¿Cuándo y dónde habrá un evento de helada?

Machine Learning



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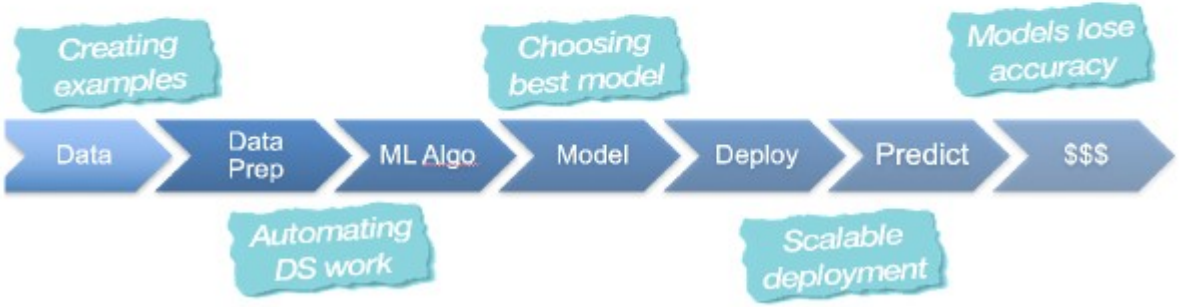
UNIVERSIDAD TECNOLÓGICA NACIONAL

- **The Machine Learning Workflow**



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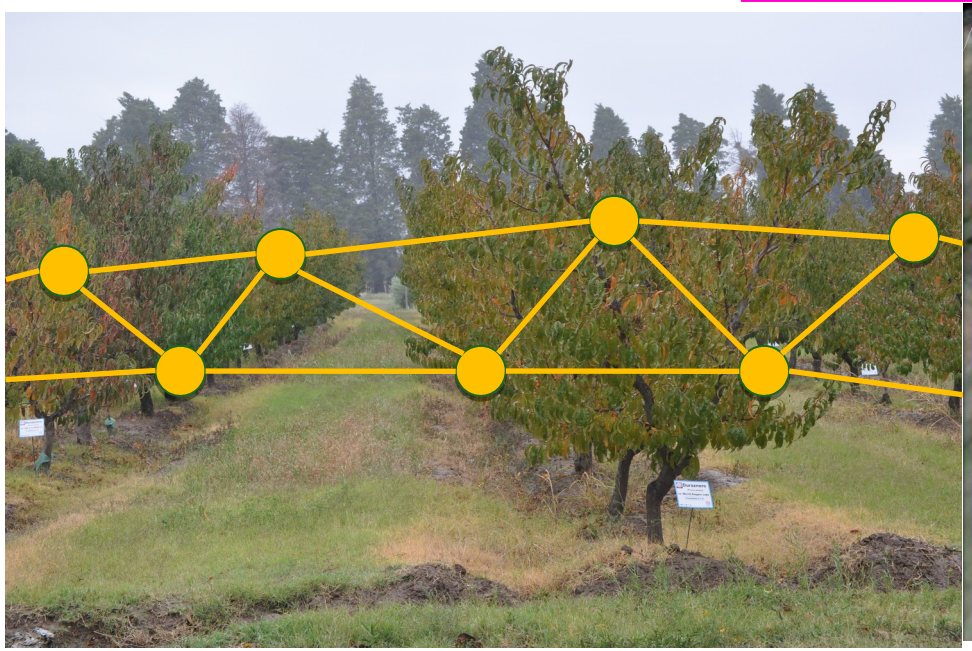
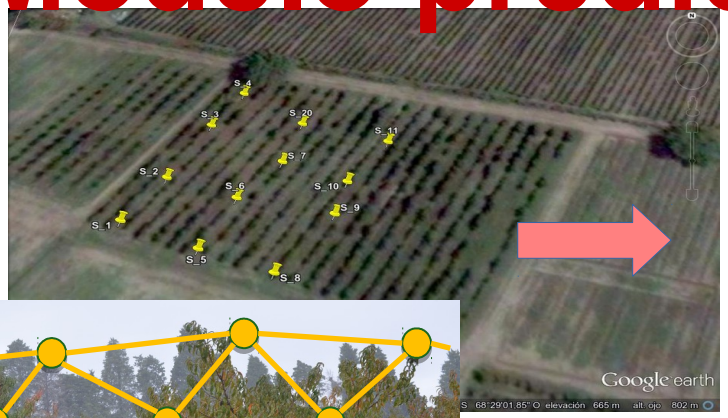
Enfoque de selección de variables

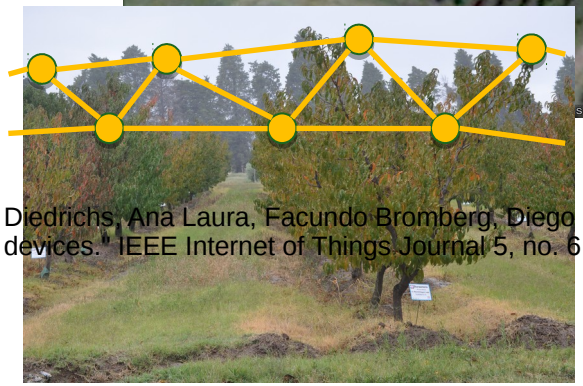


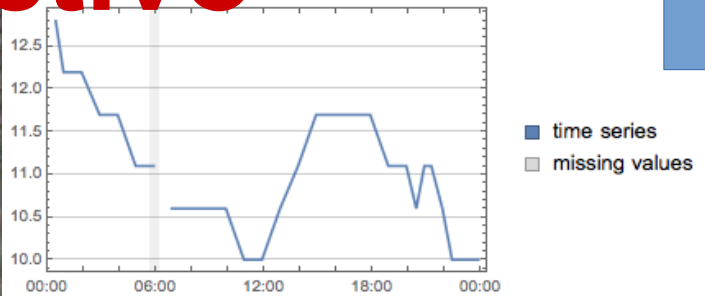
Es posible mejorar la predicción de la temperatura mínima al utilizar información de sensores vecinos. Dada la temperatura en un sitio determinado, nos preguntamos si la información de otro sitio puede ser de ayuda para la predicción de I.

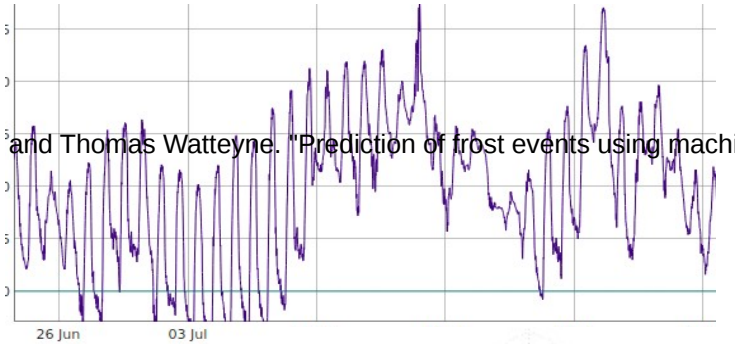
Caso de estudio: predicción de temperatura mínima

Modelo predictivo



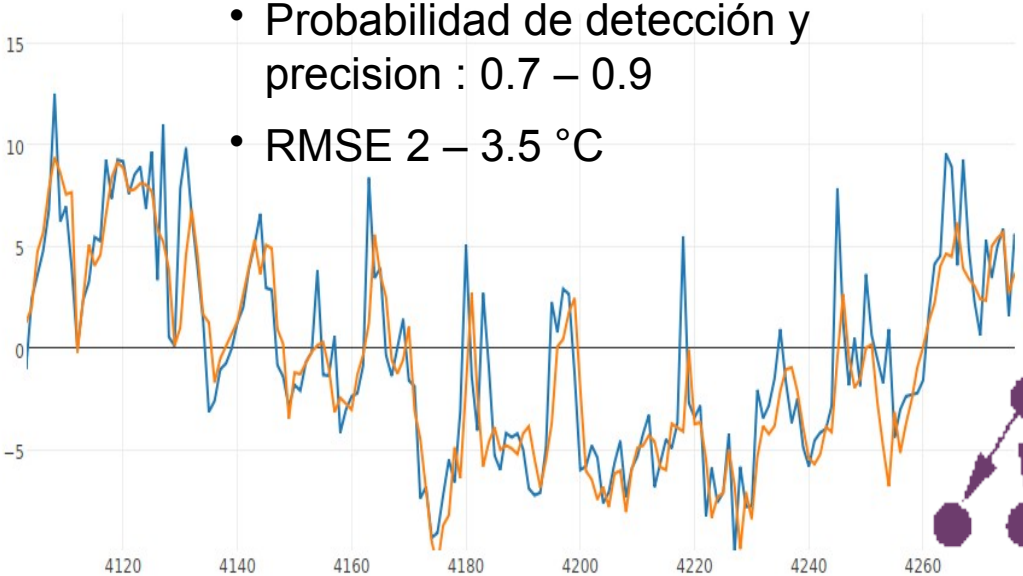


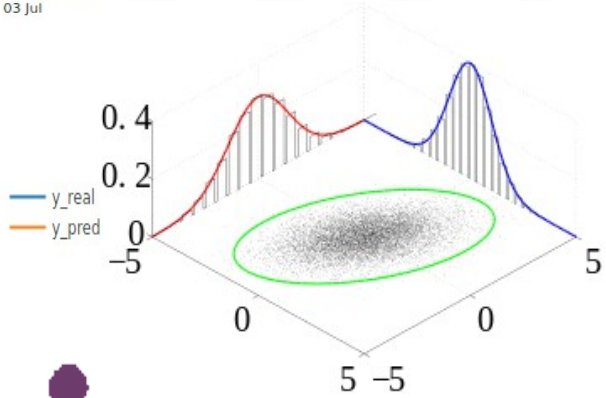


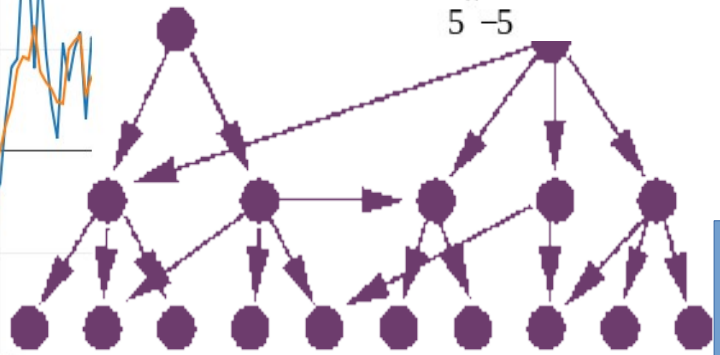


Diedrichs, Ana Laura, Facundo Bromberg, Diego Dujovne, Keoma Brun-Laguna, and Thomas Watteyne. "Prediction of frost events using machine learning and IoT sensing devices." IEEE Internet of Things Journal 5, no. 6 (2018): 4589-4597.

- Resultados preliminares predicción temperatura mínima/heladas
- Probabilidad de detección y precision : 0.7 – 0.9
- RMSE 2 – 3.5 °C







Limpieza de Datos

Configuración Del Entrenamiento

Variables S_(kt-1), k=1..N

Construcción del modelo

Evaluación

Salida: predictor de heladas

• Prediction of frost events using machine learning & IoT

Diedrichs, Ana Laura, Facundo Bromberg, Diego Dujovne, Keoma Brun-Laguna, and Thomas Watteyne. "Prediction of frost events using machine learning and IoT sensing devices." IEEE Internet of Things Journal 5, no. 6 (2018): 4589-4597.

IoT in Agriculture applications have evolved to solve several relevant problems from producers. Here, we describe a component of an IoT-enabled frost prediction system. We follow current approaches for prediction that use machine learning algorithms trained by past readings of temperature and humidity sensors to predict future temperatures. However, contrary to current approaches, we assume that the surrounding thermodynamical conditions are informative for prediction. For that, a model was developed for each location, including in its training information of sensor readings of all other locations, autonomously selecting the most relevant ones (algorithm dependent). We evaluated our approach by training regression and classification models using several machine learning algorithms, many already proposed in the literature for the frost prediction problem, over data from five meteorological stations spread along the Mendoza Province of Argentina. Given the scarcity of frost events, data was augmented using the Synthetic Minority Oversampling Technique (SMOTE). The experimental results show that selecting the most relevant neighbors and training the models with SMOTE reduces the prediction errors of both regression predictors for all five locations, increases the performance of Random Forest classification predictors for four locations while keeping it unchanged for the remaining one, and produces inconclusive results for Logistic regression predictor. These results demonstrate the main claim of these work: that thermodynamic information of neighboring locations can be informative for improving both regression and classification predictions, but also are good enough to suggest that the present approach is a valid and useful resource for decision makers and producers.

Prediction of minimum temperature for frost forecasting in agriculture

build passing | DOI 10.5281/zenodo.1239974

Description

This package contains a compilation of empirical methods used by farmers and agronomic engineers to predict the minimum temperature to detect a frost event.

These functions use variables such as environmental temperature, relative humidity, and dew point.

Installation

If you don't have package **devtools** installed, run the following commands.

```
install.packages("devtools")
```

```
library(devtools)
```

To install the package from the GitHub repo, run

```
install_github("anadiedrichs/frost")
```

Frost R package repo
https://github.com/anadiedrichs/frost

• ¿Cómo continuar o integrarlo con AgroIndustria?

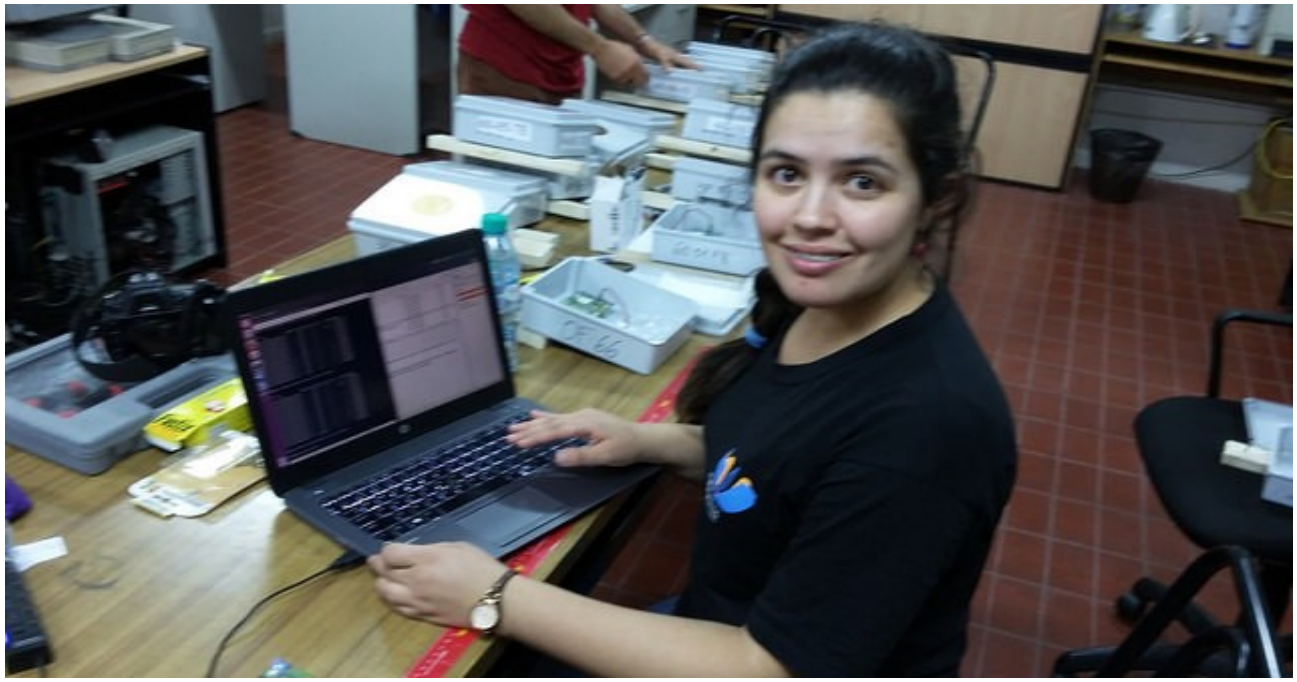
- ¿Qué falta para integrarlo a un producto final?
  - + datos
  - Software o módulo para cliente (página web, servidores,etc)
  - Servicios de alerta
- Actores interesados: productores, gobierno, etc.
- Financiamiento

- ¡Muchas gracias! (SASE + ISOC)
- ana.diedrichs@frm.utn.edu.ar
- @anadiedrichs

grid T ICs
Tecnologías de la
Grupo UTN de I&D

UTN FACULTAD REGIONAL MENDOZA

DHARMA

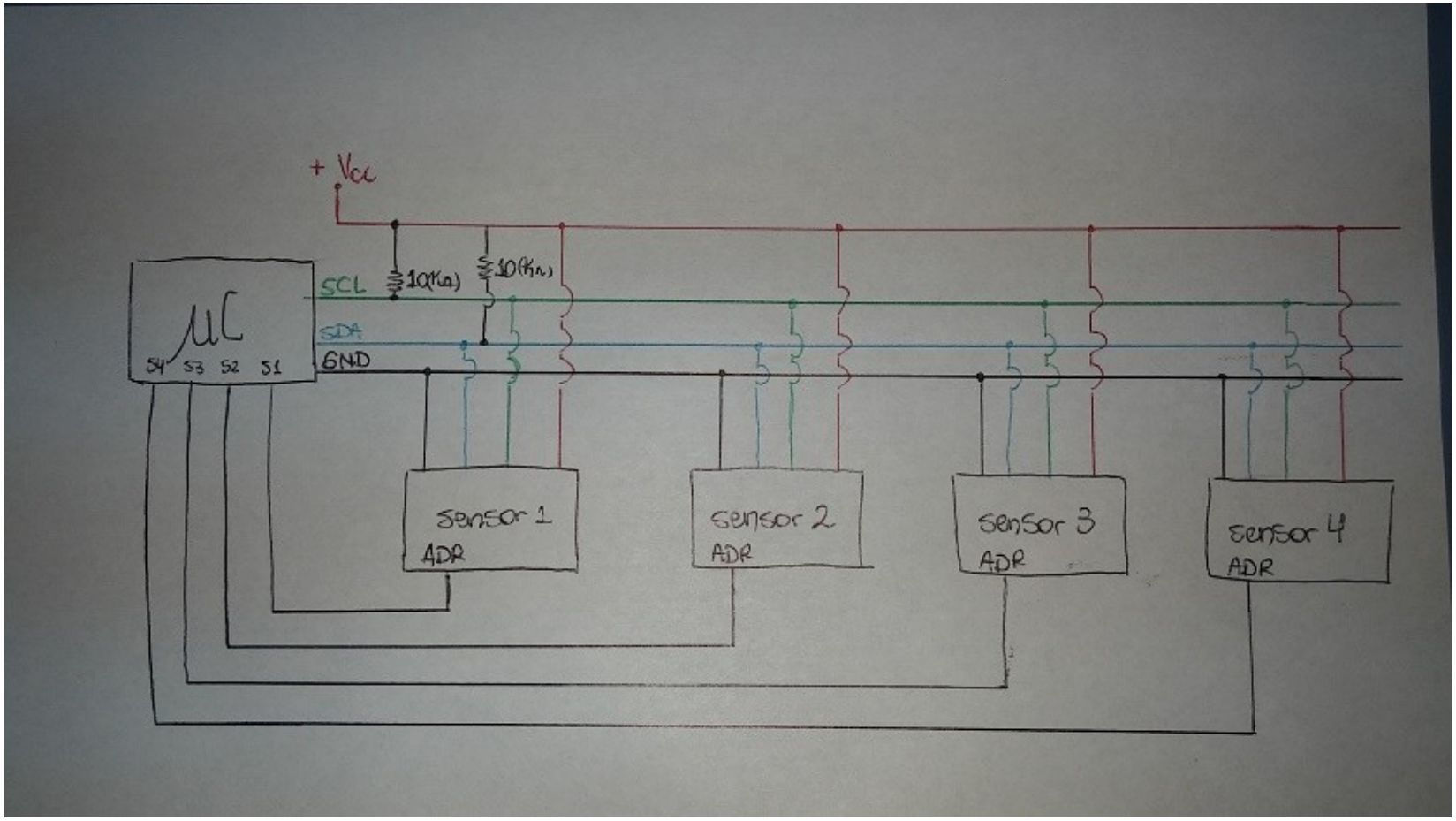


SASE 2019

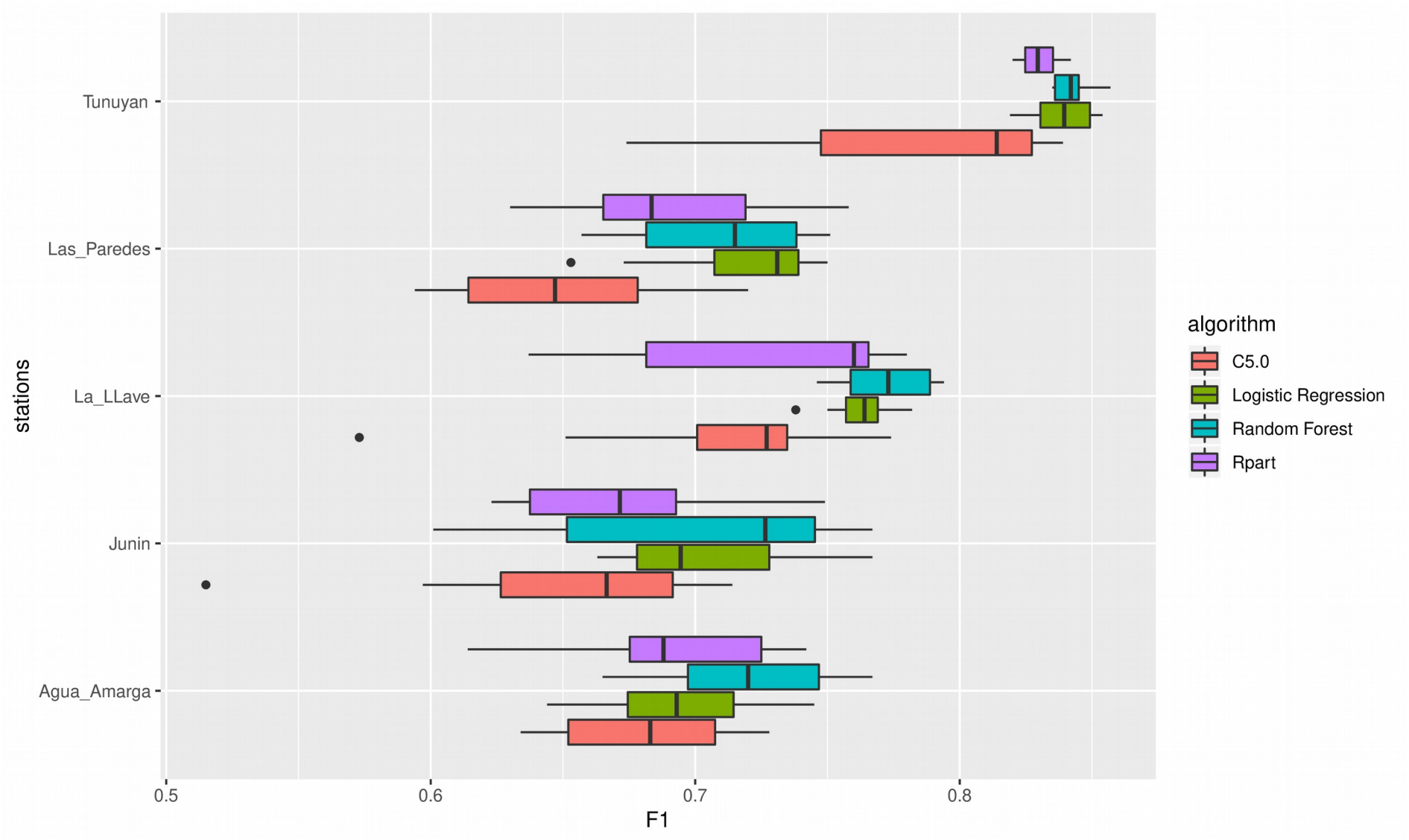
SIMPOSIO ARGENTINO DE SISTEMAS EMBEBIDOS

17 | 18 | 19 DE JULIO

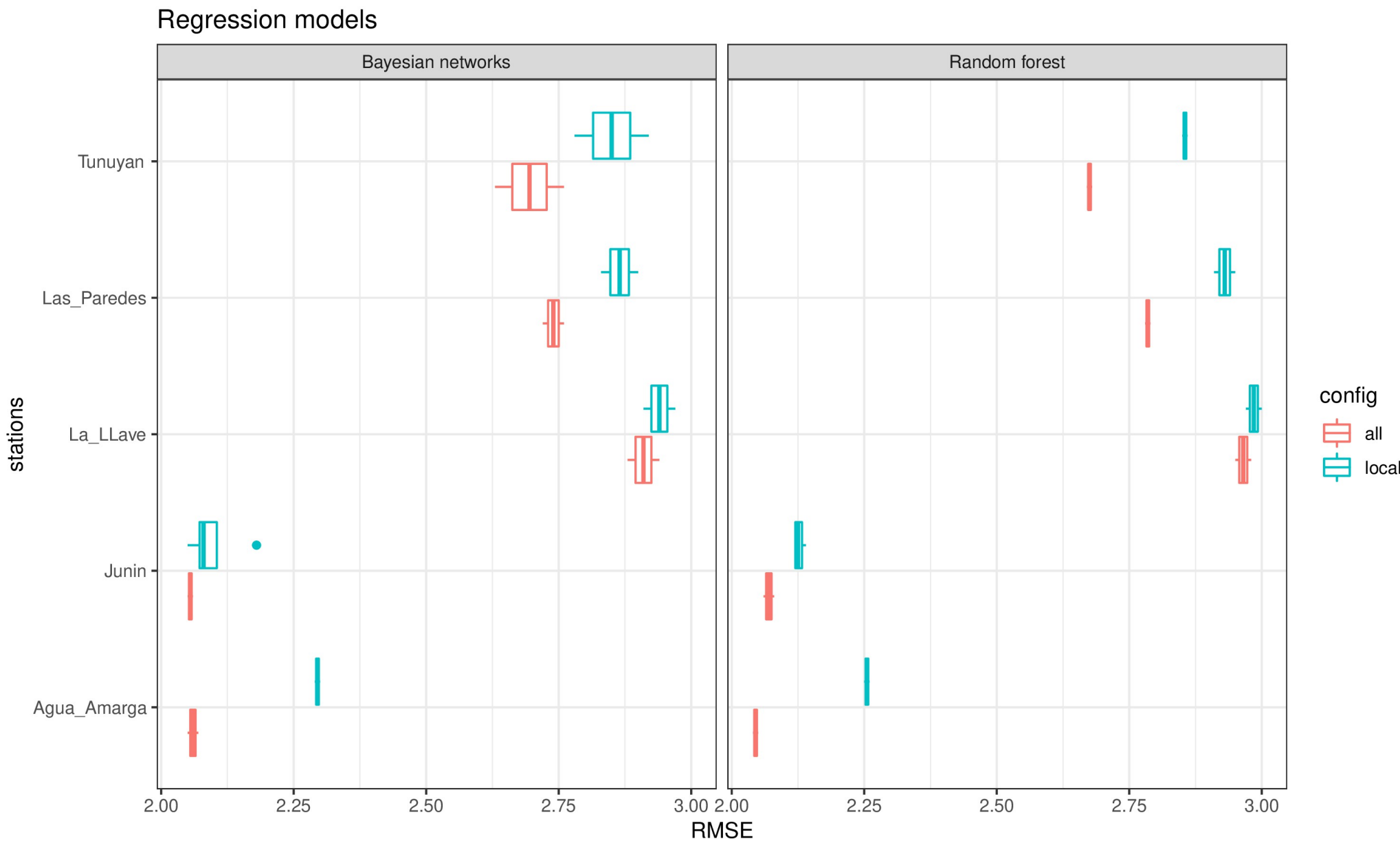
Extras – spare slides


+ Vcc
µC
S4 S3 S2 S1
SCL
SDA
GND
10(kΩ)
10(kΩ)
sensor 1
ADR
sensor 2
ADR
sensor 3
ADR
sensor 4
ADR

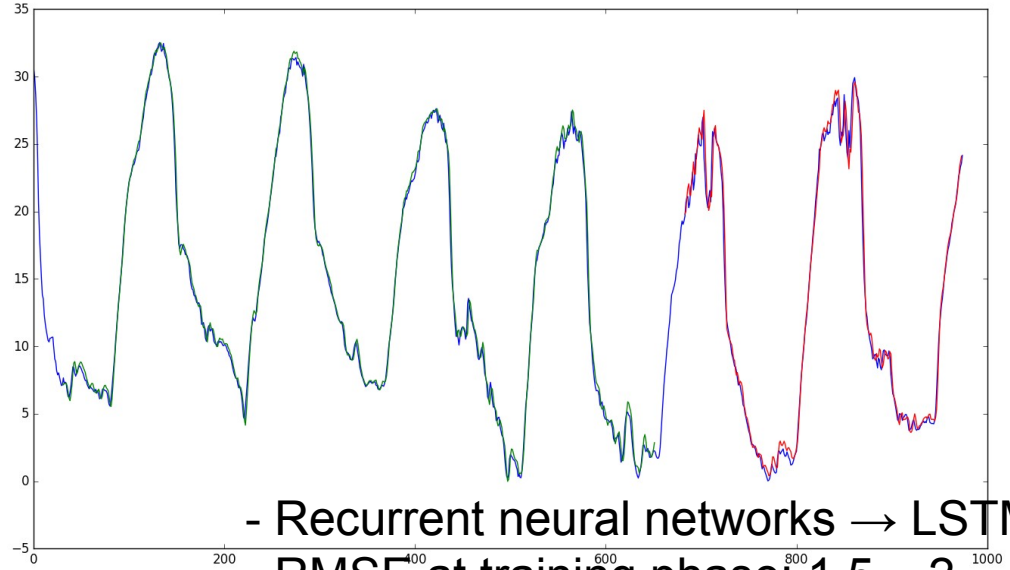
Variabilidad por estación



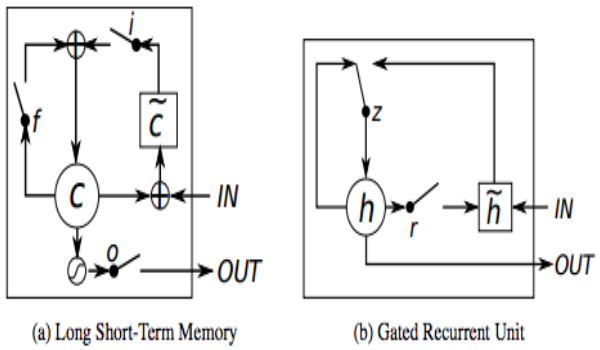
Local vs all


Regression models
Bayesian networks
Random forest
Tunuyan
Las_Paredes
La_LLave
Junin
Agua_Amarga
stations
2.00
2.25
2.50
2.75
3.00
RMSE
config
all
local

- Previous model can predict how much "frost" is going to be
But not when or at what time
- Recurrent neural networks models such as LSTM and GRU have a good performance to predict sequences.

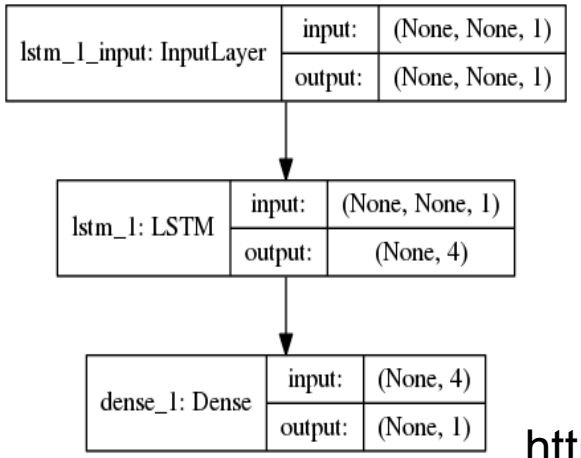


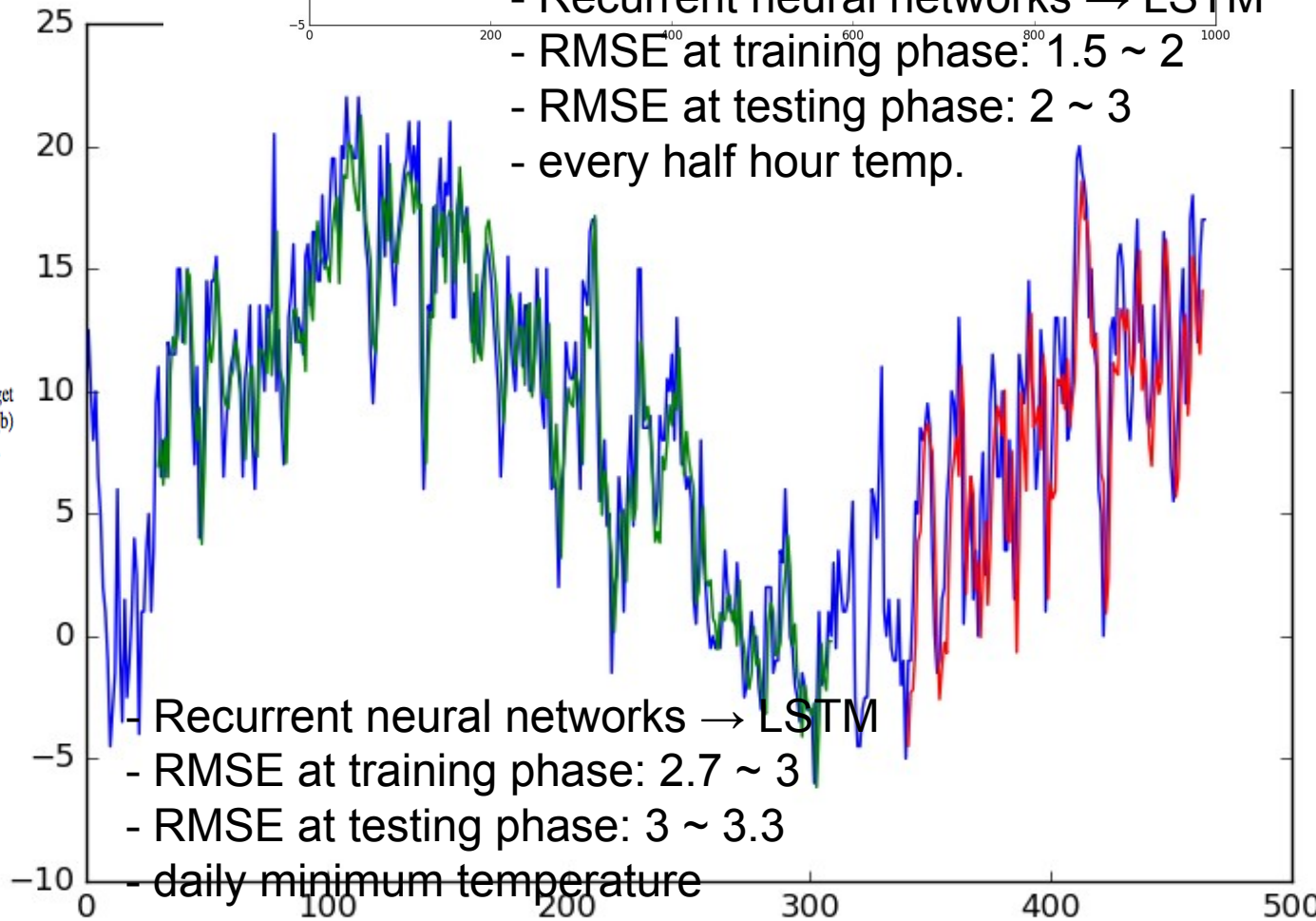
- Recurrent neural networks → LSTM
- RMSE at training phase: 1.5 ~ 2
- RMSE at testing phase: 2 ~ 3
- every half hour temp.



(a) Long Short-Term Memory (b) Gated Recurrent Unit

Figure 1: Illustration of (a) LSTM and (b) gated recurrent units. (a) i, f and o are the input, forget and output gates, respectively. c and $\tilde{c}$ denote the memory cell and the new memory cell content. (b) r and z are the reset and update gates, and h and $\tilde{h}$ are the activation and the candidate activation.





- Recurrent neural networks → LSTM
- RMSE at training phase: 2.7 ~ 3
- RMSE at testing phase: 3 ~ 3.3
- daily minimum temperature

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Other trends

- A deep learning approach for spatial temporal prediction (convLSTM networks)
- how many sensors and where to deploy
- Thanks! ana.diedrichs@frm.utn.edu.ar

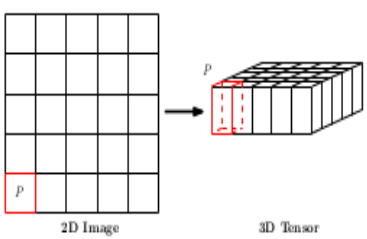


Figure 1: Transforming 2D image into 3D tensor

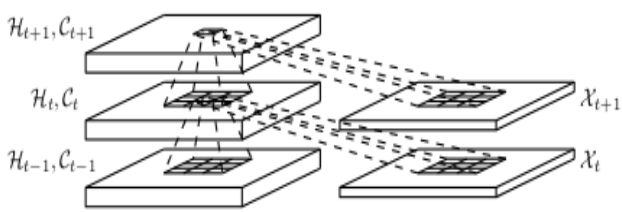
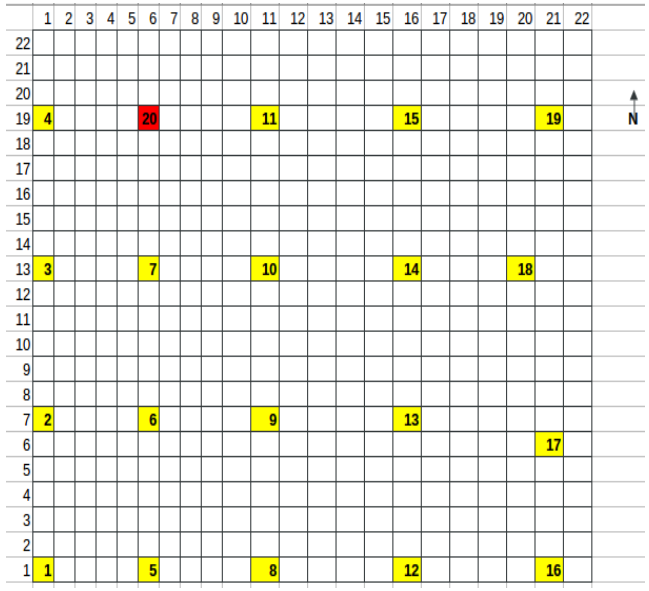


Figure 2: Inner structure of ConvLSTM



Xingjian Shi, et al. 2015. Convolutional LSTM Network: a machine learning approach for precipitation nowcasting. In Proceedings of the 28th International Conference on Neural Information Processing Systems (NIPS'15),

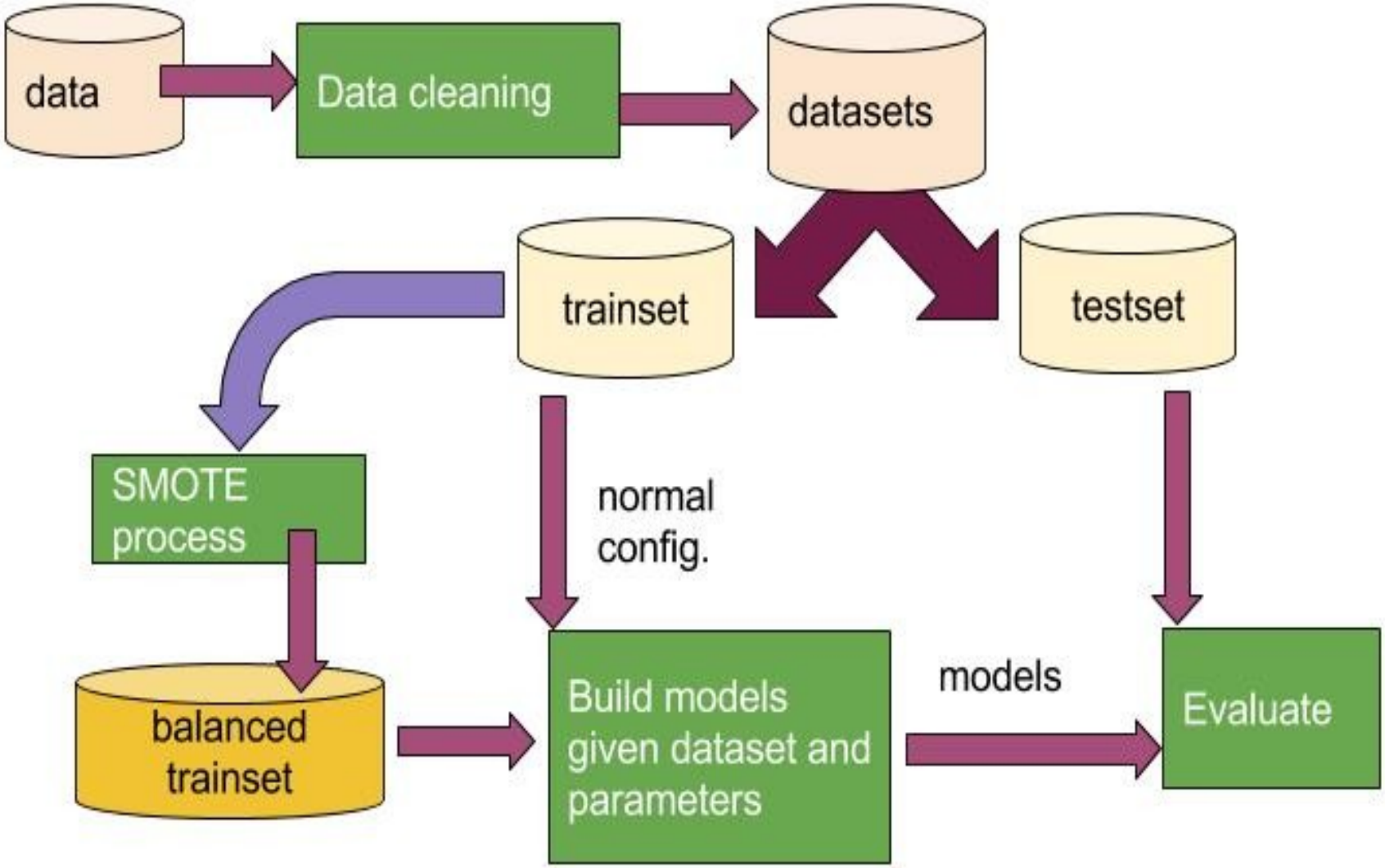
Ana Laura Diedrichs

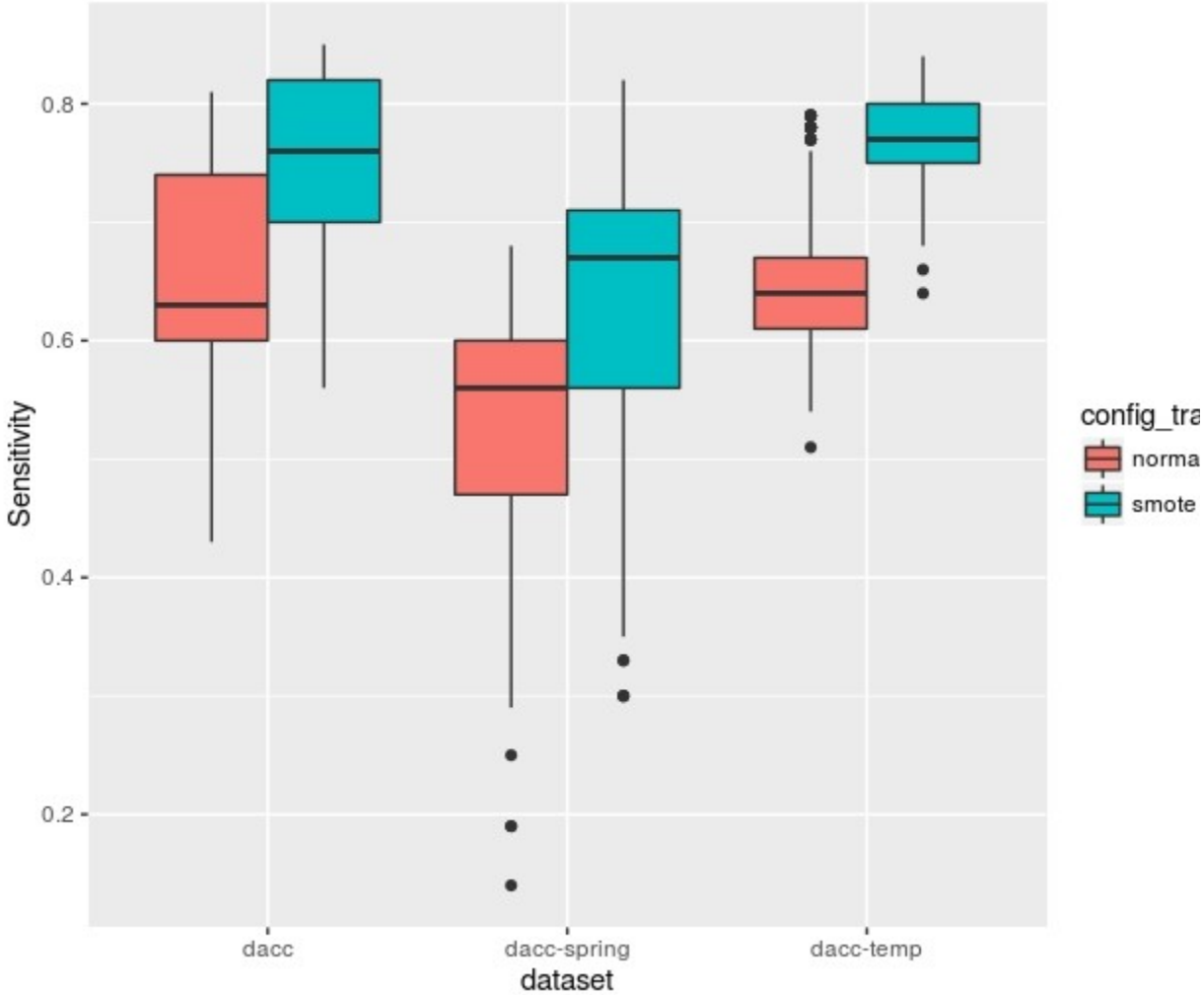
Telegram / twitter @anadiedrichs

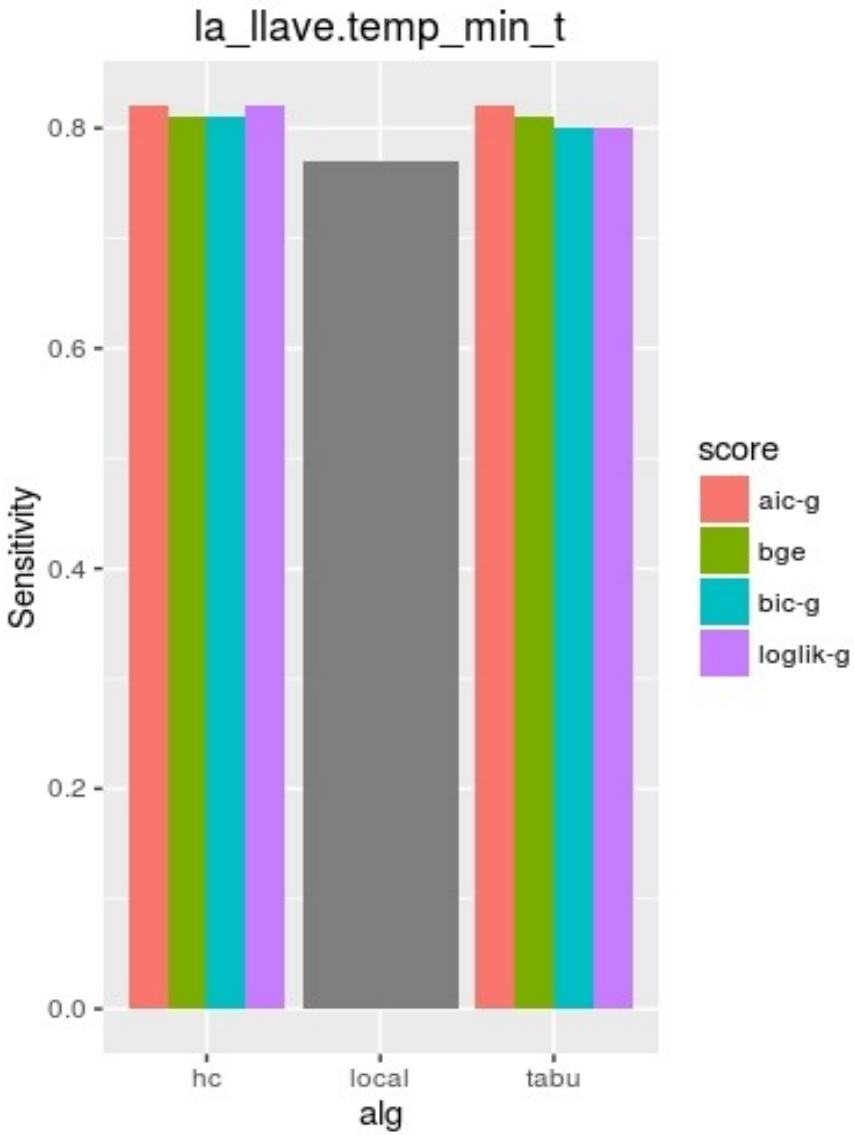
web http://anadiedrichs.github.io/

Frost R package repo
https://github.com/anadiedrichs/frost

Workflow


data
Data cleaning
datasets
trainset
testset
SMOTE process
normal config.
balanced trainset
Build models given dataset and parameters
models
Evaluate





- Resultados preliminares predicción temperatura mínima/heladas
- Probabilidad de detección y precision : 0.7 – 0.85
- RMSE 2 – 3.5 °C

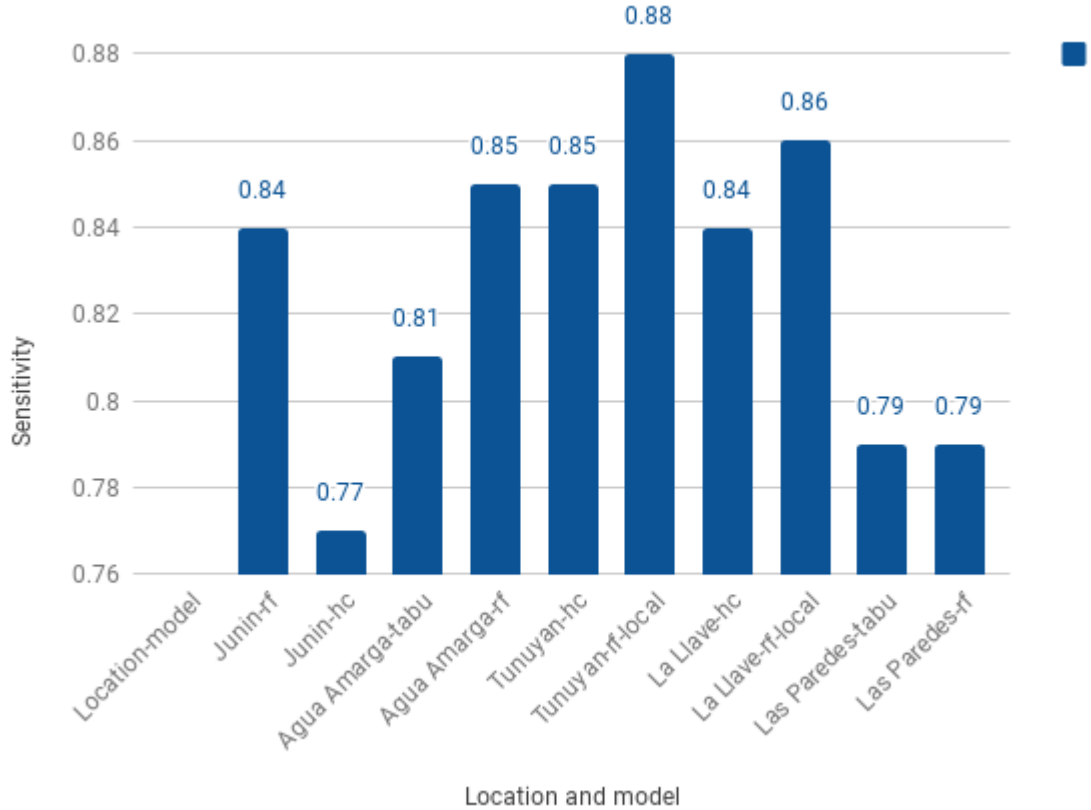
	Reference	
Predicted	Event	No Event
Event	A	B
No Event	C	D

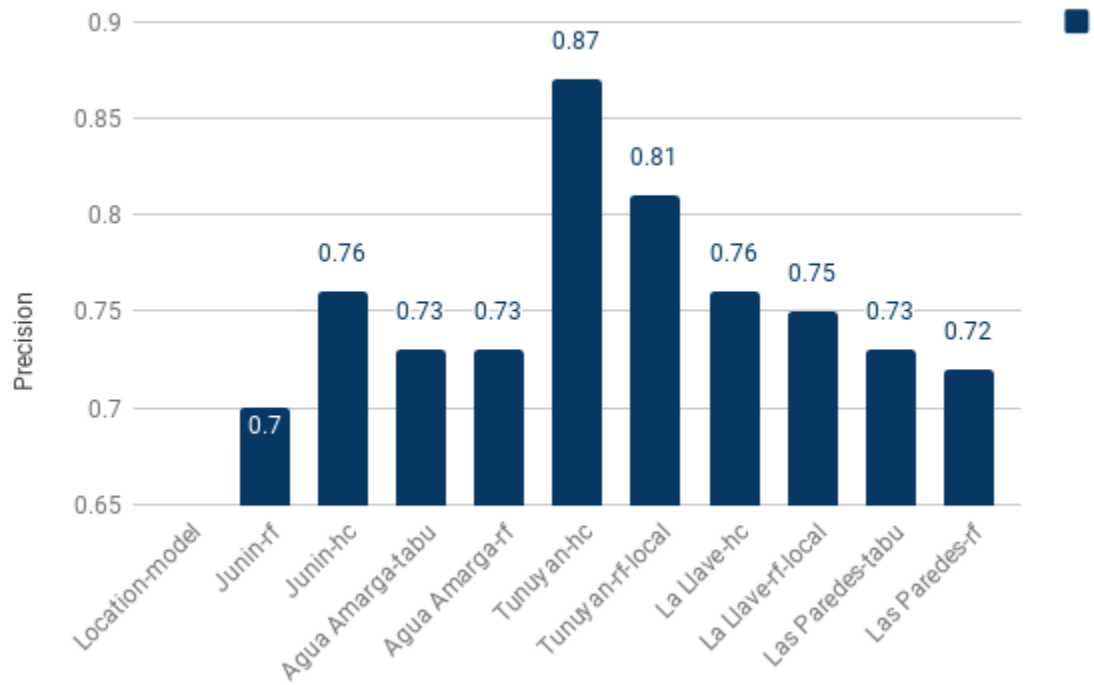
The formulas used here are:

$$Sensitivity = \frac{A}{A+C}$$
$$Specificity = \frac{D}{B+D}$$
$$Prevalence = \frac{A+C}{A+B+C+D}$$
$$PPV = \frac{sensitivity \times prevalence}{((sensitivity \times prevalence) + ((1 - specificity) \times (1 - prevalence))}$$
$$NPV = \frac{specificity \times (1 - prevalence)}{((1 - sensitivity) \times prevalence) + ((specificity) \times (1 - prevalence))}$$
$$Detection\ Rate = \frac{A}{A+B+C+D}$$
$$Detection\ Prevalence = \frac{A+B}{A+B+C+D}$$
$$Balanced\ Accuracy = (sensitivity + specificity)/2$$

$$Precision = \frac{A}{A+B}$$
$$Recall = \frac{A}{A+C}$$
$$F1 = \frac{(1+\beta^2) \times precision \times recall}{(\beta^2 \times precision) + recall}$$

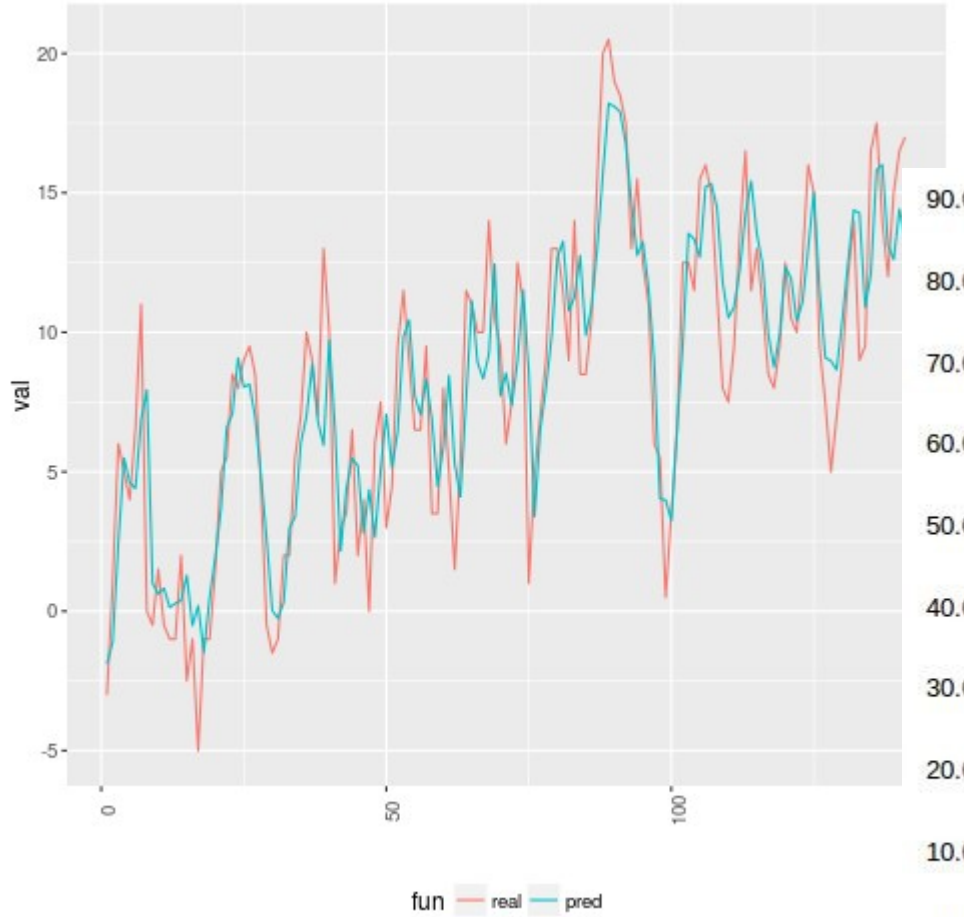
Sensitivity
Recall
True positive rate

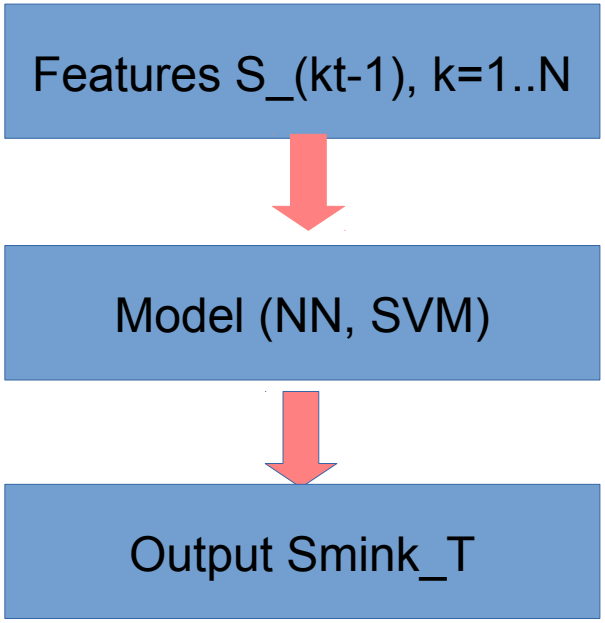


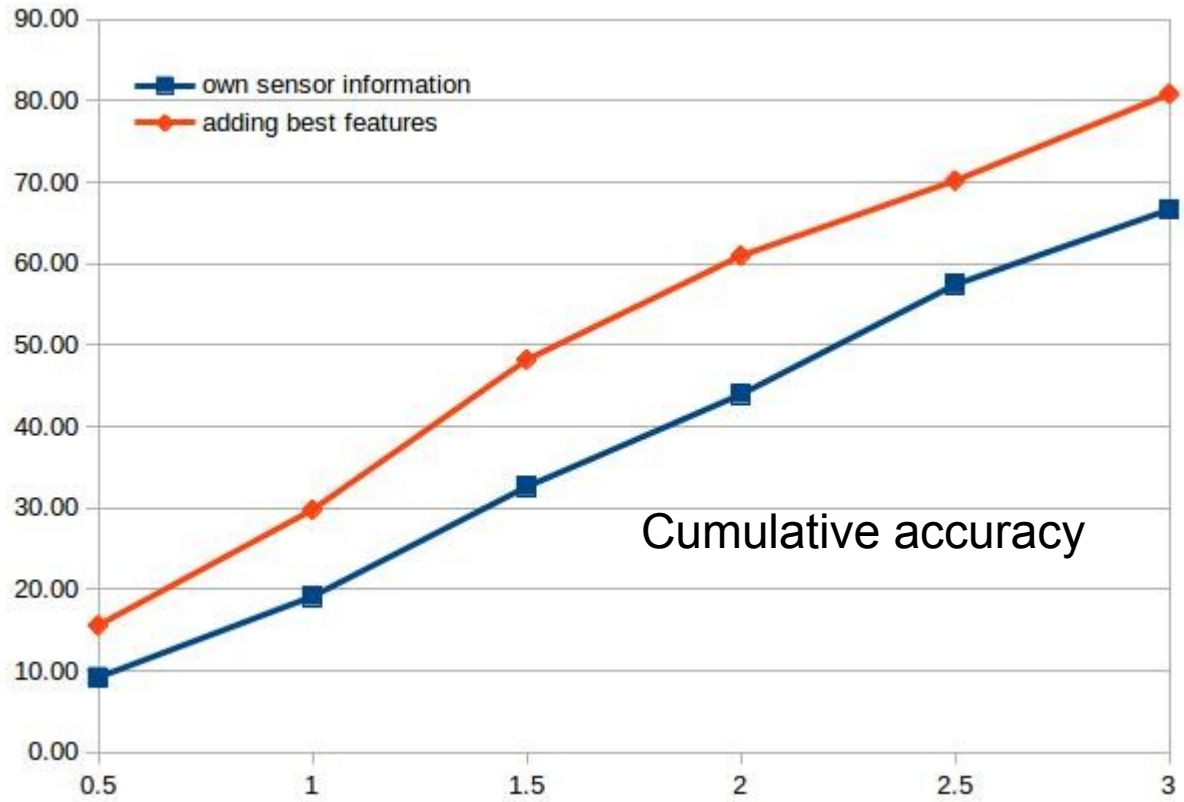


location	dataset	days	alg	ntree	mtry	score	rmse	r2	sensitivity	accuracy	precision	specificity
Junin	dacc-temp	2	rf	1500	23		2.17	0.9	**0.84**	0.94	**0.7**	0.95
Junin	dacc-temp	2	hc			loglik-g	2.14	0.9	**0.77**	0.94	**0.76**	0.97
Agua Amarga	dacc-temp	3	tabu			bge	2.23	0.89	**0.81**	0.93	**0.73**	0.95
Agua Amarga	dacc-temp	1	rf	2000	11		2.24	0.88	**0.85**	0.93	**0.73**	0.95
Tunuyan	dacc	2	hc			bge	2.59	0.87	**0.85**	0.91	**0.87**	0.94
Tunuyan	dacc-temp	1	rf-local	2500			2.97	0.83	**0.88**	0.9	**0.81**	0.91
La Llave	dacc	3	hc			loglik-g	2.94	0.85	**0.84**	0.9	**0.76**	0.92
La Llave	dacc	3	rf-local	1500			2.97	0.84	**0.86**	0.91	**0.75**	0.92
Las Paredes	dacc	2	tabu			aic-g	2.82	0.84	**0.79**	0.91	**0.73**	0.93
Las Paredes	dacc-temp	1	rf	1500	15		3.08	0.81	**0.79**	0.91	**0.72**	0.93

- Regression problem:
minimum daily temperature prediction
- Supervised machine learning (ML) approach
- Feature selection using conditional mutual information:
    - to simplify the ML model
    - to help nodes/sensors to decide which neighbors are important (routing schemes)
- The most important features help to improve accuracy of prediction







To be published soon

Fórmulas empíricas

$T_{min} = T_w(t) - a\,T(t) - b$	Ångström: 1920, 1921, 1923.
$T_{min} = T_w(t) - \frac{1}{4} \times (T_d(t) + a)$	Allen: 1957.
$T_{min} = T_d(t) - a$	Pick: 1928.
$T_{min} = T_d(t) + ae(t) - b$	Ueki: 1950.
$T_{min} = a\,T(t) + b\,T_d(t)$	Peatfield: 1937.
$T_{min} = a\,T(t) + b\,T_d(t) + c$	Flower y Davies: 1934. MacDonald: 1939.
	Jefferson: 1951.
náx)] + e	Boyden: 1937.
náx)] + f(v, n)	McKenzie: (citado por Sutton: 1953).

133

$T_{min} = T_d(t) + a + bf(t) + cf^2(t)$	Smith et al.: 1920.
$T_{min} = T_d(t) - \frac{f-a}{4}$	Donnel: 1912.
$T_{min} = T_d(t) - \frac{f-a}{4} + Vd + Vh$	Young: 1920.

en donde T_{min} significa temperatura mínima propuesta de $T_d(t)$

$$\text{Brunt}: \quad T(t_{\text{sunset}} + \Delta t) = T_{\text{sunset}} - 0.129 \frac{2}{\sqrt{\pi}} R_{\text{L}}\uparrow \frac{\sqrt{K\Delta t}}{k} \tag{1}$$

where T_{sunset} is the temperature at sunset (°C), t_{sunset} the sunset time, K the soil thermal diffusion coefficient ($\text{m}^2\,\text{s}^{-1}$), k the soil thermal conductivity coefficient ($\text{W m}^{-1}\,{}^\circ\text{C}^{-1}$), $R_{\text{L}}\uparrow$ the long-wave radiation balance (positive if outgoing) (W m^{-2}) and Δt is the time elapsed from sunset (h).

$R_{\text{L}}\uparrow$ in Brunt's equation has been calculated in two different ways (eqs. 2.1 and 2.2):

$$\text{Brunt}: \quad R_{\text{L}}\uparrow = \sigma T^4 (a_0 - b_0\sqrt{e})(1 - ac) \quad (\text{W m}^{-2}) \tag{2.1}$$

$$\text{Swinbank}: \quad R_{\text{L}}\uparrow = 5.31 \times 10^{-13}\, T^6 \quad (\text{W m}^{-2}) \tag{2.2}$$

where σ is the Stefan–Boltzmann constant ($=5.671 \times 10^{-8}\,\text{W m}^{-2}\,\text{K}^{-4}$), T the temperature (K), a_0 and b_0 are the constants, respectively = 0.526 and 0.0065, a the constant depending on cloud type, c the sky cover (in 10ths) and e is the vapour pressure (Pa):

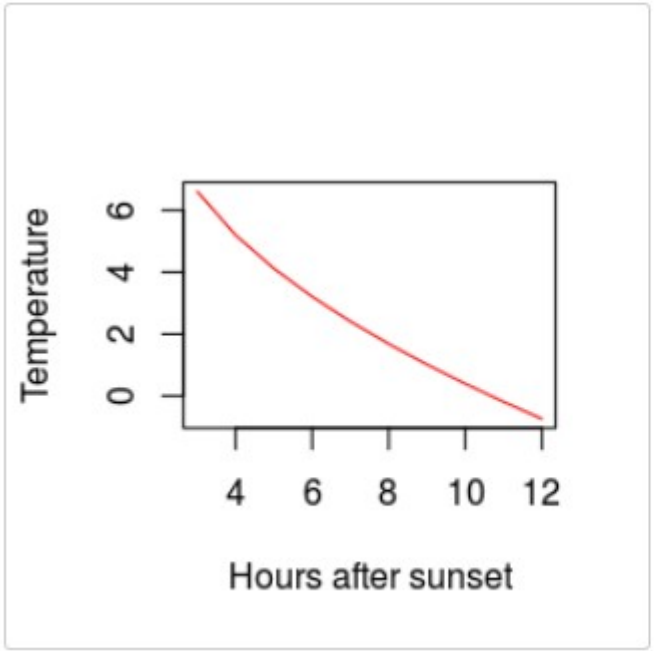
Empirical formula used in Mendoza

The empirical formula for estimating the minimum temperature is $T_{min} = \frac{T_{max}+T_{dew}}{2} - K$. For calculating K, we call `buildMdz` function. Then for prediction we use `predMdz`.

```
# just an example
dw <- c(-2,-5,2,6,8)
tempMax <- c(10,20,30,25,29)
tmin <- c(-1,-2,3,5,10)
out <- buildMdz(dw,tempMax,tmin)
print(out)
#> $model
#>
#> Call:
#> lm(formula = tmin ~ ., data = as.data.frame(dd))
#>
#> Coefficients:
#> (Intercept)           dw      tempMax
#>     -0.2365       0.7847       0.0800
#>
#>
#> $k
#> [1] -9.3
#>
#> $kmean
#> [1] -9.3
predMdz(dw = -3, tempMax = 15, K=out$k)
#> [1] 15.3
```

```r
# We use the results of the model to have the coefficients for the formula
current_temp <- 10
current_dw <- 2
ptmin <- predFAO(out$a,out$b,out$c,current_temp,current_dw)
cat("The predicte minimum temperature is ",ptmin," °C")
#> The predicte minimum temperature is  -0.7409219  °C

# We plot the temperature trend, we have 12 hours until sunrise
getTrend(Tmin = ptmin ,t2 = current_temp,n = 12,plot=TRUE) # in °C degress
```



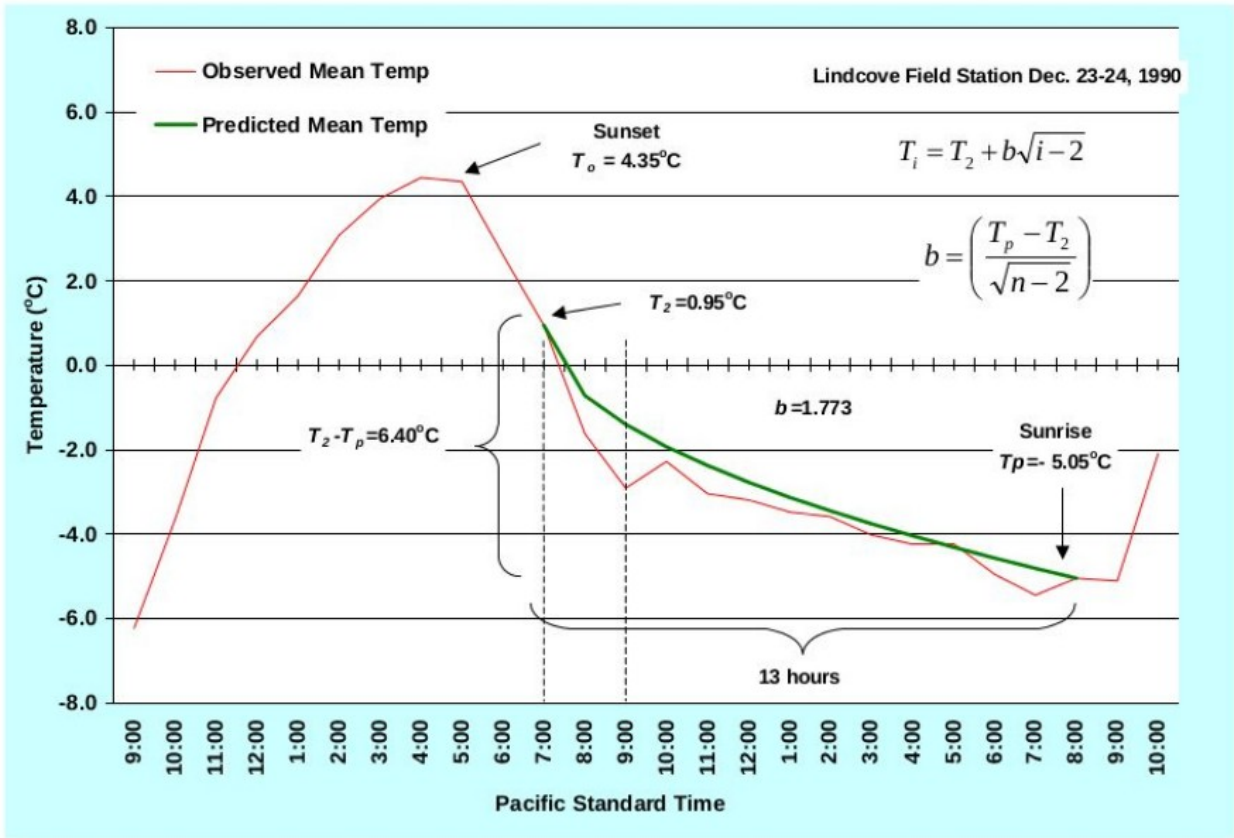


Figure 8. Observed and predicted hourly mean temperatures (°C) during a radiation freeze on December 23, 1990 at the University of California Lindcove Field Station.

We can use the output of `plotTrend` to plot using other libraries such as ggplot2.

```
library(frost)
var <- getTrend(Tmin = -5.45,t2 = 0.95,n = 15) # in °C degress
require(ggplot2)
#> Loading required package: ggplot2
# just plotting points
ggplot(var,aes(x=x,y=y)) + geom_point(color="blue")
# add trend line
ggplot(var,aes(x=x,y=y)) + geom_point() + geom_smooth(color="red")
#> `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```